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PDF issue: 2026-11-25

Circularity of Food Resources in Japan: Consumers' Incentives for Ethical Consumption and Food Recycling

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(Degree)
博士（学術）

(Date of Degree)
2024-09-25

(Date of Publication)
2026-09-25

(Resource Type)
doctoral thesis

(Report Number)
甲第9032号

(URL)
https://hdl.handle.net/20.500.14094/0100492541

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Doctoral Dissertation

Circularity of Food Resources in Japan: Consumers' Incentives for Ethical Consumption and Food Recycling

(日本における食品資源の循環性：倫理的消費と食品リサイクルに対する消費者のインセンティブ)

July 2024

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Abstract

A critical stakeholder in moving food systems towards sustainability are the consumers. From the moment of purchase to moment of disposal, people's decisions can have a substantial effect on limiting climate change. This doctoral dissertation posits that to design policy interventions that successfully boost pro-environmental behaviour adoption and mitigate climate change, it is necessary to have a holistic view on the role of Japanese consumers on building an economically, socially, and environmentally sustainable food supply chain. More precisely, the present research aims to contribute to food consumption and waste management state of art by 1) Presenting a comprehensive model to describe the Japanese decision process of purchasing food ethically; 2) Exploring the patterns and contrasts existent across the Japanese population on the adoption rates of ethical purchasing, waste reduction, and food waste recycling PEB; 3) Identifying what are the main drivers to the decision to compost in Japan; 4) Identifying the main reasons that lead Japanese consumers to stop composting; and finally, 5) Presenting a review of the ongoing Japanese initiatives to prompt more sustainable lifestyles, in particular to initiatives that foster food waste recycling.

Based on the obtained results, waste prevention seems to be a concept embedded in Japanese society as many households stated been doing it. On the other hand, Ethical Consumption and Food Waste Recycling methods are not as popular. Food waste recycling methods have very low adoption rates. By looking at the results of the decision-models on Ethical Food Consumption and Household Composting, fostering knowledge about these topics is a key driver to adoption. Nonetheless, the how and what knowledge is transmitted should not be disregarded. Information vehicles should clarify the connection between food recycling and ethical food consumption and explain how to deal with vermin, bad smells, and minimize "lost time" to prevent dropouts. Relying on communication vehicles that allow building social norms may be particularly effective to boost PEB engagement in Japan.

The current manuscript extends the previous applications of the Stimulus-Organism-Response (S-O-R) and the Theory of Consumption Values (TCV) frameworks. The latter theoretical frameworks were used to explain green food consumption and household composting behaviour. On statistical grounds, less commonly applied algorithms such as clustering using a *Mahalanodis* distance, a Partial Least Squares Structural Equation Modelling (PLS-SEM) with a multi-group assessment (MGA) with more than 2 groups, and the categorical extension of the PLS-SEM (OrdPLS) were also used as analytical tool, which present meaningful analytical results. Clustering algorithms were also used to identify profiles related to eco-friendly food consumption behaviours. Household composting dropout reasons and ongoing Japanese sustainable initiatives

were analysed with non-parametric significance tests and the SWOT analysis framework, respectfully.

Additionally, solutions for people with and without a gardening interest should be provided. One of the food waste recycling solutions which seems to tackle the connection between purchase, usage, and disposal consumption stages, is a system where consumers compost and then return the final output to a central entity. In this manuscript, they are referred as Hybrid solutions. These solutions can be a compromise option between central and decentralized schemes with possible positive spillover effects in other areas of a consumer's life. Many municipalities subsidize the purchase of composting equipment but do not offer much more support. Moreover, people do not seem to be somewhat unaware of these incentives. Approximately 17% of the municipalities have some kind of food waste segregation scheme, implying that decentralized approaches are not widespread in Japan yet.

Acknowledgements

Sometimes I still cannot believe I moved to a country halfway around the world from my hometown to do a PhD. But that is what happened, and I could not be more thankful to those who made it possible. I would like to express my gratitude to the Japanese Embassy in Portugal and the MEXT Scholarship Program for considering me a suitable candidate to embark on this journey. I would also like to thank the staff at the Student Office of the Faculty of Agriculture at Kobe University, my professors and colleagues in the Food and Environmental Department, and particularly my advisor, Professor Ishida Akira, and co-advisors, Professor Nagano Takanori and Professor Shoji Koichi, for their guidance and assistance.

For always being there, regardless the physical distance, I am deeply grateful to my family, specially my two brothers, my mother, my father, and my grandparents. I also wish to thank my cousin Constança and my Portuguese friends Nuno, Sofia, Ricardo, Leonor, Mafalda, and Leonor (a different one) for taking a little of their time to visit me. Additionally, I would like to express how my friends from Kobe University made these three years memorable. Last but not least, I want to thank Conor Grice for his unconditional support.

"When life gets you down, you know what you gotta do?

Just keep swimming."

"Dori", Finding Nemo

Contents

Chapter 1: Introduction 1
1.1 Motivation 1
1.2 Main Contributions 1
1.3 Scientific Results 2
1.4 Structure of the Dissertation 2
Chapter 2: General Background and Methodology 4
2.1 Introduction to Japanese Social and Political Context 4
2.1.1 Japanese Sustainability and Food Waste Policies 4
2.1.2 Japanese Consumer 6
2.2 Analytical Tools 7
2.2.1 PLS-SEM and OrdPLS 7
2.2.2 Data Reduction 11
2.2.3 Clustering Analysis 12
2.2.4 Non-Parametric Significance Tests 13
2.2.5 Likert-Scales 14
2.2.6 SWOT Analysis 14
Chapter 3: Ethical Food Consumption Drivers in Japan. A S–O-R framework application using PLS-SEM with a MGA assessment based on clustering 15
3.1 Introduction 15
3.2 Background and Methodology 17
3.2.1 Japanese Market: 17
3.2.2 Model Hypothesis 17
3.2.3 Statistical Tools 26
3.2.4 Data Collection and questionnaire: 28
3.3 Results 29
3.3.1 Descriptive Analysis 29
3.3.2 Assessment of the measurement (outer) model 33
3.3.3 Assessment of the structural (inner) model 36
3.3.4 Mediation analysis 39
3.3.5 Clustering and Profiling 40
3.3.6 PLS multi-group analysis assessment 45
3.4 Discussion 47
3.4.1 Theoretical Contributions 49
3.4.2 Social and Management Contributions 50
3.5 Chapter Conclusion and Future Research 51

Chapter 4: Ethical Consumption and Food Recovery Hierarchy Behaviours: A Clustering Analysis in Japan. 54
4.1 Introduction 54
4.2 Background and Methodology 56
4.2.1 PEB and Food Waste Recovery Hierarchy 56
4.2.2 Clustering Algorithm 58
4.2.3 Data Collection and Questionnaire 59
4.3 Results 61
4.3.1 Descriptive Analysis 61
4.3.2 Data Reduction 63
4.3.3 Clustering and Profiling 65
4.4 Discussion 74
4.4.1 Theoretical Contributions 74
4.4.2 Social and Management Contributions 74
4.5 Chapter Conclusion and Future Research 78
Chapter 5: Composting Behaviour in Japan: An application of the Theory of Consumption Value and look on drop out reasons. 81
5.1 Introduction 81
5.2 Background and Methodology 83
5.2.1 Theory of Consumption Values: Model Hypotheses 83
5.2.2 Statistical Tools: Ordinal PLS-SEM 94
5.2.3 Data Collection 95
5.3 Results 95
5.3.1 Descriptive Results 95
5.3.2 Assessment of the measurement (outer) model 96
5.3.3 Assessment of the structural (inner) model 100
5.4 Discussion 102
5.4.1 Theoretical Implications 102
5.4.2 Social and Management Implications 104
5.5 Chapter Conclusion and Future Research 106
Chapter 6: A closer look on composting dropout reasons in Japan 108
6.1 Introduction 108
6.2 Background and Methodology 109
6.2.1 Dropout background 109
6.2.2 Statistical Tools 111
6.2.3 Data Collection 111
6.3 Results 111
6.4 Discussion 119

6.4.1 Theoretical Implications 119
6.4.2 Social and Management Implications 121
6.5 Chapter Conclusions and Future Research 122
Chapter 7: Ethical Consumption and Composting Facilitators in Japan: A case study household/community incentives 124
7.1 Introduction 124
7.2 Background and Methodology 125
7.2.1 Food Recycling Systems and Interventions Data Collection 125
7.3 Food Waste Recycling Schemes in Japan 127
7.3.1 Central Food Waste Recycling Alternatives and Incentives in Japan 127
7.3.2 Decentralized Household Composting Incentives in Japan 136
7.3.3 A point in between. Composting Collection Systems. A SWOT Analysis 144
7.4 Discussion 148
7.5 Chapter Conclusion and Future Research 149
Chapter 8: Conclusions 151
References 154
Appendix 185

List of Figures:

Figure 3.1 Model Hypothesis (adapted from Jacoby (2002)). For simplification of the figure LAB and KNG were presented within the stimuli main area and not on the interception of S and O. 19
Figure 3.2 Methodological Flow 27
Figure 3.3 Ethical Consumption item's score by income range. 31
Figure 3.4 Ethical Consumption Items. 32
Figure 3.5 PEB adoption rates. 33
Figure 3.6 Path coefficient results (significant at 0.05); To be aligned with Figure 3.1, LAB and KNG were presented solely in the S area. 39
Figure 3.7 PCA Scree Plot 41
Figure 3.8 Cluster's Boxplots of PCA Factors and a summated EC scale. 43
Figure 4.1 Food Recovery Hierarchy (adapted from UK Parliament (2014)) 57
Figure 4.2 Consumption Stages, PCA Results, and Food Recovery Hierarchy (adapted from UK Parliament (2014)) 64
Figure 4.3 Factor's boxplots for a 4 and 3 clusters solution. 66
Figure 4.4 PEB excluded during the PCA and Dietary Concerns 72
Figure 4.5 Food Related Habits by Cluster 73
Figure 4.6 Composting Intention 73
Figure 4.7 Gardening/ Farming Interest 74
Figure 5.1 TCV Model Results 102
Figure 6.1 Respondents distribution per age group (10 years) 113
Figure 6.2 Respondents' gardening/farming interest distributions. 114
Figure 6.3 Respondents' composting intention distributions. 115
Figure 6.4 Dropouts' Food Waste Recycling (composting) frequency. 115
Figure 6.5 Dropout respondent's reasons for and against composting. 116
Figure 6.6 Reasons for Have Never Composting/Having Had Stopped 118
Figure 6.7 Reasons for Composting/Having Tried Composting 119
Figure 7.1 Central Composting systems requirement (retrieved from Kawai et al. (2020)) 129
Figure 7.2 (1) Plastic Bag (Tsuchiura City 2024); (2) Plastic Bucket (Maniwa City 2019); (3) Ikedas's Paper Bag (retrieved from Kawai et al. (2020) 131
Figure 7.3 (1) Compactor Truck retrieved from Tsuchiura City (2024); (2) Flatbed Truck (Osaki Town 2020) 131
Figure 7.4 Free compost opportunity in Tsushima city's Promotional Flyer (Tsushima City, 2024) 133
Figure 7.5 Waste Inspection (Osaki Town 2020) 134
Figure 7.6 (1) Nagai city's compost label; (2) Motegi town's compost label; (3) Ikeda town's antenna shop; (4)(5)(6) Ikeda town's compost labels; (7) Kaga city antenna shop (Kawai et al. 2020; Kaga City 2021; Ikeda Town Agricultural Corporation 2024) 134
Figure 7.7 Yahaba city's waste collection calendar (Yahaba City 2024). 135
Figure 7.8 Satsuma town's food waste flow; Tsushima city's flyer; Maniwa city's food waste separation rules (Maniwa City, 2019; Satsuma Town, 2024, 2023; Tsushima City, 2024) 136
Figure 7.9 Composting/Gardening Seminars in the cities of Odawara, Fukuoka, and Sapporo 140
Figure 7.10 Kobe city monitoring program guidelines booklets 142
Figure 7.11 Sendai city's Waste Mascot Merchandize 143
Figure 7.12 Food System Flow 145
Figure 7.13 Different models of composting bags and an example of an electric composter (retrieved from Komatsu City (2024), LFC (2024), Ibuki Farm (2024), and Chikyu-Labo (2024)) 146

