

**Motivating student engagement: Strategies
to enhance waste sorting behavior in student
housing**

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Preface

The culmination of my master's thesis marks the conclusion of my time as a master student in the Netherlands. The period dedicated to working on the thesis has been a significant chapter in my master's journey in the Netherlands. Ultimately, it represents a noteworthy milestone in my life.

At this stage, when I cast my thoughts back to the period during which I worked on my thesis, there are specific individuals I would like to acknowledge with deep gratitude. Firstly, I want to express my deep gratitude to my thesis committee. Zhaowen Liu, my first supervisor, guided me through the maze of my thesis, igniting my passion for the subject. Her patient explanations, consistent support, and encouragement was invaluable. I sincerely appreciate her contributions. I also extend my heartfelt thanks to Dr. Tong Wang, my second supervisor, for her unwavering support and uplifting presence throughout the challenges of this journey. Her cheerful demeanor added positivity to the experience. Lastly, I'm grateful to Dr. Daan Schraven, our committee chair, for providing essential feedback and insights that have played a pivotal role in helping me refine my thesis.

I want to express my gratitude to all who participated in the interviews and filled out the questionnaire. To the interviewees, your insights were invaluable in shaping my thesis. To those who completed the questionnaire, your time and effort meant a lot to me.

Lastly, I want to express my heartfelt thanks to my parents for their unwavering support even across the miles. Their selfless love has illuminated my darkest moments during my master's journey. I'm also appreciative of my friends in China. Our frequent conversations make it feel like they are physically by my side. I eagerly anticipate returning to China to have a wonderful time with them. And not to be forgotten, my friends in the Netherlands have provided me with abundant support and joy. The memories of our study sessions, leisure activities, and shared laughter will forever stay with me. I nearly forgot to thank myself:

"You know you do a great job today, every day as always."

Yidan Hu
Delft Library, October 2023

Executive summary

Introduction

Owing to urbanization and population growth, the increasing generation of waste draws much more attention to Municipal solid waste management (MSWM). Sorting waste is a crucial aspect of MSWM that can improve waste quality, subsequently boosting recycling rates. This drives forward the circular economy process and contributes to the fulfillment of the European Union's goals regarding the reuse and recycling of municipal solid waste.

Despite the city producing a substantial amount of waste, only a limited portion is being separated and recycled (Owusu et al., 2013). Zooming in on the regional level in the Netherlands, it is observed that there is significant variation in household waste separation rates, ranging from a low of 45% to a high of 74% in 2021 (CBS Statline, 2023). The unsatisfied performance in household waste sorting can be attributed to several factors, notably the insufficient involvement of citizens in the sorting process. When it comes to involving citizens in sorting household waste, there has been limited research and exploration of the waste sorting behavior of college students. Within society, college students, as a young and well-educated group, possess the potential to play a substantial role in promoting engagement in household waste sorting. Additionally, given that the majority of college students reside in student housing, it is essential to investigate their waste sorting practices within this specific housing context.

Research Objective and Question

The objective of this research is to understand college students' waste sorting behavior in student housing and recommend interventions that motivate students to engage in waste sorting. To achieve the research objective, the main research question is formulated as:

How to motivate college students to participate in waste sorting within student housing?

Research Methodology

The research employed a mixed research methodology that incorporated both qualitative and quantitative approaches in a sequential manner. The objective is to refine and focus on the factors that truly impact students' waste sorting behavior within student housing, moving from a broader context to a more specific one.

It started with semi-structured interviews as part of the qualitative research phase. The aim is to tailor the generic factors identified in the literature review to the research context and confirm their relevance in relation to students' waste sorting behavior within student housing. Furthermore, thematic analysis was employed to examine the transcribed semi-structured interview transcripts, supplemented by two rounds of coding, which included deductive and inductive coding. The final qualitative results were used to formulate the hypothesis and construct the questionnaire for the subsequent quantitative research phase.

In the quantitative research phase, an online questionnaire survey was employed to identify the specific factors that significantly influence waste sorting behavior among students living in student housing. This phase utilized the partial least squares structural equation modeling (PLS-SEM) method to validate hypotheses and quantify the relationships between these specific factors and waste sorting behavior. Specifically, the PLS-SEM analysis involves the evaluation of both the measurement model and the structural model. Once the criteria for the measurement model are met, ensuring the data's reliability and validity, the examination of the structural model can proceed. A valid conclusion can be reached only if both the measurement model and the structural model meet the criteria.

Results

The qualitative research revealed tailored factors that could potentially impact students' waste sorting behavior within the student housing. These factors include a mix of certain generic factors obtained from the literature review and newly identified factors from the semi-structured interviews. They encompass psychological factors such as attitudes, subjective norms, perceived behavioral control, personal norms, and knowledge, intention to waste sorting, as well as situational factors like waste sorting facilities, information publicity, and economic incentives. The qualitative findings aided in both the construction of the questionnaire and the development of hypotheses for the quantitative phase.

The quantitative results include the validation of hypotheses and the quantification of the significant relationship between specific factors and waste sorting behavior. The quantitative findings confirm that subjective norm and perceived behavioral control exert a significant influence on students' intention to sort waste, with correlation coefficients of 0.208 and 0.242, respectively. Additionally, students' waste sorting behavior is directly impacted by their intention to sort waste, the availability of waste sorting facilities, and the extent of information publicity, with correlation coefficients of 0.224, 0.217, and 0.288, respectively.

Academic Implications

This research has several academic implications. In terms of theory, it extended the Planned Behavior Model (TPB) by integrating both the Norm Activation Model (NAM) and the Attitude-Behavior-Condition Model (ABC). This integration was designed not only to address the limitations of the TPB but also to offer a more holistic perspective on waste sorting behavior. Furthermore, this integrated model has the potential to analyze various other pro-environmental behaviors.

Regarding the methodology, this research used semi-structured interviews in an innovative way to both validate and explore under-explored research questions. Specifically, from a validation perspective, these interviews served the purpose of confirming factors identified in the literature review within a specific context. From an exploration perspective, the newly identified factors that have emerged from inductive thematic analysis contribute fresh insights to the TPB framework when applied to the context of college students.

Furthermore, in terms of the PLS-SEM method, this research utilizes refinement procedures akin to the modification process seen in CB-SEM as an innovative approach to enhance the original research model. This refinement aims to improve the performance of the original PLS-SEM model and draw valid conclusions.

Practical Implications

The practical implications are determined by taking into account the key factors that impact the waste sorting behavior of college students. These factors include situational aspects like information publicity and waste sorting facilities, as well as psychological factors such as the subjective norms and the perceived behavioral control.

First of all, the findings found that improving information publicity within student housing has the strongest influence on students' waste sorting behavior. This can be achieved by prominently displaying informational prompts in common areas of student housing, such as elevators and entrances. Placing these prompts near waste sorting facilities also holds the potential to capture the attention of students and encourage them to engage in waste sorting. Additionally, waste sorting information can be more extensively distributed via social media platforms like Facebook managed by the student housing organization.

Secondly, the results indicated that improving waste sorting facilities directly encourages student participation in waste sorting. This can be accomplished by ensuring convenient access to communal waste sorting facilities and maintaining their cleanliness. Additionally, for private waste sorting facilities, it would be advantageous to equip each room with compactable waste bins capable of accommodating different types of waste to ensure both accessibility and ease of waste sorting.

Finally, the results indicate that raising the intention of college students to sort waste can boost their chances of actually participating in waste sorting. This can be done by strengthening the sense of social norm within student housing, where the manager regularly assesses waste sorting facilities and keeps students informed about their waste sorting efforts. Additionally, integrating waste sorting education into the college curriculum can enhance the perceived level of control over this behavior.

Limitations

The research has several drawbacks. The primary limitation is the relatively small sample size. Although the sample size is adequate for analyzing the refined PLS-SEM model in this research and obtaining valid results, it remains somewhat limited for assessing the complex PLS-SEM model and delivering reliable and valid outcomes.

Moreover, the use of waste sorting facilities as a proxy for individuals' perceptions, rather than an accurate reflection of the facilities themselves. This divergence in perception has the

potential to introduce measurement bias. Similarly, the assessment of waste sorting behavior relies on self-reports rather than direct observation, which could also introduce measurement bias.

Furthermore, the qualitative analysis does not incorporate the concept of waste sorting habit, since habit in this research is perceived as predominantly arising in response to regulations, indicating the significant impact of social pressure. However, there are constraints in omitting habit as an individual factor rather than incorporating it, as doing so could provide fresh perspectives for better understanding waste sorting behavior.

Further recommendations

There are several suggestions for future research. Firstly, it is crucial to explore methods for translating waste sorting intentions into actual behavior. Secondly, incorporating additional socio-demographic factors, such as academic faculty and country of origin, could provide deeper insights into waste sorting behavior. Finally, validating the proposed intervention through simulation methods in future studies would be advantageous.

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List of acronyms

ABC	Attitude-Behavior-Condition Model
ATT	Attitude
AVE	Average variance extracted
CBS	Centraal Bureau voor de Statistiek
CB-SEM	Covariance-Based Structural Equation Modeling
CEAP	Circular Economy Action Plan
EI	Economic Incentives
HTMT	Heterotrait-Monotrait
IP	Information Publicity
ISB	Infrastructure, service and behavior model
KN	Knowledge
LM	Linear Model
MICOM	Measurement Invariance of Composite Model
MSW	Municipal Solid Waste
MSWM	Municipal Solid Waste Management
NAM	Norm Activation Model
PBC	Perceived Behavioral Control
PLS-SEM	Partial Least Square Structural Equation Modeling
PMD	Plastic Packaging, Metal Packaging and Drinking Cartons
PN	Personal Norm
RMSE	Root Mean Squared Error
SEM	Structural Equation Modeling
SN	Subjective Norm
TPB	The Theory of Planned Behavior
VBN	Value Belief Norm
VIF	Variance inflation factor
WCS	Waste Collection System
WFD	Waste Framework Directive
WSB	Waste Sorting Behavior
WSF	Waste Sorting Facilities
WSI	Waste Sorting Intention

1. Introduction

This chapter is structured into five sections. [Section 1.1](#) provides an overview of the research background, including Municipal Solid Waste Management (MSWM) and related policies. Subsequently, [Section 1.2](#) highlights the present problems in waste sorting. Following this, [Section 1.3](#) identifies the gaps in existing research. Considering the identified problems and gaps, [Section 1.4](#) outlines the research objectives and questions. Lastly, [Section 1.5](#) presents the research outlines and design flow.

1.1 Background

The increasing generation of waste due to rapid population growth and urbanization draws more and more attention to waste management. Waste management aims to ensure clean and hygienic living conditions and protect the environment by minimizing waste generation at the source and maximizing recycling efforts (Demirbas, 2011). To be more specific, as illustrated in Figure 1, municipal solid waste management (MSWM) involves various interrelated activities, from the beginning of the waste generation, collection and transportation, and treatment, to final disposal (Demirbas, 2011; Larsen, 2009). Improper MSWM leads to negative impacts on the environment and human health. In terms of the environment, improper waste disposal pollutes the air, soil, and water (Alam & Ahmade, 2013). For example, uncontrolled dumping of waste leads to the contamination of the soil and water, and inappropriate incineration of waste results in air pollution (Alam & Ahmade, 2013). Moreover, significant amounts of greenhouse gases are produced when waste is incinerated or breaks down in landfills (Alam & Ahmade, 2013), contributing to global warming. Regarding human health, waste directly influences the health of the employee who works with the waste facilities, such as composting facilities (Domingo & Nadal, 2009; Giusti, 2009), and indirectly affect the residents who live near the waste facilities. The environmental issues and the human health problems caused by improper handling of waste highlight the significance of municipal solid waste management (MSWM).



Figure 1 Municipal solid waste management (MSWM)

Waste management holds significant importance within the circular economy as it plays a vital role in recovering used materials through recycling (Salmenperä et al., 2021). Furthermore, the circular economy aims to not only promote the effective utilization of resources, but also simultaneously addressing environmental challenges and boosting economic growth (Ghisellini et al., 2016; Kirchherr et al., 2017). Ultimately, the circular economy strives to deliver

advantages across the economy, environment, and society (Ghisellini et al., 2016). The circular economy concept involves shifting from a linear model of material usage to a more sustainable and circular one (Lieder & Rashid, 2016). In specific, the linear economy model “take-make-dispose” exacerbated the natural resources depletion issues and the waste generation pressure (Zhang et al., 2022). Contrary to the linear economy, the circular economy aims at closing the loop involving minimizing waste generation and utilizing the waste as a resource to some extent by implementing reduce-reuse-recycle (3Rs) principle (Yuan et al., 2008; C. Zhang et al., 2022). In March 2020, European Commission implemented the new Circular Economy Action Plan (CEAP) to promote the circular economy process (European Commission, 2020). The action plan highlights the need for an improvement in waste policy to prevent waste and promote the circularity of the material.

The EU's waste policy utilizes the Waste Framework Directive (WFD) as a legal framework to manage and treat waste in the EU (European Commission, 2018). The WFD introduced the "Waste hierarchy" which outlines the preference order for waste management methods, as illustrated in Figure 2. Compared to the “3R” rules in the circular economy, the waste hierarchy involves prevention of the waste as the most preferable choice and disposal of waste as the least preferred option in waste management. The waste hierarchy provides a structured framework that outlines the movement of materials through various interconnected stages of waste management, and its impact on waste management is substantial (Gharfalkar et al., 2015; Hyman et al., 2015). For example, the quality of waste prepared for re-use is a crucial factor that is influenced by the preceding collection stage and has implications for the subsequent recycling stage. Furthermore, in order to achieve a more efficient systems, the higher order such as the prevention and preparing for re-use should draw much attention. While prioritizing waste prevention is vital, the significant increase in waste generation requires greater focus on managing the steps that come after waste is produced. This shift in attention places more emphasis on the second tier of the waste hierarchy, which is preparing for re-use.



Figure 2 Waste hierarchy (European Commission, 2022)

Moreover, EU has established targets related to the preparation for re-use and recycling of municipal waste through the legislative framework. These targets are outlined in Figure 3, according to Directive 2008/851 (Article 11). By the year 2025, there is a requirement to increase the preparation for re-use and recycling of municipal waste to a minimum of 55% by weight from Directive 2008/851 (Article 11). To meet the reuse and recycling targets outlined in Figure 3, it is essential to enhance the efficiency of involved waste management stages, including separation, collection and transportation as well as recycling. Enhancing waste separation at its source can facilitate material reuse by preventing waste contamination and enhancing the quality of recyclable materials, consequently increasing the recycling rate. Furthermore, Chioatto & Sospiro (2023) highlighted that the importance of efficient waste separation and collection in enhancing recycling targets, as it plays a critical role in persevering the quality of the waste materials.

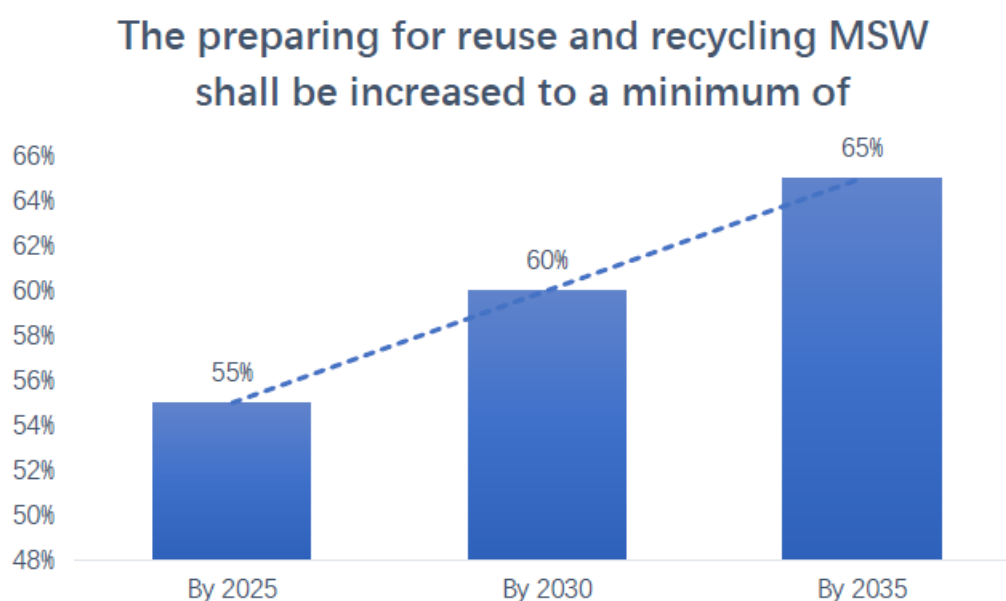


Figure 3 Municipal waste targets (Article 6,11 Directive 2008/85)

1.2 Problem statement

According to Owusu et al. (2013), a large amount of the waste are generated in the cities, but only limited amount of waste has been sorted and recycled. This phenomenon emerged in many countries. In the European countries, the recycling rate varies from different countries. According to Eurostat's data (Eurostat, 2023), the average recycling rate for municipal waste in the 28 EU countries in 2021 was 49.6%, and the Netherlands achieved a recycling rate of 57.8%. Even though the Netherlands' recycling rate as a whole was not bad, the data (Eurostat, 2023) demonstrates that the recycling rate in the Netherlands have been increasing at a slow pace from 2018 to 2021, as depicted in Figure 4. Besides that, there were significant variations in the recycling rates among different cities in the country. For instance, Amsterdam had 27% recycling rate which was the lowest in the Netherlands when the national average recycling rate was 51% in 2018 (RecyQ - Zero Waste International, 2018). To narrow the recycling rate disparities among regions and raise the overall national recycling rate, each municipality needs

to exert greater efforts in establishing an efficient waste management system, thereby reducing the discrepancies between them.

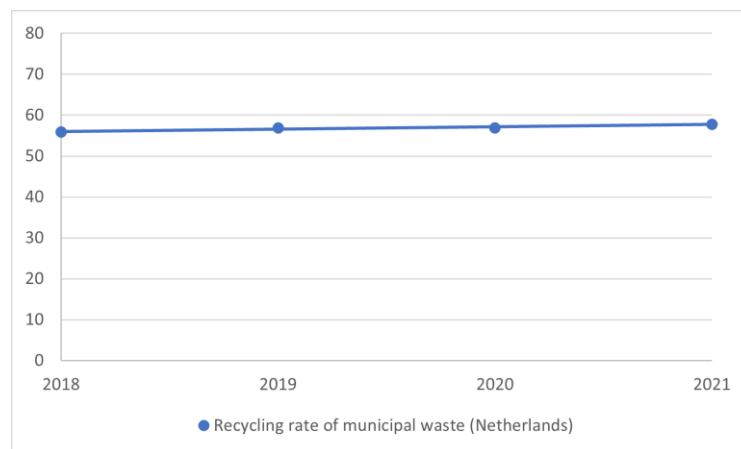


Figure 4 Dutch Recycling rate from 2018 to 2021(Eurostat, 2023)

To improve the recycling rate, waste sorting plays a necessary role. Proper waste sorting can result in higher quality and quantity of recyclable waste streams, which will contribute to effective waste recycling. Emphasized by the waste policies (European Commission, 2020), separate collection of waste should be improved by considering more perspectives to achieve a more efficient system. However, there are several issues regarding waste separated collection. Based on data from the Centraal Bureau voor de Statistiek (CBS), there is a disparity in household waste separation rates across various regions. More precisely, in 2021, Gelderland recorded the highest household waste separation rate at 74%, while Zuid Holland had the lowest

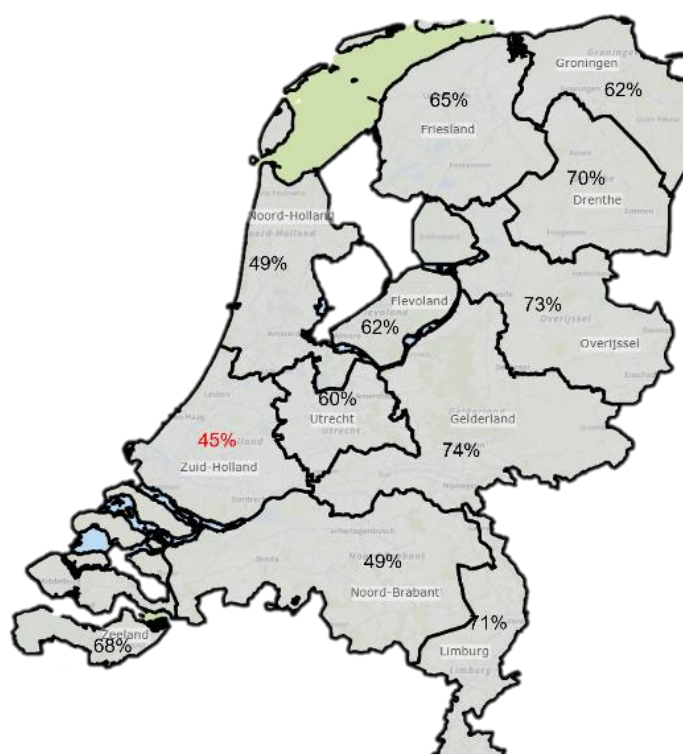


Figure 5 Dutch provinces household waste separation rate (Source: CBS, OpenStreetMap)

rate at just 45%, as indicated in Figure 5. These discrepancies among different regions suggest that the practices of waste separation collection vary among the provinces in the Netherlands.

The variation in waste separation rates across different regions in the Netherlands can be attributed to several factors, such as variations in policies (Rousta et al., 2020), disparities in infrastructure (R. Timlett & Williams, 2011) and socio-demographic differences (Miafodzyeva & Brandt, 2013). First, the policy differences can be observed through the establishment of individual legislative frameworks by Dutch municipalities. For example, according to the *Environmental Management Act, Article 10.21* (2020), each municipality in the Netherlands is responsible for collecting its own household waste. While there are slight variations in the legislative frameworks implemented by different municipalities, it is crucial that they adhere to the national policy, including the Environmental Management Act and National Waste Management Plan, in order to establish a legal framework (*Environmental Management Act*, n.d.; *National Waste Management Plan*, n.d.).

Second, there are variations in waste management infrastructures across different regions. The variation in waste production rates and the availability of resources like manpower and machinery in different regions contribute to this discrepancy (Scharff & Vogel, 1994), which can be attributed to the geographical diversity in waste properties (Dahlén & Lagerkvist, 2010). For instance, owing to the limitation of the source separation in the high-rise building and highly urbanized areas, some municipalities in the Netherlands have opted for post-separation as a more favorable option (Feil et al., 2017; *Post-Separation*, n.d.). This aspect not only entails variations in policies among municipalities but also contributes to the presence of different waste sorting facilities in different regions. Moreover, in municipalities where post-separation policies are implemented, the provision of waste sorting facilities differs among various areas within the cities. As illustration, in high-rise building, the waste sorting facility are designed to collect a limited range of waste streams, whereas in districts with other types of buildings such as detached houses, there are more options available for waste stream collection.

Third, the diverse separation rates among municipalities can also be attributed to internal factors like socio-demographic differences. Different regions are composed of distinct socio-demographic groups, and the presence of diverse socio-demographic variables, such as gender, age, and education level, results in variations in waste separation practices. For example, some researchers (Pakpour et al., 2014; Swami et al., 2011) found that age is positively associated with household waste behavior, indicating that older people might have greater availability of time or a stronger inclination to preserve resources for the benefit of future generations. However, it is equally important to recognize the role of young generations shaping waste separation practices for the future. In line with this, Miafodzyeva & Brandt (2013) conducted research that indicated a positive correlation between higher levels of education and engagement in waste sorting and recycling practices. These findings emphasize the significance of involving young and educated groups in waste sorting practices as well.

Addressing the problems resulting in the lower separation rate has become a priority task in some municipalities. Some research has found that the low waste separation rate is caused by

inadequate citizen engagement. (Robinson & Read, 2005; S. Wang et al., 2019). There are many factors contributing to the insufficient citizen engagement in household waste sorting. Some studies (B. Zhang et al., 2019b; S. Zhang et al., 2016)) have revealed that the attribute of the waste sorting facilities, such as convenient accessibility, play a significant role in influencing citizen engagement. Apart from the factor of waste sorting facilities, some researchers (Y. Ma et al., 2020; Wan et al., 2014; Wan & Shen, 2013) identified that the regulations also have an impact on motivating the citizen engagement. As a results, it is significant to thoroughly analyze these determining factors and incorporate them into an intervention strategy to promote the citizens waste sorting behavior.

1.3 Research gap

Drawing from the problem stated in the previous section, it can be inferred that motivating citizen involvement in waste sorting holds great importance. Extensive research (Czajkowski et al., 2014; Govindan et al., 2022; S. Wang et al., 2020) has focused on exploring the factors influencing citizen engagement in the household waste sorting. In contrast to the extensive research focused on the waste sorting behavior of the general citizen population, there is relatively less emphasis on investigating specific demographics, particularly young and educated groups like the college student population (Robertson & Walkington, 2009). College students possess professional skills and knowledge that facilitate their understanding and implementation of waste sorting practices (Yang et al., 2021; H. Zhang et al., 2017). As a result, college student has a potential to make significant contribution to waste sorting efforts. Moreover, college students include a significant number of international students who may bring diverse waste sorting practices from their respective cultural and social backgrounds. This diversity has the potential to result in varied waste sorting practices among the student population.

Furthermore, the majority of research of waste separation in student populations(Aikowe & Mazancová, 2021; M. Hao et al., 2020a; Liao & Li, 2019) has concentrated on on-campus, rather than within their households. In the Netherlands, there is a distinction between student waste sorting on university campuses and student waste sorting within households. The waste sorting practices on campuses fall under the private domain, and the responsibility lies with the university itself. Conversely, household waste sorting is categorized as part of the public domain and is the responsibility of the municipality. Therefore, due to the diverse waste sorting systems, there is a potential difference in waste sorting behavior observed among students between the campus and their households.

Moreover, the waste sorting facilities and regulations vary depend on the types of housing in which college students reside. A significant proportion of college students live in student housing provided by the student housing associations, primarily in high-rise buildings. As mentioned in the problem statement, these high-rise buildings have distinct waste sorting facilities and regulations as well as services compared to other types of residential structures (R. Timlett & Williams, 2011). This creates a research gap concerning how students participate in household waste sorting within the student housing.

1.4 Research objective and questions

To address the identified problems and gaps, the objective of the research is to understand college students' waste sorting behavior in student housing and suggest interventions that motivate students to engage in waste sorting. To achieve the research goal, the main research question of the study is designed:

How to motivate college students to participate in waste sorting within student housing?

To address the main research question, four sub questions are formulated, as shown below in Table 1:

Table 1 Sub questions

	Sub questions (SQ)	Method
<i>SQ1</i>	<i>What are the factors that influence household waste sorting behavior?</i>	Literature review
<i>SQ2</i>	<i>How to capture the identified factors from the literature review in the context of students living in the student housing?</i>	Semi-structured interview
<i>SQ3</i>	<i>To what extent do the specified factors impact the students' waste sorting behavior within the context of the student housing?</i>	Online survey
<i>SQ4</i>	<i>What are the implications with regard to the most salient factors of students' waste sorting behavior?</i>	Discussion

1.5 Research outline

The research is divided into six chapters. [Chapter 1](#) introduces the background, highlights identified problems and gaps, and establishes the research's objective and main question. Following that, [Chapter 2](#) presents a comprehensive literature review, including an analysis of widely recognized behavioral theories to understand waste sorting behavior. This involves identifying factors that influence household waste sorting behavior within a broader context.

[Chapter 3](#) outlines the research methodology, which includes both qualitative and quantitative methods for data collection and analysis. [Chapter 4](#) presents the findings obtained through both qualitative and quantitative approaches. [Chapter 5](#) displays the discussion of the findings in terms of the college student population and student housing context to fill the research gap. Additionally, [Chapter 5](#) explores the academic and practical implications of the research.

Finally, [Chapter 6](#) concludes the study by addressing the main research question, acknowledging the research's limitations, and offering recommendations for future research. The overall research design flow and outline are shown in Figure 6.

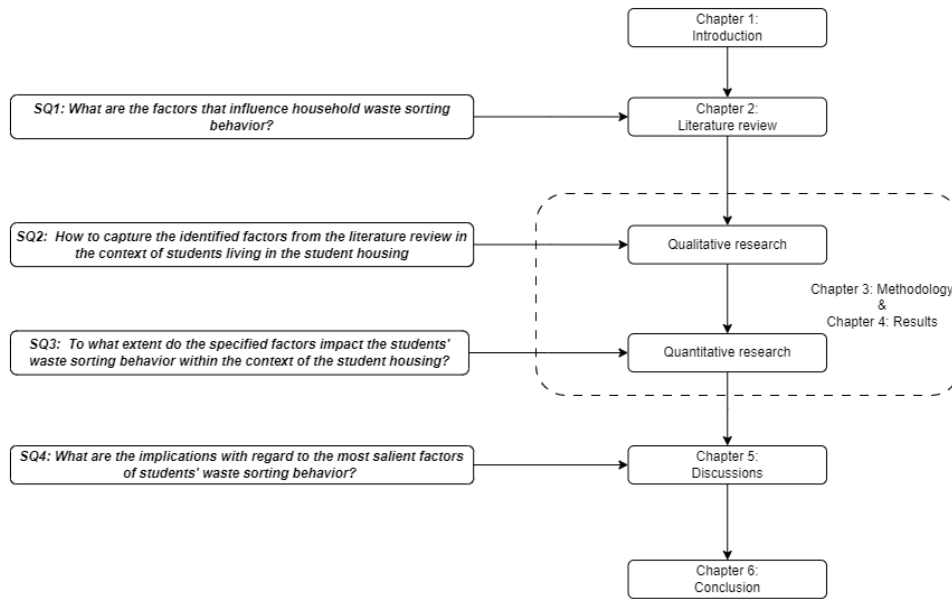


Figure 6 Research flow

2. Literature review

As one of the pro-environmental behaviors (Gong et al., 2023), waste sorting has been studied by some researchers from different theoretical perspectives (Czajkowski et al., 2014; Huang et al., 2022; Q. Liu et al., 2022). Traditionally, some behavioral scientists have adapted the psychological theoretical framework and theories to explore the factors that affected pro-environmental behavior (Raghu & Rodrigues, 2020). This is because theory contains the collected expertise about how behavior operates and the hypothesis of the causal relationship of the behavior (Davis et al., 2015; Raghu & Rodrigues, 2020). Moreover, the theory is substantiated by scientific proof and a thorough assessment. This can provide the researchers with a solid scientific foundation for comprehending behavior. However, from the systematic literature review, some scholars only analyze the relationship between specific factors without employing any theoretical theory (Ekere et al., 2009; Vicente & Reis, 2008). In this case, studies fail to provide a comprehensive analysis as it focuses only on a limited number of variables (Ertz et al., 2021). Hence, employing behavioral theory can offer researchers a comprehensive scientific framework for understanding behavior while avoiding implicit hypothesis lacking a scientific background (Davis et al., 2015; Raghu & Rodrigues, 2020).

There is no well-defined guidance for researchers to choose the appropriate the behavioral theory. Marx & Cronan-Hillix (1987) emphasized the advantage of examining various theories related to the intended behavior before choosing a specific one. Moreover, Valle et al. (2005) highlighted the significance of using an integrated behavioral theory to better comprehend this behavior. For analyzing pro-environmental behavior, the most dominant behavioral theory utilized is the theory of planned behavior (TPB) which was introduced by Ajzen (1991). However, there are other theoretical models utilized to comprehend the pro-environmental behavior, such as the Norm Activation model (Schwartz & Howard, 1981), Value-Belief-Norm (Stern, 2000), Attitude-behavior-condition (Guagnano et al., 1995).

In this chapter, it starts with the review of different related behavioral theories ([Section 2.1](#)). Subsequently, the selected theories are justified and further integrated into one main theoretical framework. Based on the integrated theoretical framework, [Section 2.2](#) provides detailed elaboration of situational factors emphasized by the attitude-behavior-condition theory. Additionally, the precise identification of situational factors aids in the definition of the waste collection system and establishes the boundary for the subsequent research. In [section 2.3](#) and [2.4](#), other additional potential factors are identified and finally incorporated into the framework. Finally, [Section 2.5](#) presents a summary as the conclusion of this main chapter.

2.1 Behavioral theory

2.1.1 Theory of planned behavior (TPB)

The theory of planned behavior (TPB) has been widely used for predicting and explaining human behavior among specific activities (Ajzen, 1991), such as ecological behavior (Kaiser & Gutscher, 2003), household recycling behavior (Babaei et al., 2015), waste sorting behavior

(Xia et al., 2021; Huang et al., 2022). When using TPB as a tool for predicting human behavior, it hypothesizes that individual behavior is driven by the behavioral intention rather than directly perform their action. And the intention is jointly affected by the three factors: attitudes, subjective norms, and perceived behavior control (Ajzen, 1991; Karim Ghani et al., 2013a; Y. Ma et al., 2020). While TPB is used for explaining human behavior, it draws upon an individual's beliefs. There are salient beliefs, including behavioral beliefs, normative beliefs, and control beliefs, that influenced individual's intentions and actions (Ajzen, 1991). Moreover, every belief serves as an antecedent to its corresponding factors, thereby aiding in the comprehension of each factor. For instance, behavioral beliefs shape one's attitude towards the behavior, normative beliefs encompass the fundamental influencers of subjective norms, and control beliefs offer fundamental perceptions of behavior control (Ajzen, 1991).

Attitude refers to how human evaluates behavior in a negative or positive way and is frequently used to examine individuals' emotions (Ajzen, 1991; Huang et al., 2022). From Fishbein & Ajzen (1975) expectancy-value model, attitude is formed rationally from the individual's belief, which are in turn linked to associated attributes of the object in general. However, when it comes to attitudes towards a specific behavior, beliefs are not only linked to the attributes of the object but also developed based on the anticipated outcomes of the behavior (Ajzen, 1991). Therefore, attitude is interpreted based on two dimensions: experiential and instrumental (Ajzen, 2002; Voss et al., 2003; Wan et al., 2017). The experiential dimension of attitude is linked to emotions and affective response. The affective dimension of the attitude implies the favorable or unfavorable evaluation of behavior. Batra & Ahtola (1991) regards this dimension of the attitude as the hedonic dimension. For example, people based on their emotions like feeling good and pleasant to do the waste sorting. While behavior is not only originated from the hedonic dimension, but also driving by the utilitarian purpose (Batra & Ahtola, 1991). This is in align with the instrumental dimension indicated from Ajzen & Driver (1992). For instance, individuals may associate waste sorting with the outcomes of the behavior such as being beneficial for the environment, thereby influence their attitudes towards waste sorting and participate in the waste sorting.

Subjective norm is a social factor that refers to the perception of the social pressure of performing the behavior. Moreover, it reflects the normative belief about the extent to which influential individuals or groups, serving as references, will engage in this behavior (Ajzen, 1991). According to McClelland's theory of needs (McClelland, 1988), Individuals are inclined to conduct the behavior approved by influential groups as they seek social acceptance within the group.

Different from other two factors of the TPB, perceived behavioral control (PBC) may directly influence the actual behavior, especially when the behavior is perceived as challenge to conduct (Ajzen, 1991; Knussen et al., 2004). According to Ajzen (1991), PBC corresponds to individual perceived self-efficacy, which means that individual perceived their confidence in the capability of performing behavior. Moreover, PBC is based on the control belief that is associated with the previous experience with the behavior and anticipating obstacles for performing the behavior (Ajzen, 1991).

In summary, these three factors from TPB can interact with each other therewith influence the behavioral intention. In general, when an individual has a strong positive attitude towards a behavior, feels substantial social pressure to perform it, and perceived greater control over it, their likelihood of intending to engage in that behavior increases (Karim Ghani et al., 2013). Wang et al. (2020) found that all factors in TPB were directly and significantly influence waste sorting intention. Khalil et al. (2017) demonstrated that all TPB factors have an impact on recycling intention. Nevertheless, the existing research has not provided consistent findings regarding the significance of attitude, subjective norm, and perceived behavior control in predicting waste sorting behavior. It remains uncertain whether all three factors are equally important or if one particular factor stands out as the most significant predictor, due to the different cases under the different social context, due to diverse cases observed across different social contexts (J. Hu et al., 2021; Stoeva & Alriksson, 2017).

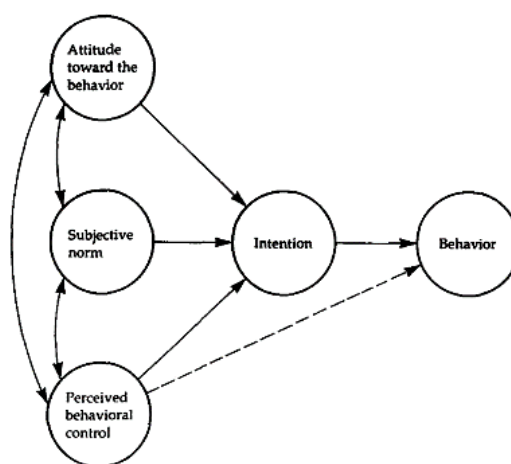


Figure 7 The theory of planned behavior (TPB)(Ajzen, 1991)

Although the TPB has been widely used, the theory has been received some criticized by some scholars. One criticism is that factors from TPB account for only 27% of the variance in behavior and 39% of the variance in behavioral intention (Wang et al., 2021). From the same study, Wang et al. (2021) indicated that TPB is capable of explaining the variance in the past behavior, but it is unable to account for most variance in the future behavior. Owing to the limitation of explanatory power, the predictive validity of TPB is insufficient and inadequate (H. Hu et al., 2018; S. Wang et al., 2020)

Moreover, some scholars have raised concerns about TPB since its focus on the subjective norms while neglecting personal norms when studying an individual's pro-environment (S. Wang et al., 2020). Subjective norms and personal norms are two normative factors that have an influence on an individual's pro-environmental behavior (S. Wang et al., 2020). Some scholars highlighted the significance of personal moral norms as an essential factor to consider when examining an individual's pro-environmental behavior (J. Li et al., 2018; B. Meng & Choi, 2016). Hence, relying solely on TPB without incorporating personal moral norms is inadequate in explaining waste sorting behavior.

Another criticism is that TPB put more weight on the intention and neglecting the discrepancy between the intention and behavior within the framework (Orbell & Sheeran, 1998; Sniehotta et al., 2014). Similar findings from other studies (S. Wang et al., 2020; X. Zhang et al., 2018) noted that there is a discordance between the waste sorting intention and the actual behavior. Despite a strong intention to sort waste at the household level, the rate of actual waste sorting is minimal (Czajkowski et al., 2014).

Lastly, TPB is argued about the emphasis on the psychological factors without considering the external factors (Boldero, 1995; Y. Hao et al., 2020). The social environment in which individuals live has constantly changes with times and became complex over time (Fan et al., 2019). This complexity can promote or constrain pro-environmental behavior (Stern et al., 1999). Thus, incorporating the external factors into the framework of TPB is significant.

Considering the limitations discussed earlier in relation to the TPB, it became essential to integrate additional variables that are relevant to the specific research context and background (Mak et al., 2019). Furthermore, incorporating insights from other psychological theories can further enhance the predictive power of the model (L. Xu et al., 2017). As mentioned by Ajzen (1991) in the theory, the TPB is a flexible framework that can be combined with other variables to account for a significant portion of variance in behavior.

2.1.2 Norm Activation Model (NAM)

According to the Matthies et al. (2012), the personal norm from the norm activation model (Schwartz, 1977) is often used to explain the pro-environmental behavior. The personal norm is the individual's anticipation of a particular behavior in the given context. It involves the awareness of the consequences that result from performing the particular behavior and experiencing a sense of responsibility for that behavior (Schwartz, 1977). According to De Groot & Steg (2009) 's findings, NAM is a mediator model, indicating that personal norms should be activated under some mediators (Figure 8). The individual must recognize that failure to engage in pro-environmental behavior will have adverse consequences for other individuals. In addition to that, the individual bears a responsibility towards others who may be affected by the negative outcomes (Concari et al., 2020). According to Miafodzyeva & Brandt (2013), residents are more likely to engage in waste sorting when they feel the personal responsibility to do so. Xu et al. (2016) supported this finding and further explained the residents acknowledged the waste sorting as the civic duty. When individuals have a moral obligation, it can reduce the perception perceived efforts or costs associated with performing the behavior (Berglund, 2006).



Figure 8 Norm activation model, adopted from (De Groot & Steg, 2009)

Furthermore, another theoretical framework for explaining pro-environmental behavior is the Value-Belief-Norm (VBN) model, which was introduced by Stern (2000). This model incorporates personal values, beliefs, norms, and behaviors in a sequential relationship, forming an integrated theory that builds upon the NAM model (Klöckner, 2013). Compared to the NAM, VBN emphasizes its value orientation that including self-interest, altruism towards other humans, and altruism towards other species and the biosphere (Stern et al., 1999). Moreover, the theory has faced criticism for the challenge of distinguishing between values, beliefs, and norms (Ertz et al., 2021; Ghazali et al., 2019). Owing to this critique and its similarities with the NAM, the theory has been excluded from the study.

Given that waste sorting behavior belongs to the moral domain (Thøgersen, 1996), merely adopting the theory of planned behavior in research cannot account for the impact of personal norm. Integrating the personal norm into the TPB model (Figure 9) is crucial as the exclusion of this factor may result in underestimation of its significance. Some scholars have integrated the concept of personal norms into the TPB model and observed that the impact of personal norms on behavior is mediated through intentions (Onwezen et al., 2013). Additionally, studies that incorporating personal norms into the theory of planned behavior (NAM-TPB) leads to a greater proportion of the variance in behavioral intentions and actions being accounted for (Harland et al., 1999; Onwezen et al., 2013). Through the application of the NAM-TPB model, Zhang et al. (2019) deduce that personal norm play the most crucial role in influencing waste sorting behavior.

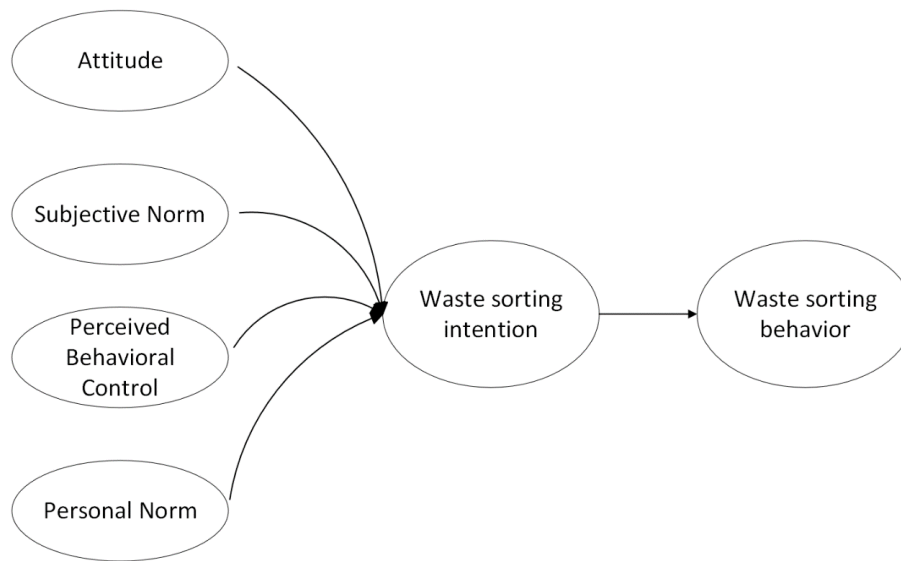


Figure 9 NAM-TPB model

2.1.3 Attitude-behavior-condition (ABC)

Stern (1987) proposed a complex causal model that the related environmental behavior is influenced by a series of interconnected external and internal factors. Subsequently, Guagnano et al. (1995) simplified the model and introduced the attitude-behavior-condition model (ABC) to predict recycling behavior, which stated that individual behavior (B) is driven by collectively individual's attitude (A) and external conditions (C). Moreover, external conditions are defined in a broad sense to encompass physical, financial, legal, and social aspects of external factors that either provide support or discourage certain behaviors (Guagnano et al., 1995).

Olander & Thøgersen (2005) states that external condition has a moderate effect on the attitude-behavior relationship. This implies that when external conditions reach extreme values, they have the potential to either enhance or diminish the connection between attitude and behavior (Miliute-Plepiene et al., 2016). For example, if the external conditions make waste sorting highly convenient and effortless, the individual's attitude towards waste sorting behavior becomes less significant. Conversely, if the external conditions make waste sorting challenging and inconvenient, it discourages people from participating in waste sorting regardless of their attitude. The conclusion from Hage et al. (2009) verified this point, showing that when external conditions make recycling easy, the significance of moral norms decreased. Furthermore, external conditions not only moderately influence the attitude-behavior relationship, but when incorporated into the TPB (TPB-ABC), they also facilitate the transformation from intention to behavior (Wang et al., 2020). Hage et al. (2008) have concluded that the external conditions play a significant role in relationship between intention and behavior. Wang et al. (2020) found that the external condition such as the incentive measures can strengthen the relationship between the intention and behavior. Accordingly, the external conditions could influence the gap between intention and behavior.

Given the emphasis placed on external conditions in the ABC theory, it is crucial to consider external factors when evaluating waste sorting behavior. Additionally, some scholars have found that incorporating external conditions into the TPB model, as in the integrated TPB-ABC model, can increase the explanatory capacity of the analyzed behavior. Zhang et al. (2022) has indicated that the separation facilities and government policies as external conditions have impact on the household solid waste separation. Similarly, Meng et al. (2019) provide evidence that the convenience of environmental facilities and services contributes mostly in promoting the waste separation behavior. Moreover, Fan et al. (2019) has demonstrated that availability of infrastructure have an impact not only on waste sorting behavior directly but also exhibit a moderated effect on the behavior.

2.1.4 Integrated theoretical framework

In summary, the majority of studies employing the TPB-ABC model in existing literature highlight the moderating effect of situational factors on the relationship between intention and behavior, as well as the direct impact on behavior. However, there is also a considerable amount of literature that analyzes the influence of situational factors on intention. As a result, the complete definition of the impact of situational factors remains varied from different studies. Therefore, based on different impact of the situational factors, the illustration of TPB-ABC model provided in Figure 10. The integration of the TPB, NAM, and ABC models is illustrated in Figure 11.

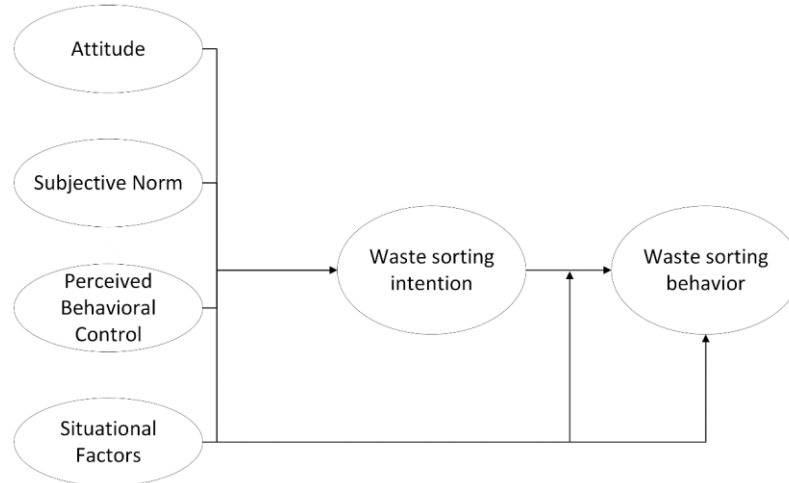


Figure 10 TPB-ABC model

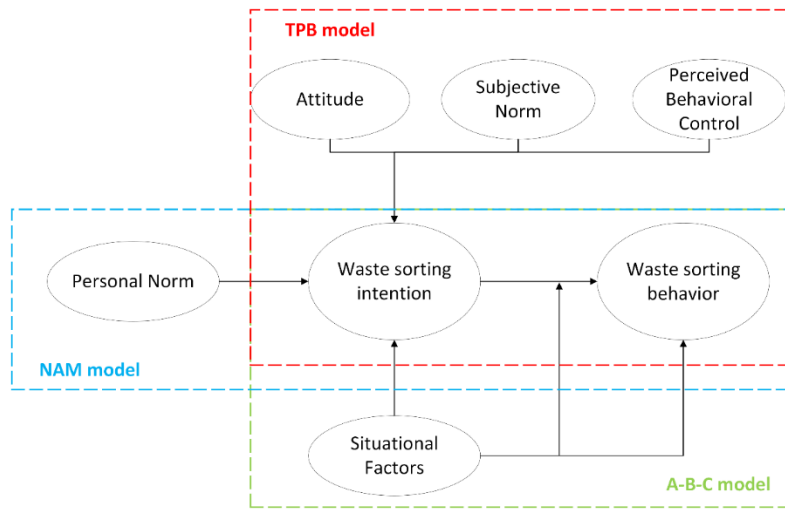


Figure 11 Integrated theoretical framework

2.2 Situational factors

The last section only introduces a concise overview of situational factor from the ABC model. In this section, a detailed exploration of specific situational factors is conducted.

Generally, the function of specific variables such as the time and space required to perform a behavior is not clearly delineated. Some scholars recognize these variables as individual factors affecting behavioral intention, labelling them as perceived convenience and effort (Fan et al., 2019; Peng et al., 2021), while others categorize them as aspects of perceived behavioral control (Liao et al., 2018). Furthermore, some scholars acknowledge the need to link these variables with associated situational factors (Zhang et al., 2019). This is because they are significant to the behavioral context, as they are closely associated with infrastructure and service provisions (Knickmeyer, 2020), while perceived behavior control and other psychological factors emphasizes the subjective perceptions and feelings (B. Zhang et al., 2019b). Moreover, B. Zhang et al. (2019) argued that perceived convenience and effort reflects the accessibility of the facilities, where accessibility of the facilities represents an objective external condition for carrying out the behavior. Overall, there is no defined guideline to determine whether these particular variables should be classified as psychological or situational. The key point is to ensure that these variables are in accordance with the research subject and scope. Therefore, in this study, the time and space variables will be designated as elements associated with waste sorting facilities to evaluate the convenience of these facilities for waste sorting.

2.2.1 Waste sorting facilities

Waste sorting facilities as important physical assets in the waste management, especially collection system management. From infrastructure, service and behavior model (ISB) introduced by Timlett & Williams (2011), waste sorting facilities as an significant situational

factor can have a positive impact on the effective recycling behavior. In this research, waste sorting facilities refer to the various types of containers used for temporarily collecting household waste disposal, including those specifically designed for waste sorting purposes. In the existing literatures, it can be generally classified by type, material and size (Bilitewski et al., 2010; Nilsson, 2010). When exploring the relationship between waste sorting facilities and the behavior, Varotto & Spagnolli,(2017) have noticed that behavior can be shaped in the desired direction through interventions on the facilities. This type of intervention is through designing the convenient and user-friendly physical asset to influence the pro-environmental behavior.

Previous studies have examined various factors associated with waste sorting facilities, including their provision, accessibility, location, and physical settings. The perceived lack of waste sorting facilities are the primary aspects that are typically discussed in the existing literature (Barr & Gilg, 2005; Chen & Tung, 2010; Khalil et al., 2017; Knussen et al., 2004). The provision of waste sorting facilities that include adequate containers for various waste streams is the fundamental condition for waste sorting. This implies that the absence of waste sorting facilities acts as a barrier for people to engage in waste sorting. According to the Chen & Tung (2010), consumers' perception of lack of waste facilities serves as a moderator, amplifying the relationship between subjective norms and recycling intentions, while simultaneously diminishing as the link between perceived behavioral control and recycling intentions. Moreover, Knussen et al. (2004) also shows that the individual perceived strong lack of waste facilities have low intention on recycling. The main discovery from Barr & Gilg (2005) indicates that having recycling bins available can enhance the likelihood of individuals who initially have no intention to recycle participating in recycling activities. This highlights the importance of presence of waste sorting facilities in promoting waste sorting behavior.

The provision of the waste sorting facilities is a premise for further designing to achieve the convenient and user-friendly physical asset. The majority of previous studies have indicated that the perceived convenience of waste facilities is closely related to their accessibility (Barr & Gilg, 2005; Varotto & Spagnolli, 2017; S. Zhang et al., 2016). The accessibility is not well-defined, as it always refers to various attributes, including the location of recycling bins (Leeabai et al., 2019) and the ease of use of the facilities (Zhang et al., 2019). The accessibility proximity is quantified by measuring the distance between individual households and waste sorting facilities (Zhang et al., 2016). In general, individuals are more inclined to participate in waste sorting when they perceive waste sorting facilities to be closer, as they perceive it requires less effort (Ando & Gosselin, 2005a; Hage et al., 2009).

Owing to the urbanization, residents live in the compactable and dense place, thereby the space for the waste sorting facilities become scarce. The related issues such as inadequate facilities for waste sorting, and lack of space to store the waste have been emerged (Barr & Gilg, 2005). Therefore, the quantity and the capacity of the waste sorting facilities attracts more consideration to promote the waste sorting behavior. Implementing size limitations on refuse bins and emphasizing the prominence of recycling bins are regarded as significant and effective nudging strategies to encourage residents to engage in recycling (Knickmeyer, 2020). However,

imposing size limitations on refuse bins can potentially result in improper waste disposal. Pattnaik & Reddy (2010) noted that the limited waste storage capacity results in the illegal dumping on the roadside.

The physical settings including the arrangement and exterior of the trash bins have been suggested as necessary factors that affect waste sorting (Jiang et al., 2021; Leeabai et al., 2019; Miller et al., 2016). According to Leeabai et al. (2019), the arrangement of the separated trash bins have the potential to affect individual's behavior in sorting waste. However, the conclusion of the same study demonstrated that arrangement of the trash bins has no significant impact on the waste sorting in practice. Furthermore, visual prompts and notifications have been noted as peripheral cues or nudge strategies to guide the behavior change (Montazeri et al., 2012). Jiang et al. (2021) suggest that incorporating preferred colors in the recycling bin could be effective in encouraging people to sort waste, as highlighted by Montazeri et al. (2012) who emphasized that using the brighter color in the recycling bins can attract people to recycle. In addition to change the color of the waste sorting facilities, providing the instructions and guidance of waste sorting knowledge around waste sorting facilities is crucial for promoting effective waste sorting. This serves as a straightforward tool of providing accurate information and preventing confusion among individuals when they sort their waste (Knickmeyer, 2020). Miller et al. (2016) found that adding information prompts above trash bins is more effective in waste recycling than not having them.

In terms of physical infrastructure, waste sorting facilities are not only considered as communal waste collection points that serve the community at a broader level, but also include the available space within individual households (Ando & Gosselin, 2005a; McDonald & Oates, 2003; Roustae et al., 2017). According to McDonald & Oates (2003), the primary obstacle faced by individuals who do not participate in waste sorting is the lack of interior space to accommodate recycling bins. Furthermore, the results obtained from Ando & Gosselin, (2005) align with this findings. Hence, the availability of storage space within the household is a significant factor influencing waste sorting behavior.

Table 2 Waste sorting facilities factors

	Factors	Literature
Waste Sorting Facilities (WSF)	Perceived lack of waste sorting facilities	(Chen & Tung, 2010; Barr & Gilg, 2005; Knussen et al, 2004)
	Distance to the waste sorting facilities	(Ando & Gosselin, 2005; Hage et al., 2009)
	Quantity and capacity of the waste sorting facilities	(Pattnaik & Reddy, 2010; Knickmeyer, 2020)
	Colors of waste sorting facilities	(Montazeri et al., 2012; Jiang et al., 2021)
	Information prompts around the waste sorting facilities	(Miller et al., 2016)
	Available waste storage space within household	(Ando & Gosselin, 2005; McDonald & Oates, 2003)

2.2.2 Waste collection services

According to the ISB model mentioned earlier (Timlett & Williams, 2011), waste collection services are also significant situational factors that influence the waste sorting behavior. Waste collection services that need to be customized to suit the specific conditions of the area, the types of waste being collected, and other logistical considerations (Bilitewski et al., 2010). In general, waste collection services are supplied by waste management company or the local municipality agency, which entails the frequency of collection, management of the waste sorting facilities, and transportation. However, these waste collection services do not directly determine individual's waste sorting behavior. The characteristic of the services (i.e., convenience) and the outcomes of the services (i.e., cleanness of the collection sites) are the decisive factors that directly influence people's engagement in the waste sorting process.

In general, there are two primary types of collection services commonly utilized in most countries: curbside collection system and drop-off system (Bilitewski et al., 2010; Rodrigues et al., 2016a). Folz (1991) found that participation rate in the curbside collection system was more than the drop-off system. This finding emphasizes the significance of convenience in curbside collection system. In addition to the aforementioned service, some management company offer services like door-to-door collection service in person to save time for the residents (Tong et al., 2023). Regardless of the types of waste collection services, its purpose is to offer convenience to the residents. As a result, the types of waste collection services have no effect on waste sorting behavior.

The cleanness of collection sites has been identified as an important situational factor. In terms of the cleanness of the collection sites, some scholars found that the litter and over-full container leading to unhygienic and unattractive waste collection sites, which demotivate people to sort their waste (Miafodzyeva & Brandt, 2013; Petersen & Berg, 2004). To ensure the environmental condition of sorting facilities, the frequency of waste collection and the management of the waste collection becomes significant factors. Gellynck et al. (2011) mentioned that higher frequency of waste collection leading to the cleanliness of waste sorting facilities and thereby motivating recycling behavior. Theoretically, a higher frequency of collection can contribute to maintaining a clean environment in the facilities, thereby influencing waste sorting. However, the frequency of waste collection is not only determined by the volume of waste produced but also by factors such as the capacity of the trash bins, and the associated costs and labor. In practice, taking labor and costs into account, the frequency of waste collection regarding to the curbside collection is fixed and tailored according to the specific needs of each local area. For example, there are two types of collection frequency in England: alternate weekly collection and fortnightly collection (Wilson & Williams, 2007). Given the fixed collection schedule, the punctuality of waste collection becomes more significant to ensure the environmental condition of waste sorting facilities. As a result, instead of the frequency of waste collection, the timely and reliable waste collection service is a factor (Tabernero et al., 2016). Furthermore, the proper management of the waste sorting facilities also ensure the cleanliness. Consequently, based on reliable waste collection services, the presence of a clean and organized environment within these facilities fosters and encourages waste sorting behavior.

Table 3 Waste collection services factors

	Factors	Literature
Waste Collection Service	Cleanliness of collection sites Timely and reliable waste collection services	(Petersen & Berg, 2004; Gellynck et al., 2011) (Tabernero et al., 2016)

2.2.3 Public policy instruments

Public policy instruments proposed by government institutions at all levels (community, municipal, provincial, regional, national, and supra-national) are a significant external factor that influence waste sorting behavior (Concari et al., 2020; Knickmeyer, 2020). The public policy instrument includes regulation, information instruments and the incentive instruments (Y. Ma et al., 2020). Moreover, several studies have found that the implementation of the policy instruments has the potential to shape individual behavior (Wan & Shen, 2013; H. Wang et al., 2021).

2.2.3.1 Information and Education

The lack of knowledge is widely regarded as a significant barrier for waste sorting, but education and informative programs have been suggested as an effective intervention to address the problem (Knickmeyer, 2020; Miafodzyeva & Brandt, 2013). Through these programs, government can develop moral responsibility and spread of environmental values and knowledge to raise residents' awareness, thereby shape residents' behavior (Hage et al., 2009). According to Iyer & Kashyap (2007) have found that the recycling program can provide residents with proper information regarding the recycling and thereby change their attitude towards waste recycling behavior. Moreover, Concari et al. (2020) emphasized the critical role of an information program in facilitating the dissemination of the regulation.

Even though the majority of studies agreed on that the information and education program have a positive influence on the recycling behavior (Steg & Vlek, 2009; Wan et al., 2014), it is worth to notice that not every information could be successful. This is due to the dependency on the content of the information (Iyer & Kashyap, 2007; Knickmeyer, 2020). Information should be carefully customized and accurate for the targeted recipient to prevent any discomfort. Furthermore, it would be beneficial to provide residents with information about the waste sorting knowledge and regulations. Spreading the information should not only limited to education and informative programs. It also extends to various social media channels, such as TV, newspaper and the Internet (Knickmeyer, 2020; J. Ma & Hipel, 2016). From this perspective, information delivery can be considered as one of the communication strategies (Iyer & Kashyap, 2007). The communication strategies developed from the conventional means, such as mailing, newspaper, leaflet, to the Internet media, such as television, mobile phone (Varotto & Spagnolli, 2017). In contrast to conventional methods, the Internet allows for the rapid dissemination of information. Ma & Zhu (2021) have concluded that distributing the waste classification information through the Internet media is significant.

2.2.3.2 Incentives instruments

Furthermore, most scholars emphasized that incentive instruments including the material incentives and economic motivations to promote the pro-environmental behaviors (Luo et al., 2020). Incentive instruments including the taxes, subsidies, deposit-refunds motivate the individual's waste sorting (Y. Ma et al., 2020).

In many countries, various forms of local tax are used to finance waste collection system (Miafodzyeva & Brandt, 2013). One commonly utilized waste charge is unit pricing, which includes two primary types of waste charge systems: volume-based and weight-based billing. These types of waste charges not only serve as a means of financial support for waste collection systems (Bilitewski et al., 2010), but also contribute to regulating behavior to some degree. For example, weight-based schemes can be effective to promote the waste minimizing behavior (Dahlén & Lagerkvist, 2010; Hage et al., 2009) and deal with the illegal dumping problem (Hage & Söderholm, 2008). However, there is no evidence to support that implementing taxation can promote waste sorting behavior (Miafodzyeva & Brandt, 2013). Instead of implementing taxation, an alternative approach could involve reducing or exempting waste taxes as an incentive to encourage waste sorting behavior (Y. Zhang et al., 2022).

Economic incentives always refer to the benefits, such as money, coupon, obtained from residents when participating in recycling programs (Schultz et al., 1995; Varotto & Spagnolli, 2017). The findings regarding the implementation of economic incentives as a tool to promote waste sorting behavior are not always consistent. Few studies shown that there is no correlation between the economic incentives and the waste sorting behaviors (Allen et al., 1993; R. E. Timlett & Williams, 2008). While other research has found that the economic incentives can be effective intervention to foster waste sorting behavior (C. J. Li et al., 2017; L. Xu et al., 2018). For instance, numerous waste separation programs have been initiated in various cities across China. Typically, households can earn rewards based on their performance in participating in these programs. Additionally, the findings have confirmed the effectiveness of this type of intervention (C. J. Li et al., 2017; L. Xu et al., 2018). This can be attributed to the fact that external rewards make a behavior more attractive and thereby promote behavior (Geller, 1989; Schultz et al., 1995). Apart from that, economic incentives also serve as a form of feedback that validates individuals' performance and can potentially enhance their motivation to contribute (Thøgersen, 2005; L. Xu et al., 2018).

However, there are some arguments of this kind of recycling programs. Firstly, some scholars noticed that the external economic incentives offered by the program diminish the internal motivation for waste sorting (ölander & Thøgersen, 1995; Phulwani et al., 2020). This might result in individuals heavily depending on external financial rewards, leading these programs only produce short-term effects. Once the program finished, external incentives taken away, people who are motivated by the external incentives have no justification to perform this behavior (Burn, 1991; Schultz et al., 1995). Lastly, scholars who have done the cost-benefits analysis of the behavior found that the expense associated with implementing such interventions consistently outweigh the economic advantages derived from the behavior

(Berglund, 2006; Burn, 1991; Schultz et al., 1995).

Table 4 Public policy instrument factors

	Factors	Literature
Public policy instrument (Information program)	The provision of information and education program	(Iyer & Kashyap, 2007)
	The provision of information in public places	(Ma & Zhu, 2021)
	The provision of information through Internet and social media	(Ma & Zhu, 2021)
Public policy instrument (Incentive instrument)	The provision of economic incentives	(Li et al., 2017; Xu et al., 2018)
	The reduction or exemption of waste taxes	(Zhang et al., 2022)

2.2.4 Definitions of waste collection system (WCS)

By analyzing the preceding situational factors, it is important to acknowledge that waste sorting facilities, waste collection services, and policy instruments hold significance as contextual components within this research. These situational factors are essential components of the waste collection system (WCS), but they cannot be represented for the whole WCS. This can be attributed to the complexity of the WCS, which involves complex operational challenges due to the participation of various stakeholders with different interests. Hence, it is necessary to establish a clear boundary for a WCS within the scope of this research.

WCS plays an important role in MSWM as they are responsible for collecting and transporting waste from the source to the treatment facilities after it is generated (Larsen, 2009). WCS differs across countries and regions, with local governments or private industries responsible for domestic waste collection (Demirbas, 2011). This is due to differences in waste generation rates, as well as varying levels of available resources such as labor and machinery in different areas (Scharff & Vogel, 1994). Therefore, it is important to analyze the WCS within the context of the local conditions and policies.

WCS involves multiple stakeholders with diverse interests, including local government, private parties, and citizens. Among these stakeholders, the local government is responsible for establishing waste sorting regulations, managing waste facilities, and providing collection services. Hence, the policies that govern the WCS implemented by the local government are considered a part of the WCS. Additionally, the local government can contract private companies to handle the collection of household waste. Residents are obliged to sort their waste and dispose of it in the designated waste bins.

Apart from the stakeholders, WCS contains various elements, including container and vehicle type, type of services, as well as types of residential areas (Larsen, 2009; Rodrigues et al., 2016). Specifically, containers refer to the waste sorting facilities that vary in types (i.e., bags,

underground), materials (i.e., plastic, metal), and size (i.e., small, medium, large) (Pires et al., 2019). Meanwhile, vehicle types encompass a range of trucks used for waste collection and transportation, such as rear loaders and top loaders. Regarding collection services, there are two main types: drop-off and curbside collection. Furthermore, policies and residential areas are categorized as local contexts. Consequently, WCS is defined as comprising waste sorting facilities, vehicle types, waste collection services, residential areas, and involved stakeholders. In brief, WCS is a complex system that entails interactions among various stakeholders and the utilization of physical components by these stakeholders. The breakdown structure of the defined WCS is depicted in Figure 12.

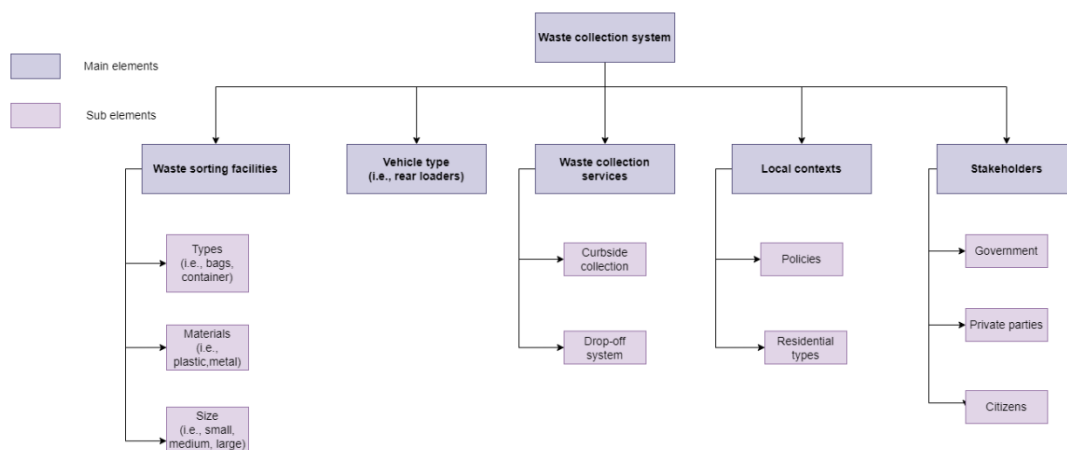


Figure 12 Breakdown structure of WCS

Given the complexity of WCS, it is crucial to narrow down the research focus to align with research goals. The study aims to gain a deeper understanding of how students living in student housing sort their waste. In this context, the primary stakeholders are the students themselves, and the primary focus is on student housing and its associated policies. Waste sorting facilities and collection services in student housing may differ from other residential types, making them important considerations in our research. However, among waste sorting facilities, only the material aspect is not identified as a potential influencer of waste sorting behavior, and it falls outside the research scope. Furthermore, attributes associated with waste sorting facilities, such as accessibility, are considered more significant within the research scope. When it comes to waste collection services, the study not only highlights the types of services but also underscores service characteristics such as timeliness and reliability as critical factors within the research.

2.3 Demographic variables

In previous studies, demographic variables have been recognized as important factors influencing the waste sorting behavior. Generally, there are five most common reported variables: gender, age, educational level, incomes, and type of dwellings (Knickmeyer, 2020; Miafodzyeva & Brandt, 2013). In practice, the correlation between these demographic variables and waste sorting behavior is not consistently observed, given that waste sorting behavior and related barriers are varied from socio-demographic and geographic (Knickmeyer, 2020). As a

result, the waste sorting behavior should be targeted at the specific social group, and the social demographic is an important factor affects the waste sorting behavior. According to the scope of the research, the research group are only focus on the college students. The potential demographic variables of the college students for analyzing the waste sorting behavior are limited. As a young generation, college students share a similar age range, with minimal variations among them. The education level of the college students does not vary greatly. In general, most college students live in the student complexes. In summary, gender will be the only demographic variable analyzed for its impact on waste sorting behavior in the study.