List of Tables:

Table 3.1 Chapter 3's Socio-Demographics....30
Table 3.2 Constructs' Reliability....34
Table 3.3 Heterotrait-monotrait ratio of correlations (HTMT)....34
Table 3.4 Items' loadings, means and standard deviations. 34
Table 3.5 Variance Inflation Factor (VIF) 37
Table 3.6 Path Coefficients Bootstrapping results. 37
Table 3.9 Mediation Effects....40
Table 3.10 PCA Results and mean and standard deviation of the PEB. 42
Table 3.11 Cluster's characteristics. 42
Table 3.12 Cluster's Socio-Demographics....43
Table 3.13 MICOM Steps 2 and 3 (p-value > 0.05)....46
Table 3.14 Non-Parametric Permutation-Based Test (Klesel et al. 2019)....47
Table 4.1. Socio-Demographics of the sample 62
Table 4.2 Items' average, standard deviation, Principal Component Analysis' (PCA) factor loadings and explained proportion. 64
Table 4.3 Spearman Correlation Matrix between PCA factors....65
Table 4.4 Kruskall Wallis' Test and Dunn's Test Results (bold values represent situations where the test hypothesis is rejected). 66
Table 4.5. Clustering Results and Clusters' Profiles 69
Table 4.6. Eco-Friendly and Bothersome Ranking 70
Table 4.7 Bothersome average score per Cluster (bold values are the top 3 highest values) 71
Table 5.1 Literature on models and interventions about household composting and food waste segregation schemes....84
Table 5.2 Reliability Measurements....97
Table 5.3 Discriminant Validity: HTMT 97
Table 5.4 Items' loadings, means and standard deviations. 97
Table 5.5 Polychor Correlation Matrix Between Items with a null HTMT2....100
Table 5.6 VIF Table....101
Table 5.7 Path Coefficients....101
Table 5.8 Indirect Effects 102
Table 6.1 Socio-demographics of the dropouts sub-sample 112
Table 6.2 Cross-table of the dropouts per cluster and gender....114
Table 6.3 Krukall Wallis' test results....116
Table 6.4 Mann-Whitney-U test results 117
Table 7.1 Waste quantity in Japan in 2021 127
Table 7.2 Municipalities running food waste collection schemes....130
Table 7.3 Financial Assistance Conditions....138
Table 7.4 Reward Programs Weight System 144

List of Abbreviations

Abbreviation	Definition
3R	Reduce, Reuse, and Recycle.
4R	Reduce, Reuse, Recycle, and Recover.
AVE	Average Variance Extracted.
CB-SEM	Covariance-based Structural Equation Modelling.
CC	Circular Cities. Cities which promote circular economy.
CE	Circular Economy.
EC	Ethical Consumption. In Chapter 3, it refers specifically to the ethical consumption of food products.
EM	Effective Micro-organisms.
Food Waste	Any food, and inedible parts of food, removed from the food supply chain to be disposed or recovered.
FWRH	Food Waste Recovery Hierarchy.
GDP	Gross Domestic Product.
GHGs	Greenhouse Gases.
HTMT	Heterotrait-monotrait ration of correlations.
IC Card	Integrated Circuit cards which are used in Japan as a payment method for transportation and other service.
ICT	Information and Communications Technology.
Kanto Region	Geographical region of Japan comprising the following prefectures: Gunma, Tochigi, Ibaraki, Saitama, Tokyo, Chiba, and Kanagawa.
KPI	Key Performance Indicator.
LIV	Latent Instrumental Variable.
LPLC	Local Production for Local Consumption Japanese initiative.
MAE	Mean Absolute Error.
MAFF	Japanese Ministry of Agriculture, Forestry and Fisheries.
METI	Japanese Ministry of Economy, Trade and Industry.
MGA	Multi-Group Analysis.
MHLW	Japanese Ministry of Health, Labour, and Welfare.
MICOM	Measurement Invariance of Composite Models.
MOE	Japanese Ministry of the Environment.
MOJ	Japanese Ministry of Justice
NDT	Non-Parametric Distance-Based Test.
NEP	New Environmental Paradigm.
NGO	Non-Governmental Organization.
NPO	Non-Profit Organization.
NPT	Non-Parametric Permutation-Based Test.
OLS	Ordinary Least Squares.
OrdPLS	Ordinal Partial Least Squares.
PCA	Principal Component Analysis.
PEB	Pro-Environmental Behaviour. A behaviour with a neutral or positive impact to the planet.
PLS-SEM	Partial Least Squares Structural Equation Modelling.
RESET	Regression Specification Error Test.
RMSE	Root Mean Square Error.
SGDs	Sustainable Development Goals.
S-O-R	Stimulus-Organism-Response behavioural theory.

SRMR	Standardized Root Mean Square Residual.
TCV	Theory of Consumption Values.
TPB	Theory of Planned Behaviour.
VIF	Variance Inflation Factor.

Chapter 1: Introduction

1.1 Motivation

Although indispensable to human lives, food systems are a major contributor to land erosion, water pollution, and greenhouse gas emissions (Ritchie et al. 2022). Additionally, from the total amount of food produced, a significant portion is wasted without ever being consumed. Only in 2021, 5.23 million tons of food were discarded in Japan throughout the entire food system (MOE 2023a). To minimize this negative impact of the food industry, several countries and international corporations have set sustainable policies, indices, and strategies (United Nations 2022). Many of these strategies rely on incentivizing the adoption of pro-environmental behaviours (PEB), which are actions that have a neutral or positive impact on the environment (Steg and Vlek 2009). In Japan, these aim to decrease greenhouse gas emissions, reduce chemical fertilizer usage, increase the hectares of land dedicated to less intensive and organic methods of agriculture, and promote circular closed loops of resources (Circular Economy, CE) (MAFF 2021; Herrador et al. 2023). Besides contributing to chemical-free farming, promoting recovery loops is also instrumental in decreasing the amount of waste that ends up in landfills. Without such decreases the expected remaining landfill capacity in Japan is 23 years and a half (MOE 2023a).

A critical stakeholder in moving food systems towards sustainability are the consumers (Monroe et al. 2015). From the moment of purchase to moment of disposal, people's decisions can have a substantial effect on limiting climate change (Abrahamse 2020). For instance, in 2021, the Japanese Ministry of Agriculture, Forestry and Fisheries (MAFF) estimated that around 2.44 million tons of waste (almost half of the total amount of waste) came from households (MAFF 2023a). Additionally, even though the land dedicated to organic food is growing in Japan, registering 10,792 hectares of agricultural land it in 2019 (Willer et al. 2020; Nakagawa and Zimmerman 2021), the share of organic products remains small in the consumers' basket (Dentsu Macromill Insight Inc. 2021; Nakagawa and Zimmerman 2021). Consumers' decision-making process has several complex nuances (Shaw et al. 2016), and so understanding the psychological mechanisms behind behavioural change is an essential component of designing effective interventions (Steg and Vlek 2009; Abrahamse 2019, 2020).

1.2 Main Contributions

This doctoral research argues that to design policy interventions that successfully boost pro-environmental behaviour adoption and mitigate climate change, it is necessary to identify the

object of change and examine the main factors underneath it (Steg and Vlek 2009; Linder et al. 2018). Therefore, the main goal of this work is to present a holistic view on the role of Japanese consumers and households on building an economically, socially, and environmentally sustainable food supply chain. More precisely, the present research aims to contribute to food consumption and waste management academia by 1) Presenting a comprehensive model to describe Japanese decision making process of purchasing food ethically; 2) Exploring the patterns and contrasts across the Japanese population on the adoption rates of ethical purchasing, waste reduction, and food waste recycling PEB; 3) Identifying the main drivers to the decision to compost in Japan; 4) Identifying the main reasons that lead Japanese consumers to stop composting; and finally, 5) Presenting a review of ongoing Japanese initiatives to prompt more sustainable lifestyles, in particular to initiatives that foster food waste recycling. Japan was chosen as the subject of study because, despite its promising food waste decreasing trends, it is one of the highest amounts of food waste in the world weight wise (McCarthy 2021; Forbes et al. 2024). With this in mind, when compared with European countries or the US, less is known about how Japan's cultural background can shape the way people purchase, use and discard their food.

Besides its policy implications, the current manuscript extends the previous applications of the Stimulus-Organism-Response (S-O-R) (Mehrabian and Russell 1974; Jacoby 2002) and the Theory of Consumption Values (TCV) (Sheth et al. 1991) frameworks. Latter theoretical frameworks were used to explain green food consumption and household composting behaviour. Regarding statistical methods, less commonly applied algorithms such as clustering using a *Mahalanodis* distance, a Partial Least Squares Structural Equation Modelling (PLS-SEM) (Wold 1985) with a multi-group assessment (MGA) with more than 2 groups, and the categorical extension of the PLS-SEM (OrdPLS) (Cantaluppi 2012; Cantaluppi and Boari 2016) were also used as analytical tool in the following chapters.

1.3 Scientific Results

As of this manuscript's submission date, two papers concerning the results of Chapters 3 and 4 have been published, and another three, regarding the findings of Chapters 5, 6, and 7, are under review (Morais and Ishida 2024; Morais et al. 2024).

1.4 Structure of the Dissertation

The document is structured in 8 chapters. After this introductory section, Chapter 2 gives the social and policy context for this dissertation and presents the theoretical background of the

statistical tools used on Chapters 3, 4, 5, 6 and 7. Chapter 3 focused on the first step of consumption, the purchase. The main drivers to ethical food consumption were identified via a Stimuli-Organism-Response (S-O-R) framework application using a PLS-SEM algorithm with a Multi-Group Analysis (MGA) assessment based on clustering. The following chapter, Chapter 4, looked at the nuance in practice rates of food related PEB adoption profiles throughout consumption (purchase, usage, disposal). To do so, a two-step clustering analysis was done. Chapter 5 focused on food waste disposal, the last step of consumption. By using the Theory of Consumption Values (TCV) framework with a OrdPLS algorithm, the main household composting drivers in Japan were identified. Chapter 6 further explores household composting behaviour, but instead of focusing on engagement factors, it concentrates on identifying the major reasons for households to drop out of composting. Next, in Chapter 7, some of the on-going Japanese solutions to encourage sustainable lifestyle were analysed. Finally, the main conclusions of this dissertation as well as limitations encountered are summarized in Chapter 8.