Oztekin et al. (2017) identified that the factors influencing intention differ between females and males, with perceived behavior control playing a key role for females and past behavior being more influential for males. Moreover, Liu et al. (2022) discovered that women generally exhibit more supportive attitudes towards waste sorting compared to men. Saphores et al. (2012) indicated that males without college education are less inclined to engage in recycling activities. Therefore, it is necessary to analyze the impact of the demographic variable, such as gender, on waste sorting behavior among college students.

2.4 Other individual factors

Apart from the individual psychological factors from aforementioned theories, there are still some individual factors that are not included when exploring the waste sorting behaviors, such as environmental concerns (Ekere et al., 2009), knowledge (Huang et al., 2022; K. Wang et al., 2021), past behaviors (Knussen et al., 2004; Oztekin et al., 2017), and habits (Fan et al., 2019; Knussen et al., 2004). This study will only integrate knowledge into the framework to examine its impact on behavior.

Knowledge about the waste sorting is significant when performing the waste sorting behavior. According to S. Wang et al. (2020), there is a significant correlation between residents waste sorting intention and their knowledge of waste sorting. Waste sorting knowledge includes not only the understanding of proper waste sorting but also includes an awareness of consequences associated with waste sorting (S. Wang et al., 2020). However, some existing studies have considered the environmental concerns as an independent variable that linked to the recognition of consequence related to waste sorting (Ekere et al., 2009; Saari et al., 2021). For example, Ekere et al. (2009) found that environmental concerns is a significant factor that influencing the waste sorting behavior. As a result, in this study, the environmental concerns will be incorporated into the knowledge factor, rather than being listed separately as an additional factor for analysis. According to S. Wang et al. (2020), waste sorting knowledge has significant impact on the waste sorting intention. Moreover, Wang et al. (2021) indicated that waste sorting knowledge has the moderating effect on the relationship between the intention and behavior. Based on that, if an individual possesses the knowledge of proper waste sorting and understand the implications of waste sorting, their intrinsic motivation towards engaging in waste sorting will be elevated.

2.5 Summary

The literature review is mainly based on three widely used behavioral theories, namely the Theory of Planned Behavior (TPB), Norm Activation Model (NAM), and the Attitude-Behavior-Condition (ABC) model. These theories each emphasize different important elements. TPB emphasizes that waste sorting behavior is driven by an individual's intention, which is influenced by the attitude, subjective norm, and perceived behavior control. While NAM highlights an individual's personal norm, which encompass their sense of responsibility and awareness of the consequences associated with waste sorting behavior. Moreover, the ABC model indicated that waste sorting behavior is strongly influenced by external conditions. Given that external conditions are just briefly introduced in the ABC model, a specific and more detailed elaboration on these external conditions has been conducted subsequently.

The external conditions discussed in the study refer to various situational factors, including waste sorting facilities, waste collection services, and public policy instruments such as economic incentives and publicity information. The literature review reveals the significant influence of these situational factors on waste sorting behavior. For instance, individuals may possess a strong intention to engage in waste sorting; however, if they perceive certain external conditions as challenging, they may not actually perform the behavior. This underscores that analyzing the influence of different situational factors becomes crucial due to the diverse effects they exert on waste sorting behavior. Specifically, some factors may moderate the relationship between waste sorting intention and behavior, while others may directly impact either intention or behavior. Subsequent, according to the identified situational factors, the waste collection system (WCS) is defined within the scope of this research, including waste sorting facilities, waste collection services, residential types, and related public policy.

Apart from the psychological factors mentioned from the behavioral theories, there are other factors could influence the waste sorting behavior. The literature review brings attention to demographic variables, such as gender, which may have different levels of psychological factors that ultimately impact waste sorting behavior. Additionally, knowledge is identified as an individual factor that has been emphasized by certain scholars for its impact on waste sorting intention. Drawing from the findings of the literature review, it can be concluded that waste sorting behavior is a multifaceted action that is impacted by various factors. The conceptual model illustrating the factors that influence student waste sorting behavior is depicted in Figure 13.

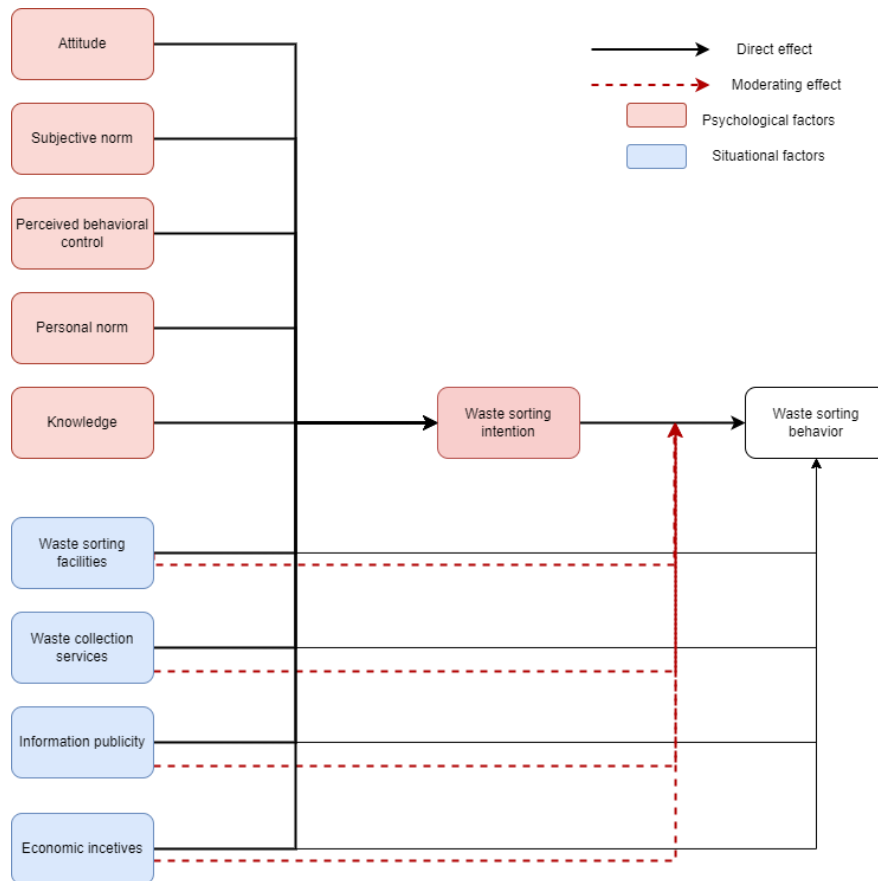


Figure 13 Theretical framework

3. Methodology

This chapter displays the methodology of the study. It starts with an introduction to the case study in [Section 3.1](#). Subsequently, [Section 3.2](#) provides a rationale for the selection and implementation of a mixed research methodology. The subsequent [Section 3.3](#), details the approach used for data collection, and [Section 3.4](#) illustrates the various methods of data analysis.

3.1 Case study

3.1.1 Case selection: Delft student housing

The city of Delft in the Netherlands (hereinafter referred to as Delft) is selected as the case study for several reasons. Firstly, Delft is situated in the province of South Holland which has the lowest separation rate among all provinces in the Netherlands. Secondly, Delft is home to a significant student population due to the presence of educational institutions. For example, in 2022, Delft University of Technology had 27,824 students (*Student Numbers at TU Delft Stable*, n.d.), accounting for approximately 26.61% of the total population of the Delft municipality in the same year (*City Population*, n.d.). The diversity within the student group offers valuable insights for the study. Notably, international students constitute 25.4% of the student population (*Facts and Figures*, n.d.). Thirdly, Delft has numerous student housing operated by different institutions. Due to various institutions, the waste sorting facilities, and the level of waste sorting information dissemination in each student housing might vary. Additionally, most of these student complexes are high-rise buildings that have different waste sorting facilities compared to those provided for regular apartment-dwelling residents, due to the limited communal space within these high-rise buildings. Even though the municipal waste collection service remains uniform across the city, the presence of various waste sorting facilities increases the complexity of the waste collection system.

3.1.2 Contextual information

In alignment with the research focuses, as outlined in [Section 2.2.4](#), the contextual information is primarily about the WCS in Delft. Hence, this section specifically focuses on the policies that regulate waste sorting and collection practices in the city, as well as waste sorting facilities and services provided in student housing. This information is collected through desk research, which involves collecting data from the official websites of the Delft municipality and student housing associations.

The Dutch government develops political instruments, such as the Environmental Management Act and National waste management plan, to provide the legal framework (*Environmental Management Act*, n.d.; *National Waste Management Plan*, n.d.). According to the *Environmental Management Act, Article 10.21* (2020), the municipalities are responsible for collecting the household waste in the Netherlands. Municipalities establish their own legislative framework that complies with the national policy on the waste collection. To obtain financial assistance for managing the collection and processing of household waste, each municipality

imposes a waste disposal tax on every household (*Waste Disposal Levy- Regionale Belasting Groep Personal*, 2022). Furthermore, municipalities have the authority to assign the responsibility of collecting to certain parties. In Delft, Avalex company is a joint arrangement that was founded by the municipalities of Leidschendam, Rijswijk, and Voorburg to collect waste on behalf of these municipalities (*Over Avalex - Avalex*, n.d.).

In terms of the waste sorting practices, MSW can be separated into six main waste streams in Netherlands. There are PMD (Plastic packaging, Metal Packaging and Drinking cartons), paper/cardboard, glass, textile, organic waste, and residual waste. In student housing within Delft, waste sorting facilities are typically provided for separating paper waste from general waste. Additionally, certain student complexes may offer additional waste sorting options, such as the separation of PMD. In contrast to low-rise building, high-rise student housing lacks organic waste disposal facilities, thus exempting students living in the student housing from the obligation of sorting organic waste (Delft Waste Regulation Implementing Decree 2020, 2021). Furthermore, some neighborhoods where student housing is located have either above or underground waste containers, designated for collecting glass and textile waste. These containers are available for use by all households, regardless of their residential types. The presence of diverse waste sorting facilities regarding waste streams in various student housing introduces complexity into the WCS for Delft student housing. Regarding the container types, the student complexes provide identical roller containers for collecting various types of waste generated by student households (Delft Waste Regulation Implementing Decree 2020, 2021). This roller container provided by the student housing is larger than the one offered to low-rise building.

Concerning waste collection services for Delft student housing, it involves not only the waste collection truck supplied by Avalex, but also the management services provided by the student housing manager. This falls with the category of curbside collection. On a weekly basis, the student housing manager transports the roller containers to a designated collection point near the student housing premises, typically one day prior to the scheduled collection. On the collection day, Avalex takes charge of emptying the waste from the containers. Once emptied, the student housing manager is responsible for returning the emptied roll containers back to the student housing. The waste collection system within the context of Delft student housing is depicted in the Figure 14.

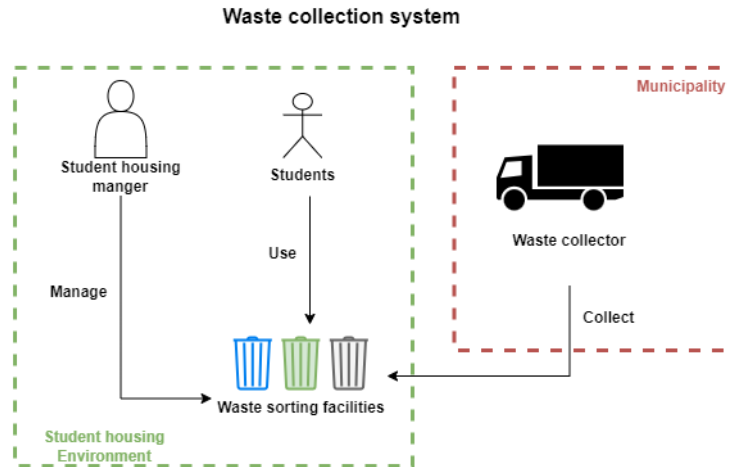


Figure 14 Waste collection system within student housing

3.2 Mixed Research Methodology

In order to explore the specific factors that influence the student's household waste sorting behavior in Delft student housing, the mixed research methodology is used in this research. The mixed research methodology includes both qualitative and quantitative methods. According to Creswell (2015), there are three basic mixed methodologies: the convergent method, the explanatory sequential method, and the exploratory sequential method. Each method possesses its own strengths and limitations. The convergent method involves the simultaneous collection of both quantitative and qualitative data, followed by merging and comparing the outcomes of the two data analyses. The explanatory method initially utilizes the quantitative method and subsequently employs the qualitative results to clarify the findings obtained through the quantitative approach. The exploratory sequential method is particularly suitable for questions that may be unknown, beginning with qualitative analysis to explore the problem and then using the qualitative results to build the framework or instrument for subsequent quantitative analysis.

To effectively address the research question in this study, the most suitable approach is the exploratory sequential method. The rationale for opting for the exploratory sequential method is demonstrated as follows: The investigation into waste sorting behavior among students living in Delft student housing is underexplored, especially given the different waste collection system within this housing context, which differs from low-rise building. Therefore, it is essential to begin by investigating how students sort their waste within the WCS in Delft student housing through the qualitative approach. Employing qualitative methodology allows for a comprehensive understanding of students' waste sorting behavior within the context of the student housing.

Furthermore, utilizing semi-structured interview as qualitative method can be useful to contextualize the study by preliminary validating the framework of generic factors influencing waste sorting behavior to the specific research context. This approach enables the identification

of particular factors that influence waste sorting among students living in student housing. The rationale for this lies in the fact that factors obtained from the literature review tend to be more general, primarily focusing on households in a broad sense, lacking specificity. It may encounter that different factors emerge or that some of the generic factors are not applicable when these generic factors are applied within the specific research context. Through the qualitative approach, pre-validated generic factors, along with the newly discovered specific factors, become the final full list of tailored specific factors with the potential to impact waste sorting behavior among students in student housing. However, it is important to note that these identified specific factors are based on a small sample size, which lacks the statistical strength to draw generalized conclusion. Consequently, these customized specific factors are employed in constructing the instrument, which is the questionnaire survey for the subsequent phase, to achieve quantitative validation. Alongside that, the conceptual model, initially derived from the literature review, undergoes modifications in alignment with the customized specific factors, becoming a newly adopted model. This newly adapted model aids in formulating the hypotheses.

Given the constraints in generalizing findings due to the small sample size during the qualitative phase (Creswell, 2015), the quantitative method is utilized subsequently. The quantitative method in this research has a dual purpose: first, it validates the tailored factors identified from qualitative analysis by evaluating their relationship with waste sorting behavior among students living in student housing. Simultaneously, it facilitates the testing of hypotheses formulated based on the qualitative results. Furthermore, the qualitative results can yield more generalized findings owing to the collection of a larger sample size that is also representative. Apart from that, the quantitative method enables the statistical quantification of relationships, contributing to the formulation of conclusions that are more firmly grounded in empirical evidence.

The complete methodology is structured as depicted in Figure 15. According to this figure the exploratory sequential methodology adopted in this study is divided into two main phases. The first phase includes the utilization of qualitative method, including activities such as qualitative data collection, analysis, and resulting insights. Building upon the qualitative findings, a questionnaire is developed and subsequently employed in the second quantitative phase. The second quantitative phase includes tasks such as quantitative data collection, analysis, and the resulting outcomes.

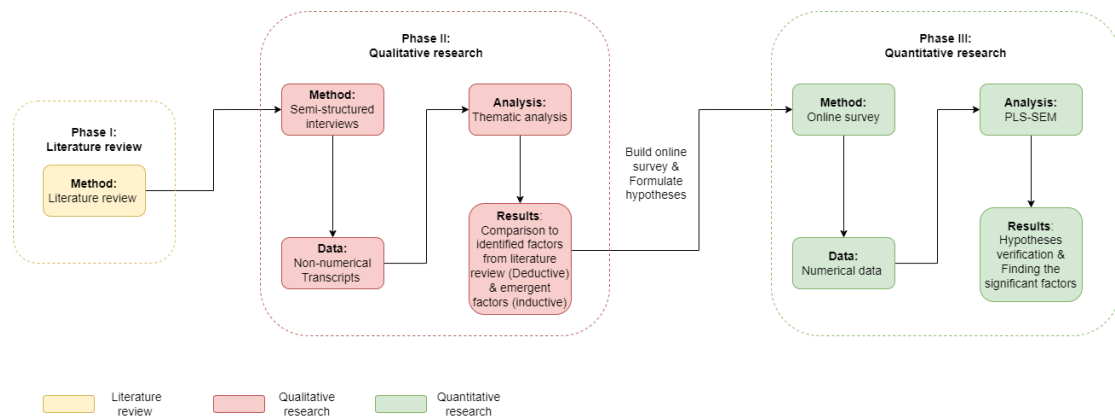


Figure 15 Flow of methodology

3.3 Data collection

This chapter provides the data collection for both qualitative and quantitative methods. Specifically, the semi-structured interview is conducted as the qualitative method, shown in [Section 3.3.1](#), while an online survey is used as the quantitative method, shown in [Section 3.3.2](#).

3.3.1 Semi-structured interviewing for collecting qualitative data

The purpose of the qualitative method is to comprehensively understand the student's household waste sorting within the context of the Delft student housing. Specifically, it is to seek the specific and contextualized factors derived from the students' perspectives regarding their involvement in waste sorting when living in the Delft student housing. In order to achieve this goal, a semi-structured interview is adopted. The semi-structured interview is designed based on the identified factors for general household waste sorting behavior from the literature review. From the literature review, two primary categories of factors affecting household waste sorting behavior are recognized: psychological factors and situational factors. Within each category, there are five specific psychological factors and four specific situational factors. Each factor corresponds to an individual open-ended question in the semi-structured interview. Participants have the freedom to share their perspectives on these questions during the interview. The semi-structured interview has benefits in discovering factors that may not have been previously identified through literature review but have the potential to influence student's household waste sorting behavior. Furthermore, it can potentially uncover more precise elements linked to each factor.

The sample size of the qualitative method is determined by the purpose of the qualitative design (Sandelowski, 1995). Given that the purpose of the qualitative research is to understand the student's household waste sorting behavior, which is align with phenomenon study, the recommended sample size for this type of study is three to ten participants (Creswell, 2015). Considering the recommended sample size, a sample of five participants was chosen for the semi-structured interview to explore factors impacting student household waste sorting behavior. The selection criteria encompass two aspects: firstly, participants must reside in Delft student housing, and secondly, they must be students themselves.

The face-to-face semi-structured interviews were conducted online through Microsoft Teams, following the acquisition of informed consent from voluntary participants. Each interview process adheres to the prescribed protocol outlined in [Appendix A](#), focusing on three main thematic areas: participants' experiences with waste sorting while living in student housing, their internal motivation for engaging in the waste sorting process, and their perception of contextual information related to waste sorting. A total of 11 open-ended questions were inquired during the interviews, accompanied by prompts to gain a comprehensive understanding of participants' waste sorting behavior. Each interview lasted approximately 45 minutes and was recorded and transcribed.

3.3.2 Online survey for collecting quantitative data

The research adopts a quantitative method following the analysis of the semi-structured interview. This method involves utilizing an online questionnaire survey to verify the relationship between the identified factors and waste sorting behavior oriented toward a large student population. The Qualtrics platform is used for designing and conducting the data collection process through the questionnaire. The questionnaire is structured based on four sections: demographic information, psychological aspects, situational aspects, and waste sorting intentions and behaviors. The specific factors selected for psychological and situational aspects are derived from the qualitative analysis. Each factor is paired with relevant questions, developed by integrating existing literature and insights from the qualitative analysis. A comprehensive overview of the questionnaire's development is presented in following [section 3.4.2.3](#).

The survey was started in the middle of July and finished at the beginning of August, spanning approximately 20 days. Among the numerous student housing options in Delft, it is difficult to conduct the survey in all student housing in the city of Delft. As a result, four student complexes were selected at random to serve as the focus of the study. Since the survey was conducted during the summer break, a period when many students are away, online distribution through social media platforms like Facebook and WhatsApp groups was considered a more effective method. However, the initial week of online distribution to the WhatsApp groups of each selected student housing did not yield an active response rate. Hence, along with the online distribution, the intercept survey was conducted on the selected student housing. The survey was ended when there was no new response. The following Table 5 indicates the number of responses obtained from each data collection method. Altogether, a total of 163 responses were gathered.

Table 5 Survey collection method

Collecting Method	No. of Participants
Social Media (Facebook, WhatsApp Group)	66
Intercept survey	97
Total	163

3.4 Data analysis

This chapter includes two sections that describe the analysis techniques used for qualitative and quantitative data, respectively. The first [section 3.4.1](#) demonstrates the utilization of thematic analysis to examine qualitative data, while the subsequent [section 3.4.2](#) demonstrates the implementation of Partial Least Square Structural Equation Modeling (PLS-SEM) for the analysis of quantitative data.

3.4.1 *Qualitative data analysis*

The process of qualitative analysis is carried out using the ATLAS.ti software. Thematic analysis, a widely employed qualitative analysis technique in the social science (Swain, 2018), is employed within this research. This approach delves deeper to identify the patterns and trends, offering a more comprehensive comprehension of the textual information (Vaismoradi et al., 2013). More specifically, it involves extracting essential information systematically from the extensive content and organizing the findings into categories and themes (Gibbs, 2007). In thematic analysis, there are two primary ways to identify the themes within the data: inductive approaches and deductive approaches. Inductive analysis, also known as data-driven coding, means that the codes are directly derived from the textual data (Vaismoradi et al., 2013). Specifically, inductive analysis involves reading the text and developing the theme and findings to answer the research questions (Bingham & Witkowsky, 2021). In contrast, deductive analysis, also known as concept-driven coding, involve generating codes based on previous theories (Vaismoradi et al., 2013).

Inductive analysis and deductive analysis are not mutually exclusive when applied in thematic analysis; some researchers (Li & Liu, 2023; Swain, 2018) have used a hybrid of these two methods in their research. Furthermore, Fereday & Muir-Cochrane (2006) highlighted that this hybrid method offers advantages by integrating the principles of social phenomenology into the deductive thematic analysis, simultaneously allowing themes to naturally emerge from the data through inductive coding. In addition, the hybrid approach can exhibit equilibrium and a holistic perspective of the data (Xu & Zammit, 2020). As deductive coding offers a framework for identifying themes within a theoretical context, and inductive analysis delves into associated elements originating from textual data, this research employs a hybrid approach that combines both methods.

The research's thematic analysis process adheres to Braun & Clarke (2006) guidelines, with adjustments that involve incorporating deductive analysis, as shown in the Figure 16 It commences by becoming familiar with the transcribed transcripts. Following this, there are two rounds of coding, where the first round entails deductive coding, and the second round involves inductive coding. Deductive coding uses the predesigned codebook, which includes the predefined code categories (themes) corresponding to factors from the literature review, the actual codes representing measurable items tied to these factors, and their descriptions. Part of codebook is shown in Table 6, along with Figure 17, as an illustrative example for illustrating deductive coding procedure. In the deductive coding phase, transcripts that align in meaning with the codebook descriptions are chosen and coded specified in the codebook. Consequently,

these codes are automatically attributed to the relevant themes. Following that, inductive coding is carried out. During inductive coding, transcripts containing elements different from the codebook are identified and labelled as inductive codes. These inductive codes that share similarities and are closely interrelated are then categorized into newly formed themes or incorporated into existing potential themes. After completing two rounds of coding, the ultimate themes and codes are synthesized. Furthermore, through the synthesis of codes and themes, a new conceptual model is formulated, serving as the foundation for constructing hypotheses.

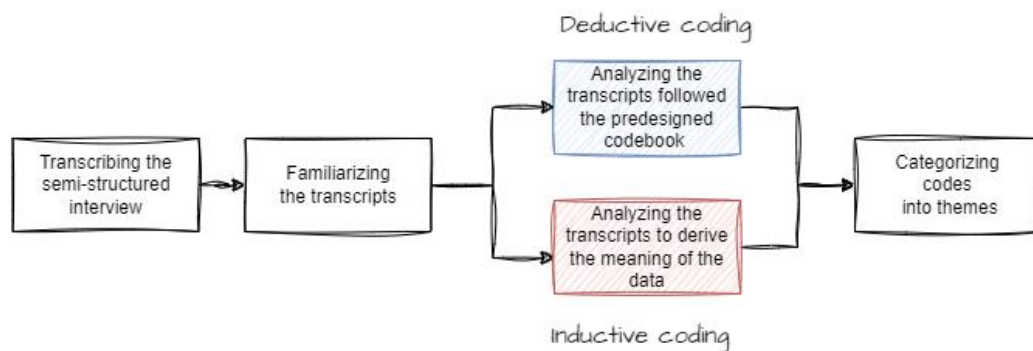


Figure 16 Thematic Analysis

Table 6 Codebook for deductive coding

Themes	Codes	Description
Attitude	Experiential feeling	All statements associated with the feeling and affection about conducting the behavior
	Instrumental perception	All statements associated with the person's subjective perception of the behavior

Code	Interview 1	Quotation	Interview 2	Quotation	Interview 3	Quotation	Interview 4	Quotation	Interview 5	Quotation	Frequency
			Attitude Question: What feeling do you have when you sort the waste?								
Attitude:Experiential			No influence	Actually, sometimes I feel it's an achievement for me if I do sort my waste						But at the beginning, I will find it a little bit annoying.	2/5
Attitude:Instrumental		I think it's very useful and it's sustainable and it's green.				So, I think it's better to just separate it. From when I throw it away, I think to help the manager to sort the waste.		I have the feeling that's good for the environment			3/5

Figure 17 Example of deductive coding

3.4.2 Quantitative data analysis

Once the quantitative data has been gathered, it is essential to select the appropriate statistical techniques for analysis. This chapter starts with introducing structural equation modeling (SEM) in [Section 3.4.2.1](#). Following that, [Section 3.4.2.2](#) presents an examination of two primary methods of structural equation modeling (SEM): covariance-based SEM (CB-SEM) and partial least squares SEM (PLS-SEM), providing a rationale for the selection of PLS-SEM.

Subsequently, the application of PLS-SEM is presented in [Sections 3.4.2.3](#) and [3.4.2.4](#). Finally, the analysis procedure is detailed in [Section 3.4.2.5](#).

3.4.2.1 Structural equation modeling (SEM)

For quantitative data analysis, structural equation modeling (SEM) is used in this research. SEM is a multivariable data analysis technique to examine the relationship between multiple variables. This method is useful to test or validate the hypothesis from the theoretical models (Thakkar, 2020). According to Haenlein & Kaplan (2004), in contrast to first-generation multivariable data analysis, including multiple regression analysis, logistic regression, and analysis of variance, SEM as a second-generation data analysis technique possesses several advantages that address the limitations found in first-generation techniques. SEM has the strength to handle complex models that involve a large number of variables simultaneously, whereas the multiple regression method is limited to simple models (J. F. Hair et al., 2021). Moreover, first-generation multivariable data analysis requires variables to be directly observed and measurable, whereas SEM is not bound by this constraint and can incorporate latent variables (J. F. Hair et al., 2021). Additionally, the first-generation techniques are applicable only when measurable variables have neither systematic nor random errors. However, it is nearly impossible to have variables without any measurement error in reality. SEM, on the other hand, addresses this issue by accounting for measurement errors in the variables (J. F. Hair et al., 2021). Given that SEM has a strong capability for handling complex structures, multiple measurements of concepts, and measurement models, it has been widely used in social and behavioral science (Bollen & Noble, 2011). For example, Liu et al. (2020) applied the SEM to explore the relationship between environmental knowledge and pro-environmental behaviors. Furthermore, most researchers (Fan et al., 2019; Wang et al., 2020; Xia et al., 2021) used SEM to explore the factors that affect waste sorting behavior.

The SEM model consists of two sub-models: the measurement model (shown in from Figure 18) and the structural model (shown in Figure 18). The measurement model incorporates both observed and latent variables, where observed variables represent the underlying latent variables within the measurement model. To illustrate, latent variables are hard to directly observe, such as the satisfaction level of certain products. Therefore, the measurement of the latent variables should be facilitated by a set of corresponding directly observed variables (also called items or manifest variables). On the other hand, the structural model comprises exogenous variables and endogenous variables, establishing the hypothesized relationships between each variable. Detailly, exogenous variables are those that remain unaffected by other variables in the model, whereas endogenous variables are influenced by other variables within the model (Thakkar, 2020).

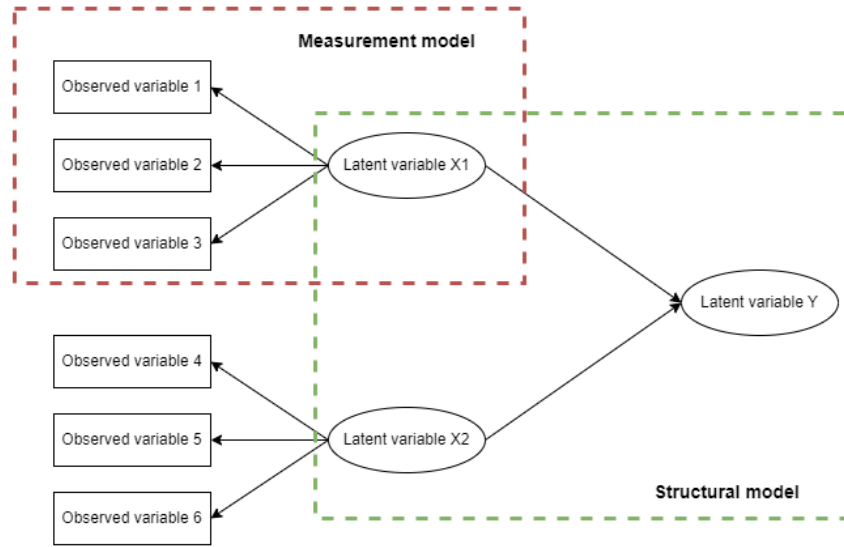


Figure 18 SEM model

3.4.2.2 Selection of PLS-SEM

SEM has two popular methods to estimate the relationships: covariance-based SEM (CB-SEM) and partial least square SEM (PLS-SEM) (J. F. Hair et al., 2021). The distinction between the two methods lies in how they estimate model parameters and the assumptions they make about measurement. Regarding model parameters, CB-SEM is targeted at reducing the disparities between the estimated and sample covariance matrices. On the other hand, PLS-SEM focuses on maximizing the proportion of variance in the endogenous constructs through ordinary least square regressions.

In this research, the PLS-SEM is preferred over the CB-SEM for several reasons. PLS-SEM is less constrained by sample size compared to CB-SEM. CB-SEM is strictly with the large sample size, as it ensures reliable results (J. F. Hair et al., 2019). Conversely, PLS-SEM can efficiently handle small sample sizes and complex models (Cassel et al., 1999). In this case, the minimum required sample size is determined through the minimum R-squared approach introduced by Hair et al. (2022), which ensures a specific level of statistical power. Most researchers adopt this approach to attain an 80% power level, and this study similarly aims to achieve an 80% statistical power at a significance level of 0.05. Referring to the provided table, as depicted in Table 7 for the minimum R-squared method and considering the maximum of nine arrows pointing a construct (which is waste sorting intention in this case), a minimum sample size of 88 is required to achieve a 25% R-squared value. Therefore, the sample size utilized in this study is 155, meeting the minimum sample size requirement.

Table 7 Minimum R-Squared approach (Hair et al. (2022))

Maximum number of arrows pointing at a construct	Minimum R^2 in the model			
	.10	.25	.50	.75
2	110	52	33	26
3	124	59	38	30
4	137	65	42	33
5	147	70	45	36
6	157	75	48	39
7	166	80	51	41
8	174	84	54	44
9	181	88	57	46
10	189	91	59	48

Another advantage of PLS-SEM is that it does not require data to follow a normal distribution. Considering that the responses are measured on an ordinal or nominal scale, the certainty of data normality is uncertain. For this reason, PLS-SEM is the preferred choice in this context. Furthermore, in the measurement model, there is no restriction on the number of items representing the underlying latent variable, making the application of PLS-SEM more flexible. Additionally, the conceptual model in this study is relative complex, which is composed of 10 latent variables (constructs) and over 30 indicators. Utilizing CB-SEM for handling this model is not feasible, as CB-SEM is designed for simpler structured models encompassing fewer than 5 constructs (J. Hair et al., 2017).

3.4.2.3 Measurement model development

Similar to the conventional SEM model, the PLS-SEM model also comprises the measurement model (referred to as the outer model in PLS-SEM) and the structural model (known as the inner model in PLS-SEM). However, the measurement model in PLS-SEM includes two categories: reflective and formative constructs. These two categories exhibit three key differences, encompassing the construct's inherent nature, causal relationship direction, and indicator characteristics (Hanafiah, 2020). Regarding the nature of the constructs, items depend on the latent variables through some functional relationship in the reflective measurement model (Borsboom et al., 2009), while the latent variable depends on the items in the formative measurement model. As a results, in the reflective measurement model, items are regarded as consequences of the latent variables, while the opposite holds true for formative measurement model. Therefore, it leads to two different directions of causality between reflective measurement model and the formative measurement models, as shown in the Figure 19. Furthermore, a significant distinction between reflective constructs and formative constructs lies in the characteristic of the items. Within a reflective measurement model, the items can be interchangeable with one another, given their shared underlying theme of the latent variables. The validity of the content of the reflective measurement model is not influenced by the inclusion or exclusion of any other items (Hanafiah, 2020; Jarvis et al., 2003). In contrast, the formative measurement model is highly dependent on the number of the items, as the conceptual interpretation of the construct can be altered by the inclusion or removal of a single item (Hanafiah, 2020). In this research, all variables are intentionally designed to be reflective,

and their development is detailed in the subsequent subsection.

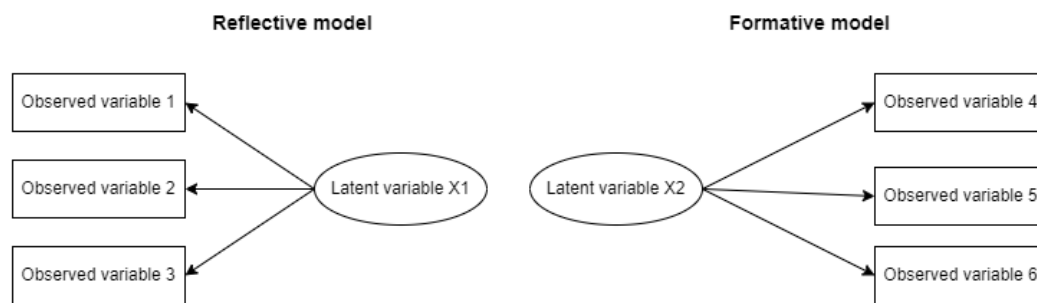


Figure 19 Reflective and formative measurement model

This section shows how the measurable scales were developed for each variable in the theoretical framework. All items have been formulated to enhance its reliability by drawing upon existing literature reviews and customizing them to suit the context of Delft student housing, which is shown in [Appendix B](#). Moreover, a 5-point Likert scale is applied to all the scales, spanning from “strongly disagree” to “strongly agree,” except for the waste sorting behavior, which assesses the frequency of sorting various types of waste streams.

Attitude scale

The scale of attitude was adapted from Ajzen (2002). Ajzen (2002) developed 5 items to assess attitude, a variable that evaluates the performance of the behavior, including instrumental and experimental components. However, qualitative analysis revealed that participants’ attitudes were specifically linked to the environment. Therefore, three items from Wang et al. (2020) were ultimately used to assess the instrumental component of the attitude.

Subjective norm scale

The subjective norm scale was developed by integrating elements from both Karim Ghani et al. (2013), with the adaptation within the context of this research. Through qualitative analysis, it was noticed that participation behavior is influenced by the desire for acceptance from reference groups but also by the social pressure from others. Consequently, four items were selected to assess the subjective norm, including both the desired social acceptance from reference groups and the influence of societal pressure.

Perceived behavioral control scale

The perceived behavioral control scale was derived from Zhang et al. (2015), consisting of three items aimed at assessing individuals’ self-efficacy regarding a particular behavior. Through qualitative analysis, it was found that perceived behavioral control decreased when participants perceived more effort when conducting the behavior. Therefore, this research includes an additional element related to perceived effort, combining with original three items from Zhang et al. (2015).

Personal norm scale

The scale of the personal norm was adopted from Tonglet et al. (2004), comprising seven items to evaluate the moral obligations. However, specific modifications were made within the context of this research, resulting in the selection of only three items. These chosen items inquire about individual's moral obligations, feelings of guilt, and sense of responsibility.

Knowledge scale

The knowledge scale was developed from Wang et al. (2020), consisting of three items to ask the knowledge regarding the waste sorting. However, based on the results of the qualitative analysis, some modifications were made on the items. These scales were evaluated with a 5-Likert scale. Moreover, the evaluation of participants' waste sorting knowledge on how to correctly sort waste was designed using a multiple-choice format, which is included in [Appendix B](#). It is worth noting that the knowledge in this research refers to the individual's existing understanding of sorting waste, which is shaped by their past experiences and education.

Waste sorting facilities scale

The scale for waste sorting facilities were developed from Fan et al. (2019), consisting of four items assessing capacity, guidance, labels and management aspects. Based on qualitative findings, these four items were adjusted to inquire about facility management, accessibility, internal space as well as the provision of label and guidance of the waste sorting facilities.

Information publicity scale

The information publicity scale were derived from Y. Zhang et al. (2022), consisting of three items to evaluate the government policy. In the context of this research, the focus was on evaluating the dissemination of waste sorting policies. It refers to the current level of publicity within student housing and social media. As a result, the final items were designed to inquire about the public dissemination of the waste sorting policy and how individuals perceived the effectiveness of this dissemination.

Economic Incentives scale

The scale of economic incentives was developed from Wang et al. (2020). It consisted of three items evaluating the extent to which individuals engage in certain behaviors due to incentive measures. The original items included both monetary incentives and emotional incentives, such as honorary titles. However, based on qualitative findings participants demonstrated a stronger inclination towards being motivated by monetary incentives in the form of rewards or penalties. As a result, the economic incentives construct encompasses the penalty imposed for without conducting waste sorting, rather than evaluating emotional incentives through individual items.

Waste sorting intention and waste sorting behavior

Waste sorting intention is assessed using a set of five items, with each item corresponding to a specific waste stream. Participants are prompted to express their inclination to sort these types of waste by selecting a response on a Likert scale with five points, spanning from “strongly disagree” to “strongly agree”. The waste sorting behavior is assessed based on how frequently

individuals engage in this practice, following the TPB questionnaire guidance formulated by Ajzen (2002). Consequently, the questions were designed to inquire about participants' frequency of sorting each type of waste.

3.4.2.4 Structural model development

The structural model is built upon hypotheses drawn from qualitative discoveries grounded in the theoretical framework established in the literature review (J. F. Hair et al., 2022). The structural model encompasses exogenous variables such as attitude, subjective norm, perceived behavioral control, knowledge, and personal norm, alongside the endogenous variable: waste sorting behavior. Notably, waste sorting intention functions as both an endogenous and exogenous variable. This duality arises from its susceptibility to influence by the aforementioned exogenous variables while also exerting influence on these same exogenous variables. In this case, hypotheses are formulated based on the conceptual model derived from the qualitative phase.

3.4.2.5 Analysis of PLS-SEM model

PLS-SEM analysis is executed within SmartPLS 3 (Ringle et al., 2015), and this process is illustrated in Figure 20. According to Hair et al. (2022), testing the hypothesis theory using PLS-SEM involves two fundamental steps. The first step is to assess the validity and reliability of the measurement model. Once the measurement models are verified, the second step involves testing the structural model. The process of examining the PLS-SEM sequences ensures reliability and validity prior to making inferences concerning the connections between constructs (Hulland, 1999).

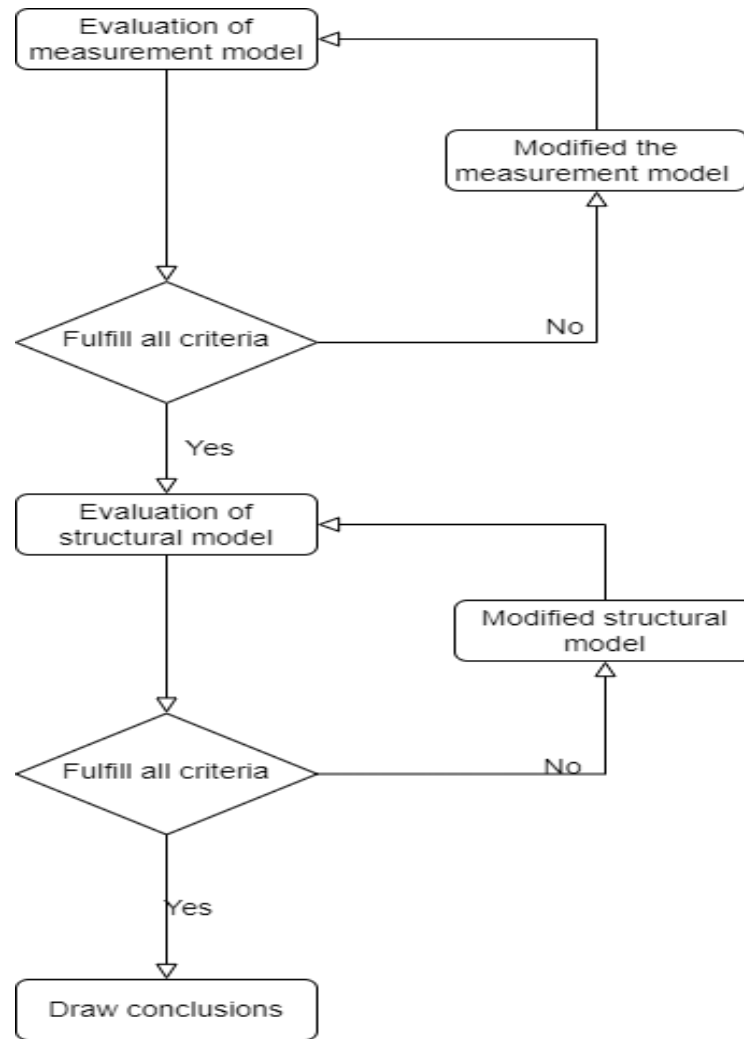


Figure 20 Procedure of analysis of PLS-SEM model

Concerning evaluating measurement model, different criteria are used for the reflective and formative measurement models. Given that the constructs are reflective constructs in this study, the procedure of examination of the reflective measurement model is followed. The assessment of the measurement model's reliability and validity includes three different perspectives: individual item reliability, internal consistency reliability, convergent validity, and discriminant validity (J. F. Hair et al., 2019; Hulland, 1999). The detailed procedure of the evaluation of the measurement model is presented in the Table 8.

After confirming the adequacy of the measurement model, the next step involves evaluating the structural model. This entails the assessment of several criteria, including the coefficient of determination (R^2), effect size (f^2), the cross-validated redundancy measure (Q^2), out-of-sample prediction $PLSpredict$ and the statistical significance and relevance of the path coefficients (J. F. Hair et al., 2019). The evaluation criterion for assessing the structural model is shown in Table 8. The main objective of evaluating the structural model is to ascertain that it possesses sufficient explanatory and predictive capabilities. Based on this foundation, the goal is to validate the formulated hypotheses and derive valid conclusions.

Table 8 Evaluation criteria for PLS-SEM model

Assessment	Criterion	Aim	Explanation
Evaluation of measurement model			
Factor loading	>0.708	Ensure the individual item reliability	Factor loading signifies the degree to which the construct accounts for the variance in the indicators.
Cronbach's alpha	>0.7	Ensure the internal consistency reliability within the construct	This is to ensure that each item within a construct measures the same underlying concept
Composite reliability	0.7-0.9		
Average variance extracted (AVE)	>0.5	Convergent validity	Each item from the same construct is correlated positively with other items
Square root of AVE	Square root of the AVE for each construct should be greater than the largest correlation it has with any other construct	Discriminant validity	The construct differs from other constructs within the structural model
Heterotrait-monotrait (HTMT) ratio	<0.85		
Evaluation of structural model			
Variance inflation factor (VIF)	<3	Collinearity	The collinearity can introduce the bias into the regression outcomes. Additionally, testing for collinearity ensures accurate interpretation
Coefficient of determination (R ²)	>0.26-substantial; 0.13-moderate; 0.02-weak	Explanatory power of the model	It measures the number of variances that can be explained in each of the endogenous constructs
Effect size (f ²)	0.35-substantial; 0.15-moderate; 0.02-minor	Facilitating assessment to explain the R ²	It measures when a construct is diminished from the structural model, the change of the R ²
Cross-validated redundancy measure (Q ²)	0.5-substantial; 0.25-moderate; 0-small	Predictive power of the model	It measures the predictive power of the model

Assessment	Criterion	Aim	Explanation
Q^2_{predict}	Prediction errors < naïve benchmark	Out-of-sample predictive ability	
Statistical significance	95% confidence level (in this research)	Hypothesis testing	It indicates that the observed relationship is likely to be real and not simply result of the random variability in the data
Path coefficients		Quantify the correlation	It measures how variable correlated to other variables

Furthermore, the research analyzed the moderating effect of situational factors. The discrepancy between the student's intention to sort waste and actual sorting behavior was previously confirmed during the qualitative analysis. In order to draw the generalized findings, it is necessary to confirm the statistical significance of the relationship between students' waste sorting intentions and behavior in the quantitative analysis, which is shown in detail in [section 4.2.2](#). Additionally, the qualitative analysis revealed the presence of moderating effects associated with situational factors, such as waste sorting facilities and information publicity. This discovery aligns with the moderating effects of situational factors identified in the literature review. However, due to the limited sample size in the qualitative analysis, it is not possible to generalize the findings regarding the moderating effects of situational factors. Therefore, it is crucial to conduct an analysis of situational factors as moderators in the quantitative analysis. The moderating analysis is presented in [Section 4.2.4.1](#).

When assessing both the measurement and structural models, if an undesirable outcome arises in either model, resulting in an inconclusive result, it becomes crucial to improve the PLS-SEM model. Hence, in order to ensure the PLS-SEM analysis yields reliable and valid conclusions, the research utilize a model refinement approach akin to the model modification made in CB-SEM (Willaby et al., 2015). This involves assessing whether it is necessary to introduce additional paths or constructs to improve the explanatory power of model (Willaby et al., 2015), or alternatively, removing paths or constructs to ensure the adequate statistical power. Therefore, the PLS-SEM model refinement is presented in [Section 4.2.5](#) to showcase the accurately improved model and to derive valid conclusions.

4. Results

This chapter presents both qualitative and quantitative results. The qualitative result shows tailored factors that could potentially impact students' waste sorting behavior within the student housing. These factors include a mix of certain generic factors obtained from the literature review and newly identified factors from the semi-structured interviews. In essence, they comprise psychological factors such as attitudes, subjective norms, perceived behavioral control, personal norms, and knowledge related to waste sorting, as well as situational factors like waste sorting facilities, information publicity, and economic incentives, as detailed in [Section 4.1](#). Based on these identified specific factors, the corresponding hypotheses are formulated, and a questionnaire is created for subsequent quantitative analysis.

[Section 4.2](#) presents the quantitative results, which include the validation of hypotheses and the quantification of the significant relationship between specific factors and waste sorting behavior. The quantitative findings confirm that subjective norm and perceived behavioral control exert a significant influence on students' intention to sort waste, with correlation coefficients of 0.208 and 0.242, respectively. Additionally, students' waste sorting behavior is directly impacted by their intention to sort waste, the availability of waste sorting facilities, and the extent of information publicity, with correlation coefficients of 0.224, 0.217, and 0.288, respectively. In summary, each phase, from the qualitative phase to the quantitative phase, builds upon the preceding phase with the goal of pinpointing the specific factors that genuinely affect students' waste sorting behavior, as depicted in Figure 21.

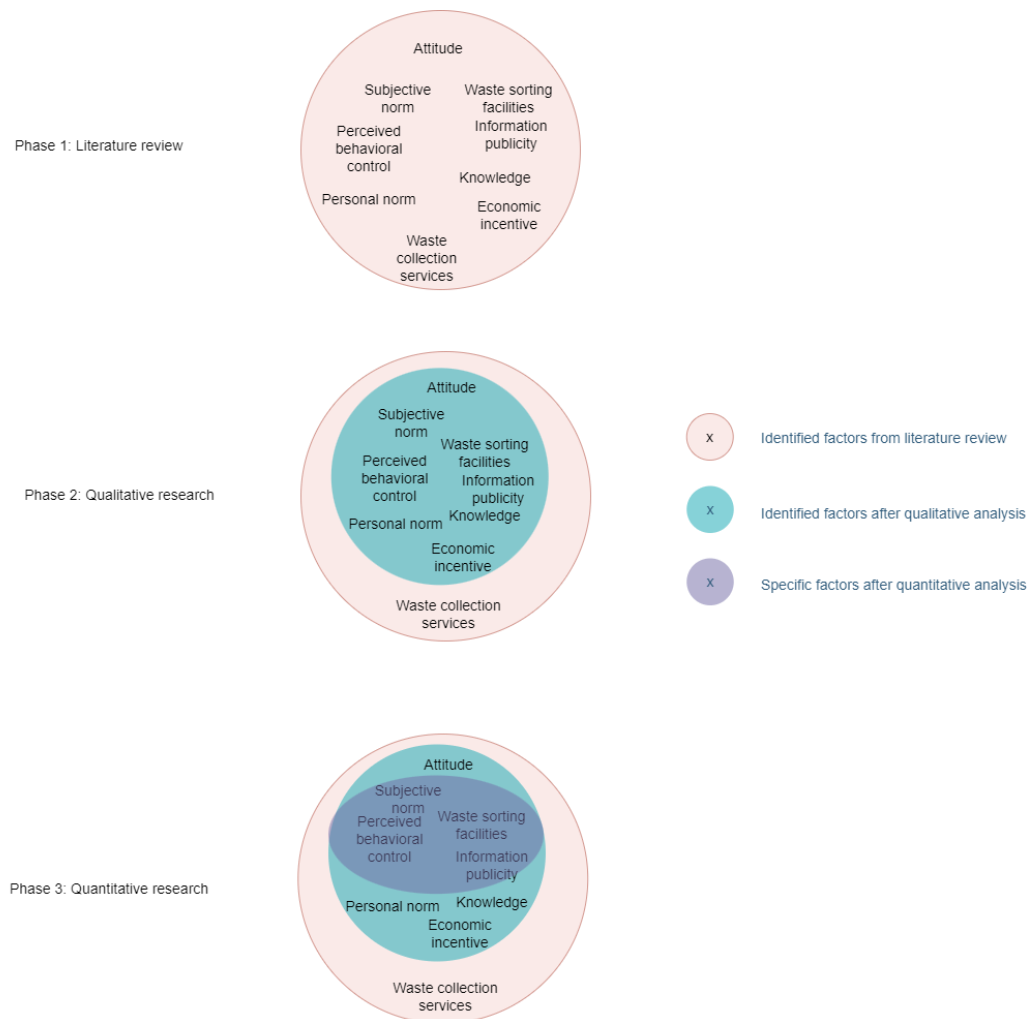


Figure 21 Results from different phases

4.1 Qualitative results

Through the use of thematic analysis, most themes and codes were identified deductively by comparing the transcripts with the codebook detailed in [Section 4.1.1](#). These themes and codes align with the identified factors and related elements from the literature review. The reason for this consistency is that the identified factors from the literature review are focused on the waste sorting behavior of the general household, which includes the student population as well. However, during the deductive coding, certain codes are omitted due to differences in waste sorting behaviors across various research contexts and groups. In addition to the deductive coding, there are notable elements derived from the inductive coding, as shown in [Section 4.1.2](#), which have been tailored to capture the waste sorting practices specific to student households in student housing. Ultimately, [Section 4.1.3](#) provides a summary of the qualitative findings.

4.1.1 Deductive qualitative results

4.1.1.1 Psychological factors

The majority of interviewees exhibited either an experiential or instrumental aspect of their attitude towards waste sorting behavior. Those who engaged in waste sorting tended to perceive it as beneficial and advantageous in an instrumental sense. Additionally, their motivation is driven by instrumental sense. On the other hand, for interviewees who did not practice waste sorting, if they tried it once, they experienced a more positive emotional response towards the behavior.

In relation to the findings on subjective norm, the majority of interviewees expressed their desire for acceptance within the community and their willingness to conform to societal expectations. As a result, they engaged in the waste sorting given the perception of waste sorting from the community or their friends. The interviewees did not mention the social influence from their family when discussing waste sorting behavior, as the focus was primarily on their friends and community. This can be attributed to the specific context of the student housing environment, where students frequently interact with their friends and neighbors.

The findings related to perceived behavioral control indicated that interviewees who engage in waste sorting perceive the behavior as easy, whereas those who do not sort waste consistently perceive it as challenging. According to the definition of the perceived behavioral control in the TPB theory, it also includes the concept of self-efficacy. This implies that individuals have confidence in their ability to engage in waste sorting. It was observed that interviewees who had confidence in their capabilities found the behavior easy to perform. Confidence is closely linked to the perception of the behavior's simplicity.

As demonstrated in the literature review, the concept of the personal norm encompasses the moral obligation that arises from being aware of the consequences and accepting responsibility. However, the awareness of consequences overlaps with the instrumental aspects of the attitude, which is not included in the design. The majority of interviewees showed an awareness of the environmental consequences related to not engaging in waste sorting. This awareness led them to feel a responsibility to sort waste and contribute to environmental protection. Additionally, it was observed that most interviewees view waste sorting as an obligation to fulfill rather than being closely tied to their moral principles and beliefs.

Knowledge exclusively refers to understanding how to properly sort waste in the deductive analysis. Additionally, it refers to the individual's current state of knowledge regarding sorting waste. The majority of interviewees expressed a limited level of knowledge regarding waste sorting techniques. However, it is intriguing to observe that even though certain interviewees lacked knowledge of proper waste sorting techniques, they actively engaged in the process of sorting waste. Due to the fact that they believe waste sorting is a mandatory requirement in their student housing.

Additionally, it was noted that every interviewee expressed their intention to sort their waste.

However, not all interviewees conduct the actual behavior of waste sorting. This underscores the differentiation between the intention to sort waste and the actual behavior of doing so. Most interviewees emphasized that various contextual factors hinder the transition from intention to action. For instance, one interviewee, as depicted in Table 9, pointed out that the lack of waste sorting facilities is the primary obstacle to practicing waste sorting.

Table 9 Deductive codebook of psychological factors

Theme	Codes	Description	Quotes	Frequency
Attitude	Experiential feeling	All statements associated with the feeling and affection about conducting the behavior	<i>"Actually, sometimes I feel it's an achievement for me if I do sort my waste"</i>	2/5
	Instrumental perception	All statements associated with the person's subjective perception of the behavior	<i>"I think waste sorting is very useful and it's sustainable and it's green."</i>	3/5
Subjective norm	Peer pressure from friends	All statements that include the peer pressure and influence of friends	<i>"If I see my friends or my neighbor sort the waste in front of me, I will do the waste sorting."</i>	3/5
	Peer pressure from community	All statements that include the peer pressures of neighborhood from the student housing or the society		3/5
	Social acceptance from friends	Statements that indicate the desire of acceptance by their friends	<i>"I think it's my preference to sort the waste, but I think my friend also sorted their waste."</i>	1/5
	Social acceptance from community	Statements that indicate the acceptance from the neighborhood of the student housing or the society	<i>"It's the local rules to sort the waste, and as a person coming into a different culture, I want to fit the rules of that culture."</i> &	3/5

			<i>"My roommates sort their waste, So I just follow their habits."</i>	
	Social influence from family	All statements that include the social pressures from family		
Perceived behavioral control	Difficult	Statement that indicates the person perceive the difficulty of the behavior and have no confidence for doing that	<i>"I think waste sorting is too complicated, maybe that's also one of the reasons that I don't want to sort my waste"</i>	2/5
	Easy	Statement that indicates the person perceive the ease of the behavior and have ability to conduct the behavior	<i>"One of the motivations for me to sort the waste is that it is not too hard to do so"</i>	3/5
	Confidence	Statement that indicates the person has the confidence to believe that they can perform the behavior	<i>"I mean, the second motivation to do the waste sorting is not too hard to do."</i>	3/5
Personal norm	Moral obligation	Statements that indicated they conduct the behavior following by their moral principles and beliefs	<i>"Even though I really care about the environment, I think my actions did not comply with my belief."</i>	1/5
	Personal Responsibility	All statements that indicate the person feel the responsibility to perform the behavior	<i>"I think it's my responsibility to sort the waste."</i> & <i>"I don't want to spoil the environment"</i>	4/5
Knowledge	Waste sorting knowledge	Statements that associated with the knowledge about sorting the waste	<i>"I don't really know exactly information of separating waste. But I will still sort my waste according to my knowledge"</i>	2/5

Waste sorting intention	Intention	All statements that indicate individual willingness to conduct the behavior or their likelihood to perform the behavior	<i>“I hope I can do that, but I don’t have the environment to do that”</i>	5/5
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4.1.1.2 Situational factors

The waste sorting facility is identified as an important situational factor that impact the household waste sorting behavior. This factor is associated with several elements, including the provision of sorting facilities, convenient access, quantity and capacity, color, information prompts around waste sorting facilities, and internal storage space. However, during the deductive analysis, not all of these elements were emphasized by the interviewees. Notably, the quantity and capacity of the waste sorting facility were not identified as factors influencing waste sorting behavior. In other words, increasing the number of bins for the same waste type in student housing does not impact waste sorting behavior. This is because interviewees who engaged in waste sorting highlighted the importance of separating waste at the source, meaning they sorted their waste at home and then brought it to the communal waste sorting facility in student housing. Therefore, the quantity and capacity of the waste sorting facility only affect waste disposal behavior, rather than waste sorting behavior.

Furthermore, the provision of the waste sorting facility was frequently emphasized by the majority of the interviewees. Most of them demonstrated a tendency to follow the presence of waste sorting facilities and engage in sorting their waste accordingly. For example, one participant mentioned, *“Actually the motivation for me to sort the waste is that there are waste separation facilities in my student housing. However, it is only for collecting the paper and rest.”* However, some interviewees mentioned that they sort the organic waste at the source, even when specific trash bins for organic waste are not provided. In spite of their attempts to separate organic waste, the absence of dedicated trash bins results in the organic waste being ultimately disposed of in an unrecyclable waste bin. This indicates that the lack of adequate waste sorting facilities has the potential to impede waste sorting practices, even when participants are strongly motivated to sort their waste. Profoundly, it signifies the influence of waste sorting facilities as a moderator. Moreover, the location, color, and informational prompts displayed around the waste collection facility were identified as important factors. However, the findings indicated that interviewees who actively engage in waste sorting do not view internal storage space as a decisive factor. On the contrary, for those who do not practice waste sorting, the presence of adequate storage space becomes a significant consideration.

Table 10 Deductive codebook for waste sorting facilities

Theme	Codes	Description	Quotes	Frequency
Waste sorting facilities	Provision of waste sorting bins	Statements indicate that provision of the waste sorting facilities leading to the waste sorting intention	<i>"If they provide me the necessary facilities for it, I will do the waste sorting"</i>	4/5
	Location	Statements indicate that close location, and the easy accessibility of the waste sorting facilities has impact on waste sorting intention	<i>"Nearby the student housing, there is a trash area where there are trash bins with more types of categories. But we still need to walk there. It takes time."</i>	2/5
	Quantity and capacity	Statements indicate the number of trash bins, or the capacity of trash bins has impact on waste sorting intention	-	-
	Color	Statements indicate that the color of the trash bins has impact on waste sorting intention	<i>"The brighter color definitely draws your attention to the fact that there are different types of waste. I think it will motivate you to sort the waste"</i>	3/5
	Labels and guidance	Statements that indicate the label, guidance around the trash bins has impact on waste sorting intention	<i>"Actually, I don't know which one is the paper one which one is for the organic one when I live in the student housing. "</i>	3/5

	Storage space	Statements that indicate the space in the personal household	<i>"Area of my room is small, so if I need to sort the trash in my room and need at least four trash bins. But I don't have that big room for me to do that."</i>	2/5
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The waste collection services refer to both maintaining the cleanliness of the waste collection facilities by the student housing manager and providing timely and reliable waste collection by the waste collector. When discussing the waste collection services provided by the student housing manager, two interviewees emphasized its significance, particularly due to the bad condition resulting from the lack of maintenance on the waste sorting facilities. This demotivated them from engaging in waste sorting. However, other interviewees expressed that this factor was not crucial to their waste sorting behavior. They stated that even if the environment of the waste sorting facilities was unfavorable, they would still continue to practice waste sorting. For instance, one interviewee stated that, *"Even if the environment of the waste sorting facility is not good owing to the absence of waste collection services, it will not demotivate me to sort the waste, because waste sorting is good for the environment."* These findings indicate that the waste collection services indirectly influence the motivation for waste sorting behavior, with the condition of the waste sorting facilities being the most significant factor. Moreover, all the interviewees unanimously agreed that the timely and reliable waste collection services had no impact on their waste sorting behavior. This lack of impact can be attributed to the fixed frequency of waste collection, which ensures consistent and dependable services for the student housing. As a result, waste collection services will be excluded from the questionnaire design.

The information publicity and the economic incentive are identified as important factors from the interviewees. The literature review highlights that the provision of a program is a crucial factor in relation to information publicity. This program can effectively enhance knowledge and motivation for waste sorting by educating individuals and providing them with relevant information. This study discovered that the majority of interviewees did not consider participation in such programs as an effective intervention to encourage them to sort their waste. They expressed that participating in these programs requires effort and time, which they considered ineffective in motivating them to sort waste. Instead of implementing such programs, they believed that providing waste sorting information publicly or through the internet would be more effective. One interviewee acknowledged that information publicity would increase the intention to sort waste, but the impact of information publicity translating intention into actual behavior remains uncertain. This indicates that information publicity has the moderating effect. Particularly, one interviewee suggested the idea of placing information posters in public areas of student housing, such as elevators, stating, *"Instead of programs, I find posters to be effective. It's a great idea to have them in the elevator."* Furthermore, all interviewees acknowledged that economic incentives could motivate them to sort the waste. Regarding the

waste tax fee, there are noteworthy observations shared by interviewees. One interviewee mentioned that imposing the waste tax fee diminishes their sense of responsibility for waste sorting, as expressed in the statement: *"Paying the waste tax makes me believe it's not my duty to sort waste."* This reflects that economic incentives might weaken the relationship between intention and actual behavior. In addition, four interviewees stress that the magnitude of the reduction in waste fees plays a more crucial role in motivating them to engage in waste sorting.

Table 11 Deductive codebook for information publicity and economic incentives

Theme	Codes	Description	Quotes	Frequency
Information Publicity	Provision of program	Statements that indicate the waste sorting program have impact on waste sorting intention	<i>"I don't feel too strongly about the influence of the program. So, I don't think I would participate in such a program, it takes some time"</i>	-
	Provision of information in public	Statement that indicated the waste sorting or recycling information in public places have an impact on waste sorting intention	<i>"If I see it regularly maybe it will motivate me, but I don't know how big the impact."</i>	4/5
	Provision of information through Internet and social media	Statements that indicate the waste sorting or recycling information on the Internet and social media have an impact on waste sorting intention	<i>"I would say provision of information is very important for me because that's how I found out waste sorting through the municipal website"</i>	4/5
Economic incentives	Provision of economic incentives	Statements that indicate the money or monetary reward have an impact on waste sorting intention	<i>"The economic incentives really motivate me"</i>	5/5

	The reduction or exemption of waste taxes	Statements that indicate the reduction of the waste taxes have an impact on waste sorting intention	<i>“Regarding the waste fee reduction, it depends on to what extent of deduction of the waste sorting. If it is a few, then it does not influence. But if it’s a lot, then it matters”</i>	4/5
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4.1.2 Inductive analysis

Moreover, during the analysis, additional codes were identified through an inductive approach, which were not originally included in the deductive codebook. These inductive codes were found to be associated with the deductive analysis and are more specific to the waste sorting behavior of students in Delft student housing. These inductive identified codes contribute to a better understanding and explanation of their behavior within the context of Delft student housing.

The inductive analysis revealed that regulations play a significant role in motivating individuals to sort their waste. However, it is important to note that perceptions regarding these regulations vary among different people. Those who do not engage in waste sorting mentioned that they do not view it as a mandatory regulation. On the other hand, interviewees who actively participate in waste sorting perceive it as an obligatory and mandatory regulation that they must obey. This can be interpreted through the viewpoint of the community's social influence. Specifically, individuals strive to be accepted by the community and therefore feel compelled to adhere to its cultural norms and regulations. Regarding the different perception of the policy, it is caused by inadequate information about advocating waste sorting. It is recommended that student housing authorities promote waste sorting publicly or through online channels to address this issue. Additionally, the implementation of regulations can be enhanced by incorporating a penalty system. One participant suggested that imposing fines for non-compliance with waste sorting would be a highly effective measure, stating, *"If there's a penalty, like a monetary fine for not sorting waste, I would definitely sort my waste."*

Owing to the large portion of international students living in the student housing, there is a possibility that new neighborhoods in the student housing are unaware of the waste sorting regulations and information. This lack of information contributes to the occurrence of non-sorting behavior within the student housing community. Consequently, simply providing general information in the public may not yield effective results. Instead, it is crucial to deliver targeted waste sorting information to individuals, particularly those who are new to the environment. This intervention is more effective and important in promoting proper waste sorting practices in the student housing community.

Furthermore, the state of waste collection facility was emphasized by some interviewees as a

determined factor. Many individuals mentioned that they are inclined to sort their waste based on the state of the waste collection facility, taking into consideration factors such as its aesthetics, cleanliness, and overall organization. However, in the literature review, waste collection services also refer to the aspect of cleanliness of the waste collection facilities managed by the student housing manager. But through the inductive analysis, it was revealed that interviewees primarily focused on the design of the waste collection facilities when considering their state. One interviewee went as far as comparing the condition of the waste collection facilities and expressed, *"If the waste sorting facilities in our student housing are similar to the ones outside our building, I would feel more motivated to sort waste because they look prettier and more colorful."*

Moreover, there are also emerging codes that frequently mentioned by interviewees. For example, several interviewees highlighted their waste sorting behavior has become into a habit. The habit of waste sorting is a significant motivator for translating intention into actual waste sorting behavior. However, the analysis revealed that the development of the habit is influenced by situational factors such as regulations and subjective norms within the community. In other words, the habit of waste sorting can be effective with the implementation of regulations. For example, in the absence of regulations, individuals who have developed the habit of waste sorting may choose not to sort their waste. Consequently, the habit in this case will be analyzed as a response to the social pressure within the framework of regulation, rather than being regarded as an individual factor in the questionnaire design. In addition to the habit, the effort was highlighted by some interviewees. Interviewees expressed that the effort involved in waste sorting acted as a barrier for them. The perceived effort associated with this behavior can result in low perceived behavioral control and behavioral intention even if they had a positive attitude towards waste sorting. Interviewees indicated that the effort required for waste sorting posed a challenge for them. This perceived effort could lead to a low level of perceived behavioral control and intention to engage in the behavior, even if they had a positive attitude towards waste sorting. It was noticed that despite having a positive attitude, interviewees would choose not to participate in waste sorting if they felt that the effort outweighed the positive outcomes. For example, one interviewee expressed, *"I am willing to do it, if I mean the feeling of achievement that is exceeding the feeling of the effort of doing something."*

Table 12 Inductive analysis

Codes	Description	Quotes	Frequency	Themes
Regulation	Statements that indicate the regulation have an impact on waste sorting behavior	<i>"Following their regulation is the only reason that can drive me to sort my waste."</i> <i>"I think it's kind of obligation for us to do the waste sorting."</i>	5/5	Subjective norm; Information publicity

Information introduction to the new neighbor	Statements that indicate the information introduction to the new neighbor is important	<i>“But I think for international student new to the student housing. I think it's good to have that information available”</i>	3/5	Information publicity
The state of waste sorting facilities	Statements that indicate the state of waste sorting facility have an impact on waste sorting	<i>“The trash room is a big factor that demotivate me to sort the waste. It's very dark and ugly, as well as smelly.”</i>	3/5	Waste sorting facilities
Habit	Statements that indicate the sorting the waste becomes a habit	<i>“But when I sort it like for months and more, I think I get used to it. So, it's kind of like a daily routine for me”</i>	3/5	Subjective norm
Efforts	Statements that indicated the person takes the time and energy to conduct the behavior	<i>“We can also recycle bottles to the supermarket and get some money back. But because supermarket is far, so I don't want to waste my energy to bring the bottles back to the supermarket.”</i>	2/5	Perceived behavioral control

4.1.3 Summary of qualitative results

To summarize, all psychological factors identified in the literature review were emphasized by the interviewees during the deductive analysis. Additionally, waste sorting facilities, information publicity, and economic incentives were deductively identified as important factors. However, specific aspects related to waste sorting facilities, such as quantity and capacity, and interventions related to information publicity, such as programs aimed at improving information delivery, were found to be ineffective factors in promoting waste sorting. Furthermore, it was observed that there is a gap between the waste sorting intention and waste sorting behavior. Even if some interviewees expressed their intention to sort their waste, the actual execution of this behavior might not occur due to factors such as the lack of waste sorting facilities, the required effort. Apart from the gap between intention and behavior, some interviewees demonstrated the moderating effect of situational factors, including information publicity and waste sorting facilities. This aligns with the finding from the literature review that situational factors can act as moderators in the relationship between waste sorting intention and behavior.