Chapter 2: General Background and Methodology

2.1 Introduction to Japanese Social and Political Context

Japan is an Asian economic power with one of the world's highest Gross Domestic Product (GDP), alongside U.S.A., Germany, China, and India (Forbes 2024). As of first October of 2022, Japanese population was 124,947million people scattered by 47 Prefectures and a total of 1718 municipalities plus the 23 special wards of Tokyo (Koizumi 2022; Inaba et al. 2022). In 2021, from the 47 Prefectures approximately 37% of the population lives in Tokyo, Kanagawa, Osaka, Aichi, and Saitama (Statistics Bureau of Japan 2021). As it is happening in other developed countries, Japan has been struggling with aging population and the migration of citizens from rural areas to urban regions. Such circumstances can result in several challenges, in sectors like waste management (Kawai et al. 2022). however, with almost half of the municipalities being in depopulated areas, opportunities for the sustainable use of jurisdictional natural resources may also arise (Herrador et al. 2023).

2.1.1 Japanese Sustainability and Food Waste Policies

In 2015, MAFF settled the goal of increasing organic food production by 25% (MAFF 2021). Due to the low food self-sufficiency rate and lack of available landfill sites for disposal, the Ministry of the Environment (MOE) and MAFF also set the goal of halving the 2000's food loss and waste rate by 2030 (MAFF 2019; Umeda 2019). One of the foundations for these KPIs is the Japanese Food Waste Recycling Law that was first enacted in 2001, and ever since it was amended twice (in 2007 and 2015) (Joshi and Visvanathan 2019). This Act intends to promote waste prevention and recycling loops (turn waste across the supply chain into animal feed or fertilizer) in the food industry (Parry et al. 2015; Liu et al. 2016; Fujii and Kondo 2018; Umeda 2019). In 2019, the Japanese government enacted a complementary law, in which, to reduce household food waste, the local and central authorities are to educate businesses and consumers as well as facilitate food re-distribution projects (Umeda 2019).

Also in 2001, the Japanese Government passed an Act on the Promotion of Procurement of Eco-Friendly Goods and Services (Parry et al. 2015; MOE 2017). The latter act covers 21 categories including emergency supplies (e.g., emergency food/water, portable batteries), and public works (e.g. recycling treatment of sludge, compost, greening rooftops) (MOE 2017; Miyamoto et al. 2020; EU-Japan Centre for Industrial Cooperation 2021). As far as organic

farming is concerned, the act promoting this type of agriculture was passed in 2006 and later amended in 2011 (MOJ 2011). Additionally, even though the Eco-Town initiative started in 1997 (Higuchi and Norton 2008), and both the law for promoting the effective utilization of the resources and the Japanese Circular Economy Vision declaration date back to 1991 (Kurisu and Bortoleto 2011; METI 2020), recent years have seen increasing attention given to the promotion of Circular Cities (CC) and Circular Economy (CE) programs (Herrador et al. 2022, 2024). As a result, the Circular Economy Vision was updated in 2020, with a stronger focus in the latter aspects. The Eco-towns initiative had its origin as a subsidy system established by METI (Ministry of Economy, Trade and Industry of Japan) and MOE to foster local recycling and zero emission strategies through local innovation and entrepreneurship (Higuchi and Norton 2008). Circular Cities and Circular Economy are interconnected concepts, where Circular Economy can be seen as a holistic approach that fosters the optimization of material loops and increases resource usage efficiency to reduce negative environmental impacts (Herrador et al. 2022). Circular cities are cities that have policies to promotes such circular economy principles and try to enhance social well-being and economy while living in harmony with the environment (Herrador et al. 2022, 2024).

Upon these targets, acts, and national government initiatives, each municipality enables them according to regional conditions. While many local governments engaging mechanisms relied on 3R (Reuse, Reduce, and Recycle) policies, the "*mottainai*" philosophy, which implies showing gratitude for the food and a sense of regret for waste (Sirola et al. 2019; Izumi et al. 2020; Hata 2021; Setouchi City 2021; Inaba et al. 2022), and the "*satoyama*" ideology, which means to live sustainably with their nearby forest and mountains (Dublin and Tanaka 2014; Herrador et al. 2024), a wide range of implementation strategies can be found throughout Japan (Hotta and Aoki-Suzuki 2014; Inaba et al. 2022). This variety of strategies have been pointed out as one of the reasons for regional differences in the adoption of waste prevention behaviours from consumers (Kurisu and Bortoleto 2011; Lee et al. 2013; Hotta and Aoki-Suzuki 2014). For example, Kurisu and Bortoleto (2011) highlighted that composting and "*Bring Your Own Chopsticks*" were unpopular behaviours, whereas refillable products and the use of the own bag when shopping ("My bag") where among the most adopted, especially in Aichi (this prefecture was one pioneer regions on waste reduction policies (Kurisu and Bortoleto 2011; Hirose 2015). Furthermore, Nakamura et al. (2022) found differences between waste generation motives in urban and rural areas. Thus, scholars called for further efforts on understanding and promoting systematically sustainable lifestyles, food waste reduction and recycling, specially at the consumer level (Liu et al. 2016; Wei et al. 2017; Kawai and Huong 2017; Abrahamse 2020; Talwar et al. 2022).

2.1.2 Japanese Consumer

Japanese consumers have been sketched as relatively homogeneous, informed, collective oriented, possessing strong aesthetic values, and more risk-averse when compared with other cultures (Synodinos 2001; Ando et al. 2007, 2010). While in the U.S. and the Netherlands traditional values seem to act as a barrier (Aoyagi-Usui et al. 2003; Kawasaki et al. 2022), in Japan, PEB were positively related with both a traditional education and altruistic values (Aoyagi-Usui et al. 2003; Kawasaki et al. 2022). Later studies showed once again that long-term, personal, in-group trust relations associated with Japanese culture (McGreevy and Akitsu 2016) and food safety can boost organic sales (Yang et al. 2022). On the other hand, this risk-aversion can also have an impact on how people discard food. For instance, Nakamura et al. (2022) findings suggest that safety awareness and checking labels, if combined with knowledge and especially in large cities, can contribute for less waste generation. However, in absence of adequate knowledge the effect is the opposite (Nakamura et al. 2022). Moreover, food waste avoidance was also positively associated with individuals who expressed strong feelings towards *"mottainai"* ideas (Sirola et al. 2019). These findings seem to support the decision of some cities and schools to base their interventions is such a concept (Sirola et al. 2019; Setouchi City 2021; Kawasaki et al. 2022). Using this ideology to nourish waste reduction may catalyse a wide spectrum of behaviours, like saving water, energy, or the reduction and recycling of both organic and non-organic waste.

Overall previous Japanese literature seems to point to women as more aware of household waste generation. They are also more engaged in waste prevention and ethical food consumption PEB by being more responsible for cooking and house chores (Kurisu and Bortoleto 2011; Lee et al. 2013; Qian et al. 2020; Nakamura et al. 2022). This tendency does not seem to be exclusive to Japan, as studies have shown women are keener on ethical consumption in Australia and the U.S. (Burke et al. 2014; Witzling and Shaw 2019), and in waste prevention in the U.K., Italy, and Denmark (Barr 2003; Aschemann-Witzel 2018; Annunziata et al. 2022). However, the role of gender toward PEB adoption and Environmental Attitude has not been consistent in literature (Kurisu 2015; Simões et al. 2022). For instance, Hazuchova et al. (2020) did not find differences between men and women waste generation in Czechia, and in Brazil men more often engaged in some of the observed reusing activities (Bortoleto et al. 2012). In a multi-country study, there was no clear gender distinction between related food-related lifestyles (Brunsø et al. 2021), and gender was not significant to organic food purchase in a study in India (Singh and Verma 2017). Moreover, instead of a direct, effect Tandon et al. (2021) found gender acted as a moderator to the purchase of organic food in Japan.

Similar contradictions can be found regarding age (Kurisu 2015). In Japan, while older people seemed to engage more frequently in waste prevention PEB, the use of public transportation and "trendy" PEB like the use of one's own coffee cup was more popular in younger generations (Kurisu and Bortoleto 2011; Lee et al. 2013; Phuphisith et al. 2020). The age often associated with children bearing reported more frequent use of recycling stores and flea markets (Kurisu and Bortoleto 2011; Kurisu 2015). Despite children usually implying more waste (Simões et al. 2022), they can also incentivize families to engage inactivities like gardening, composting (Iijima and Egahiro 2014; Coogan 2019; Honami et al. 2022), and purchasing organic food (Yang et al. 2022).

Moreover, time availability has been reported as impactful in food waste reduction (Nakamura et al. 2022). Throughout the years, long workdays have become a standard practice in Japanese corporate culture, resulting in significant physical and mental stress as well as impeding women entering the workforce (Ono 2018; Kawashukuda 2022). It would be expected that such workers are less inclined to engage in behaviours considered time-consuming. Interestingly, a study in the U.S. found that instead of objective lack of time, subjective lack of time was more of a barrier to food waste kerbside separation (Wu et al. 2019).

2.2 Analytical Tools

The following chapters have as basis of analysis similar statistical tools, namely: Partial Least Squares Structural Equation Modelling (PLS-SEM), Ordinal Partial Least Squares (OrdPLS), Principal Component Analysis (PCA), clustering algorithms (Hierarchical Clustering, *K-Means*, and *K-Medoids*) and non-parametric significancy tests (Mann-Whitney U test, Kruskal Wallis's test, and Dunn's test). Therefore, on the present section the main assumptions of these tools were explained. The main concepts related to the SWOT analysis used in Chapter 7 were also clarified.

2.2.1 PLS-SEM and OrdPLS

Partial Least Squares Structural Equation Modelling (PLS-SEM) is a multivariate analysis technique which belongs to the family of structural equation modelling (that also includes the Covariance-Based Structural Equation Modelling, CB-SEM) (Hair et al. 2018). and Ordinal Partial Least Squares Structural Equation Modelling (OrdPLS) is an extension of PLS-SEM that can cope with categorical data by using the polychoric correlation matrix (Cantaluppi 2012; Schuberth et al. 2018; Sarstedt et al. 2022a). When compared with other techniques such as

Ordinary Least Squares (OLS), PLS-SEM and its extensions have two advantages. First, they allow the use of abstract concepts (latent) variables as part of the model. Second, they can estimate multiple dependence relationships (Hair et al. 2018). The main model hypothesises of Chapter 3 and Chapter 5 were tested via PLS-SEM and OrdPLS.