The inductive analysis revealed that regulations, information introduction to the new

neighborhood, and the state of waste collection facilities were frequently emphasized by the interviewees as important factors. Specifically, the aesthetic and pleasant environment of waste collection facilities was found to be important. Furthermore, it was found that providing information to new neighborhood of student housing is crucial and impactful in increasing awareness and encouraging waste sorting among individuals who are entering a new environment. The figure labeled as "Figure 22" illustrates codes encompassing both deductive and inductive elements, while another "Figure 23" represents the themes resulting from code categorization. Additionally, "Figure 24" presents a conceptual model incorporating both themes and codes.

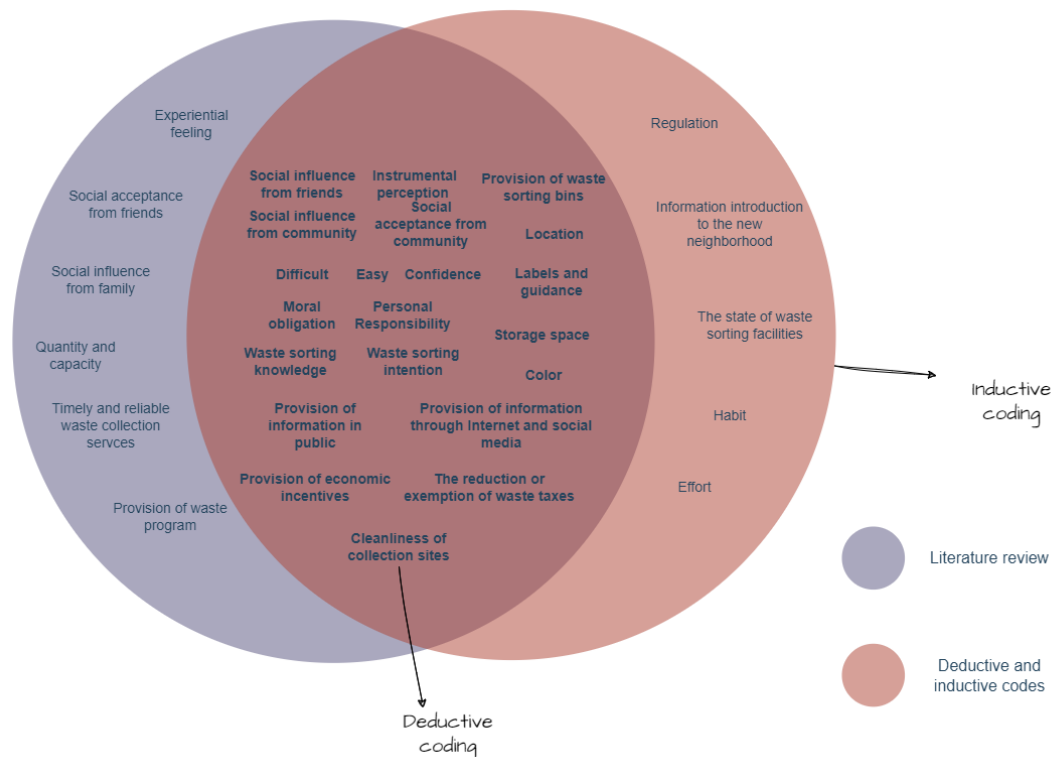


Figure 22 Coding step

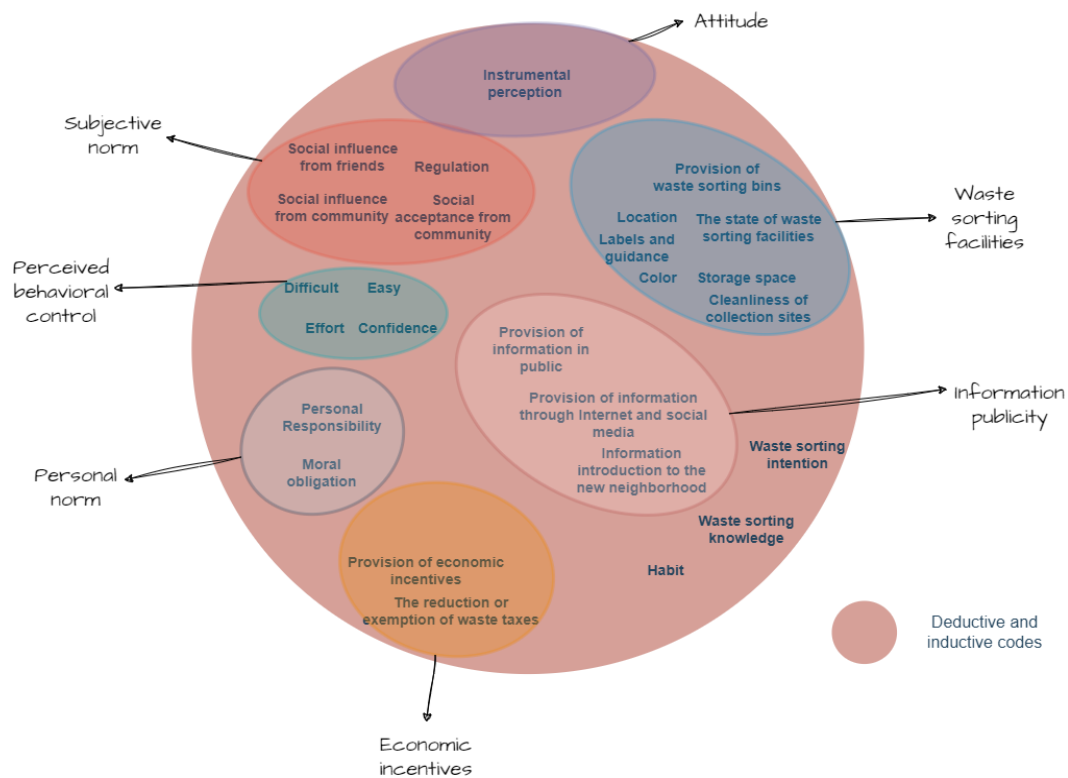


Figure 23 Categorizing codes into themes

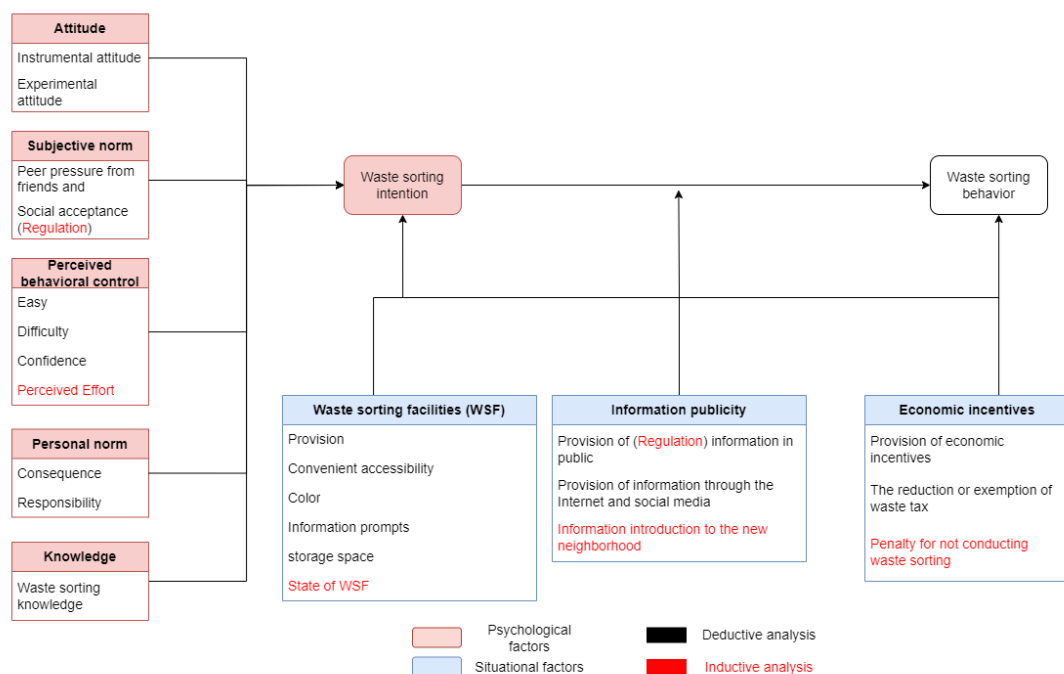


Figure 24 Qualitative results

4.1.3.1 Hypotheses development

Drawing from the qualitative findings, the hypotheses are formulated as shown below. The research model, featuring hypotheses, is visually depicted in Figure 25.

- H1: Students' attitudes (ATT) positively impact on their waste sorting intention (WSI).*
H2: Subjective norm (SN) positively impacts on students' WSI.
H3: Perceived behavioral control (PBC) positively impacts on students' WSI.
H4: Knowledge (KN) positively impacts on students' WSI.
H5: Personal norm (PN) positively impacts on students' WSI.
H6: Students' WSI positively impacts on WSB.
H7: Waste sorting facilities (WSF) positively impacts students' WSI.
H8: WSF positively impacts students' WSB.
H9: WSF as a moderator in promoting intention-behavior conversion.
H10: Information publicity (IP) positively impacts students' WSI.
H11: IP positively impacts students' WSB.
H12: IP as a moderator in promoting intention-behavior conversion.
H13: Economic incentives (EI) positively impact students' WSI.
H14: EI positively impacts students' WSB.
H15: EI as a moderator in promoting intention-behavior conversion.

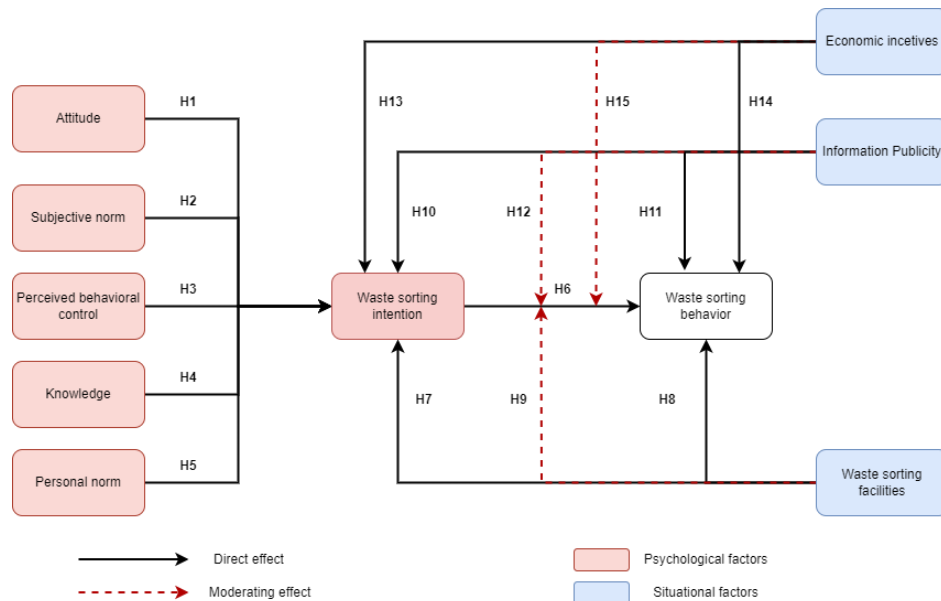


Figure 25 Research model with hypotheses

4.2 Quantitative Results

Regarding this chapter, [Section 4.2.1](#) provides the results of descriptive statistics for the collected quantitative data. Subsequently, in [Section 4.2.2](#), it confirms the existence of a disparity between waste sorting intention and actual behavior. Following the PLS-SEM analysis procedure, [Section 4.2.3](#) demonstrates that the measurement model meets all the required

criteria, indicating that the variables possess reliability and validity. Based on the reliable and valid measurement model, [Section 4.2.4](#) presents the evaluation of the structural model. However, the structural model does not meet all the necessary criteria, particularly due to its inadequate statistical power to draw valid conclusions. Consequently, [Section 4.2.5](#) outlines the refinement of the PLS-SEM model, encompassing the refinement procedure and a reassessment of the new measurement and structural models.

4.2.1 Descriptive statistics

Of the 163 responses that have been collected, 155 usable responses have been used as the final sample for analysis. Eight questionnaires were dropped owing to incompleteness. SPSS 28.0 statistical analysis software was used for the descriptive statistical analysis. The demographic descriptive results as shown in Table 13.

The sample consists of nearly equal proportions of males (50.3%) and females (49.7%), indicating a balanced representation of genders. Moreover, the majority of participants fall within the 18-34 age range, with a mere 4.5% of respondents being older than 35. In terms of educational status, 60.6% of the sample comprises master's students, 25.8% were bachelor's students, and the remaining 13.5% were Ph.D. students.

Table 13 Demographic descriptive statistics

Demographic characteristics	Number of cases	Percentage (%)
Gender		
Male	78	50.3
Female	77	49.7
Age		
18-24	94	60.6
25-34	54	34.8
>35	7	4.5
Education level		
Bachelor's degree	40	25.8
Master's degree	94	60.6
PhD	21	13.5

Table 14 presents the mean value and the standard deviation of each factor. The item for each factor has a range of 1 to 5. Among these factors, three factors have averages greater than 4. The attitude factor has the highest mean of 4.419, followed by economic incentives (4.112) and knowledge (4.092). On the other hand, waste sorting behavior has the lowest mean of 2.608, and information publicity's mean value comes next at 2.778. The mean value of the other factors ranges between 3 and 4. Most factors show a moderate spread from the mean, as indicated by their standard deviations, which are around 1. However, waste sorting behavior stands out with the highest standard deviation of 1.386, signifying greater variability in its data points from the average. Moreover, in terms of the particular waste sorting knowledge, participants were queried about recognizing fundamental waste categories, encompassing residual waste, paper

waste, PMD waste, and organic waste. The accuracy rate for each waste category is depicted in Figure 26. Notably, it is observed that only about 57% of the participants provided accurate responses concerning residual waste. In more detail, from Figure 27, roughly half of the participants correctly answered the entire set of waste sorting questions. This underscores the inadequacy of students' knowledge regarding waste sorting.

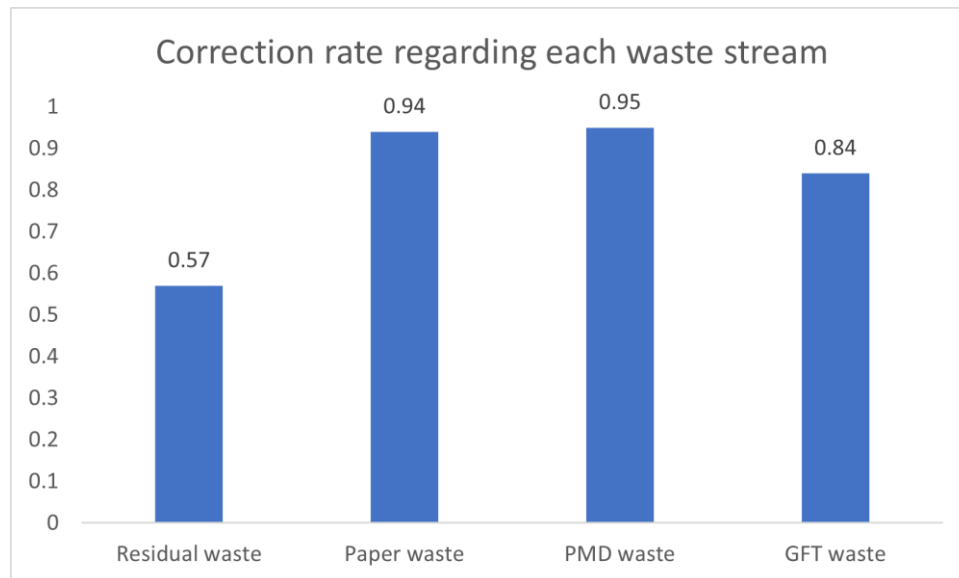


Figure 26 Correction rate regarding each waste stream

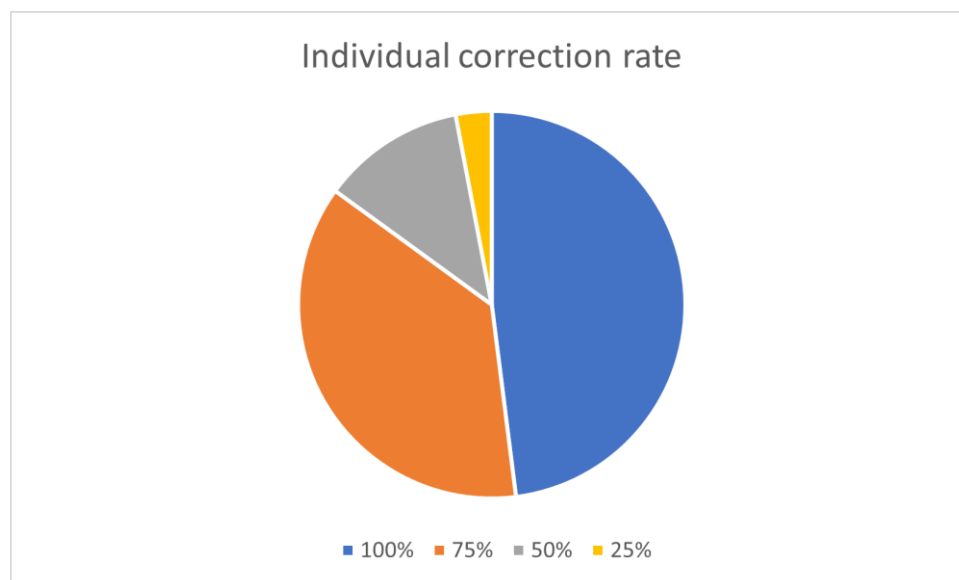


Figure 27 Correct response to the waste sorting questions

Table 14 Descriptive statistic of each construct

Construct	Number of items	Mean	Standard deviation
Attitude (ATT)	3	4.419	0.792
Subjective norm (SN)	4	3.976	0.933
Perceived behavioral control (PBC)	4	3.956	0.946
Knowledge (KN)	3	4.092	0.853
Personal norm (PN)	3	3.791	1.038
Waste sorting facilities (WSF)	4	3.282	1.200
Information publicity (IP)	3	2.778	1.220
Economic incentives (EI)	3	4.112	0.963
Waste sorting intention (WSI)	5	3.862	1.049
Waste sorting behavior (WSB)	5	2.608	1.386

4.2.2 Gap between the intention and waste sorting behavior

According to the description statistic shown in the Table 14, the mean value and the standard deviation of the waste sorting intention are 3.862 and 1.049 respectively, while the mean value and standard deviation of waste sorting behavior are 2.608 and 1.386 respectively. This indicates a disparity between the intention and the actual behavior of waste sorting. Despite the noticeable distinction in mean values, it is important to substantiate this with statistical analysis. Consequently, both a parametric paired sample t-test and a nonparametric Wilcoxon signed-ranked test were performed by using SPSS 28.0 to determine the significance of this difference.

The paired sample t-test outcomes reveal that the average difference between behavioral intention and waste sorting behavior is 1.254, as shown in Table 15. This falls within the 95% confidence interval ranging from 1.077 to 1.432. The two-tailed t-value is 13.949 ($p < 0.01$), indicating substantial statistical significance. This paired sample t-test underscores a noteworthy distinction between waste sorting intention and waste sorting behavior. Specifically, it can be concluded that there is a significant reduction from behavioral intention to waste sorting behavior.

Table 15 Paired sample test

Paired Samples Test									
Average_ WBI – Average _ WSB	Paired Differences							Significance	
			Std. Error Mean	95% Confidence Interval of the Difference				One- Sided p	Two- Sided p
Mean	Std. Deviation		Lower	Upper	t	df			
1.254	1.119	0.089	1.076	1.431	13.949	154	0.000	0.000	

Furthermore, the outcome of the nonparametric test demonstrates the rejection of the null hypothesis with a significance level of 0.01. In this context, the null hypothesis is that the

median difference between behavioral intention and waste sorting behavior equals 0. This result implies a statistically significant difference between waste sorting intention and waste sorting behavior. This nonparametric test result aligns with the findings of the paired sample t-test, providing additional evidence for the significant decrease from behavioral intention to waste sorting behavior. In summary, the findings indicate a disparity between the intention to sort waste and the actual behavior of waste sorting. This manifests as a decline from the intended behavior to the actual waste sorting behavior.

Hypothesis Test Summary				
	Null Hypothesis	Test	Sig. ^{a,b}	Decision
1	The median of differences between BI_AVE and SB_AVE equals 0.	Related-Samples Wilcoxon Signed Rank Test	.000	Reject the null hypothesis.

a. The significance level is .050.

b. Asymptotic significance is displayed.

Figure 28 Non parametric test

4.2.3 Evaluation of measurement model

4.2.3.1 Factor loading

It is important to assess the loading for each indicator in the reflective measurement model since it indicates the extent to which the variance of indicators is explained by the constructs. Thereby, the loading of each indicator should be above 0.708, which is the acceptable value (J. F. Hair et al., 2019; Hulland, 1999). As depicted in Table 16, the factor loading of each item in each construct is greater than 0.70. Even though the first waste sorting behavior indicator (WSB1) scored 0.701, slightly below the acceptable threshold, it was retained to maintain content validity. The results indicate that each measurement model effectively accounts for the variance in its associated indicators. And the measurement model can proceed further to be evaluated against other criteria.

Table 16 Factor loading of each item

	Factor loading	Mean	Standard deviation	Cronbach's alpha	Composite Reliability	AVE
ATT1	0.936	4.368	0.835	0.914	0.946	0.853
ATT2	0.917	4.4	0.775			
ATT3	0.918	4.49	0.757			
SN1	0.84	3.632	0.99	0.854	0.9	0.693
SN2	0.829	3.71	0.957			
SN3	0.841	4.323	0.842			
SN4	0.818	4.239	0.923			
PBC1	0.897	3.813	0.995	0.897	0.928	0.764
PBC2	0.846	3.923	0.954			
PBC3	0.893	4.232	0.826			
PBC4	0.859	3.858	0.987			

KN1	0.836	3.89	0.839	0.851	0.907	0.764
KN2	0.869	4.09	0.845			
KN3	0.915	4.297	0.866			
PN1	0.881	3.787	1.01	0.844	0.904	0.758
PN2	0.809	3.561	1.096			
PN3	0.919	4.026	0.996			
WSF1	0.789	2.929	1.229	0.858	0.903	0.699
WSF2	0.838	3.581	1.152			
WSF3	0.869	3.206	1.284			
WSF4	0.846	3.413	1.112			
IP1	0.862	3.077	1.122	0.831	0.898	0.746
IP2	0.84	2.742	1.207			
IP3	0.89	2.516	1.312			
EI1	0.928	4.013	0.943	0.89	0.931	0.818
EI2	0.904	4.103	0.91			
EI3	0.882	4.219	1.024			
WSI1	0.748	4.452	0.91	0.848	0.892	0.623
WSI2	0.812	4.529	0.918			
WSI3	0.812	3.723	1.15			
WSI4	0.771	3.245	1.086			
WSI5	0.8	3.361	1.135			
WSB1	0.701	3.032	1.272	0.789	0.855	0.542
WSB2	0.782	2.987	1.197			
WSB3	0.712	2.697	1.447			
WSB4	0.737	2.077	1.439			
WSB5	0.746	2.245	1.525			

4.2.3.2 Internal consistency reliability

Subsequently, the second criterion is to evaluate internal consistency reliability. The conventional approach for assessing this involves examining Cronbach's alpha, where the value should exceed 0.7 (Bagozzi & Yi, 1988). However, Cronbach's alpha has faced criticism for being less precise, attributed to its utilization of unweighted items (J. F. Hair et al., 2019). Due to these limitations, there is an alternative technique for evaluating internal consistency reliability, referred to as composite reliability. A satisfactory range for composite reliability lies between 0.7 and 0.9 (Bagozzi & Yi, 1988). Moreover, the composite reliability exceeding 0.95 results from the presence of semantically redundant items, which is considered undesirable (J. F. Hair et al., 2022).

Given the limitation of Cronbach's alpha, the results include an assessment of internal consistency reliability using both Cronbach's alpha and composite reliability. Table 16 displays that the Cronbach's alpha for each measurement model surpasses 0.7, while the composite reliability ranges between 0.85 and 0.95 for all measurement models. These findings imply a desirable level of internal consistency reliability for each measurement model.

4.2.3.3 Convergent validity

The third criterion is to assess the convergent validity of each construct. This criterion aims to measure how much each indicator correlates positively with other indicators in the same construct (J. F. Hair et al., 2022). In order to indicate one specific reflective construct, the items should converge or display a substantial shared amount of variability. The metric for assessing the construct's convergent validity is average variance extracted (AVE). An AVE value greater than 0.5 is considered satisfactory, denoting that constructs account for over fifty percent of the variance in their indicators (J. F. Hair et al., 2022). Table 16 shows that the AVE value of each construct is higher than 0.5. This outcome demonstrates that each construct exhibits a strong average shared variance, thus confirming satisfactory convergent validity.

4.2.3.4 Discriminant validity

The last criterion is to evaluate the discriminant validity of each construct. Discriminant validity refers to how much a reflective construct differs from other reflective constructs within the structural model. Typically, Fornell-Larcker criterion is used to determine the discriminant validity, which involves comparing the square root of the AVE value with the correlations between latent variables (Fornell & Larcker, 1981). This approach is based on the fact that the reflective constructs share a greater amount of variance among their indicators compared to other constructs within the structural model. Hence, the square root of the AVE for each construct should be greater than its largest correlation with any other construct. The bold values on the diagonal of Table 17 represent the square root of AVE and are larger than the values outside the diagonal. This finding validates the satisfactory discriminant validity within each measurement model, as assessed by the Fornell-Larcker criterion.

Table 17 Correlation within each construct

Constructs	ATT	SN	PBC	KN	PN	WSF	IP	EI	BI	WSB
ATT	0.924									
SN	0.524	0.832								
PBC	0.332	0.512	0.874							
KN	0.337	0.347	0.303	0.874						
PN	0.469	0.565	0.519	0.405	0.871					
WSF	0.129	0.294	0.181	0.205	0.188	0.836				
IP	0.18	0.307	0.221	0.152	0.162	0.432	0.864			
EI	0.224	0.377	0.35	0.062	0.346	0.241	0.074	0.905		
WSI	0.128	0.299	0.328	0.111	0.232	0.122	0.09	0.065	0.789	
WSB	0.152	0.328	0.382	0.113	0.184	0.371	0.396	0.209	0.274	0.736

Note: The diagonal number displays the square root of AVE of each construct

However, the validity of the Fornell-Larcker criterion has been doubted by Henseler et al. (2015), particularly when there are minor variations in indicator loadings on a construct (Henseler et al., 2015). Consequently, Henseler et al. (2015) introduced the heterotrait-monotrait (HTMT) ratio as an alternative measure for assessing discriminant validity. The threshold for establishing discriminant validity among constructs is met when the HTMT ratio

is below 0.9, although a more conservative threshold is set at 0.85 (Henseler et al., 2015). In addition to that, it's important to utilize a statistical test for the HTMT ratio to confirm if there is a significant difference from the specified lower threshold values like 0.85 or 0.9 (Franke & Sarstedt, 2019).

Table 18 HTMT ratio

Constructs	ATT	SN	PBC	KN	PN	WSF	IP	EI	BI	WSB
ATT										
SN	0.587									
PBC	0.365	0.582								
KN	0.375	0.404	0.597							
PN	0.522	0.66	0.361	0.497						
WSF	0.145	0.349	0.206	0.247	0.211					
IP	0.211	0.383	0.258	0.185	0.209	0.503				
EI	0.241	0.425	0.394	0.089	0.401	0.276	0.107			
WSI	0.152	0.347	0.377	0.142	0.265	0.163	0.134	0.109		
WSB	0.187	0.399	0.449	0.166	0.235	0.43	0.477	0.274	0.336	

Hence, the results of the HTMT ratio are shown in Table 18, offering more tangible insights to illustrate the strong discriminant validity of each construct. It's evident that all HTMT values are noticeably below the more conservative threshold of 0.85. Furthermore, it's imperative to evaluate whether the HTMT ratios significantly differ from the threshold of 0.85. To examine the statistical significance, a one-tailed test with a 5% significance level was conducted. The confidence level, presented in [Appendix.C](#), includes the 5% lower bound and the 95% upper bound, serving to assess statistical significance. As the one-tailed test focuses on the right tailed of the distribution, in correspondence with the upper bound of the confidence intervals, all values in the 95% column are smaller than 0.85. In summary, both the confidence intervals and the HTMT ratio indicates the discriminant validity of the constructs.

In conclusion, each measurement model in this research establishes reliability and validity by meeting the required threshold for each criterion. This is the premise for drawing some valuable insights during the subsequent evaluation of the structural model.

4.2.4 Evaluation of structural model

After confirming the adequacy of the measurement model, the next step involves evaluating the structural model. This entails the assessment of several criteria, including the coefficient of determination (R^2), effect size (f^2), the cross-validated redundancy measure (Q^2), PLSpredict and the statistical significance and relevance of the path coefficients (J. F. Hair et al., 2019).

Collinearity assessment should be conducted before the evaluation of the structural model. As collinearity can introduce bias into regression outcomes, it's essential to scrutinize variance inflation factor (VIF) values as a metric for assessing collinearity. A VIF value exceeding 5 indicates significant collinearity, whereas a VIF value below 3 suggests minimal impact on the

estimation of the structural model (J. F. Hair et al., 2019). Due to evaluating the structural model, only VIF values of exogenous constructs, which serves as independent variables in the structural model, are displayed in the following Table 19. Table 19 shows that all VIF values provided are smaller than 3, indicating that collinearity among the independent variables is not a critical issue for estimating the structural model. Hence, the structural model in this study can be subjected to evaluation against other criteria.

Table 19 Value of VIF

	WSI	WSB
ATT	1.504	
SN	2.021	
PBC	1.581	
KN	1.31	
PN	1.849	
WSF	1.345	1.308
IP	1.318	1.233
EI	1.312	1.065
WSI		1.018

Generally, the explanatory power of the structural model is quantified using R^2 , which is derived from the squared correlation between a specific endogenous construct and the predicted endogenous construct (J. F. Hair et al., 2022). R^2 indicates the extent to which the variance in endogenous constructs is accounted for by all connected exogenous constructs (J. F. Hair et al., 2022). Furthermore, R^2 lies within the range of 0 to 1, with a higher value indicating strong explanatory power. Nevertheless, the acceptable R^2 value depends on the research context. In this research, three specific threshold are identified for R^2 from Cohen (1998) : 0.26 denotes substantial explanatory capability, 0.13 signifies moderate explanatory capacity, and 0.02 indicates limited explanatory effectiveness. Apart from that, some researchers (Cohen, 1998; J. F. Hair et al., 2022) also used the assessment of f^2 effect size as the facilitating assessment to explain the R^2 . This is because the f^2 effect size calculate the changes in the R^2 value that occurs when a specific exogenous construct is excluded from the structural model (J. F. Hair et al., 2022). As outlined by Cohen (1998), f^2 values of 0.02, 0.15, and 0.35 correspond to a minor, moderate, and substantial impact, respectively, of a predictor construct on an endogenous construct.

As depicted in Figure 29, the R^2 values of behavioral intention and waste sorting behavior are 0.149 and 0.270, respectively. To elaborate, the R^2 value of waste sorting behavior highlights that 27% of its variance can be accounted for by factors including behavioral intention, waste sorting facilities, information publicity, and economic incentives. This demonstrates that the structural model possesses a significant capacity to explain waste sorting behavior. On the other hand, behavioral intention can be explained by its connected exogenous variables to an approximate extent of 15%. From the values of f^2 presented in the Table 20, subjective norm and perceived behavioral control have a minor effect size of 0.029 and 0.051, respectively, on the behavioral intention. Moreover, the waste sorting facilities, information publicity, and

economic incentives and behavioral intention all yield small effect sizes on waste sorting behavior. Regarding waste sorting intention (WSI), it is observed that the variables EI, WSF, ATT, KN, IP, and PN exhibit effect sizes below 0.02, shown in red in Table 20, indicating that they do not contribute significantly to the explanation of WSI.

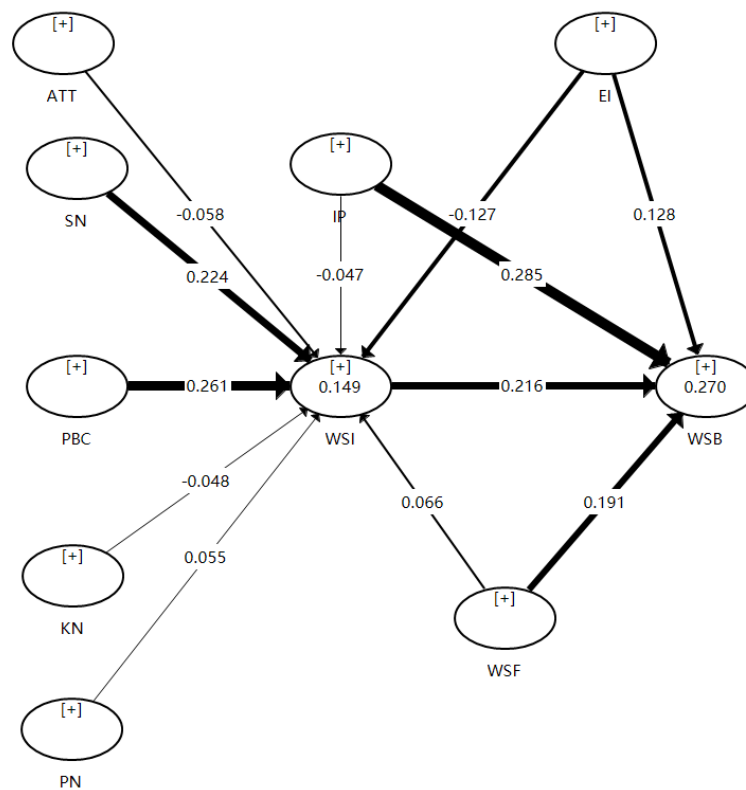


Figure 29 Research structural model

Table 20 Value of *f*-square

	WSI	WSB
ATT	0.003	
SN	0.029	
PBC	0.051	
KN	0.002	
PN	0.002	
WSF	0.004	0.038
IP	0.002	0.09
EI	0.014	0.021
WSI		0.063

The PLS-SEM model should yield generalized results that are broadly applicable, facilitating

researchers in making managerial decisions (J. F. Hair et al., 2022). Therefore, solely assessing the explanatory power of the structural model is insufficient; evaluating the model's predictive capability is equally important. A suitable means to do so is through the Stone-Geisser's Q^2 statistic (Geisser, 1974; Stone, 1974). A higher Q^2 value implies greater predictive accuracy. Q^2 values exceeding 0, 0.25, and 0.5 indicate slight, moderate, and substantial predictive power of the model, respectively (J. F. Hair et al., 2019). In this research, the Q^2 values of the behavioral intention and waste sorting behavior are 0.08 and 0.134, respectively. This finding suggests a slight predictive capability of the structural model.