A PLS-SEM approach was preferred to CB-SEM, once PLS-SEM holds softer assumptions on normality, observation independence, sample size and it does not have identification issues (Wold 1985; Hair et al. 2018). Academics also pointed out PLS algorithms are more adequate when the research has a predictive side, the goal goes beyond testing established theoretical frameworks, or the analysis comprises formative variables (Hair and Alamer 2022). Despite, the core features of PLS being its lack of distributional assumptions and the sample size requirements, the case of OrdPLS is slightly distinct (Cantaluppi 2012; Schuberth et al. 2018; Hair and Alamer 2022). As OrdPLS is based on polychoric correlation, which assumes normality for the latent variables, OrdPLS can no longer be declared free of distributional assumptions (Cantaluppi 2012; Schuberth et al. 2018). This might appear to be a strong assumption, but the OrdPLS algorithm is prepared to deal with manifest variables that derive from normality, and it can actually counterbalance the additional bias associated with PLS techniques (Cantaluppi 2012; Schuberth et al. 2018).

PLS-SEM modelling comprises the estimation of two models: the outer (measurement) model and the inner (structural) model. The measurement model displays the relationships between the constructs and the indicator variables. They can be either reflective or formative. A reflective relation implies the indicators are a "manifestation" of the latent concept (Wold 1985). On the other hand, a formative relation implies the construct is a linear combination of its indicators (assumed not highly correlated) (Hair and Alamer 2022).

The author acknowledges that PLS-SEM is a composite-based approach, so some scholars recommend the use of PLSc (or OrdPLSc) when the model has reflective variables (Dijkstra and Henseler 2015; Schuberth et al. 2018; Sarstedt et al. 2022a; Hair and Alamer 2022; Henseler and Schuberth 2023; Ringle et al. 2023). Nonetheless, due to the ongoing debate among PLS scholars about the advantages and disadvantages of using such extension and the scarce literature available on PLS categorical applications, neither PLSc nor OrdPLSc were used (Schuberth et al. 2018; Sarstedt et al. 2022a; Hair and Alamer 2022; Henseler and Schuberth 2023; Ringle et al. 2023).

The inner model displays the relationships (paths) between the constructs (latent variables). They can be direct or indirect depending on the existence of mediating construct. When testing mediation effects, one can gain a deeper understanding of the causal mechanism that underlies underlying the relationship between two variables (Henseler 2021). To assess the model

quality, both outer and inner models should be evaluated. First the outer and after the inner. If the outer model is not examined with scrutiny, the analysis of the inner model can be compromised.

Evaluation of the reflective measurement model: reflective measurement models should be evaluated regarding constructs internal consistency reliability (Cronbach's α and Joereskog's rho, also known as ρ_c, as lower and upper boundaries respectively, $0.70 \leq x < 0.95$), indicators' reliability (loadings ≥ 0.708), convergent validity (Average Variance Extracted (AVE) ≥ 0.50), and discriminant validity (Heterotrait-monotrait ratio of correlations (HTMT/HTMT2) < 0.85 or < 0.90 for similar concepts) (Sarstedt et al. 2022a; Ringle et al. 2023).

Evaluation of the formative measurement model: Latent variables, modelled as formative should be evaluated regarding their convergent validity (redundancy analysis ≥ 0.708), internal collinearity (VIF ≤ 5, preferably ≤ 3) and size of the coefficients and significancy of the indicators' weights and loadings (Hair Jr. et al. 2021; Sarstedt et al. 2022a; Ringle et al. 2023).

Evaluation of the structural model: Similarly to the inner collinearity of formative constructs, one should check for collinearity issues among the model constructs (VIF < 3 is uncritical, 3 < VIF < 5 is usually uncritical) (Ringle et al. 2023). Following, the significance and relevance of the structural model relationships (p-values of path coefficients), the explanatory power, the predictive power, and model fit should be evaluated. Concerning explanatory power, a $R^2 > 0.75$ is often considered substantial, and a $R^2 > 0.50$ moderate (Hair Jr. et al. 2021). However, R^2 values depend on context and its interpretation should be done based on the research domain being examined (Hair and Alamer 2022).

When the focus of the analyses is both prediction and explanation, researchers should consider the trade-off between these two aspects (Ringle et al. 2023). Thus, the present analyses assessed the standardized root mean square residual (SRMR) to address the explanatory side of the method (Schuberth et al. 2023) and compared the model prediction errors (Mean Absolute Error - *MEA* or Root Mean Square Error - *RMSE*) of the dependent variable to the ones of a naive linear model benchmark (Shmueli et al. 2019; Hair Jr. et al. 2021). At least half of errors should be inferior to the benchmark model (Shmueli et al. 2019) and the SRMR should be no bigger than 0.08 (Cho et al. 2020; Dash and Paul 2021). It is important to note, however, that under the presence of composite variables and categorical items such cut-off values may not be accurate (Schuberth 2022; McNeish 2023).

Mediation Analysis: Mediation analysis allow scholars to understand the causal mechanism underlying the relationship of two variables (Henseler 2021). As PLS-SEM models are frequently applied to complex frameworks with multiple relationships (Carrión et al. 2017), a multi-path mediating effect or multiple mediation constructs within a path might occur. When making a mediation analysis, researchers may find cases of non-mediation (if the indirect effect

is non-significant), full mediation (direct effect is non-significant), complementary partial (indirect and direct effect point in same directions), or competitive partial mediation (direct and indirect effects have opposite directions) (Carrión et al. 2017).

Multi-group Analysis: Moderation describes a situation in which the strength or direction of a relationship between two constructs depends on a third one (Hair Jr. et al. 2021). Thus, analysing such effects allow scholars to consider heterogeneity and contingencies of sub-populations within the sample (Henseler et al. 2016). When researchers hypothesise that the relationships of the structural model depend on a third observed categorical trait, multi-group analysis (MGA) has shown to be a resourceful and widely applied tool (Hair Jr. et al. 2021; Cheah et al. 2023).

According to Cheah et al. (2023)'s guidelines on MGA, prior the analysis *per se,* researchers should prepare the data, assess the measurement model, the measurement invariance via MICOM (Measurement Invariance of Composite Models proposed by Henseler et al. (2016)), and set an analysis goal. Only after, if the previous steps succeeded, proceed to model comparisons. Literature have suggested different MGA approaches concerning the number of groups on the analysis. While a two groups MGA can be based on a parametric test or on a non-parametric test (Hair et al. 2017; Hair Jr et al. 2017), if there are at least three groups, researchers should opt for procedures like an Omnibus test of group differences (OTG) or a Non-Parametric Distance-Based Test (NDT) proposed by Klesel et al. (2019), followed by a Non-Parametric Permutation-Based Test (NPT).

MICOM comprises three sequential steps. Step 1 assesses configural invariance, step 2 compositional invariance and step 3 checks the equality of composite mean values and variances (Hair et al. 2017; Hair Jr et al. 2017). If 1) and 2) are confirmed, partial measurement invariance is confirmed. Additionally, if step 3 is satisfied, full measurement invariance is set (Henseler et al. 2016). In case the analysis is done for more than two groups, it is necessary to employ a correction technique (e.g., Bonferroni) to avoid family-wise errors (Henseler et al. 2016). The MGA methodology followed in Chapter 3 was based on the guidelines of Carrión et al. (2017), Hair Jr et al. (2017), and Hair et al. (2017).

Robustness tests: With increasing usage of PLS-SEM algorithms authors have been also developing additional robustness tests to this analytical tool. Particularly, recent publications highlighted the importance of testing nonnormality, endogeneity, nonlinearity, unobserved heterogeneity and heteroskedasticity issues, similarly to what is done for other analytical methods (Guenther et al., 2023; Sarstedt et al., 2020; Vaithilingam et al., 2024). Detailed information about these robustness test can be found in literature such as Hair et al. (2019), Guenther et al. (2023), and Vaithilingam et al. (2024).

Despite PLS-SEM being considered distribution free, it is important assess the univariate and multivariate normality of the items, so: 1) one can justify the use of PLS-SEM (note, that non-normality should not be the sole reason for choosing PLS-SEM analytical tool) (Vaithilingam et al. 2024); 2) The researcher can assess the existence of highly peaked or skewed distribution, as it may affect bootstrapping results. Among other coping strategies, when analysing bootstrapping results percentile-based, confidence intervals should be preferred (Aguirre-Urreta and Rönkkö, 2018; Guenther et al., 2023). The most common method to assess univariate normality is through the kurtosis and skewness of the variables. If univariate normality is verified, one should test for multivariate normality via, for instance, a Mardia's test. Under PLS-SEM, normality values between − 2 and +2 can generally be considered acceptable (Hair et al., 2022).

Moreover, when testing endogeneity under PLS-SEM algorithms, researchers can use approaches such as control variables, instrumental variables, Gaussian copula, or Latent instrumental variables (LIV) (Huit et al. 2018; Becker et al. 2022). While Gaussian copulas can an instrumental variable-free interesting approach, in the analyses done in this manuscript endogeneity was addressed by using control variables. Besides dealing with endogeneity, there has been controversy about the role they play in the field of study for this doctoral research. As previously mentioned, heterogeneity can be dealt with multi-groups assessments or moderation analysis, as presented in Chapter 3. There are also PLS-SEM extensions which allow to detect unobserved heterogeneity such as FIMIX-PLS and PLS-POS (Sarstedt et al. 2020; Guenther et al. 2023; Vaithilingam et al. 2024). Such extensions were not used as there is already limited literature about Ord-PLS which the algorithm applied in Chapter 5.

As far as heteroskedasticity and non-linearity are concerned, according and Vaithilingam et al. (2024), few PLS-SEM literature has addressed them. Particularly, while suggestions have been made about assessing non-linearity via the Regression Specification Error Test (RESET) (Ramsey 1969), scholars who have used this test or actual quadratic terms in SEM literature remain uncommon (Basco et al., 2021; Guenther et al., 2023; Hair Jr et al., 2017; Kumar and Purani, 2018; Riggs et al., 2023; Sarstedt et al., 2020; Vaithilingam et al., 2024). Once again, based on the limited literature available about these topics and the already less common usage of the PLS categorical extension in Chapter 5, these tests were not run. While this dissertation does not fully grasp the robustness tests of PLS-SEM, it would be expected that more information about them will become available in the coming years, thus facilitating the implementation of these tests in PLS-SEM studies across various areas.

2.2.2 Data Reduction

When the sample contains a large number of variables, the task of visualizing and

interpreting the information from a cluster analysis becomes more complex (Hair et al. 2018). Thus, prior to the clustering analytical steps of Chapter 3 and Chapter 4, a Principal Component Analysis (PCA) was done in both chapters. According to Hair et al. (2018), a PCA *"considers the total variance and derives factors that contain small proportions of unique variance and, in some instances, error variance"*. Once a factor rotation can increase the interpretability of the obtained factors (Hair et al. 2018) different rotation possibilities were analysed within the PCA analyses done. There are two main rotation types, orthogonal and oblique ones (Hair et al. 2018). Orthogonal rotations, like the *varimax* rotation, rotate the factor while maintaining the independence of the factors, whereas Oblique rotations are not constrained by a 90 degrees relation between axes (Hair et al. 2018). Thus, in cases where correlation between the factors is not intended, Oblique rotations, such as the *promax* rotation, should be avoided.