However, the Q^2 values does not evaluate the out-of-sample prediction. To address this issue and evaluate the model's predictive capability, it is necessary to perform PLSpredict. The results of PLSpredict are shown in the Table 21. To ensure that the predictions outperform the basic naïve benchmark, the Q^2_{predict} should be verified first with a value greater than 0 (Shmueli et al., 2015). Because of the low WSI5 score, it can be inferred that the latent variable WSI does not surpass the performance of the naïve benchmark. This suggests that WSI lacks predictive power in out-of-sample situations, whereas WSB outperforms the naïve benchmark and can withstand subsequent verification. On the basis of the verification of Q^2_{predict} , it becomes imperative to assess the prediction statistics. The criteria for evaluation are established following guidelines from Shmueli et al. (2019), which involve a comparison between PLS_RMSE and a naïve benchmark. From Table 21, it is observed that PLS_RMSE for all WSB indicators is lower than LM_RMSE. Consequently, it can be concluded that the endogenous variable WSB has predictive power.

Table 21 Result of PLSpredict (out-of-sample prediction)

	PLS-SEM	RMSE		Q^2_{predict}
		LM (naïve benchmark)		
WSI1		0.913	0.976	0.007
WSI2		0.904	0.972	0.045
WSI3		1.153	1.249	0.01
WSI4		1.084	1.234	0.014
WSI5		1.156	1.293	-0.021
WSB1		1.173	1.258	0.161
WSB2		1.111	1.187	0.145
WSB3		1.417	1.421	0.057
WSB4		1.373	1.476	0.103
WSB5		1.474	1.668	0.082

After ensuring that the explanatory and predictive power are sufficient, the significance and relevance of the path coefficients in the structural model should be assessed. The aim of testing the statistical significance of the path coefficients is to ascertain if the correlations between the exogenous constructs and endogenous constructs are statistically meaningful. This assessment involves calculating t-values and p-values. For instance, under a significance level of 5%, if the p-values are less than 5%, the null hypothesis can be rejected, leading to the conclusion that the path coefficient is significant at a 95% confidence level.

The result of the significance test of the structural model path coefficients are shown in the Table 22. As presented in the same table, subjective norm and perceived behavioral control exhibit a positive and statistically significant association with waste sorting behavioral intention. To be precise, the impact of the subjective norm on the intention to sort waste is nearly the same as that of perceived behavioral control, with values of 0.224 and 0.261 correspondingly. Consequently, hypotheses H2 and H3 are supported. Furthermore, attitude, knowledge, personal norm, waste sorting facilities, information publicity and economic incentives have no significant influence on the waste sorting intention. Hypotheses H1, H4, H5, H7, H10, H13, H14 are not supported.

Simultaneously, waste sorting facilities, information publicity, and waste sorting intention all display positive and significant effects on waste sorting behavior. Among these three factors, information publicity displays the most substantial effect on waste sorting behavior, as evidenced by the path coefficient of 0.285. Following closely is the waste sorting intention, represented by a path coefficient of 0.261. Waste sorting facilities exert the least influence on waste sorting behavior. Consequently, hypotheses H6, H8, and H11 receive support. However, it's worth noting that there is no significant correlation found between economic incentives and waste sorting behavior, leading to the non-support of hypothesis H14.

Table 22 Results of hypothesis verification

					95%		
		Path		P	Confidence	Significance	
Hypothesis		coefficient	T Statistics	Values	intervals	(p<0.05)	Results
ATT → WSI	H1	-0.058	0.668	0.504	[-0.227,0.123]	No	-
SN → WSI	H2	0.224*	2.139	0.032	[0.013,0.422]	Yes	Verified
PBC → WSI	H3	0.261**	2.756	0.006	[0.075,0.445]	Yes	Verified
KN → WSI	H4	-0.048	0.451	0.652	[-0.281,0.173]	No	-
PN → WSI	H5	0.055	0.535	0.593	[-0.131,0.274]	No	-
WSI → WSB	H6	0.216*	2.172	0.03	[0.028,0.42]	Yes	Verified
WSF → WSI	H7	0.066	0.619	0.536	[-0.153,0.269]	No	-
WSF → WSB	H8	0.191*	2.358	0.018	[0.031,0.346]	Yes	Verified
IP → WSI	H10	-0.047	0.47	0.638	[-0.238,0.151]	No	-
IP → WSB	H11	0.285**	3.797	0	[0.138,0.435]	Yes	Verified
EI → WSI	H13	-0.127	1.371	0.17	[-0.302,0.06]	No	-
EI → WSB	H14	0.128	1.386	0.166	[-0.064,0.304]	No	-

*p<0.05, **p<0.01

4.2.4.1 Moderation analysis

Moderation includes a third variable, known as the moderator variable, affects the relationship between two constructs. The moderator can influence the strength of this relationship and, in some cases, even alter the direction of the relationship between the two connected constructs (J. F. Hair et al., 2022). In this research, the waste sorting facilities, information publicity, and

economic incentives are three distinct moderators that are hypothesized to impact the relationship between waste sorting intention and behavior.

In order to examine the moderating effect of the waste sorting facilities, information publicity and economic incentives, interaction terms were created as depicted in the green ellipses in Figure 30. By incorporating the moderating effect, the R^2 value for waste sorting behavior is increased from 0.269 to 0.304. This finding indicate that the moderating factors of waste sorting facilities, information publicity, and economic incentives increase the explanatory capacity for waste sorting behavior.

From Table 23, the p-values for the three moderators are greater than 0.05, suggesting that waste sorting facilities, information publicity, and economic incentives do not exhibit a significant moderating effect. Consequently, the hypotheses H9, H12 and H15 are rejected. Waste sorting facilities, information publicity, and economic incentives, do not directly influence the relationship between waste sorting intention and waste sorting behavior.

Table 23 Moderation effect of the situational factors

Hypothesis		Original Sample (O)	T Statistics	P Values	Results
WSI * WSF → WSB	H9	-0.145	1.328	0.184	Rejected
WSI * IP → WSB	H12	0.115	1.076	0.282	Rejected
WSI * EI → WSB	H15	-0.057	0.633	0.527	Rejected

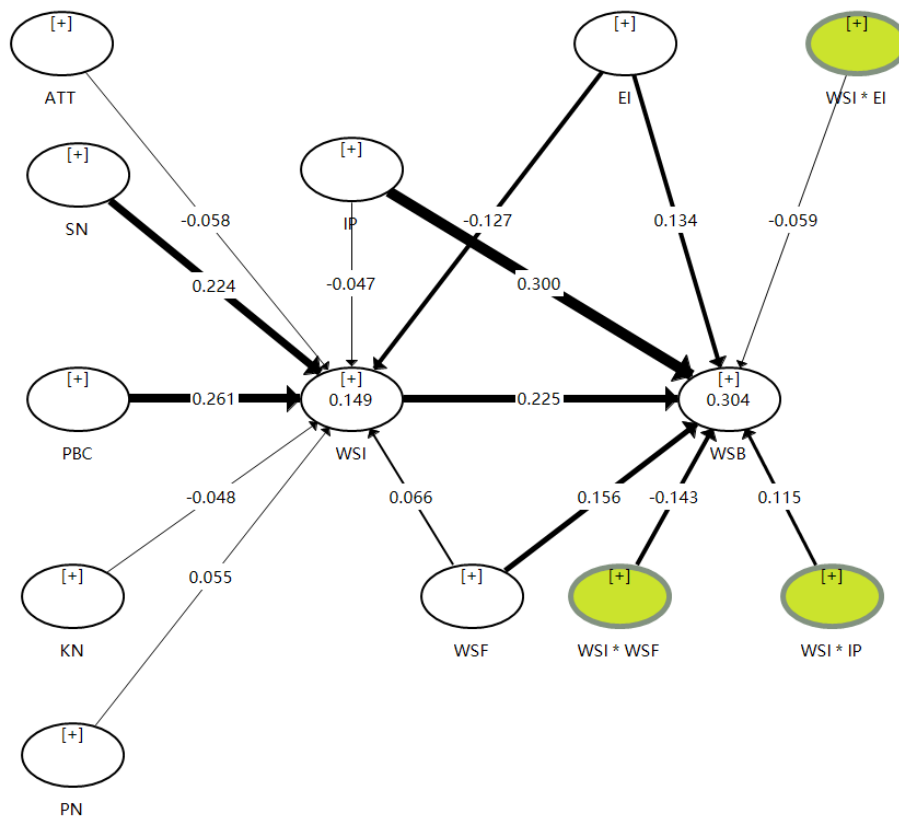


Figure 30 Research model with moderating analysis

4.2.4.2 Summary of evaluation of structural model

To sum up, the structural model in this study exhibits inadequate explanatory and predictive abilities, as it only partially meets the specified criteria. In particular, when considering effect sizes, a considerable portion of exogenous variables do not display any acceptable effect size in explaining their corresponding endogenous variables. Moreover, a significant number of hypotheses were rejected, indicating that the structural model lacks sufficient statistical power. Due to these factors, the structural model cannot yield valid conclusions, underscoring the need for model refinement.

4.2.5 Refinement of PLS-SEM model

In the research, the presence of numerous paths that lack statistical significance and lead to rejection indicates a deficiency in the statistical power of the initial PLS-SEM model to make valid conclusions, as shown in Table 22. This limitation can be attributed to the complexity of the model (Figure 29), which encompasses 10 constructs and 15 paths, all within the constraints of a relatively small sample size.

Furthermore, aside from the sample size, the effect size is another factor that affects statistical power (Sullivan & Feinn, 2012). In this study, Table 20 in [Section 4.2.4](#) illustrates that the

majority of variables have no effect size concerning WSI, while variables related to WSB only show a weak effect size. Therefore, the effect size could be another contributing reason to the model's limited statistical power. Moreover, the explanatory and predictive abilities of the WSI variable are comparatively weak in comparison to the WSB variable. Therefore, there is a need for enhancement in the PLS-SEM model.

In order to draw valid conclusions based on a model with enough statistical power, it is necessary to refine the PLS-SEM model, owing to the time limit of collecting more data. Based on the original data set, it is better to simplify the PLS-SEM model by decreasing the variables and connected paths. This procedure is according to the path coefficient and the effect size of variables. From Table 22, it is found that the low correlations from KN, PN, WSF, and IP to WSI. From Table 20, the KN, PN, WSF, and IP have no effect size to explain the WSI. Therefore, these paths were excluded from the model.

Moreover, in the preliminary quantitative analysis, the moderating effect of situational factors was analyzed. The outcomes, as illustrated in Table 23, did not provide empirical support for any of the moderation hypotheses. Aguinis et al. (2017) suggests that this lack of support could be attributed to inadequate statistical power. Consequently, to ensure reliable conclusions and given the constraints of the limited sample size, the analysis of the moderation effect for situational factors is not included in the refined PLS-SEM model.

In order to ensure the model possesses adequate statistical power for drawing valid conclusions, it is imperative to refine the PLS-SEM model due to limitations in collecting additional data within the given time constraints. To simplify the PLS-SEM model based on the original dataset, it is advisable to reduce the number of variables and associated paths. This simplification process is guided by both the path coefficient and the effect size of the variables. As indicated in Table 22, it becomes evident that there are weak correlations between ATT, KN, PN, WSF, IP and EI with respect to WSI. Additionally, Table 20 reveals that these variables (ATT, KN, PN, WSF, IP, EI) lack any significant effect size in explaining WSI. As a result, all of these paths were excluded from the model except for the connection between ATT and WSI. This exception was made because attitude is an essential factor in the fundamental TPB theory and is also highlighted in the ABC model.

Moreover, EI has been excluded from the model. The reason for this exclusion is that the economic factor is closely associated with socio-economic status to a significant degree. As indicated in Knickmeyer (2020), it is noted that economic incentives can be a potent motivator for individuals in lower-income populations. However, in this specific context, students who have a strong academic orientation may have limited or no income. Qualitative findings in this research underscore that economic incentives are considered a pivotal factor in encouraging students to engage in waste sorting. Additionally, when compared to WSF and IP, the effectiveness of WSB appears to be less reliant on EI (Knickmeyer, 2020). In summary, the modified PLS-SEM model, incorporating the new hypotheses, is presented below. This updated model comprises a total of 7 constructs and 6 hypotheses.

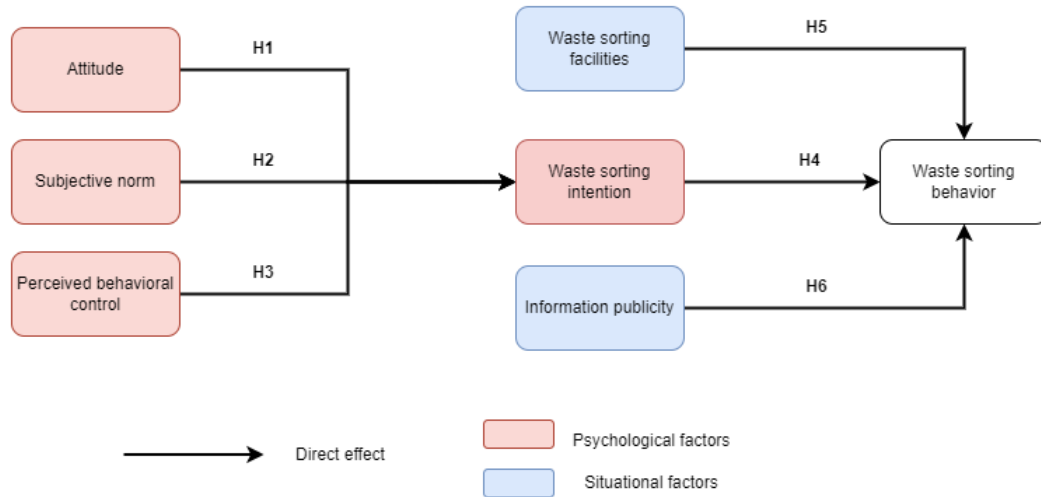


Figure 31 Refined PLS-SEM model with hypotheses

The upcoming steps replicate the previous quantitative analysis, as elaborated in [Sections 4.2.3](#) and [4.2.4](#). This sequence begins by assessing the measurement model, followed by an evaluation of the structural model.

4.2.5.1 Evaluation of refined PLS-SEM measurement model

As depicted in Table 24, the factor loading of each item in each construct is greater than 0.70, except WSI1, which achieves 0.674. Nonetheless, the factor loading for item WSI1 falls within the range of 0.4 to 0.7, a range that is considered acceptable but requires justification as specified in Hair & Alamer (2022). The item assesses the intention regarding PMD waste, aligning with item WSB1, which evaluates the behavior related to PMD waste. Moreover, this item meets acceptable levels for other validity and reliability measures, as shown in the following steps. Consequently, it can be concluded that this item maintains its content validity. The results indicate that each measurement model effectively accounts for the variance in its associated indicators. Presented within the same Table 24, both Cronbach's alpha and the composite of each construct surpass the threshold of 0.7, signifying strong internal consistency reliability. Regarding convergent validity, the AVE values for each construct exceed 0.5, affirming that each construct demonstrates adequate convergent validity.

Table 24 Factor loading of each construct (Refined PLS-SEM model)

	Factor loading	Mean	Standard deviation	Cronbach's alpha	Composite Reliability	AVE
ATT1	0.937	4.368	0.835	0.914	0.946	0.853
ATT2	0.916	4.4	0.775			
ATT3	0.918	4.49	0.757			
SN1	0.839	3.632	0.99	0.854	0.9	0.693
SN2	0.829	3.71	0.957			
SN3	0.842	4.323	0.842			

SN4	0.819	4.239	0.923				
PBC1	0.897	3.813	0.995	0.897	0.928	0.764	
PBC2	0.846	3.923	0.954				
PBC3	0.893	4.232	0.826				
PBC4	0.859	3.858	0.987				
WSF1	0.796	2.929	1.229	0.858	0.902	0.698	
WSF2	0.828	3.581	1.152				
WSF3	0.872	3.206	1.284				
WSF4	0.845	3.413	1.112				
IP1	0.857	3.077	1.122	0.831	0.898	0.746	
IP2	0.84	2.742	1.207				
IP3	0.894	2.516	1.312				
WSI1	0.674	4.452	0.91	0.848	0.892	0.623	
WSI2	0.757	4.529	0.918				
WSI3	0.707	3.723	1.15				
WSI4	0.766	3.245	1.086				
WSI5	0.77	3.361	1.135				
WSB1	0.759	3.032	1.272	0.789	0.855	0.541	
WSB2	0.821	2.987	1.197				
WSB3	0.804	2.697	1.447				
WSB4	0.764	2.077	1.439				
WSB5	0.796	2.245	1.525				

Concerning the discriminant validity, the Fornell-Larcker criterion, as shown in Table 25, and HTMT ratio, presented in Table 26, have been evaluated. Additionally, the HTMT confidence interval, provided in [Appendix D](#), is assessed to ensure a comprehensive evaluation. The values meet the required criteria, affirming that there is adequate discriminant validity within each measurement model. In conclusion, the measurement model of the refined PLS-SEM model demonstrates both reliability and validity.

Table 25 Correlation within each construct (Refined PLS-SEM model)

Constructs	ATT	SN	PBC	WSF	IP	WSI	WSB
ATT	0.924						
SN	0.524	0.832					
PBC	0.332	0.512	0.874				
WSF	0.13	0.294	0.181	0.836			
IP	0.181	0.306	0.221	0.436	0.864		
WSI	0.131	0.301	0.329	0.117	0.089	0.789	
WSB	0.147	0.316	0.37	0.369	0.403	0.275	0.736

Note: The diagonal number displays the square root of AVE of each construct

Table 26 HTMT ratio of refined PLS-SEM model

Constructs	ATT	SN	PBC	WSF	IP	WSI	WSB
ATT							
SN	0.587						
PBC	0.365	0.582					
WSF	0.145	0.349	0.206				
IP	0.211	0.383	0.258	0.503			
WSI	0.152	0.347	0.377	0.163	0.134		
WSB	0.187	0.399	0.449	0.43	0.477	0.336	

4.2.5.2 Evaluation of refined PLS-SEM structural model

Firstly, the structural model is evaluated against the collinearity issues. Based on the information in Table 27, the collinearity among the independent variables in the refined PLS-SEM model does not pose a significant concern when estimating the structural model.

Table 27 Value of VIF (Refined PLS-SEM model)

	WSI	WSB
ATT		1.39
SN		1.677
PBC		1.365
WSF		
IP		
WSI		

Secondly, the explanatory power of the structural model is assessed by examining R^2 values and effect size f^2 . R^2 values of behavioral intention and waste sorting behavior are 0.135 and 0.258, respectively, as indicated in Figure 32. This suggests that 25.8% of the variation in WSB can be explained by WSI, IP, and WSF. Additionally, WSI can be elucidated to an extent of 13.5% by SN and PBC. Except for ATT, which has no effect size, all constructs exhibit a weak effect size in explaining their respective connected endogenous constructs, WSI and WSB, as illustrated in Table 28.

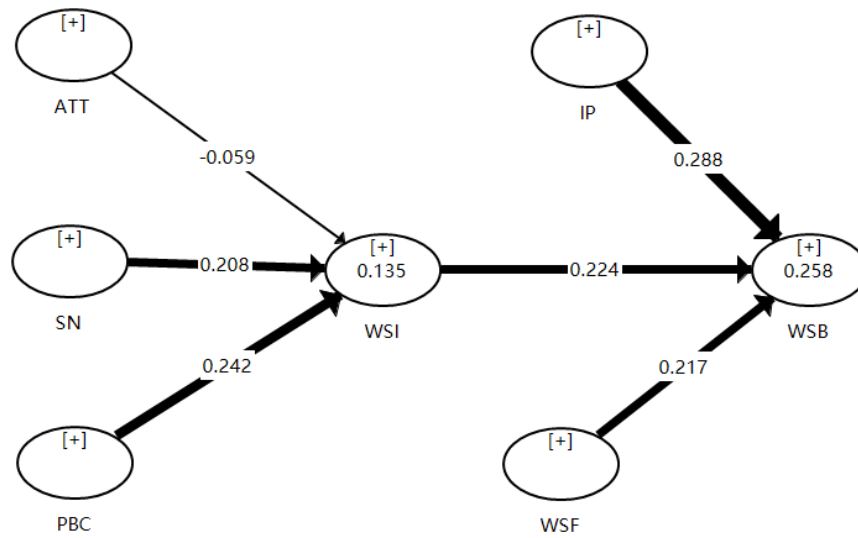


Figure 32 Refined PLS-SEM model

Table 28 Effect size of each construct in refined PLS-SEM model

	WSI	WSB
ATT	0.003	
SN	0.03	
PBC	0.05	
WSF		0.051
IP		0.09
WSI		0.067

Thirdly, the predictive power of the structural model is examined. The Stone-Geisser's Q2 values for behavioral intention and waste sorting behavior are 0.08 and 0.127, respectively. Furthermore, considering out-of-sample prediction, the result of PLSpredict as shown in Table 29. The observation from Table 29 reveals that PLS_RMSE for all WSI indicators is lower than LM_RMSE. However, there is only one instance where the prediction error for a WSB indicator exceeds the naïve benchmark, indicated in red. Therefore, it can be concluded that the model demonstrates acceptable predictive capability.

Table 29 Result of PLSpredict (Refined PLS-SEM model)

	RMSE			Q ² predict
	PLS-SEM	LM (naïve benchmark)		
WSI1		0.882	0.928	0.069
WSI2		0.876	0.922	0.099
WSI3		1.135	1.184	0.038
WSI4		1.067	1.157	0.046
WSI5		1.129	1.233	0.025

WSB1	1.192	1.223	0.137
WSB2	1.131	1.182	0.122
WSB3	1.423	1.377	0.046
WSB4	1.348	1.366	0.134
WSB5	1.45	1.57	0.109

Lastly, we analyze the path coefficients and the significance of these coefficients, as depicted in Table 30. In the same table, it is observed that SN and PBC have a positive and statistically significant association with WSI. More precisely, the influence of SN and PBC on the intention to engage in waste sorting is reflected in values of 0.208 and 0.242, respectively. This provides support for hypotheses H2 and H3. However, it's worth noting that ATT does not significantly influence WSI, leading to the lack of support for Hypothesis H1. Simultaneously, WSF, IP, and WSI all exhibit positive and significant effects on WSB. Among these three factors, IP has the most substantial effect on WSB, with a path coefficient of 0.288, followed closely by WSI, with a path coefficient of 0.224. WSF has the least influence on WSB. Consequently, hypotheses H4, H5, and H6 receive support.

Table 30 Results of hypothesis verification (Refined PLS-SEM model)

					95%	
		Path	T	P	Confidence	
Hypothesis		coefficient	Statistics	Values	intervals	Results
ATT → WSI	H1	-0.059	0.751	0.453	[-0.212,0.098]	Rejected
SN → WSI	H2	0.208*	2.219	0.027	[0.027,0.397]	Accepted
PBC → WSI	H3	0.242**	2.772	0.006	[0.078,0.42]	Accepted
WSI → WSB	H4	0.224*	2.287	0.022	[0.042,0.424]	Accepted
IP → WSB	H5	0.288**	3.984	0	[0.15,0.433]	Accepted
WSF → WSB	H6	0.217**	2.603	0.009	[0.052,0.378]	Accepted

*p<0.05, **p<0.01

Regarding the refined PLS-SEM structural model, it demonstrates both acceptable explanatory and predictive capabilities. Additionally, it maintains satisfactory statistical power, with only one path showing statistical insignificance. As a result, reliable and valid conclusions can be drawn based on this refined PLS-SEM model.

5. Discussions

This chapter includes a discussion of the findings, which is divided into three sections. [Section 5.1](#) delves into the analysis of students' waste sorting behavior in the context of Delft student housing. [Section 5.2](#) outlines the academic contribution of this research. Finally, [section 5.3](#) presents the practical implications of motivating college students and recommendations for interventions that focus on the situational context to engage students in sorting waste.

5.1 Reflection

Within this section, the reflection focuses on two perspectives regarding students' household waste sorting behavior within the context of student housing. The first perspective is focused on the insights from the college student population, as they are a young and well-educated population group. The second perspective is focused on the context of the student housing, given that most of the student housing is in a high-rise setting with limited interior space and extensive communal areas.

5.1.1 Reflection on the college student population

This research has analyzed student's waste sorting behavior while living in the student housing, using the case study of Delft. The student population, especially college students, is generally acknowledged as a highly educated young generation in society. Due to their professional skills and knowledge, college students are seen as playing an important role in advocating and promoting pro-environmental behavior like waste sorting. This research has yielded specific insights targeted at the student group from the practical point of view.

Firstly, this research revealed that attitude does not exert a significant influence on college students' intentions to sort household waste. This discovery is consistent with a prior study conducted by Shen et al. (2019) concerning young people. The results of the study by Shen et al. (2019) reveal that, even though young individuals are aware of the environmental benefits associated with waste sorting, they do not display an elevated inclination to participate in the behavior. In contrast to young individuals, college students are characterized not only by their youth but also by their high level of education. In this research, college students were found to have a positive attitude towards waste sorting, as they perceive it is beneficial for the environment. This suggests that college students, being a well-educated group, possess a high level of environmental consciousness. However, this high awareness seems to be superficial and does not translate into a strong inclination among college students to engage in waste sorting. One possible explanation for this could be that college students perceive waste sorting as a communal responsibility rather than an individual one. In other words, they may believe that waste sorting should be the responsibility of the community or local authorities, particularly given their contribution through waste fees.

Secondly, the research observed a significant influence of subjective norms on the waste sorting behavior of college students. This finding aligns with previous research conducted by Zhang et al. (2017) on waste sorting behavior among college students in campus settings. Although the

finding remains consistent, there are variations in the context and measurement dimensions. In the research conducted by Zhang et al. (2017), subjective norm primarily measured the influence of peer pressure from surrounding friends and its impact on waste sorting behavior. The common finding is that college students are sensitive to the peer pressure exerted by their surrounding friends. In contrast, this research includes social pressure as a component within the assessment of the subjective norm. Hence, college students are likely to engage in waste sorting not only due to peer pressure but also because of social pressure exerted by the student housing community or society. Furthermore, the college student population includes a considerable number of international students residing in student housing. International students tend to possess a high desire for acceptance from both the community and their peers. This desire for social acceptance directly correlated with their willingness to adhere to waste sorting regulations within the student housing.

Finally, it is observed that the perceived behavioral control exerts an influence on college students' intention to sort household waste. This finding is consistent with the research conducted by Shen et al. (2019). The research conducted by Shen et al. (2019) indicates that young people perceive the difficulty or ease of the task can directly impact their intention to engage in waste sorting. This is consistent with the college students. In addition to their status as a young generation, college students, as a well-educated group, show that their actions are strongly influenced by their level of confidence in performing the behavior. This is because college students typically possess advanced cognitive abilities and a substantial capacity for comprehension, which increase their confidence when engaging in waste sorting activities.

5.1.2 Reflection on the context of student housing

Student housing is known for its high-rise structures that feature a substantial number of individual rooms. According to the different household types, the waste sorting behavior might vary (Rousta et al., 2017). One of the most prominent features is the interior space between the low-rise building and the high-rise building. Low-rise buildings, particularly those designed for single-family households, offer more private space for waste sorting. In contrast, the interior space available in high-rise buildings is quite limited. Research conducted on multi-family dwellings by Ando & Gosselin (2005) has demonstrated that interior space is a factor influencing waste sorting behavior. This discovery aligns with the findings of this research on student housing, which shares the characteristic of limited interior space. In this study, students' waste sorting behavior is directly affected by waste sorting facilities, including considerations for interior space. Students may lack motivation to sort waste when there is insufficient room to accommodate separate waste bins for different waste streams. In contrast, low-rise buildings can utilize private exterior spaces like gardens for placing waste sorting facilities.

Additionally, this study also examines how the convenient accessibility of waste sorting facilities in communal spaces can impact students' waste sorting behavior. This finding aligns with research conducted on student housing by DiGiacomo et al. (2018). In study from DiGiacomo et al. (2018), it was observed that placing waste sorting facilities on each floor, rather than on the ground floor or in the basement, can enhance students' recycling behavior. In this research, waste sorting facilities are situated within the student housing but are placed on

the ground floor. This results in students having to sort their waste at their room and then transport it to the communal waste sorting facilities on the ground floor. This process can lead students living on higher floors to perceive waste sorting as more effortful. In contrast, residents in low-rise buildings, especially single-family dwellings, have the directly advantage of utilizing their private waste sorting facilities rather than communal ones. This makes the waste sorting process more convenient for them.

However, it is worth noting the intriguing variation in the connection between information publicity and waste sorting behavior in different types of buildings. In the study (Bernstad, 2014) examining household food waste separation behavior in low-rise buildings, it was observed that information publicity did not have a significant impact on waste sorting behavior. This disparity in findings may be attributed to the fact that high-rise buildings provide residents with communal and collective spaces where they can directly access information, whereas low-rise buildings have fewer communal areas for displaying such information.

5.2 Academic contribution

The research contributes to the existing research regarding the student's waste sorting behavior within the student housing. There are several academic contributions with respect to the theory and methodology, as shown in the following.

First of all, from a theoretical standpoint, this research has developed an integrated conceptual model by combining multiple theories, including TPB, NAM, and ABC. This approach offers a variety of theoretical viewpoints for comprehending waste sorting behavior. While some prior studies have also incorporated these theories into a single framework, most have concentrated on integrating TPB with NAM (B. Zhang et al., 2019) or combining TPB and ABC into a single model (S. Zhang et al., 2021). This research takes a step further by incorporating two additional theories into the core TPB framework. By incorporating NAM, waste sorting behavior can be understood from a moral perspective. Additionally, concerning the inclusion of the ABC model, the research specifically outlines situational factors related to waste sorting facilities, information dissemination, and economic incentives, as opposed to incorporating vague situational factors into the primary TPB model. Furthermore, this integrated model has the potential to analyze various other pro-environmental behaviors.

Secondly, besides integrating NAM and ABC into the core TPB framework, this research also incorporates other potential influencing factors like waste sorting knowledge within the expanded TPB framework. This inclusion of waste sorting knowledge aligns the extended TPB model with a prior study by Pongpunpurt et al. (2022). Notably, the key distinction lies in the fact that Pongpunpurt et al.'s extended TPB model omitted the personal moral obligation aspect of individuals and did not specify situational factors.

Thirdly, from a methodological standpoint, this research employed semi-structured interviews as a means of both validation and exploration. This is an innovative approach to address the under explored research questions. More precisely, the utilization of semi-structured interviews aimed to validate the factors identified in the literature review within the specific contextual

setting. Furthermore, from an exploratory perspective, these interviews proved valuable in gaining a deeper understanding of waste sorting behavior and uncovering new, emerging factors that diverged from the findings in the existing literature.

Fourthly, the newly identified factors that have emerged from inductive analysis contribute fresh insights to the TPB framework when applied to the context of college students. For instance, most of the existing literature (Yang et al., 2021; H. Zhang et al., 2017) primarily examined subjective norms from the perspective of peer pressure among college students. However, inductive analysis in this research reveals that subjective norms also encompass the idea of conforming to community-established regulations as a means to gain social acceptance. Furthermore, the majority of previous studies typically measure perceived behavioral control by emphasizing self-efficacy, focusing on evaluating the ease or difficulty of performing a behavior and the individual's confidence in their ability to do so. However, this research has uncovered that perceived effort is an additional subcomponent that influences people's self-efficacy in carrying out the behavior.

Lastly, regarding the PLS-SEM method, due to the inadequate statistical power of the initial PLS-SEM model, the research involves refining the PLS-SEM model. It is worth noting that refining the SEM model is not a common practice in the context of Partial Least Squares (PLS), but it is widely utilized in conventional SEM models. The reason for this distinction is that Conventional SEM, like CB-SEM, relies on model fit indices as reference indicators when adjusting the overall structural model, whereas PLS-SEM does not estimate model fit (Willaby et al., 2015). Therefore, in line with the modification approach used in CB-SEM, the research incorporates the practice of removing constructs with low effect sizes and paths with low path coefficients. The refinement approach can be seen as an innovative method for dealing with the underperforming PLS-SEM model, with the goal of improving its performance and obtaining valid conclusions.

5.3 Practical implications and interventions recommendations

The practical implications are formulated by considering the key factors that influence waste sorting behavior among college students, which encompass situational and psychological aspects. Therefore, the practical implications are centered around these identified situational and psychological factors.

First of all, from the results, the information publicity has the strongest direct impact on the college students waste sorting behavior within the context of the student housing. Hence, it is essential to improve the information publicity within student housing. The information dissemination can be enhanced through two means: physical and virtual channels. Concerning the physical approach, information prompts about waste sorting could be prominently displayed in communal areas of the student housing, such as elevators and entrances, to capture the attention of students and provide them with related information. Another straightforward method is to provide information prompts near waste sorting facilities. This not only provide the accurate sorting instructions to students interested in waste sorting but also serves as a gentle reminder to encourage students to participate in waste sorting. In addition, strengthening

communication between the student housing manager and the residents of student housing, with a special focus on incoming college students, can be highly beneficial. This ensures that incoming college students have a direct channel to access waste sorting information, including local waste sorting regulations and location of waste sorting facilities. Regarding the virtual channel, waste sorting information can be more extensively distributed via social media platforms like Facebook managed by the student housing organization.

Secondly, the findings indicate that waste sorting facilities exert a positive impact on waste sorting behavior, even though the influence is not stronger than the information publicity. Waste sorting facilities enable direct engagement with users and encourage students to participate in waste sorting. The enhancement of waste sorting facilities within student housing can be approached from two perspectives: communal waste sorting facilities and individual waste sorting facilities. Regarding communal waste sorting facilities, they should be improved to ensure convenience and maintain a hygienic environment. This research has revealed that due to limited space within student housing, students often lack adequate room for waste sorting in their individual accommodations. Therefore, it would be beneficial to provide each room with compactable waste bins that can accommodate various types of waste to ensure the availability and ease of waste sorting.