Before using this technique on a data set scholars should check if the data is suitable to be factorized via a Kaiser-Meyer-Olkin (KMO) test, a Bartlett's test, and a Cronbach's Alpha. The ideal number of factors was decided based on the factors' eigenvalues (>1) and the scree test's "elbow" (Hair et al. 2018). In both Chapters 3 and 4, the PCA results were used to calculate summated scales.

2.2.3 Clustering Analysis

Clustering algorithms are exploratory, non-inference techniques used on multivariate *datasets* (Hair et al. 2018). They find "natural" structures among observations based on their response patterns and have been widely used across research fields, with purposes such as consumer segmentation and target marketing in mind (Hair et al. 2018). Notwithstanding, these techniques have not been extensively applied to Ethical Consumption nor Waste Disposal behaviours yet. Among several clustering techniques, a two-step clustering approach was applied in both Chapter 3 and Chapter 4. In the first step, a Hierarchical Clustering was used, followed by a centroid-based algorithm: a *K-Medoids* on Chapter 3 and a *K-Means* on Chapter 4.

Hierarchical Clustering: Hierarchical clustering solutions are fast and can be used with a wide range of measures of similarity, however once they group (if agglomerative) or ungroup (if divisive) observations recursively, two observations cannot be separated after being paired (Han et al. 2012; Hair et al. 2018). The grouping criteria relies on the distance matrix between observations and which observations are used to merge two groups (linkage criteria) (Hair et al. 2018). Several distances and linkage criteria can be used with clustering algorithms. Euclidean distance (see equation (1)) is the most widespread among scholars (Hair et al. 2018). However,

when the variables are correlated, *Mahalanodis* distance (see Equation (2)) should be preferred as it weights each variable equally even in correlation circumstances (Hair et al. 2018). The distance matrix in Chapter 4 was calculated based on the Euclidean distance. Whereas the *Mahalanodis* distance was used in Chapter 3. Ward's linkage criterion was chosen in both analyses. Such linkage method attempts to minimize the Sum Squared Errors (SSE) originated when merging clusters (Hair et al. 2018).

$$Euclidean\ Distance = d_{euc}(x, y) = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2} \quad (1)$$

Where x and y are two vectors of length n.

$$Mahalanobis\ Distance = D^2 = (x - m)^T C^{-1} (x - m) \quad (2)$$

Where m is the vector of mean values of independent variables, C^{-1} represent the inverse covariance matrux of independent variables, and the *T* indicates it is the transposed vector.

K-Means: *K-Means* is a partitional-based clustering technique commonly used by researchers (Hair et al. 2018). It separates the data into a user-specified number of groups and in this case the ones suggested by the hierarchical algorithm. The grouping occurs iteratively until the homogeneity within the cluster cannot be improved (Hair et al. 2018).

K-Medoids**:** *K-Medoids* also referred PAM (Partition Around Medoids) is a partitional-based clustering technique proposed by Kaufman and Rousseeuw (2009). It derives from the *K-Means* algorithm, but instead of using mean of all objects in the cluster as cluster *centroids*, it uses actual points of the *dataset*. Besides being considered more robust than *K-means* to outliers (Kaufman and Rousseeuw 2009), it supports the analytical decision made in Chapter 3 of calculating the distance matrix based on the *Mahalanodis* distance. According to Schubert and Rousseeuw (2019), non-euclidean data clustering is a hard task that can result in initialization problems under a *K-Means* application (Ghosh 2020). Therefore, by using *K-Medoids* such hurdles were avoided in Chapter 3.

2.2.4 Non-Parametric Significance Tests

When assessing if a particular continuous variable is different among groups, a researcher can use parametric or non-parametric significance tests. Once the majority of the analysis done in this document used analytical tools who did not hold assumptions towards the normality of the

variables' distributions, non-parametric significance tests in the analysis of Chapter 3, Chapter 4, and Chapter 6 was used. In situations where there are more than two groups the Kruskal Wallis' Test was applied (Kruskal and Wallis 1952). If the latter was rejected, a Dunn's Test with a Bonferroni correction was used to understand the pairwise dynamics of the analysed groups (Dunn 1964; Dinno 2015). When there were only two groups, the test used was the Mann-Whitney-U test (Wilcoxon 1945; Mann and Whitney 1947).

2.2.5 Likert-Scales

According to Hair et al. (2018) and Joshi et al. (2015) long is the debate whether Likert-scales should be considered categorical (ordinal) or not. In a review study, Norman (2010) pointed out that Likert-scales hold robust results in several parametric applications, even in presence of unequal variances, small sample sizes, and non-normal distributions. Moreover, several studies within the environmental and behavioural scope have found significant results with a continuous assumption (Kopaei et al. 2021; Dorce et al. 2021; Kunszabó et al. 2022). Thus, it is was also decided to consider the Liker-scales items present in the datasets of the analyses of Chapters 3, 4, 5, and 6 as interval scales.

2.2.6 SWOT Analysis

A SWOT analysis stands for Strengths, Weaknesses, Opportunities, and Threats analysis (Sammut-Bonnici and Galea 2015; Zheng et al. 2017). This framework was used to analyse one of the food waste recycling layouts that can be found in Japan, in Chapter 7, because it is a widespread business management that facilitates strategic planning and discussion (Sammut-Bonnici and Galea 2015; Zheng et al. 2017). Strengths and weaknesses are internal aspects of an organization's environment, whereas opportunities and threats are external factors (Sammut-Bonnici and Galea 2015). Strengths and Weaknesses concern aspects such as capabilities, resources, core competencies, and competitive advantages (Sammut-Bonnici and Galea 2015). On the other hand, market opportunities and threats relate to competitors' resources, the industry environment, and the general environment (Sammut-Bonnici and Galea 2015).

Chapter 3: Ethical Food Consumption Drivers in Japan. A S–O-R framework application using PLS-SEM with a MGA assessment based on clustering

3.1 Introduction

This chapter is dedicated to first step of consumption, the purchasing moment. More precisely the aim is to identify which factors are significant to a Japanese consumer to purchase in a more sustainable way. The main findings of this chapter are published in Morais et al. (2024). Ethical Consumption, also referred to as green (Dhir et al. 2021b; Rivas et al. 2022; Han et al. 2022) or sustainable (Mcneill and Moore 2015; Rambabu et al. 2023), can be defined as engaging in the practice of buying products/services produced in a manner that reduces social and environmental harm, while avoiding those with a negative impact on society or the environment (Institute of Grocery and Distribution 2007). While some previous literature focused on cosmetics or apparel consumption, the main focus of this analyses as well as the following chapters is the food sector (Sadiq et al. 2021; Dhir et al. 2021b; Vergura et al. 2022; Suphasomboon and Vassanadumrongdee 2022).

In comparison with other Ethical Food Consumption (EC) literature, the current analysis presents three main novelty points: 1) the geographic location of the study, 2) the ethical food consumption scope; 3) and the applied methodology. Previous cross-country studies have pointed out that Japanese PEB adoption motives might differ from countries such as Germany, or the U.S hi(Ando et al. 2007, 2010), highlighting the importance of testing predictors in different cultures and contexts (Shaw and Clarke 1999; Steg and Vlek 2009). Therefore, in the present work, the methods proposed in the literature about the Japanese ethical food consumption market are extended.

When it comes to sustainable food consumption the majority of the studies seem to focus solely in one type of product like organic (Asif et al. 2018), local (Hempel and Hamm 2016), fair trade (Rashid and Byun 2018), or a particular family of products (Dorce et al. 2021). This chapter, however, gives a broader perspective on sustainable food purchase by including under the ethical consumption variable aspects related to biodiversity/environmental concerns, and support of disaster-stricken areas. The ethical facet of supporting disaster-stricken areas would be expected to be particularly relevant in a country that is frequently assaulted by natural disaster like Japan.

Moreover, the methodology used comprises a two-step analysis. In the first instance, to determine the main drivers of the decision process, a Stimulus-Organism-Response (S-O-R)

model (Mehrabian and Russell 1974; Jacoby 2002) was tested via a PLS-SEM to the whole sample. Following, in order to detect possible heterogeneity within the sample, a multi-group analysis based on a two-step clustering technique on the adoption rates of other PEB like recycling and waste reduction was done. S-O-R applications have been used successfully in fields like retail and e-commerce (Molinillo et al. 2021). Nonetheless, in the sustainable consumption field, it is still less spread than other behavioural frameworks such as the Theory of Planned Behaviour (TPB) (Ajzen 1991), the Altruistic Behaviour Model (Schwartz and Howard 1984), or the Theory of Consumption Values (TCV) (Sheth et al. 1991).

In contrast with TPB, S-O-R does not hold the assumption that people are rational in their actioning (Lee and Yun 2015). Thus, it is able to present a holistic perspective on the decision-making process which includes the emotional, cognitive, and affective factors (Tandon et al. 2021). More precisely, the S-O-R framework is a neo-behaviouristic approach that relies on three elements (stimuli, organism, and response) for understanding consumer behaviour. (S)timuli are environmental, usually external features to the individual at a given moment (Jacoby 2002). The latter affects one's internal state (O), activating cognitive and affective processes that trigger a (R)esponse (Tandon et al. 2021). It is relevant for the present chapter's research to note that responses depend not only on the organic factors but can also be a direct result of the stimuli (Jacoby 2002).

In the Ethical Food Consumption sphere, S-O-R researchers have explored the impact of price (Lee and Yun 2015; Rödiger and Hamm 2015; Lee et al. 2020), food quality and sensory appeal (Lee and Yun 2015; Konuk 2019; Utama et al. 2021), health consciousness/content (Tandon et al. 2021; Talwar et al. 2021), labels (Lee et al. 2020), communication and media (Anisimova et al. 2019; Sultan et al. 2021), and lifestyle (Utama et al. 2021). With the exception of Lee and Yun (2015), Lee et al. (2020), and Utama et al. (2021) such factors were mostly studied separately. Additionally, S-O-R literature which has analysed the impact of variable related to knowledge (Vergura et al. 2022), consumer's economic confidence (Han et al. 2022), optimism/pessimism (Dhir et al. 2021b), and altruistic/egoistic values (Rambabu et al. 2023) can also be found. However, the latter were focused on overall sustainable consumption, apparel, and care/cosmetic products. Following the approach of Lee and Yun (2015) and Lee et al. (2020), the current study also includes several stimuli within a model but extends the previous by adding knowledge and media information constructs. It also explores a different organic structure (based on Talwar et al. (2021) and Kumar et al. (2021)), has an internal and an external response (similarly to Dhir et al. (2021b) and Talwar et al. (2021) considered both intention as an internal response and buying behaviour as an external one/consequence), and allows direct relations between stimuli and response. Additionally, this study is the first, to the author's knowledge, to assess the moderation effect on an Ethical Consumption model based on a clustering between

PEB (such as waste reduction or avoiding packaging). The clustering technique used may be seen as an innovation point itself since it relies on a hierarchical clustering followed by a *K-Medoids* application, as opposed to the commonly applied *K-Means*.

The following sub-sections present a comprehensive and holistic model to describe Japanese decision process of purchasing food ethically. While doing so, this analysis extends previous applications of the S-O-R framework by 1) testing the significance of the knowledge stimuli on ethical food consumption; 2) including in one model price, health, communication, quality, knowledge, and labelling as stimuli; 3) considering both intention and action as internal and external responses; 4) allowing the direct impact of some stimuli to the external response (so impulse factors are captured); and 5) testing the possibility of using pro-environmental behaviours adoption rates as a moderation factor for a multi-group analysis.

3.2 Background and Methodology

3.2.1 Japanese Market:

Except for Talwar et al. (2021), Tandon et al. (2021) and Yang et al. (2022), the few existent research on EC in Japan focused primarily on product characteristics and attributes rather than aspects like attitudes or beliefs. Reasons like health (Kurisu and Bortoleto 2011; Tandon et al. 2021; Talwar et al. 2021; Nakagawa and Zimmerman 2021), safety (Tandon et al. 2021; Talwar et al. 2021; Nakagawa and Zimmerman 2021), freshness and origin (Sakagami et al. 2006) were found to have a positive impact to the purchase of organic food in Japan. On the other hand, Kurisu and Bortoleto (2011) and Sakagami et al. (2006) found cost/price as the main barrier to Ethical Food Consumption. Nonetheless, the scientific community called for further validation and inclusion of price and quality perceptions (Tandon et al. 2021). As previously mentioned in Chapter 2, Japanese tend to be relatively homogeneous, informed, collective oriented and risk-averse. This homogeneity seems to also apply, to a certain extent, to the trust that Japanese put on products containing the JAS label (government's organic label) certificates (Sakagami et al. 2006; Schleenbecker and Hamm 2013).

3.2.2 Model Hypothesis

A S-O-R model is a neo-behaviouristic approach to a consumer's actions based on the Input Output (I→O) model. Contrary to I→O models, the former considers organismic factors as an important part of the decision process (Jacoby 2002). Among several variations, the current methodology uses the S-O-R framework proposed by Jacoby (2002), followed by a multi-group assessment based on a clustering technique. This S-O-R variation was chosen because it poses responses do not depend solely on the organism. Instead, they can also be a direct result of stimuli (Jacoby 2002). According to Jacoby (2002), Stimuli-Response are automatic, reflex behaviours, in which unconscious stimuli lead to a behavioural response. On the other hand, literature in the consumption field also comprises work on Ways of shopping (Arenas-Gaitán et al. 2021, 2022) and impulse and unplanned buying behaviour (Bellini et al. 2017; Taghikhah et al. 2021). Impulsive purchasing can be defined as spontaneous or rapid decisions driven by an individual's sudden or irresistible urges tendency (Taghikhah et al. 2021). Therefore, it seemed appropriate to assess if some of the stimuli considered in the current study could trigger directly green consumerism. Impulse was previously studied under a S-O-R framework by Khan and Siddiqui (2019). However, instead of considering S-R direct paths, the previous authors included a separate organic construct about a person's tendency to impulse purchasing. Given the definitions of impulse buying and considering that including S-R paths can give further information on which stimulus has a higher effect on triggering the purchase, this analysis did not use the construct of Khan and Siddiqui (2019).

In the following sub-sections, the study discusses which stimuli and organic processes may be significant for sustainable food purchases. The present work considers health consciousness (HEALTH), communication and media (INF), knowledge (KNG), quality (QLT), price sensitivity (PRC), and recognition of labels (LAB) as stimuli, and perceived benefits (BEL) and price perception (PP) as organism. Intention (INT) and purchasing behaviour (EC) are both used as responses. While intention is an important predictor in the TPB framework, only a few works like Talwar et al. (2021) have included both intention and action as an extended version of S-O-R framework. Age, gender, income, education, and children in the household are used as control variables.

Following, sample observations were grouped given their PEB adoption rates in a clustering analysis (Figure 3.1). The resultant groups are used as a multi-group analysis factor.

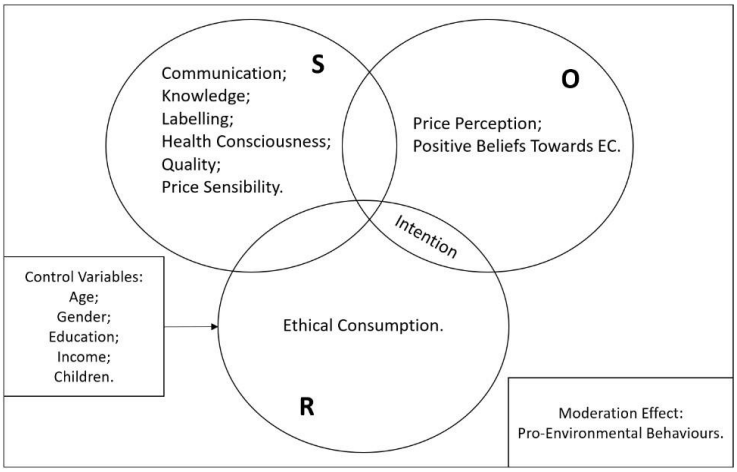

Figure 0.1 Model Hypothesis (adapted from Jacoby (2002)*). For simplification of the figure LAB and KNG were presented within the stimuli main area and not on the interception of S and O.*

3.2.2.1 Stimuli: Health Consciousness, Price sensitivity, Quality, Communication, Knowledge, and Labelling

A stimulus is external to behaviour, and it may include several persuasive factors such as brands, prices, packaging, or media (Jacoby 2002). They can be divided into object stimuli and psychological ones (Lee and Yun 2015). For example, product characteristics are regarded as object stimuli, while the surrounding environment is a psychological one (Arora 1982; Lee and Yun 2015). All the stimuli used were based on previous literature on EC. According to Rivas et al. (2022), price, product features, promotional strategy, and place (marketing mix) can be used as an innovation tool in green consumerism. Thus, besides communication stimulus, the current analysis considered stimuli which are often used by retailers and food companies in their marketing strategies, namely: health, price, quality, labelling/certification, and environmental concepts. Place aspects, which refer to products delivery, allocation, and transportation (Rivas et al. 2022) were excluded from the analysis once a previous study in Japan found the lack of availability (usage barrier) was not significant to organic food purchase (Tandon et al. 2021).

Health Consciousness (HEALTH): Health-conscious consumers may be defined as people who are aware and concerned about their health status. Thus, they try to engage in healthy behaviours to assure a good life quality (Michaelidou and Hassan 2008). Many studies mentioned health consciousness as a motivator to buy ethical food (Lindeman and Väänänen 2000; Hemmerling et al. 2015; Birch et al. 2018). In Japan, Kurisu and Bortoleto (2011) pointed out health as the main reason for people to purchase organic products. Such was recently supported by the findings of Tandon et al. (2021). Therefore, Health Consciousness was included as a stimulus in this analysis. Contrary to Talwar et al. (2021), where health and food safety concerns were divided into two separate constructs, this study merges items about safety and nutrition under

the HEALTH construct. That decision was made taking into consideration the large number of stimuli considered on present study and how it could impact both the length of the questionnaire and the quality of the results.

Health-related constructs have been included in models both as directly affecting intention/behaviour (Asif et al. 2018), or as factors mediated by attitudes or behaviour facilitators (Pham et al. 2019; Tandon et al. 2021; Dorce et al. 2021). Initially, the indirect effect of Health through positive beliefs was tested. However, after a thorough examination of the items included in the positive beliefs construct, the conclusion that current study had no means of accurately testing the mediation between health and intention by positive beliefs was reached. Nonetheless, given the relevance of comprising this construct in the analysis, the model tested the direct relationship between health consciousness and purchase intention (INT). Additionally, the idea that health consciousness impacts the price perception (PP) associated with ethical food products was hypothesised.

- H3.1: HEALTH →INT Health Consciousness is positively associated with ethical food purchase intention.
- H3.2: HEALTH →PP Health Consciousness is negatively associated with high price perception.

Price Sensitivity (PRC) and Quality (QLT): Due to its higher price when compared with conventional food (Chekima et al. 2019; Dorce et al. 2021), the cost of sustainable foods is usually regarded as a barrier to its consumption. Such seems to be the case in Japan (Sakagami et al. 2006; Kurisu and Bortoleto 2011), and especially to pragmatic consumers that have a higher sensitivity to price (Aschemann-Witzel and Zielke 2017; Kushwah et al. 2019; Dorce et al. 2021).

Multiple studies, under distinct theoretical frameworks (Gonçalves et al. 2016; Konuk 2019; Dorce et al. 2021), have included some kind of price measure in their research. Rödiger and Hamm (2015) presented a review what kind of price constructs have been used with the S-O-R framework. Some of the price measurements identified were price elasticity, price perception, and the willingness to pay (Rödiger and Hamm 2015).

Organic and local products are frequently considered a premium market segment (Nakagawa and Zimmerman 2021), where a higher price is a cue of a higher quality, safer and tastier product (Hempel and Hamm 2016; Aschemann-Witzel 2018; Pham et al. 2019; Yang et al. 2022). Thus, for someone who values quality, the perceived higher price of this market sector may act as a motivator to the purchase (Singh and Pandey 2018; Oke et al. 2020). Value, price, and quality are considered core points on consumers decisions (Carrigan and Attalla 2001), being

quality-price trade-offs a key factor to the purchase (Shaw and Clarke 1999; Oke et al. 2020). Academics like Shaw and Clarke (1999), Arenas-Gaitán et al. (2022) and Namkung and Jang (2007), pointed out freshness, taste, appearance, and healthiness as quality measures.

Additionally, cue utilization theory has also been used to explain quality perception. Cue utilization theory infers quality through both intrinsic and extrinsic cues (Olson and Jacoby 1972). Intrinsic cues comprise aspects like appearance, taste structure, colour, and shape, whereas extrinsic are not part of the physical composition of a product (Konuk 2019). For example, by manipulating extrinsic cues such price, brand name, country of origin or production information, the physical attributes of a product do not necessarily change (Olson and Jacoby 1972). In this study, QTL addresses both extrinsic (taste/freshness) and intrinsic cues (brand) under a single construct. Besides a quality sensitivity construct, this analysis approaches price in three different angles. General price sensitivity towards food as a stimulus, price perception of ethical food as a part of the organic process, and finally two of the intention construct items regard willingness to pay. The latter two points will be further explained in the organic and response sub-sections.

- H3.3: PRC →BEL Price sensitivity is positively related to perceived benefits.
- H3.4: PRC →PP Price sensitivity is positively related to high price perception.
- H3.5: PRC →EC Price sensitivity is negatively related to Ethical Consumption.
- H3.6: QLT →BEL Quality sensitivity is positively related to perceived benefits.
- H3.7: QLT →PP Quality sensitivity is negatively related to high price perception.
- H3.8: QLT →INT Quality sensitivity is positively related to intention.