Lastly, the outcome reveals that elevating the waste sorting intention of college students can increase their likelihood to engage in waste sorting. This intention is directly impacted by both subjective norm and perceived behavioral control. Targeting enhancing the subjective norm within the student housing, the manager could regularly scrutinize the waste sorting facilities and keep students informed about their waste sorting efforts. In terms of perceived behavioral control, it can be improved by integrating waste sorting education into the college curriculum to foster proficiency in waste sorting practices. This educational intervention not only enhances students' understanding of waste sorting but also works to improve their practical skills in this regard.

6. Conclusions

This chapter provides answers to individual research questions and addresses the main research question in [Section 6.1](#). Subsequently, limitations of the research study are shown in section 6.2. Finally, section 6.3 offers recommendations for future studies.

6.1 Answers to the research questions

1) What are the factors that influence household waste sorting behavior?

The first research question is answered based on the literature review. This research question endeavors to comprehend the general household waste sorting behavior with the aim of gaining a holistic understanding of the factors that affect it. Therefore, literature that delves into household waste sorting or waste separation behavior was selected for review. Additionally, to ensure the scientific validity of the identified factors, psychological theories were analyzed and applied. Through literature screening, three widely used psychological theories emerged: the theory of planned behavior (TPB), the norm activation model (NAM), and the attitude-behavior-condition theory (ABC). These theories were integrated within the overarching framework of TPB to create a new comprehensive conceptual framework. Within the new integrated framework, TPB encompasses key factors such as attitude, subjective norm, and perceived behavioral control that affect the waste sorting intention and thereby ultimately influence the waste sorting behavior. NAM emphasizes the significance of personal norms in shaping the intention to sort waste. Additionally, the ABC theory mentions the importance of situational factors that can directly influence waste sorting behavior. Consequently, the situational factors were explicitly defined as waste sorting facilities, waste collection services, information publicity, and economic incentives. Furthermore, while deriving these factors from the literature, other variables such as gender and knowledge were identified as influential determinants of waste sorting behavior.

2) How to capture the identified factors from the literature review in the context of students living in student housing?

This research question is addressed by using semi-structured interviews as a qualitative method. In order to adapt the identified factors derived from the literature review to the research context, the questions of the semi-structured interviews are designed accordingly. Additionally, the semi-structured interview not only aids in validating the factors from the literature review within the context of students living in student housing but also facilitates the researcher in discovering new emergent factors. Specifically, this is based on employing thematic analysis in the qualitative methodology to analyze the interview transcripts with both deductive coding and inductive coding. Deductive coding allows the researcher to capture factors already identified in the literature review that are applicable to the context of students living in student housing. On the other hand, inductive coding facilitates the researcher's identification of emergent factors that differ from those found in the literature review. Finally, the qualitative analysis integrates factors from both the deductive and inductive approaches into one full list of tailored factors that potentially affect student waste sorting behavior within the context of student housing.

3) *To what extent do the specified factors impact the students' waste sorting behavior within the student housing?*

This question is addressed using a quantitative approach involving an online survey. The quantitative approach utilizes the PLS-SEM to verify the formulated hypotheses from the qualitative results and quantify the specific factors that affect the students' waste sorting behavior within the student housing. During the PLS-SEM analysis, the measurement model meets all the required criteria, while the structural model does not meet all the criteria, indicating the need for refinement of the PLS-SEM model. After assessing the refined PLS-SEM model, both the measurement model and the structural model within the refined PLS-SEM model now meet all the necessary criteria. As a result, valid results are attained. The results reveal that both the subjective norm and perceived behavioral control have a positive effect on waste sorting intention, with approximately the same influence. Furthermore, with higher waste sorting intentions, students are more likely to conduct the actual behavior. Apart from the waste sorting intention, waste sorting facilities and information publicity have a positive influence on students' waste sorting behavior. Among these factors, it is noteworthy that information publicity has the most substantial impact on students' waste sorting behavior, followed by waste sorting intention, while the influence of waste sorting facilities on waste sorting behavior is comparatively lower.

4) *What are the implications with regard to the most salient factors of students' waste sorting behavior?*

In the discussion chapter, this question is addressed by contrasting the research's own findings with results from other literature and then interpreting the research's distinct outcomes. According to quantitative results, information publicity has the strongest direct impact on college students waste sorting behavior within the context of student housing. Hence, improving the dissemination of information can lead to an increase in students' engagement in waste sorting. Given that the student housing shares extensive communal areas, students have easy access to this information displayed in the public area and are more likely to be influenced by the provided information prompts. As a result, enhancing information dissemination can be achieved by placing waste sorting information prompts in communal areas of student housing, like elevators and entrances, to attract students' attention. Furthermore, it can be boosted by providing information prompts near waste sorting facilities. In addition to these physical measures, it is crucial to enhance communication between the student housing management and the residents. Improving information dissemination is not limited to physical channels alone; it is also essential to utilize virtual channels, such as sharing information through social media and the internet.

5) *Answer to the main question: How to motivate students to participate in waste sorting within student housing?*

Answering the preceding four research questions is facilitated in response to the main research question. To discover effective methods for encouraging students to participate in waste sorting while residing in student housing, it is essential to comprehend waste sorting behavior and the factors that influence it. Consequently, the research adopted a process that moves from a

broader context to a more specific one, where each phase builds upon the preceding one, with the aim of refining the factors that genuinely impact waste sorting behavior. The research starts with obtaining some insights from the existing literature regarding general household waste sorting behavior. The literature review provided a holistic view of factors affecting general household waste sorting behavior, which were subsequently integrated into one conceptual framework. By applying this framework to the Delft student housing case study, the research designed the semi-structured interview to identify potential factors that influence students' household waste sorting behavior within student housing. Furthermore, to validate these potentially influential factors, an online survey of a larger student population was conducted. The quantitative results revealed that the subjective norm and perceived behavioral control directly impact students' intentions to engage in waste sorting, which in turn, indirectly affects their waste sorting behavior. In addition, the waste sorting facilities and information publicity holds a significant influence on the student's household waste sorting behavior, with information publicity exerting a large impact on the waste sorting behavior. Consequently, based on the quantitative findings, the corresponding intervention was recommended to motivate students to participate in waste sorting within the student housing. This includes interventions directed at boosting information publicity, improving waste sorting facilities, enhancing the subjective norm within student housing, and introduce educational interventions from the college.

6.2 Limitations

However, this research has several limitations. The most prominent limitation is the limited sample size in this research. Although the sample size provides sufficient statistical power for assessing the refined PLS-SEM model, as shown in Figure 32, it falls short when it comes to drawing valid conclusions regarding the complex model, akin to the previous PLS-SEM model, depicted in Figure 29. Moreover, due to the relatively small sample size of 155 valid questionnaires, it was not possible to thoroughly examine additional relationships, such as the connection between psychological factors like personal norms and waste sorting intentions. In order to gain a more comprehensive understanding of students' household waste sorting behavior and to draw more broadly applicable conclusions, a larger sample size would be necessary.

Another limitation is that the utilization of waste sorting facilities in this study serves as a proxy for an individual's perception of these facilities, rather than accurately reflecting the factual state of waste sorting facilities. Apart from that, there is a diversity of waste sorting facilities across various student housing. This diversity and the proxy of the factual waste sorting facilities can potentially introduce bias into our measurements. Furthermore, as mentioned by Zhang et al. (2019), finding an appropriate proxy for waste sorting facilities is presently challenging, highlighting the importance of comparing survey-based data with factual data.

Furthermore, the assessment of waste sorting behavior in this study relies on self-reported frequency, rather than direct observation of actions. Some scholars have suggested that self-reports can introduce masking and memory biases (Lange & Dewitte, 2021). However, because collecting data on actual waste sorting behavior is challenging, the study employs self-reported

waste sorting behavior as a proxy. It's worth noting that Onwezen et al. (2013) have argued that self-reported waste sorting frequency is a valid measure. Consequently, to minimize potential biases, obtaining actual data would be valuable.

Additionally, there is a limitation concerning the qualitative analysis. Within this analysis, a participant mentioned the concept of a "habit" regarding waste sorting behavior. Subsequently, this habit was scrutinized from the viewpoint that it forms over an extended period, often under mandatory regulations. In other words, it was suggested that without these regulations, such habits might not develop, highlighting the significant influence of social pressure exerted by mandates. Consequently, in the qualitative analysis, this habit was categorized under the subjective norm. However, it's important to note that this perspective can be subject to debate. Some studies have considered habit as an individual factor influencing waste sorting intentions (Knussen & Yule, 2008; C. Li et al., 2021), because including habit as an individual factor can provide additional insights into understanding waste sorting behavior.

6.3 Future recommendations

There are some recommendations for the future research. Firstly, comprehending the underlying disparity between the waste sorting intention and behavior is needed. This research discovered the discrepancy between the waste sorting intention and the waste sorting behavior. Due to the constraints imposed by the small sample size, there is an insufficient level of statistical power to examine the moderating impact on the connection between waste sorting intention and waste sorting behavior. Consequently, there is a compelling interest in exploring situational factors as potential moderators in the relationship between intention and actual behavior, in order to gain a deeper understanding of the gap that exists between intention and behavior.

Secondly, the scope of socio-demographic factors considered in this study is quite limited. There are additional factors related to the students that would be valuable for future investigations. Factors such as the students' academic faculty and their country of origin could provide valuable insights. Incorporating the heterogeneity of the student population into the analysis would be beneficial for generating a more comprehensive understanding of waste sorting behavior. Lastly, given the limitations mentioned earlier, it would be valuable to include "habit" as an individual factor influencing waste sorting behavior in future analyses.

Finally, it would be advantageous to confirm the effectiveness of the suggested intervention by using the simulation method in future research. Considering that current research primarily concentrates on the static state of situational factors within the boundary of waste collection system, it fails to capture the full complexity of real-world dynamics. In the reality, the waste collection system is a complex and dynamic system, with its components undergoing dynamic changes at any time. Therefore, it would be valuable to assess the impact of the waste collection system on the student's waste sorting behavior by using simulation methods. Furthermore, the simulation model could assess the effectiveness of the recommended intervention.

Reference

- Aguinis, H., Edwards, J. R., & Bradley, K. J. (2017). Improving Our Understanding of Moderation and Mediation in Strategic Management Research. *Organizational Research Methods*, 20(4), 665–685. <https://doi.org/10.1177/1094428115627498>
- Aikowe, L. D., & Mazancová, J. (2021). Plastic waste sorting intentions among university students. *Sustainability (Switzerland)*, 13(14). Scopus. <https://doi.org/10.3390/su13147526>
- Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, 50(2), 179–211. [https://doi.org/10.1016/0749-5978\(91\)90020-T](https://doi.org/10.1016/0749-5978(91)90020-T)
- Ajzen, I. (2002). *Constructing a TpB Questionnaire: Conceptual and Methodological Considerations*.
- Ajzen, I., & Driver, B. L. (1992). Application of the Theory of Planned Behavior to Leisure Choice. *Journal of Leisure Research*, 24(3), 207–224. <https://doi.org/10.1080/00222216.1992.11969889>
- Alam, P., & Ahmade, K. (2013). *IMPACT OF SOLID WASTE ON HEALTH AND THE ENVIRONMENT*. 2(2315).
- Allen, J., Davis, D., & Soskin, M. (1993). Using Coupon Incentives in Recycling Aluminum: A Market Approach to Energy Conservation Policy. *Journal of Consumer Affairs*, 27(2), 300–318. <https://doi.org/10.1111/j.1745-6606.1993.tb00750.x>
- Ando, A. W., & Gosselin, A. Y. (2005a). RECYCLING IN MULTIFAMILY DWELLINGS: DOES CONVENIENCE MATTER? *Economic Inquiry*, 43(2), 426–438. <https://doi.org/10.1093/ei/cbi029>
- Ando, A. W., & Gosselin, A. Y. (2005b). RECYCLING IN MULTIFAMILY DWELLINGS: DOES CONVENIENCE MATTER? *Economic Inquiry*, 43(2), 426–438. <https://doi.org/10.1093/ei/cbi029>
- Babaei, A. A., Alavi, N., Goudarzi, G., Teymouri, P., Ahmadi, K., & Rafiee, M. (2015).

- Household recycling knowledge, attitudes and practices towards solid waste management. *Resources, Conservation and Recycling*, 102, 94–100. Scopus. <https://doi.org/10.1016/j.resconrec.2015.06.014>
- Bagozzi, R. R., & Yi, Y. (1988). *On the evaluation of structural equation models*.
- Barr, S., & Gilg, A. W. (2005). Conceptualising and analysing household attitudes and actions to a growing environmental problem. *Applied Geography*, 25(3), 226–247. <https://doi.org/10.1016/j.apgeog.2005.03.007>
- Batra, R., & Ahtola, O. T. (1991). Measuring the hedonic and utilitarian sources of consumer attitudes. *Marketing Letters*, 2(2), 159–170. <https://doi.org/10.1007/BF00436035>
- Berglund, C. (2006). The assessment of households' recycling costs: The role of personal motives. *Ecological Economics*, 56(4), 560–569. <https://doi.org/10.1016/j.ecolecon.2005.03.005>
- Bernstad, A. (2014). Household food waste separation behavior and the importance of convenience. *Waste Management*, 34(7), 1317–1323. Scopus. <https://doi.org/10.1016/j.wasman.2014.03.013>
- Bilitewski, B., Wagner, J., & Reichenbach, J. (2010). *Best Practice Municipal Waste Management*.
- Bingham, A. J., & Witkowsky, P. (2021). *Analyzing and Interpreting Qualitative Research*.
- Boldero, J. (1995). The Prediction of Household Recycling of Newspapers: The Role of Attitudes, Intentions, and Situational Factors¹. *Journal of Applied Social Psychology*, 25(5), 440–462. <https://doi.org/10.1111/j.1559-1816.1995.tb01598.x>
- Bollen, K. A., & Noble, M. D. (2011). Structural equation models and the quantification of behavior. *Proceedings of the National Academy of Sciences*, 108(supplement_3), 15639–15646. <https://doi.org/10.1073/pnas.1010661108>
- Borsboom, D., Cramer, A., Kievit, R., Scholten, A., & Franic, S. (2009). The end of construct validity. *The Concept of Validity*, 135–170.
- Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative*

Research in Psychology, 3(2), 77–101.
<https://doi.org/10.1191/1478088706qp063oa>

- Burn, S. M. (1991). Social Psychology and the Stimulation of Recycling Behaviors: The Block Leader Approach. *Journal of Applied Social Psychology*, 21(8), 611–629. <https://doi.org/10.1111/j.1559-1816.1991.tb00539.x>
- Cassel, C., Hackl, P., & Westlund, A. H. (1999). Robustness of partial least-squares method for estimating latent variable quality structures. *Journal of Applied Statistics*, 26(4), 435–446. <https://doi.org/10.1080/02664769922322>
- Chen, M.-F., & Tung, P.-J. (2010). The Moderating Effect of Perceived Lack of Facilities on Consumers' Recycling Intentions. *Environment and Behavior*, 42(6), 824–844. <https://doi.org/10.1177/0013916509352833>
- Chioatto, E., & Sospiro, P. (2023). Transition from waste management to circular economy: The European Union roadmap. *Environment, Development and Sustainability*, 25(1), 249–276. <https://doi.org/10.1007/s10668-021-02050-3>
- City population. (n.d.). Delft (Municipality, Zuid-Holland, Netherlands) - Population Statistics, Charts, Map and Location. Retrieved March 31, 2023, from https://www.citypopulation.de/en/netherlands/admin/zuid_holland/0503__delft/.
- Cohen, J. (1998). *Statistical Power Analysis for the Behavioral Sciences* (0 ed.). Routledge. <https://doi.org/10.4324/9780203771587>
- Concari, A., Kok, G., & Martens, P. (2020). A Systematic Literature Review of Concepts and Factors Related to Pro-Environmental Consumer Behaviour in Relation to Waste Management Through an Interdisciplinary Approach. *Sustainability*, 12(11), 4452. <https://doi.org/10.3390/su12114452>
- Creswell, J. W. (2015). *A concise introduction to mixed methods research*. SAGE.
- Czajkowski, M., Kądziela, T., & Hanley, N. (2014). We want to sort! Assessing households' preferences for sorting waste. *Resource and Energy Economics*, 36(1), 290–306. <https://doi.org/10.1016/j.reseneeco.2013.05.006>
- Dahlén, L., & Lagerkvist, A. (2010). Evaluation of recycling programmes in household waste collection systems. *Waste Management & Research: The Journal for a*

- Sustainable Circular Economy*, 28(7), 577–586.
<https://doi.org/10.1177/0734242X09341193>
- Davis, R., Campbell, R., Hildon, Z., Hobbs, L., & Michie, S. (2015). Theories of behaviour and behaviour change across the social and behavioural sciences: A scoping review. *Health Psychology Review*, 9(3), 323–344.
<https://doi.org/10.1080/17437199.2014.941722>
- De Groot, J. I. M., & Steg, L. (2009). Morality and Prosocial Behavior: The Role of Awareness, Responsibility, and Norms in the Norm Activation Model. *The Journal of Social Psychology*, 149(4), 425–449.
<https://doi.org/10.3200/SOCP.149.4.425-449>
- Delft Waste Regulation Implementing Decree 2020, (2021).
<https://lokaleregelgeving.overheid.nl/CVDR655280>
- Demirbas, A. (2011). Waste management, waste resource facilities and waste conversion processes. *Energy Conversion and Management*, 52(2), 1280–1287.
<https://doi.org/10.1016/j.enconman.2010.09.025>
- DiGiacomo, A., Wu, D. W.-L., Lenkic, P., Fraser, B., Zhao, J., & Kingstone, A. (2018). Convenience improves composting and recycling rates in high-density residential buildings. *Journal of Environmental Planning and Management*, 61(2), 309–331. <https://doi.org/10.1080/09640568.2017.1305332>
- Domingo, J. L., & Nadal, M. (2009). Domestic waste composting facilities: A review of human health risks. *Environment International*, 35(2), 382–389.
<https://doi.org/10.1016/j.envint.2008.07.004>
- Ekere, W., Mugisha, J., & Drake, L. (2009). Factors influencing waste separation and utilization among households in the Lake Victoria crescent, Uganda. *Waste Management*, 29(12), 3047–3051. Scopus.
<https://doi.org/10.1016/j.wasman.2009.08.001>
- Environmental Management Act*. (n.d.).
<https://www.government.nl/topics/environment/roles-and-responsibilities-of-central-government/environmental-management-act>
- Environmental Management Act, Article 10.21, (2020).

- <http://wetten.overheid.nl/id/BWBR0003245/2020-07-01/0/Hoofdstuk10/Titeldeel10.4/Artikel10.21>
- Ertz, M., Favier, R., Robinot, É., & Sun, S. (2021). To waste or not to waste? Empirical study of waste minimization behavior. *Waste Management*, 131, 443–452. <https://doi.org/10.1016/j.wasman.2021.06.032>
- Eurostat. (2023). [Data Browser]. Recycling Rate of Municipal Waste. https://ec.europa.eu/eurostat/databrowser/view/sdg_11_60/default/table?lang=en
- Facts and Figures. (n.d.). Facts and Figures. <https://www.tudelft.nl/en/about-tudelft/facts-and-figures/>
- Fan, B., Yang, W., & Shen, X. (2019). A comparison study of ‘motivation–intention–behavior’ model on household solid waste sorting in China and Singapore. *Journal of Cleaner Production*, 211, 442–454. Scopus. <https://doi.org/10.1016/j.jclepro.2018.11.168>
- Feil, A., Pretz, T., Jansen, M., & Thoden van Velzen, E. U. (2017). Separate collection of plastic waste, better than technical sorting from municipal solid waste? *Waste Management & Research: The Journal for a Sustainable Circular Economy*, 35(2), 172–180. <https://doi.org/10.1177/0734242X16654978>
- Fereday, J., & Muir-Cochrane, E. (2006). Demonstrating Rigor Using Thematic Analysis: A Hybrid Approach of Inductive and Deductive Coding and Theme Development. *International Journal of Qualitative Methods*, 5(1), 80–92. <https://doi.org/10.1177/160940690600500107>
- Folz, D. H. (1991). Recycling Program Design, Management, and Participation: A National Survey of Municipal Experience. *Public Administration Review*, 51(3), 222. <https://doi.org/10.2307/976946>
- Fornell, C., & Larcker, D. F. (1981). Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. *Journal of Marketing Research*, 18(1), 39. <https://doi.org/10.2307/3151312>
- Franke, G., & Sarstedt, M. (2019). Heuristics versus statistics in discriminant validity testing: A comparison of four procedures. *Internet Research*, 29(3), 430–447.

<https://doi.org/10.1108/IntR-12-2017-0515>

- Geisser, S. (1974). A predictive approach to the random effect model. *Biometrika*, 61(1), 101–107. <https://doi.org/10.1093/biomet/61.1.101>
- Geller, E. S. (1989). Applied Behavior Analysis and Social Marketing: An Integration for Environmental Preservation. *Journal of Social Issues*, 45(1), 17–36. <https://doi.org/10.1111/j.1540-4560.1989.tb01531.x>
- Gellynck, X., Jacobsen, R., & Verhelst, P. (2011). Identifying the key factors in increasing recycling and reducing residual household waste: A case study of the Flemish region of Belgium. *Journal of Environmental Management*, 92(10), 2683–2690. <https://doi.org/10.1016/j.jenvman.2011.06.006>
- Gharfalkar, M., Court, R., Campbell, C., Ali, Z., & Hillier, G. (2015). Analysis of waste hierarchy in the European waste directive 2008/98/EC. *Waste Management*, 39, 305–313. <https://doi.org/10.1016/j.wasman.2015.02.007>
- Ghazali, E. M., Nguyen, B., Mutum, D. S., & Yap, S.-F. (2019). Pro-Environmental Behaviours and Value-Belief-Norm Theory: Assessing Unobserved Heterogeneity of Two Ethnic Groups. *Sustainability*, 11(12), 3237. <https://doi.org/10.3390/su11123237>
- Ghisellini, P., Cialani, C., & Ulgiati, S. (2016). A review on circular economy: The expected transition to a balanced interplay of environmental and economic systems. *Journal of Cleaner Production*, 114, 11–32. <https://doi.org/10.1016/j.jclepro.2015.09.007>
- Gibbs, G. (2007). *Analyzing Qualitative Data*. SAGE Publications, Ltd. <https://doi.org/10.4135/9781849208574>
- Giusti, L. (2009). A review of waste management practices and their impact on human health. *Waste Management*, 29(8), 2227–2239. <https://doi.org/10.1016/j.wasman.2009.03.028>
- GmbH, A. ti S. S. D. (2023). *ATLAS.ti*. <https://atlasti.com/>
- Gong, Y., Li, Y., & Sun, Y. (2023). Waste sorting behaviors promote subjective well-being: A perspective of the self-nature association. *Waste Management*, 157, 249–255. <https://doi.org/10.1016/j.wasman.2022.12.025>

- Govindan, K., Zhuang, Y., & Chen, G. (2022). Analysis of factors influencing residents' waste sorting behavior: A case study of Shanghai. *Journal of Cleaner Production*, 349, 131126. <https://doi.org/10.1016/j.jclepro.2022.131126>
- Guagnano, G. A., Stern, P. C., & Dietz, T. (1995). Influences on Attitude-Behavior Relationships: A Natural Experiment with Curbside Recycling. *Environment and Behavior*, 27(5), 699–718. <https://doi.org/10.1177/0013916595275005>
- Haenlein, M., & Kaplan, A. M. (2004). A Beginner's Guide to Partial Least Squares Analysis. *Understanding Statistics*, 3(4), 283–297. https://doi.org/10.1207/s15328031us0304_4
- Hage, O., Sandberg, K., Söderholm, P., & Berglund, C. (2008). *Household Plastic Waste Collection in Swedish Municipalities: A Spatial-Econometric Approach*.
- Hage, O., & Söderholm, P. (2008). An econometric analysis of regional differences in household waste collection: The case of plastic packaging waste in Sweden. *Waste Management*, 28(10), 1720–1731. <https://doi.org/10.1016/j.wasman.2007.08.022>
- Hage, O., Söderholm, P., & Berglund, C. (2009). Norms and economic motivation in household recycling: Empirical evidence from Sweden. *Resources, Conservation and Recycling*, 53(3), 155–165. <https://doi.org/10.1016/j.resconrec.2008.11.003>
- Hair, J., & Alamer, A. (2022). Partial Least Squares Structural Equation Modeling (PLS-SEM) in second language and education research: Guidelines using an applied example. *Research Methods in Applied Linguistics*, 1(3), 100027. <https://doi.org/10.1016/j.rmal.2022.100027>
- Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). *A primer on partial least squares structural equation modeling (PLS-SEM)* (Third edition). SAGE.
- Hair, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P., & Ray, S. (2021). *Partial Least Squares Structural Equation Modeling (PLS-SEM) Using R: A Workbook*. Springer International Publishing. <https://doi.org/10.1007/978-3-030-80519-7>
- Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to

- report the results of PLS-SEM. *European Business Review*, 31(1), 2–24.
<https://doi.org/10.1108/EBR-11-2018-0203>
- Hair, J., Hollingsworth, C. L., Randolph, A. B., & Chong, A. Y. L. (2017). An updated and expanded assessment of PLS-SEM in information systems research. *Industrial Management & Data Systems*, 117(3), 442–458.
<https://doi.org/10.1108/IMDS-04-2016-0130>
- Hanafiah, M. H. (2020). Formative Vs. Reflective Measurement Model: Guidelines for Structural Equation Modeling Research. *International Journal of Analysis and Applications*. <https://doi.org/10.28924/2291-8639-18-2020-876>
- Hao, M., Zhang, D., & Morse, S. (2020). Waste Separation Behaviour of College Students under a Mandatory Policy in China: A Case Study of Zhengzhou City. *International Journal of Environmental Research and Public Health*, 17(21), 8190. <https://doi.org/10.3390/ijerph17218190>
- Hao, Y., Wang, L.-O., Chen, X.-S., & Wang, L. (2020). THE DETERMINANTS OF WASTE-SORTING INTENTION AND BEHAVIOR AMONG CHINESE UNDERGRADUATE STUDENTS: A CASE STUDY IN BEIJING. *The Singapore Economic Review*, 65(03), 627–652.
<https://doi.org/10.1142/S0217590817410077>
- Harland, P., Staats, H., & Wilke, H. A. M. (1999). Explaining Proenvironmental Intention and Behavior by Personal Norms and the Theory of Planned Behavior1. *Journal of Applied Social Psychology*, 29(12), 2505–2528.
<https://doi.org/10.1111/j.1559-1816.1999.tb00123.x>
- Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, 43(1), 115–135.
<https://doi.org/10.1007/s11747-014-0403-8>
- Hu, H., Zhang, J., Chu, G., Yang, J., & Yu, P. (2018). Factors influencing tourists' litter management behavior in mountainous tourism areas in China. *Waste Management*, 79, 273–286. <https://doi.org/10.1016/j.wasman.2018.07.047>
- Hu, J., Tang, K., Qian, X., Sun, F., & Zhou, W. (2021). Behavioral change in waste

- separation at source in an international community: An application of the theory of planned behavior. *Waste Management*, 135, 397–408. <https://doi.org/10.1016/j.wasman.2021.09.028>
- Huang, M., Law, K. M. Y., Geng, S., Niu, B., & Kettunen, P. (2022). Predictors of waste sorting and recycling behavioural intention among youths: Evidence from Shenzhen, China and Turku, Finland. *Waste Management and Research*, 40(6), 721–735. Scopus. <https://doi.org/10.1177/0734242X211036254>
- Hulland, J. (1999). Use of partial least squares (PLS) in strategic management research: A review of four recent studies. *Strategic Management Journal*, 20(2), 195–204. [https://doi.org/10.1002/\(SICI\)1097-0266\(199902\)20:2<195::AID-SMJ13>3.0.CO;2-7](https://doi.org/10.1002/(SICI)1097-0266(199902)20:2<195::AID-SMJ13>3.0.CO;2-7)
- Hyman, M., Turner, B., & Carpintero, A. (2015). *Guidelines for national waste management strategies: Moving from challenges to opportunities*. United Nations Environment Programme.
- Iyer, E. S., & Kashyap, R. K. (2007). Consumer recycling: Role of incentives, information, and social class. *Journal of Consumer Behaviour*, 6(1), 32–47. <https://doi.org/10.1002/cb.206>
- Jarvis, C. B., MacKenzie, S. B., & Podsakoff, P. M. (2003). A Critical Review of Construct Indicators and Measurement Model Misspecification in Marketing and Consumer Research. *Journal of Consumer Research*, 30(2), 199–218. <https://doi.org/10.1086/376806>
- Jiang, Q., Leeabai, N., Dilixiati, D., & Takahashi, F. (2021). Perceptive preference toward recycling bin designs: Influential design item depending on waste type, the impact of past perception experiences on design preference, and the effect of color design on waste separation. *Waste Management*, 127, 130–140. <https://doi.org/10.1016/j.wasman.2021.04.037>
- Kaiser, F. G., & Gutscher, H. (2003). The proposition of a general version of the theory of planned behavior: Predicting ecological behavior. *Journal of Applied Social Psychology*, 33, 586–603. <https://doi.org/10.1111/j.1559-1816.2003.tb01914.x>
- Karim Ghani, W. A. W. A., Rusli, I. F., Biak, D. R. A., & Idris, A. (2013a). An

- application of the theory of planned behaviour to study the influencing factors of participation in source separation of food waste. *Waste Management*, 33(5), 1276–1281. Scopus. <https://doi.org/10.1016/j.wasman.2012.09.019>
- Karim Ghani, W. A. W. A., Rusli, I. F., Biak, D. R. A., & Idris, A. (2013b). An application of the theory of planned behaviour to study the influencing factors of participation in source separation of food waste. *Waste Management*, 33(5), 1276–1281. Scopus. <https://doi.org/10.1016/j.wasman.2012.09.019>
- Khalil, M., Abdullah, S., Abd Manaf, L., Sharaai, A., & Nabegu, A. (2017). Examining the Moderating Role of Perceived Lack of Facilitating Conditions on Household Recycling Intention in Kano, Nigeria. *Recycling*, 2(4), 18. <https://doi.org/10.3390/recycling2040018>
- Kirchherr, J., Reike, D., & Hekkert, M. (2017). Conceptualizing the circular economy: An analysis of 114 definitions. *Resources, Conservation and Recycling*, 127, 221–232. <https://doi.org/10.1016/j.resconrec.2017.09.005>
- Klöckner, C. A. (2013). A comprehensive model of the psychology of environmental behaviour—A meta-analysis. *Global Environmental Change*, 23(5), 1028–1038. <https://doi.org/10.1016/j.gloenvcha.2013.05.014>
- Knickmeyer, D. (2020). Social factors influencing household waste separation: A literature review on good practices to improve the recycling performance of urban areas. *Journal of Cleaner Production*, 245, 118605. <https://doi.org/10.1016/j.jclepro.2019.118605>
- Knussen, C., & Yule, F. (2008). “I’m Not in the Habit of Recycling”: The Role of Habitual Behavior in the Disposal of Household Waste. *Environment and Behavior*, 40(5), 683–702. <https://doi.org/10.1177/0013916507307527>
- Knussen, C., Yule, F., MacKenzie, J., & Wells, M. (2004). An analysis of intentions to recycle household waste: The roles of past behaviour, perceived habit, and perceived lack of facilities. *Journal of Environmental Psychology*, 24(2), 237–246. <https://doi.org/10.1016/j.jenvp.2003.12.001>
- Lange, F., & Dewitte, S. (2021). Test-retest reliability and construct validity of the Pro-Environmental Behavior Task. *Journal of Environmental Psychology*, 73,

101550. <https://doi.org/10.1016/j.jenvp.2021.101550>

Larsen, A. W. (2009). *Environmental assessment of waste collection seen in a system perspective*.