Communication (INF): Attitudes towards products (e.g., price and quality perceptions) are not always based on one's experience (Chambers et al. 2007). Internet, advertising, and word-of-mouth can also play a role in the decision-making process (Anisimova et al. 2019; Arenas-Gaitán et al. 2021). Frameworks such as Theory of Planned Behaviour (TPB) include subjective norms as a predictor of intention (Peral-Peral et al. 2022). Under a S-O-R methodology, Rambabu et al. (2023) found social motivations significant and both Anisimova et al. (2019) and Sultan et al. (2021) noted controlled and uncontrolled communication stimuli have a positive impact on ethical purchase.

As previously mentioned, Japanese citizens tend to have a collective philosophy (Synodinos 2001) and to give higher importance to the norm and third-party opinions than other cultures (Ando et al. 2007, 2010). Moreover, Yang et al. (2022) found friends and family positively influence opinions on eco-friendly farming products. Thus, this analysis poses communication as a stimulus that influences price perception and positive beliefs. The construct

includes an item on friends and family influence and one concerning social media. Once previous studies have already study in detail the differences between uncontrolled and controlled communication impact (Anisimova et al. 2019; Sultan et al. 2021), the current analysis does not present such detail.

- H3.9: INF →BEL Information is associated with perceived benefits.
- H3.10: INF →PP Information negatively impacts high price perception.

Environmental Knowledge (KNG) and Organic Certificates (LAB): Besides information retrieved from third parties, the level of knowledge and/or uncertainty about a product can influence one's behaviour (Shaw et al. 2016).

In literature, knowledge is usually divided into two distinct dimensions: objective and subjective (Brucks 1985; Pagiaslis and Krontalis 2014; Loera et al. 2022). The former refers to consumers' long-term memory and the latter, which has been reported as a stronger behavioural determinant (Loera et al. 2022), refers to how much they think they know (Brucks 1985). Under the S-O-R model proposed by Jacoby (2002), the former type of knowledge belongs to the long-term memory organic sector, while subjective knowledge may be seen as a stimulus that surfaces within the organism (Jacoby 2002). Knowledge can then be separated into general (environmental) knowledge and concrete information about the process and the action itself (Pagiaslis and Krontalis 2014).

The scientific community has suggested both environmental and concrete knowledge to be positively related to ethical purchasing (Pagiaslis and Krontalis 2014; Dhir et al. 2021a; Vergura et al. 2022; Loera et al. 2022). Thus, on the present chapter, knowledge about general Ethical Consumption concepts and knowledge about concrete food labels were considered two separate constructs. Contrary to other constructs such as communication, this model has two separate constructs concerning knowledge. The first reason for this decision is that, besides Vergura et al. (2022)'s organic care products study, KNG has not been studied extensively yet under a S-O-R methodology. Secondly, it is important to keep in mind that the degree of trustfulness on information about the food attributes, organic certification bodies, and labelling a consumer hold may have an impact too (Tandon et al. 2020a). For instance, Kumar et al. (2021) reported that highly environmentally conscious consumers tended to prefer regional or locally produced products once was easier to verify the product information. Moreover, Hjelmar (2011) and Schleenbecker and Hamm (2013) discussed that trust in eco-labelling, especially government labelling systems, varies from country to country.

As mentioned earlier, Japanese consumers have been considered homogeneous, informed, risk-averse and longing for long-term, personal relations (Synodinos 2001; McGreevy and Akitsu

2016; Dhir et al. 2021a). However, while Kubota et al. (2017) showed additive-free wine labelling can have a significant impact on customer preferences, Sakagami et al. (2006) reported a certain heterogeneity regarding organic certification trust: *"while some people may rely heavily on JAS. (Japanese Agricultural Standards) or the government, others may not place much trust in JAS or the government at all. [...] Consumers have various impressions of the Japanese government and exercise various levels of trust towards it based on their past experiences"*.

Knowledge is often associated with the perceived control of a behaviour (Davies et al. 2002; Carrington et al. 2010; Loera et al. 2022), which under a TPB framework may have both a direct effect on behaviour and a mediated one through intention. Nonetheless, academics also pointed out its direct effect on beliefs (Mcneill and Moore 2015; Loera et al. 2022). Thus, the current study considers the possibility of knowledge about EC concepts impacting both organic variables (price perception and positive beliefs) and responses (intention and behaviour). Moreover, as far as recognition of labels recognition is concerned, the study argues it can influence beliefs and perceived price as well as have a direct effect on the purchase, by acting as a situational factor.

This study includes an analysis of its two knowledge constructs, Ethical Consumption related concepts and recognition of specific labels existent in Japan. Thus, consumers were asked about their familiarity with ethical food-related concepts (Ethical Consumption, Organic Food, Fair Trade, Food Mile, Food Waste, Lifestyle of Health and Sustainability (LOHAS), and Eco-Friendly Products), and to select from a list which certificate marks they were familiar with.

- H3.11: KNG →BEL Knowledge impacts perceived benefits.
- H3.12: KNG →PP Knowledge impacts perceived price.
- H3.13: KNG →INT Knowledge impacts intention.
- H3.14: KNG →EC Knowledge impacts behaviour.
- H3.15: LAB →BEL Knowledge about labels impacts perceived benefits.
- H3.16: LAB →PP Knowledge about labels impacts perceived price .
- H3.17: LAB →EC Knowledge about labels impacts behaviour.

3.2.2.2 Organism: Perceived Price and Positive Benefits

In the organic stage, stimuli processing may happen in a conscious or subconscious way (Jacoby 2002) and it is usually conceptualized as a cognitive (e.g., memory, information processing and retention) or an affective (e.g., emotions, attitudes) state (Lee and Yun 2015; Hempel and Hamm 2016; Vergura et al. 2022). Studies like Vergura et al. (2022), Lee and

Goudeau (2014) and Lee and Yun (2015) considered hedonic and utilitarian attitudes as organism factors, whereas this analysis follows the framework of Tandon et al. (2021) and Kumar et al. (2021) and utilizes facilitators (positive beliefs) and inhibitors (perceived price) as part of the organic state. Such framework was preferred because it was previously used on research about Japan (Tandon et al. 2021). When compared with Tandon et al. (2021), the present study presents a simpler organic structure as it does not desegregate facilitators nor barriers. Considering the large number of stimuli, and despite the robustness of the statistical tool used, a complex organic system could compromise the quality of the results for the current sample size.

Positive Beliefs (BEL): Beliefs are a core part of the understanding of behaviours (Shaw and Clarke 1999). According to Ajzen (1991), attitudes towards a behaviour are determined by one's salient beliefs, in this case, towards Ethical Food Consumption. Beliefs can be both behaviour/product-specific or general (Pagiaslis and Krontalis 2014), and may comprehend aspects like health, ecological welfare, and trust (Lee et al. 2020; Loera et al. 2022). Authors such as Ramayah et al. (2010) divided the attitude's spectrum on perceived environmental and perceived individual consequences of the action. The utilized BEL construct covers ecological, social, quality, safety and trust items but does not look in detail to each of this.

The idea that favourable beliefs and attitudes positively impact Ethical Food Consumption is supported in works like Paul et al. (2016), Scalco et al. (2017), Dorce et al. (2021), and Loera et al. (2022). Thus, this study hypothesised that beliefs about the benefits of Ethical Food Consumption impact the intention to purchase such products.

- H3.18: BEL →INT A favourable beliefs towards sustainable food purchase has a positive impact on intention.

Price Perception (PP): Naturally, one can also hold negative beliefs towards behaviour, which act as a barrier. The present work includes a single item about perceived high prices as a barrier. Prior literature on Japanese keenness to purchase organic food did not find availability/usage barrier significant (Tandon et al. 2021), so they were not included. Additionally, this study framed risk not as a barrier but included safety as an item for the positive beliefs. As mentioned in Section 3.2.2.1, price is a core part of decision and frequently mentioned as a barrier in Japan (Dentsu Macromill Insight Inc. 2021). Thus, besides a stimuli construct, the current study comprises organic food price perception as part of the organic process.

- H3.19: PP →INT High Price Perception negatively impacts purchase intention.

3.2.2.3 Response: Intention and Ethical Consumption

Intentions (INT): Responses can be internal or external, visible ones (Jacoby 2002). This study includes intentions as an antecedent to purchase. Intentions can be seen as an internal response that is common to both organism and response (see Figure 3.1).

Intention (in this case to purchase food ethically) is a central factor in TPB and is assumed "*to capture the motivational factors that influence the behaviour*" (Ajzen 1991). It has been used as an antecedent to the behaviour in several studies (Dorce et al. 2021), but under S-O-R applications, academics tend to use either intention (Lee and Yun 2015; Lee et al. 2020) or the behaviour (Anisimova et al. 2019; Tandon et al. 2021). The inclusion of both variables, besides allowing a more holistic analysis, contributes to academia by exploring the gap between intention and behaviour reported by previous scholars (Singh and Verma 2017; Qasim et al. 2019; Talwar et al. 2021). Part of the items used to measure intention were related to the willingness to pay for ethical food products.

Ethical Food Consumption (EC): The final goal of the current research, nonetheless, is the external response. Ethical Food Consumption is measured by items regarding the frequency of purchase of organic food, fair trade food products, locally produced/Japanese food, products supporting disaster-stricken areas, and products that consider their environmental impacts.

H3.20: INT →EC Behaviour depends on intention.

3.2.2.4 Control Variables

As mentioned in Chapter 2, the role of socio-demographics has not been consistent among PEB literature (Kurisu 2015). Thus, this chapter contributes to the debate by using the number of children, gender, educational level, income, and age as control variables to ethical food consumption. Contrary to Tandon et al. (2021), that also analysed the organic food consumption in Japan using a S-O-R methodology, neither gender nor other socio-demographics' moderation effects were not tested. The main reason for this decision relates to the fact that the present analysis included a multigroup assessment based on groups from a clustering analysis. Often, groups resulting from clustering vary not only in the analysed behaviours but also in their socio-demographics profile. Therefore, such moderation effects of socio-demographics were not explored.

3.2.2.5 Additional Pro-Environmental Behaviours

Environmental concern may be defined as one's concern for environmental problems (Kurisu, 2015), and it can influence several environmentally friendly and green consumer behaviours (Pagiaslis and Krontalis 2014). Both Kushwah et al. (2019) and Dwivedi et al. (2022) found significant moderation effect of environmental concern in different contexts (organic food and green hotel staying). Furthermore, Wooliscroft et al. (2014) suggested that PEB and ethical choices may be presented hierarchically. For instance, while recycling was a mainstream practice, only a small part of the sample avoids at all cost airline use. Such seems to be aligned with idea that behaviours which require a great effort are usually expressed by highly environmentally concerned people that lead a health, well-being, and environmentally sustainable driven lifestyle (LOHAS) (Kurisu and Bortoleto 2011; Choi and Feinberg 2021). It also relates to the concept of behavioural spillover, which suggests that adopting one PEB can catalyse the engagement in others (Truelove et al. 2014; Nash et al. 2019; Abrahamse 2019; Maki et al. 2019), as well as with the idea that environmental values can be a manifestation of a sustainable lifestyle (Biswas 2017) and several levels of manifestation can exist.