Leeabai, N., Suzuki, S., Jiang, Q., Dilixiati, D., & Takahashi, F. (2019). The effects of setting conditions of trash bins on waste collection performance and waste separation behaviors; distance from walking path, separated setting, and arrangements. *Waste Management*, 94, 58–67. Scopus. <https://doi.org/10.1016/j.wasman.2019.05.039>

Li, C. J., Huang, Y. Y., & Harder, M. K. (2017). Incentives for food waste diversion: Exploration of a long term successful Chinese city residential scheme. *Journal of Cleaner Production*, 156, 491–499. <https://doi.org/10.1016/j.jclepro.2017.03.198>

Li, C., Wang, Y., Li, Y., Huang, Y., & Harder, M. K. (2021). The incentives may not be the incentive: A field experiment in recycling of residential food waste. *Resources, Conservation and Recycling*, 168. Scopus. <https://doi.org/10.1016/j.resconrec.2020.105316>

Li, D., & Liu, Y. (2023). Professional identity development of international counseling doctoral students: A hybrid approach of deductive and inductive thematic analysis. *Counselor Education and Supervision*, ceas.12273. <https://doi.org/10.1002/ceas.12273>

Li, J., Zuo, J., Cai, H., & Zillante, G. (2018). Construction waste reduction behavior of contractor employees: An extended theory of planned behavior model approach. *Journal of Cleaner Production*, 172, 1399–1408. <https://doi.org/10.1016/j.jclepro.2017.10.138>

Liao, C., & Li, H. (2019). Environmental education, knowledge, and high school students' intention toward separation of solid waste on campus. *International Journal of Environmental Research and Public Health*, 16(9). Scopus. <https://doi.org/10.3390/ijerph16091659>

Liao, C., Zhao, D., & Zhang, S. (2018). Psychological and conditional factors influencing staff's takeaway waste separation intention: An application of the

- extended theory of planned behavior. *Sustainable Cities and Society*, 41, 186–194. <https://doi.org/10.1016/j.scs.2018.05.046>
- Lieder, M., & Rashid, A. (2016). Towards circular economy implementation: A comprehensive review in context of manufacturing industry. *Journal of Cleaner Production*, 115, 36–51. <https://doi.org/10.1016/j.jclepro.2015.12.042>
- Liu, P., Teng, M., & Han, C. (2020). How does environmental knowledge translate into pro-environmental behaviors?: The mediating role of environmental attitudes and behavioral intentions. *Science of The Total Environment*, 728, 138126. <https://doi.org/10.1016/j.scitotenv.2020.138126>
- Liu, Q., Xu, Q., Shen, X., Chen, B., & Esfahani, S. S. (2022). The Mechanism of Household Waste Sorting Behaviour—A Study of Jiaxing, China. *International Journal of Environmental Research and Public Health*, 19(4). Scopus. <https://doi.org/10.3390/ijerph19042447>
- Luo, H., Zhao, L., & Zhang, Z. (2020). The impacts of social interaction-based factors on household waste-related behaviors. *Waste Management*, 118, 270–280. Scopus. <https://doi.org/10.1016/j.wasman.2020.08.046>
- Ma, J., & Hipel, K. W. (2016). Exploring social dimensions of municipal solid waste management around the globe – A systematic literature review. *Waste Management*, 56, 3–12. <https://doi.org/10.1016/j.wasman.2016.06.041>
- Ma, W., & Zhu, Z. (2021). Internet use and willingness to participate in garbage classification: An investigation of Chinese residents. *Applied Economics Letters*, 28(9), 788–793. <https://doi.org/10.1080/13504851.2020.1781766>
- Ma, Y., Wang, H., & Kong, R. (2020). The effect of policy instruments on rural households' solid waste separation behavior and the mediation of perceived value using SEM. *Environmental Science and Pollution Research*, 27(16), 19398–19409. Scopus. <https://doi.org/10.1007/s11356-020-08410-2>
- Mak, T. M. W., Yu, I. K. M., Wang, L., Hsu, S.-C., Tsang, D. C. W., Li, C. N., Yeung, T. L. Y., Zhang, R., & Poon, C. S. (2019). Extended theory of planned behaviour for promoting construction waste recycling in Hong Kong. *Waste Management*, 83, 161–170. Scopus. <https://doi.org/10.1016/j.wasman.2018.11.016>

- Marx, M. H., & Cronan-Hillix, W. A. (1987). *Systems and theories in psychology*, 4th ed. (pp. xvi, 576). McGraw-Hill Book Company.
- McClelland, D. C. (1988). *Human Motivation* (1st ed.). Cambridge University Press.
<https://doi.org/10.1017/CBO9781139878289>
- McDonald, S., & Oates, C. (2003). Reasons for non-participation in a kerbside recycling scheme. *Resources, Conservation and Recycling*, 39(4), 369–385.
[https://doi.org/10.1016/S0921-3449\(03\)00020-X](https://doi.org/10.1016/S0921-3449(03)00020-X)
- Meng, B., & Choi, K. (2016). Extending the theory of planned behaviour: Testing the effects of authentic perception and environmental concerns on the slow-tourist decision-making process. *Current Issues in Tourism*, 19(6), 528–544.
<https://doi.org/10.1080/13683500.2015.1020773>
- Meng, X., Tan, X., Wang, Y., Wen, Z., Tao, Y., & Qian, Y. (2019). Investigation on decision-making mechanism of residents' household solid waste classification and recycling behaviors. *Resources, Conservation and Recycling*, 140, 224–234.
<https://doi.org/10.1016/j.resconrec.2018.09.021>
- Miafodzyeva, S., & Brandt, N. (2013). Recycling Behaviour Among Householders: Synthesizing Determinants Via a Meta-analysis. *Waste and Biomass Valorization*, 4(2), 221–235. <https://doi.org/10.1007/s12649-012-9144-4>
- Miliute-Plepiene, J., Hage, O., Plepys, A., & Reipas, A. (2016). What motivates households recycling behaviour in recycling schemes of different maturity? Lessons from Lithuania and Sweden. *Resources, Conservation and Recycling*, 113, 40–52. <https://doi.org/10.1016/j.resconrec.2016.05.008>
- Miller, N. D., Meindl, J. N., & Caradine, M. (2016). The Effects of Bin Proximity and Visual Prompts on Recycling in a University Building. *Behavior and Social Issues*, 25(1), 4–10. <https://doi.org/10.5210/bsi.v25i0.6141>
- Montazeri, S., Gonzalez, R. D., Yoon, C., & Papalambros, P. Y. (2012). *COLOR, COGNITION, AND RECYCLING: HOW THE DESIGN OF EVERYDAY OBJECTS PROMPT BEHAVIOR CHANGE*.
- National Waste Management Plan*. (n.d.). <https://lap3.nl/service/english/>
- ölander, F., & Thøgersen, J. (1995). Understanding of consumer behaviour as a

- prerequisite for environmental protection. *Journal of Consumer Policy*, 18(4), 345–385. <https://doi.org/10.1007/BF01024160>
- Olander, F., & Thøgersen, J. (2005). The A-B-C of Recycling. *E - European Advances in Consumer Research* Volume, 7. <http://www.acrwebsite.org/volumes/13834/eacr/vol7/E-07>
- Onwezen, M. C., Antonides, G., & Bartels, J. (2013). The Norm Activation Model: An exploration of the functions of anticipated pride and guilt in pro-environmental behaviour. *Journal of Economic Psychology*, 39, 141–153. <https://doi.org/10.1016/j.joep.2013.07.005>
- Orbell, S., & Sheeran, P. (1998). ‘Inclined abstainers’: A problem for predicting health-related behaviour. *British Journal of Social Psychology*, 37(2), 151–165. <https://doi.org/10.1111/j.2044-8309.1998.tb01162.x>
- Over Avalex—Avalex. (n.d.). Avalex. Retrieved December 31, 2022, from <https://www.avalex.nl/over-avalex-2/>
- Owusu, V., Adjei-Addo, E., & Sundberg, C. (2013). Do economic incentives affect attitudes to solid waste source separation? Evidence from Ghana. *Resources, Conservation and Recycling*, 78, 115–123. <https://doi.org/10.1016/j.resconrec.2013.07.002>
- Oztekin, C., Teksöz, G., Pamuk, S., Sahin, E., & Kilic, D. S. (2017). Gender perspective on the factors predicting recycling behavior: Implications from the theory of planned behavior. *Waste Management*, 62, 290–302. <https://doi.org/10.1016/j.wasman.2016.12.036>
- Pakpour, A. H., Zeidi, I. M., Emamjomeh, M. M., Asefzadeh, S., & Pearson, H. (2014). Household waste behaviours among a community sample in Iran: An application of the theory of planned behaviour. *Waste Management*, 34(6), 980–986. <https://doi.org/10.1016/j.wasman.2013.10.028>
- Pattnaik, S., & Reddy, M. V. (2010). Assessment of Municipal Solid Waste management in Puducherry (Pondicherry), India. *Resources, Conservation and Recycling*, 54(8), 512–520. <https://doi.org/10.1016/j.resconrec.2009.10.008>
- Peng, H., Shen, N., Ying, H., & Wang, Q. (2021). Factor analysis and policy simulation

- of domestic waste classification behavior based on a multiagent study—Taking Shanghai's garbage classification as an example. *Environmental Impact Assessment Review*, 89. Scopus. <https://doi.org/10.1016/j.eiar.2021.106598>
- Petersen, C. H. M., & Berg, P. E. O. (2004). Use of recycling stations in Borlänge, Sweden – volume weights and attitudes. *Waste Management*, 24(9), 911–918. <https://doi.org/10.1016/j.wasman.2004.04.002>
- Phulwani, P. R., Kumar, D., & Goyal, P. (2020). A Systematic Literature Review and Bibliometric Analysis of Recycling Behavior. *Journal of Global Marketing*, 33(5), 354–376. <https://doi.org/10.1080/08911762.2020.1765444>
- Pires, A., Martinho, G., Rodrigues, S., & Gomes, M. I. (2019). *Sustainable Solid Waste Collection and Management*. Springer International Publishing. <https://doi.org/10.1007/978-3-319-93200-2>
- Pongpunpurt, P., Muensitthiroj, P., Pinitjitsamut, P., Chuenchum, P., Painmanakul, P., Chawaloephonsiya, N., & Poyai, T. (2022). Studying Waste Separation Behaviors and Environmental Impacts toward Sustainable Solid Waste Management: A Case Study of Bang Chalongs Housing, Samut Prakan, Thailand. *Sustainability (Switzerland)*, 14(9). Scopus. <https://doi.org/10.3390/su14095040>
- Post-seperation*. (n.d.). Avalex. <https://www.avalex.nl/en/nascheiden/>
- Qualtrics. (2023). *Qualtrics* [Computer software]. <https://www.qualtrics.com>
- Raghu, S. J., & Rodrigues, L. L. R. (2020). Behavioral aspects of solid waste management: A systematic review. *Journal of the Air & Waste Management Association*, 70(12), 1268–1302. <https://doi.org/10.1080/10962247.2020.1823524>
- RecyQ - Zero Waste International. (2018). *Amsterdam—Zero waste action for communities in Amsterdam*. SocialChallenges.Eu. <https://www.socialchallenges.eu/en-GB/city/19/pitches/2487>
- Ringle, C. M., Wende, S., & Becker, J.-M. (2015). *SmartPLS 3*. Boenningstedt: SmartPLS GmbH. <http://www.smartpls.com/>
- Robertson, S., & Walkington, H. (2009). Recycling and waste minimisation behaviours

- of the transient student population in Oxford: Results of an on-line survey. *Local Environment*, 14(4), 285–296. <https://doi.org/10.1080/13549830902812982>
- Robinson, G. M., & Read, A. D. (2005). Recycling behaviour in a London Borough: Results from large-scale household surveys. *Resources, Conservation and Recycling*, 45(1), 70–83. <https://doi.org/10.1016/j.resconrec.2005.02.002>
- Rodrigues, S., Martinho, G., & Pires, A. (2016). Waste collection systems. Part A: A taxonomy. *Journal of Cleaner Production*, 113, 374–387. <https://doi.org/10.1016/j.jclepro.2015.09.143>
- Rousta, K., Ordoñez, I., Bolton, K., & Dahlén, L. (2017). Support for designing waste sorting systems: A mini review. *Waste Management & Research*, 35(11), 1099–1111. <https://doi.org/10.1177/0734242X17726164>
- Rousta, K., Zisen, L., & Hellwig, C. (2020). Household Waste Sorting Participation in Developing Countries—A Meta-Analysis. *Recycling*, 5(1), 6. <https://doi.org/10.3390/recycling5010006>
- Saari, U. A., Damberg, S., Frömbling, L., & Ringle, C. M. (2021). Sustainable consumption behavior of Europeans: The influence of environmental knowledge and risk perception on environmental concern and behavioral intention. *Ecological Economics*, 189, 107155. <https://doi.org/10.1016/j.ecolecon.2021.107155>
- Salmenperä, H., Pitkänen, K., Kautto, P., & Saikku, L. (2021). Critical factors for enhancing the circular economy in waste management. *Journal of Cleaner Production*, 280, 124339. <https://doi.org/10.1016/j.jclepro.2020.124339>
- Sandelowski, M. (1995). Sample size in qualitative research. *Research in Nursing & Health*, 18(2), 179–183. <https://doi.org/10.1002/nur.4770180211>
- Saphores, J.-D. M., Ogunseitan, O. A., & Shapiro, A. A. (2012). Willingness to engage in a pro-environmental behavior: An analysis of e-waste recycling based on a national survey of U.S. households. *Resources, Conservation and Recycling*, 60, 49–63. <https://doi.org/10.1016/j.resconrec.2011.12.003>
- Scharff, C., & Vogel, G. (1994). A Comparison of Collection Systems in European Cities. *Waste Management & Research*, 12(5), 387–404.

<https://doi.org/10.1177/0734242X9401200503>

- Schultz, P. W., Oskamp, S., & Mainieri, T. (1995). Who recycles and when? A review of personal and situational factors. *Journal of Environmental Psychology*, 15(2), 105–121. [https://doi.org/10.1016/0272-4944\(95\)90019-5](https://doi.org/10.1016/0272-4944(95)90019-5)
- Schwartz, S. H. (1977). Normative Influences on Altruism. In *Advances in Experimental Social Psychology* (Vol. 10, pp. 221–279). Elsevier. [https://doi.org/10.1016/S0065-2601\(08\)60358-5](https://doi.org/10.1016/S0065-2601(08)60358-5)
- Schwartz, S. H., & Howard, J. A. (1981). *A Normative Decision Making Model of Altruism*.
- Shen, L., Si, H., Yu, L., & Si, H. (2019). Factors influencing young people's intention toward municipal solid waste sorting. *International Journal of Environmental Research and Public Health*, 16(10). Scopus. <https://doi.org/10.3390/ijerph16101708>
- Shmueli, G., Ray, S., Velasquez Estrada, J. M., & Chatla, S. (2015). The Elephant in the Room: Evaluating the Predictive Performance of Partial Least Squares (PLS) Path Models. *SSRN Electronic Journal*. <https://doi.org/10.2139/ssrn.2659233>
- Shmueli, G., Sarstedt, M., Hair, J. F., Cheah, J.-H., Ting, H., Vaithilingam, S., & Ringle, C. M. (2019). Predictive model assessment in PLS-SEM: Guidelines for using PLSpredict. *European Journal of Marketing*, 53(11), 2322–2347. <https://doi.org/10.1108/EJM-02-2019-0189>
- Sniehotta, F. F., Presseau, J., & Araújo-Soares, V. (2014). Time to retire the theory of planned behaviour. *Health Psychology Review*, 8(1), 1–7. <https://doi.org/10.1080/17437199.2013.869710>
- Steg, L., & Vlek, C. (2009). Encouraging pro-environmental behaviour: An integrative review and research agenda. *Journal of Environmental Psychology*, 29(3), 309–317. <https://doi.org/10.1016/j.jenvp.2008.10.004>
- Stern, P. C. (1987). Managing scarce environmental resources. *Handbook of Environmental Psychology*, 2, 1043–1088.
- Stern, P. C. (2000). New Environmental Theories: Toward a Coherent Theory of Environmentally Significant Behavior. *Journal of Social Issues*, 56(3), 407–424.

<https://doi.org/10.1111/0022-4537.00175>

Stern, P. C., Dietz, T., Abel, T., Guagnano, G. A., & Kalof, L. (1999). A Value-Belief-Norm Theory of Support for Social Movements: The Case of Environmentalism. *Human Ecology Review*, 6(2).

Stoeva, K., & Alriksson, S. (2017). Influence of recycling programmes on waste separation behaviour. *Waste Management*, 68, 732–741. <https://doi.org/10.1016/j.wasman.2017.06.005>

Stone, M. (1974). Cross-Validatory Choice and Assessment of Statistical Predictions. *Journal of the Royal Statistical Society: Series B (Methodological)*, 36(2), 111–133. <https://doi.org/10.1111/j.2517-6161.1974.tb00994.x>

Student numbers at TU Delft stable. (n.d.). TU Delft. Retrieved March 31, 2023, from <https://www.tudelft.nl/en/2022/tu-delft/student-numbers-at-tu-delft-stable>

Sullivan, G. M., & Feinn, R. (2012). Using Effect Size—Or Why the *P* Value Is Not Enough. *Journal of Graduate Medical Education*, 4(3), 279–282. <https://doi.org/10.4300/JGME-D-12-00156.1>

Swain, J. (2018). *A Hybrid Approach to Thematic Analysis in Qualitative Research: Using a Practical Example*. SAGE Publications Ltd. <https://doi.org/10.4135/9781526435477>

Swami, V., Chamorro-Premuzic, T., Snelgar, R., & Furnham, A. (2011). Personality, individual differences, and demographic antecedents of self-reported household waste management behaviours. *Journal of Environmental Psychology*, 31(1), 21–26. <https://doi.org/10.1016/j.jenvp.2010.08.001>

Tabernero, C., Cuadrado, E., Luque, B., Signoria, E., & Prota, R. (2016). The importance of achieving a high customer satisfaction with recycling services in communities. *Environment, Development and Sustainability*, 18(3), 763–776. <https://doi.org/10.1007/s10668-015-9676-4>

Thakkar, J. J. (2020). Introduction to Structural Equation Modelling. In J. J. Thakkar, *Structural Equation Modelling* (Vol. 285, pp. 1–11). Springer Singapore. https://doi.org/10.1007/978-981-15-3793-6_1

Thøgersen, J. (1996). Recycling and Morality: A Critical Review of the Literature.

- Environment and Behavior*, 28(4), 536–558.
<https://doi.org/10.1177/0013916596284006>
- Thøgersen, J. (2005). How May Consumer Policy Empower Consumers for Sustainable Lifestyles? *Journal of Consumer Policy*, 28(2), 143–177.
<https://doi.org/10.1007/s10603-005-2982-8>
- Timlett, R. E., & Williams, I. D. (2008). Public participation and recycling performance in England: A comparison of tools for behaviour change. *Resources, Conservation and Recycling*, 52(4), 622–634.
<https://doi.org/10.1016/j.resconrec.2007.08.003>
- Timlett, R., & Williams, I. D. (2011). The ISB model (infrastructure, service, behaviour): A tool for waste practitioners. *Waste Management*, 31(6), 1381–1392. <https://doi.org/10.1016/j.wasman.2010.12.010>
- Tong, X., Yu, H., Han, L., Liu, T., Dong, L., Zisopoulos, F., Steuer, B., & de Jong, M. (2023). Exploring business models for carbon emission reduction via post-consumer recycling infrastructures in Beijing: An agent-based modelling approach. *Resources, Conservation and Recycling*, 188, 106666.
<https://doi.org/10.1016/j.resconrec.2022.106666>
- Tonglet, M., Phillips, P. S., & Read, A. D. (2004). Using the Theory of Planned Behaviour to investigate the determinants of recycling behaviour: A case study from Brixworth, UK. *Resources, Conservation and Recycling*, 41(3), 191–214.
<https://doi.org/10.1016/j.resconrec.2003.11.001>
- Vaismoradi, M., Turunen, H., & Bondas, T. (2013). Content analysis and thematic analysis: Implications for conducting a qualitative descriptive study: Qualitative descriptive study. *Nursing & Health Sciences*, 15(3), 398–405.
<https://doi.org/10.1111/nhs.12048>
- Valle, P. O. D., Rebelo, E., Reis, E., & Menezes, J. (2005). Combining Behavioral Theories to Predict Recycling Involvement. *Environment and Behavior*, 37(3), 364–396. <https://doi.org/10.1177/0013916504272563>
- Varotto, A., & Spagnoli, A. (2017). Psychological strategies to promote household recycling. A systematic review with meta-analysis of validated field

- interventions. *Journal of Environmental Psychology*, 51, 168–188.
<https://doi.org/10.1016/j.jenvp.2017.03.011>
- Vicente, P., & Reis, E. (2008). Factors influencing households' participation in recycling. *Waste Management & Research: The Journal for a Sustainable Circular Economy*, 26(2), 140–146.
<https://doi.org/10.1177/0734242X07077371>
- Voss, K. E., Spangenberg, E. R., & Grohmann, B. (2003). Measuring the Hedonic and Utilitarian Dimensions of Consumer Attitude. *Journal of Marketing Research*, 40(3), 310–320. <https://doi.org/10.1509/jmkr.40.3.310.19238>
- Wan, C., & Shen, G. Q. (2013). Perceived policy effectiveness and recycling behaviour: The missing link. *Waste Management*, 33(4), 783–784.
<https://doi.org/10.1016/j.wasman.2013.02.001>
- Wan, C., Shen, G. Q., & Choi, S. (2017). Experiential and instrumental attitudes: Interaction effect of attitude and subjective norm on recycling intention. *Journal of Environmental Psychology*, 50, 69–79.
<https://doi.org/10.1016/j.jenvp.2017.02.006>
- Wan, C., Shen, G. Q., & Yu, A. (2014). The role of perceived effectiveness of policy measures in predicting recycling behaviour in Hong Kong. *Resources, Conservation and Recycling*, 83, 141–151.
<https://doi.org/10.1016/j.resconrec.2013.12.009>
- Wang, H., Li, J., Mangmeechai, A., & Su, J. (2021). Linking Perceived Policy Effectiveness and Proenvironmental Behavior: The Influence of Attitude, Implementation Intention, and Knowledge. *International Journal of Environmental Research and Public Health*, 18(6), 2910.
<https://doi.org/10.3390/ijerph18062910>
- Wang, K., Lu, J., & Liu, H. (2021). Residents' waste source separation behaviours in Shanghai, China. *Journal of Material Cycles and Waste Management*, 23(3), 937–949. Scopus. <https://doi.org/10.1007/s10163-021-01179-7>
- Wang, S., Wang, J., Yang, S., Li, J., & Zhou, K. (2020). From intention to behavior: Comprehending residents' waste sorting intention and behavior formation

- process. *Waste Management*, 113, 41–50.
<https://doi.org/10.1016/j.wasman.2020.05.031>
- Wang, S., Wang, J., Zhao, S., & Yang, S. (2019). Information publicity and resident's waste separation behavior: An empirical study based on the norm activation model. *Waste Management*, 87, 33–42.
<https://doi.org/10.1016/j.wasman.2019.01.038>
- Waste disposal levy- Regionale Belasting Groep Personal*. (2022). Regionale Belasting Groep. <https://www.derb.g.nl/en/overview-of-taxes/waste-disposal-levy/>
- Willaby, H. W., Costa, D. S. J., Burns, B. D., MacCann, C., & Roberts, R. D. (2015). Testing complex models with small sample sizes: A historical overview and empirical demonstration of what Partial Least Squares (PLS) can offer differential psychology. *Personality and Individual Differences*, 84, 73–78.
<https://doi.org/10.1016/j.paid.2014.09.008>
- Wilson, C. D. H., & Williams, I. D. (2007). Kerbside collection: A case study from the north-west of England. *Resources, Conservation and Recycling*, 52(2), 381–394.
<https://doi.org/10.1016/j.resconrec.2007.02.006>
- Xia, Z., Zhang, S., Tian, X., & Liu, Y. (2021a). Understanding waste sorting behavior and key influencing factors through internet of things: Evidence from college student community. *Resources, Conservation and Recycling*, 174. Scopus.
<https://doi.org/10.1016/j.resconrec.2021.105775>
- Xia, Z., Zhang, S., Tian, X., & Liu, Y. (2021b). Understanding waste sorting behavior and key influencing factors through internet of things: Evidence from college student community. *Resources, Conservation and Recycling*, 174. Scopus.
<https://doi.org/10.1016/j.resconrec.2021.105775>
- Xu, D. Y., Lin, Z. Y., Gordon, M. P. R., Robinson, N. K. L., & Harder, M. K. (2016). Perceived key elements of a successful residential food waste sorting program in urban apartments: Stakeholder views. *Journal of Cleaner Production*, 134, 362–370. <https://doi.org/10.1016/j.jclepro.2015.12.107>
- Xu, L., Ling, M., Lu, Y., & Shen, M. (2017). Understanding household waste separation behaviour: Testing the roles of moral, past experience, and perceived policy

- effectiveness within the theory of planned behaviour. *Sustainability (Switzerland)*, 9(4). Scopus. <https://doi.org/10.3390/su9040625>
- Xu, L., Ling, M., & Wu, Y. (2018). Economic incentive and social influence to overcome household waste separation dilemma: A field intervention study. *Waste Management*, 77, 522–531. <https://doi.org/10.1016/j.wasman.2018.04.048>
- Xu, W., & Zammit, K. (2020). Applying Thematic Analysis to Education: A Hybrid Approach to Interpreting Data in Practitioner Research. *International Journal of Qualitative Methods*, 19, 160940692091881. <https://doi.org/10.1177/1609406920918810>
- Yang, X., Chen, X., Xiao, X., Xi, H., & Liu, S. (2021). College students' willingness to separate municipal waste and its influencing factors: A case study in chongqing, china. *Sustainability (Switzerland)*, 13(22). Scopus. <https://doi.org/10.3390/su132212914>
- Yuan, Z., Bi, J., & Moriguichi, Y. (2008). The Circular Economy: A New Development Strategy in China. *Journal of Industrial Ecology*, 10(1–2), 4–8. <https://doi.org/10.1162/108819806775545321>
- Zhang, B., Lai, K., Wang, B., & Wang, Z. (2019a). From intention to action: How do personal attitudes, facilities accessibility, and government stimulus matter for household waste sorting? *Journal of Environmental Management*, 233, 447–458. <https://doi.org/10.1016/j.jenvman.2018.12.059>
- Zhang, B., Lai, K.-H., Wang, B., & Wang, Z. (2019b). From intention to action: How do personal attitudes, facilities accessibility, and government stimulus matter for household waste sorting? *Journal of Environmental Management*, 233, 447–458. Scopus. <https://doi.org/10.1016/j.jenvman.2018.12.059>
- Zhang, C., Hu, M., Di Maio, F., Sprecher, B., Yang, X., & Tukker, A. (2022). An overview of the waste hierarchy framework for analyzing the circularity in construction and demolition waste management in Europe. *Science of The Total Environment*, 803, 149892. <https://doi.org/10.1016/j.scitotenv.2021.149892>
- Zhang, D., Huang, G., Yin, X., & Gong, Q. (2015). Residents' waste separation

- behaviors at the source: Using SEM with the theory of planned behavior in Guangzhou, China. *International Journal of Environmental Research and Public Health*, 12(8), 9475–9491. Scopus. <https://doi.org/10.3390/ijerph120809475>
- Zhang, H., Liu, J., Wen, Z.-G., & Chen, Y.-X. (2017). College students' municipal solid waste source separation behavior and its influential factors: A case study in Beijing, China. *Journal of Cleaner Production*, 164, 444–454. Scopus. <https://doi.org/10.1016/j.jclepro.2017.06.224>
- Zhang, S., Hu, D., Lin, T., Li, W., Zhao, R., Yang, H., Pei, Y., & Jiang, L. (2021). Determinants affecting residents' waste classification intention and behavior: A study based on TPB and A-B-C methodology. *Journal of Environmental Management*, 290, 112591. <https://doi.org/10.1016/j.jenvman.2021.112591>
- Zhang, S., Zhang, M., Yu, X., & Ren, H. (2016). What keeps Chinese from recycling: Accessibility of recycling facilities and the behavior. *Resources, Conservation and Recycling*, 109, 176–186. <https://doi.org/10.1016/j.resconrec.2016.02.008>
- Zhang, X., Liu, J., & Zhao, K. (2018). Antecedents of citizens' environmental complaint intention in China: An empirical study based on norm activation model. *Resources, Conservation and Recycling*, 134, 121–128. <https://doi.org/10.1016/j.resconrec.2018.03.003>
- Zhang, Y., Wang, G., Zhang, Q., Ji, Y., & Xu, H. (2022). What determines urban household intention and behavior of solid waste separation? A case study in China. *Environmental Impact Assessment Review*, 93, 106728. <https://doi.org/10.1016/j.eiar.2021.106728>

Appendix A Semi-structured interview Protocol

The interview is in a semi-structured format, with each session spanning around 45 minutes. During the semi-structured interview, a total of 11 questions are posed to the interviewee. It starts with both the interviewer and interviewee introducing themselves. Following that, there is an introduction that outlines the research objectives. Then, questions correlated to waste sorting behavior are asked. Finally, the interviewer concludes with a summary of the main takeaways and an expression of gratitude towards the interviewee.

Questions:

Past Experiences:

1. Do you sort the waste?
 - i. If so, what kind of waste do you sort from your daily life? And what motivates you to sort the waste?
 - ii. If not, what prevents you sort the waste?

Psychological factors:

2. What feeling do you have when you sort the waste?
3. How important is it to you that others engage in waste sorting as well?
4. How do you feel about the ease or difficulty of incorporating waste sorting into your daily routine?
 - i. Are there any specific aspects that make it easier or more challenging for you?
5. How would you describe your level of knowledge about waste sorting practices? What specific information or guidelines are you familiar with?
6. How important is waste sorting to you on a personal level? Can you describe the values or principles that drive your commitment to practicing proper waste sorting?

Situational factors:

7. What is your opinion on the waste sorting facilities in your student housing, for example, the trash bins in your student complexes and the facilities in your own room? To what extent do the waste sorting facilities motivate you to sort the waste?
8. What is your opinion on waste collection services in your student housing, for example, Services provided by student housing include maintaining cleanliness in waste sorting facilities and ensuring a clean environment. To what extent do the waste collection services motivate you to sort the waste?
9. To what extent does monetary reward or deduction of waste tax fee motivate you to sort the waste?

10. To what extent does the provision of waste sorting information through a public place or the Internet motivate you to sort the waste?

11. Is there anything you still want to share with me, that I forgot to ask about?

Appendix B Questionnaire design

Construct	Item	Wording	Source
Attitude	ATT1	I think household waste sorting is useful to mitigate the environmental problems	(S. Wang et al., 2020)
	ATT2	I think household waste sorting is beneficial to promote the reuse	
	ATT3	I think household waste sorting is good for the environment	
Subjective norm	SN1	My friends think I should sort out household waste	(Karim Ghani et al., 2013a)
	SN2	My neighbors from the student housing think I should sort out household waste	
	SN3	If there are regulations for waste sorting in the community, then I will sort waste according to the regulations	
	SN4	If my neighbors and other residents of the neighborhood participate in waste sorting, I would follow	
Perceived behavioral control	PBC1	For me, sorting household waste is easy	(Zhang et al., 2015)
	PBC2	Whether or not, I sort household waste is completely up to me	
	PBC3	I am confident that if I want to, I could sort my household waste	
	PBC4	I have enough time and energy to sort the household waste	
Waste sorting knowledge	KN1	I know the guidance and regulations on waste sorting	(Wang et al., 2020)
	KN2	I know how to sort household waste	
	KN3	I know where the waste sorting facilities are	
Personal norm	PN1	I feel that sorting household waste is a moral obligation	(Tonglet et al., 2004)
	PN2	If I do not sort my household waste, I will feel guilty	
	PN3	I have a responsibility to sort my household waste	
Waste sorting facilities	WSF1	Waste sorting facility in my student housing is well managed (without smell or pest)	(Fan et al., 2019)
	WSF2	Waste sorting facility in my student housing is easy to access (located in the close distance)	

	WSF3	Sorting and collecting recyclable waste don't take too much of my living space	
	WSF4	The label and guidance of the waste sorting facilities in my student housing are clear and easy to understand	
Information publicity	IP1	There is enough communication effort for household waste sorting in my student housing	(Zhang et al., 2022)
	IP2	I often see household waste sorting promotions online (i.e., university websites)	
	IP3	I often see household waste sorting promotions (i.e., posters) in the public areas of my student housing	
Economic incentives	EI 1	I will sort household waste if it can reduce the waste disposal fee	(Wang et al., 2020)
	EI 2	If there is a monetary incentive available within the community for waste sorting, such as a monetary voucher or direct payment, I will be motivated to engage in waste sorting activities	
	EI 3	I will sort the waste if there is a monetary penalty available within the student housing for failing to sort waste	
Waste sorting intention	WSI1	I intend to sort out PMD waste	
	WSI2	I intend to sort out Paper waste	
	WSI3	I intend to sort out Glass waste	
	WSI4	I intend to sort out Textile waste	
	WSI5	I intend to sort out Organic waste	
Waste sorting behavior	WSB1	What is the frequency with which you sort out PMD waste per month	
	WSB2	What is the frequency with which you sort out Paper waste per month	
	WSB3	What is the frequency with which you sort out Glass waste per month	
	WSB4	What is the frequency with which you sort out Textile waste per month	
	WSB5	What is the frequency with which you sort out Organic waste per month	

Evaluation of waste sorting knowledge:

1. Identify the category to which a dirty pizza box (with oil or leftover food) belongs

- ☐ Residual waste
- ☐ Paper waste

- ☐ PMD waste
 - ☐ GFT waste
2. Identify the category to which a shampoo bottle belongs
- ☐ Residual waste
 - ☐ Paper waste
 - ☐ PMD waste
 - ☐ GFT waste
3. Identify the category to which the Newspaper belongs
- ☐ Residual waste
 - ☐ Paper waste
 - ☐ PMD waste
 - ☐ GFT waste
4. Identify the category to which apple peels belong
- ☐ Residual waste
 - ☐ Paper waste
 - ☐ PMD waste
 - ☐ GFT waste

Appendix C HTMT confidence interval

	Original Sample (O)	2.50%	97.50%
EI → ATT	0.241	0.096	0.399
IP → ATT	0.211	0.098	0.378
IP → EI	0.107	0.073	0.295
KN → ATT	0.375	0.239	0.509
KN → EI	0.089	0.057	0.228
KN → IP	0.185	0.077	0.391
PBC → ATT	0.365	0.195	0.535
PBC → EI	0.394	0.229	0.554
PBC → IP	0.258	0.113	0.439
PBC → KN	0.361	0.178	0.55
PN → ATT	0.522	0.371	0.66
PN → EI	0.401	0.221	0.571
PN → IP	0.209	0.093	0.405
PN → KN	0.497	0.358	0.626
PN → PBC	0.597	0.449	0.741
SN → ATT	0.587	0.418	0.734
SN → EI	0.425	0.249	0.584
SN → IP	0.383	0.226	0.543
SN → KN	0.404	0.255	0.57
SN → PBC	0.582	0.43	0.723
SN → PN	0.66	0.502	0.799
WSB → ATT	0.187	0.112	0.332
WSB → EI	0.274	0.191	0.429
WSB → IP	0.477	0.318	0.637
WSB → KN	0.166	0.116	0.306
WSB → PBC	0.449	0.317	0.593
WSB → PN	0.235	0.111	0.43
WSB → SN	0.399	0.273	0.55
WSF → ATT	0.145	0.055	0.328
WSF → EI	0.276	0.134	0.438
WSF → IP	0.503	0.365	0.649
WSF → KN	0.247	0.1	0.449
WSF → PBC	0.206	0.087	0.402
WSF → PN	0.211	0.093	0.412
WSF → SN	0.349	0.163	0.527
WSF → WSB	0.43	0.283	0.588
WSI → ATT	0.152	0.079	0.322
WSI → EI	0.109	0.068	0.294
WSI → IP	0.134	0.084	0.312
WSI → KN	0.142	0.094	0.326
WSI → PBC	0.377	0.18	0.578

$\text{WSI} \rightarrow \text{PN}$	0.265	0.114	0.463
$\text{WSI} \rightarrow \text{SN}$	0.347	0.156	0.552
$\text{WSI} \rightarrow \text{WSB}$	0.336	0.217	0.595
$\text{WSI} \rightarrow \text{WSF}$	0.163	0.103	0.346

Appendix D HTMT confidence interval of defined PLS-SEM model

	Original Sample (O)	2.50%	97.50%
WSI → WSF	0.163	0.106	0.345
WSI → WSB	0.336	0.216	0.594
WSI → SN	0.347	0.153	0.551
WSI → PBC	0.377	0.18	0.575
WSI → IP	0.134	0.085	0.311
WSI → ATT	0.152	0.076	0.32
WSF → WSB	0.43	0.281	0.591
WSF → SN	0.349	0.165	0.531
WSF → PBC	0.206	0.088	0.403
WSF → IP	0.503	0.368	0.651
WSF → ATT	0.145	0.054	0.331
WSB → SN	0.399	0.278	0.551
WSB → PBC	0.449	0.318	0.591
WSB → IP	0.477	0.319	0.635
WSB → ATT	0.187	0.115	0.335
SN → PBC	0.582	0.429	0.723
SN → IP	0.383	0.224	0.539
SN → ATT	0.587	0.406	0.735
PBC → IP	0.258	0.113	0.442
PBC → ATT	0.365	0.191	0.531
IP → ATT	0.211	0.098	0.379