Thus, instead of addressing environmental concern from a conceptual perspective or via the New Environmental Paradigm Scale (NEP) (Dunlap and Van Liere 2008), this study attempts to assess its moderation effect by measuring the frequency in which people engage in PEB besides ethical food purchase. To make such analysis, respondents were asked about their adoption rates of eleven PEB, namely: separation and dispose of recycle waste; reduce garbage as much as possible; usage of environmentally friendly products; turn off electrical appliances and gas frequently; preference for recycled or refillable products; avoid excessive packaging; carry eco-friendly bags; do not pour oil down the drain; help recycle containers; grow your own vegetables and use public transportation as much as possible. These behaviours are related to waste prevention, waste reduction, and overall ethical consumption and have been included in previous PEB literature such as Fujii (2006) Kurisu and Bortoleto (2011), Wooliscroft et al. (2014), Kurisu (2015).

- HMGA: Ethical Consumers decision-making model is different across groups with distinct Pro-Environmental Behaviours (PEB) adoption rates.

3.2.3 Statistical Tools

The methodology followed in this chapter was based on the statistical tools and guidelines described in the second chapter. Figure 3.2 shows all the analytical steps done. After doing a

descriptive analysis of the sample data, the hypotheses from H3.1 to H3.20 were tested via a Partial Least Squares Structural Equation Modelling (PLS-SEM). A PLS-SEM approach was preferred to CB-SEM, once PLS-SEM holds softer assumptions on normality, observation independence, sample size and it does not have identification issues (Wold 1985; Hair et al. 2018). Furthermore, as S-O-R is a flexible, complex framework, with a somewhat exploratory character, this approach should be preferred to CB-SEM (Hair et al. 2018).

Based on the results of the PLS-SEM model a mediation analysis was conducted (Figure 3.2). The main purpose of investigating the mediation effects in this study is to provide empirical evidence of the relevance of including, if the context is adequate, direct paths between stimuli and response within a S-O-R framework.

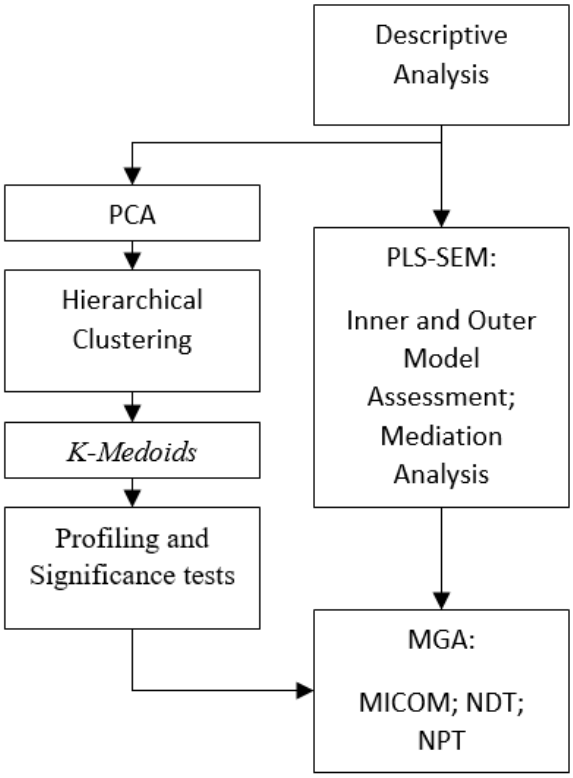

Figure 0.2 Methodological Flow

After analysing the path results for the whole sample, a multi-group analysis based on clustering was done. As mentioned earlier, the current study wishes to test the interaction effect of PEB practice clusters (categorical trait) on the ethical consumption structural model (HMGA). Although using a clustering technique combined with a multi-group is not uncommon, it has been mostly used as means to identify unobserved heterogeneity (Hair Jr et al. 2017). Instead, the present research uses clustering with the intent of identifying nuances in environmental engagement via PEB practice rates. Prior the MGA analysis, a MICOM assessment was done. As the clustering analyses resulted in more than two groups, the researcher opted for the MGA

procedure of a Non-Parametric Distance-Based Test (NDT) followed by a Non-Parametric Permutation-Based Test (NPT). The latter was preferred to an Omnibus test of group differences (OTG) as it is considered more robust (Cheah et al. 2023).

To the author's knowledge, clustering algorithms have not been extensively applied to Ethical Consumption yet. From the previous literature found, a relevant study on the field was done by segmenting consumers based on their reasons for or against green food purchase (Burke et al. 2014). Moreover, Asvatourian et al. (2018) found, via a *K-Means* clustering algorithm, that people with healthy habits tended to practice PEB more frequently. Huddart Kennedy et al. (2019) grouped people regarding their aesthetic and ethical preferences on food. In the current study, clustering is used as the basis for a multi-group analysis. Among several clustering techniques, a two-step clustering approach was applied. On the first step a Hierarchical Clustering is applied, followed by a *K-Medoids* algorithm.

Although collinearity is not an issue per se in clustering, it might function as a natural weight for distances calculation. Moreover, when the number of variables increases, visualizing and understanding the clusters profiles becomes naturally more complex (Hair et al. 2018). Thus, prior to clustering, a Principal Component Analysis (PCA) with a varimax rotation was done. A varimax rotation was used to increase the interpretability of the obtained factors. The researcher tried other Orthogonal rotations (promax and equamax), however, the varimax rotation was the one with the clearest results. Oblique rotations were not explored once they allow correlation between the factors, which was not intended in the study. After checking if the data was suitable to be factorized via a Kaiser-Meyer-Olkin (KMO) test, a Bartlett's test, and a Cronbach's Alpha, the ideal number of factors was decided and summated scales were calculated, based on them. Those scales were the ones used in the steps that followed.

Regarding the Hierarchical Clustering and the *K-Medoids* algorithms, the distance used was the *Mahalanodis* distance. Moreover, Ward's linkage criterion was chosen, because for the given set was the method with the highest agglomerative coefficient. After the clustering process, the significance of the groups was tests via a Kruskal-Wallis test and Dunn's test (with Bonferroni's correction).

3.2.4 Data Collection and questionnaire:

This chapter's analysis is based on the results of an online survey which was handled by a marketing research company. It was conducted among Japanese adult consumers (until April 2022 Japanese adulthood age was 20 years old) residing in Kanto Region (Saitama, Chiba, Tokyo, and Kanagawa prefectures) from 2020-12-11 to 2020-12-14. Within the region, Tokyo is the most populated area followed by Kanagawa, Saitama, and Chiba. To have a sample that closely

matched the general population of the area in terms of age, gender, and prefectures' population density, a quota sampling technique was used. Note that even though the survey sample includes elders over 70, as usually the number of people with such age registered for the Internet surveys is very small, the quota of the elderly group in proportion to the population composition, was based on the population with ages comprehended between 60 and 69.

Even though the dataset is aligned the scope of this manuscript, the survey was not developed under this doctoral dissertation. The survey included 22 questions containing items related to ethical food buying patterns, sustainable food purchase intention, price perception and sensitivity, willingness to pay, health habits, food attributes, PEB adoption, positive beliefs towards Ethical Food Consumption, knowledge about concrete certificates and environmental issues, and demographics. The questions were addressed in a 4-, 5- or 6-point Likert-scales, but the questionnaire also included two open questions about the reasons for purchasing or not ethical goods. The latter questions were out of the scope of the current analysis.

3.3 Results

The data was analysed with R (4.2.1) coding language via Rstudio (5.5.4). As far as the analytical packages are concerned, the PLS-SEM results and MGA tests were obtained using SeminR (2.3.1) and cSEM (0.5.0), with both packages providing identical results for path coefficients and explanation power (R^2). The clustering analysis was based on NbClust 3.0.1 (to find the ideal number of cluster), Stats 4.2.1 (Hierarchical Clustering) and ClusteR 2.1.3 (*K-Medoids* with *Mahalanobis* distance). The bootstrapping was set to 5000 times.

3.3.1 Descriptive Analysis

With a sample of 600, one respondent was excluded from the analysis, due to missing information regarding their education. Male respondents made 51% of the set, being female respondents 49% of it. A quarter of the respondents were on their 40's, 18% on their 20's, 19% on their 30's, 21% on their 50's, and the other 17% of the inquiries were over 60. The age, gender and residence location are in proportion with the Japanese population census as of first October of 2015. More than half of the respondents held a university degree (55%), 6% went through graduate school, 11% through vocational school, and 19% ended their study path on high school. Only 1% of the people on the set stopped studying in middle school. Kanto region is the economic centre and has the highest population density in Japan. Thus, such educational ratio, as well as purchasing power, may not match the rest of the country. 52% of the sample was married and

around 38% was living with at least one child. as it was calculated based on the survey question "*With whom do you live*?", the household size presented in Table 3.1 is the minimum household size estimation for each respondent. On this question respondents could answer "*grandparent*" or "*elementary school aged chil*d" but did not specify if they were living with one or more person of the same category. Thus, the household size representing the minimal possible household size. Based on this estimation the most common household arrangement seemed to of 3 people. This variable was not included in the decision-making model.

Table 0.1 Chapter 3's Socio-Demographics

Variables	Categories	N	N%
Gender	Male	307	51.2%
	Female	292	48.8%
Age	20's	109	18.2%
	30's	115	19.2%
	40's	147	24.5%
	50's	125	20.9%
	>60	103	17.2%
Region	Saitama	118	19.7%
	Chiba	99	16.5%
	Tokyo	235	39.2%
	Kanagawa	147	24.5%
Educational Level	Junior High Sch.	5	0.8%
	High Sch.	111	18.5%
	Vocational Sch.	68	11.4%
	College	50	8.3%
	University	329	54.9%
	Graduate Sch.	36	6.0%
Marital Status	Single	286	47.7%
	Married	313	52.3%
Household Size (min)	1	127	21.2%
	2	167	27.9%
	3	209	34.9%
	4	77	12.9%
	4>	19	3.2%
Children	Yes	230	38.4%
	No	369	61.6%
Household Income	< 2 million yen	48	8.0%
	2-4 million yen	89	14.9%
	4-6 million yen	123	20.5%
	6-8 million yen	92	15.4%
	8-10 million yen	62	10.4%
	10-12 million yen	35	5.8%
	>12 million yen	69	11.5%
	Not declared	81	13.5%

The most frequently reported household income range was between 4 and 6 million yen a year. Given that, according to the Japanese Ministry of Health, Labour, and Welfare (MHLW), the average salary in Tokyo was 4.5 million yen/year (375,500 yen/month) and the Japanese average available income in a household was 5.5 million yen/year in 2021 (MHLW 2023b), the sample characteristics were aligned with the country's overall statistics (MHLW 2023a, b). Moreover, it relevant to mention that approximately 14% of the sample did not declare their available income. While one of the alternatives could pass by excluding those observations from the analysis, that would imply a significant reduction in the sample size. Previous scholars mentioned some controversy about where to allocate such respondents, as studies pointed either they tended to be from a lower or higher socio-economic status (Potter et al. 2005; Kim et al. 2007). After analysing the relation of each income category with the Ethical Food Consumption items (Figure 3.3), respondents who did not declare their available income were classified as low-income (dummy = 1). The income dummy was included in the present behavioural model as control variables.

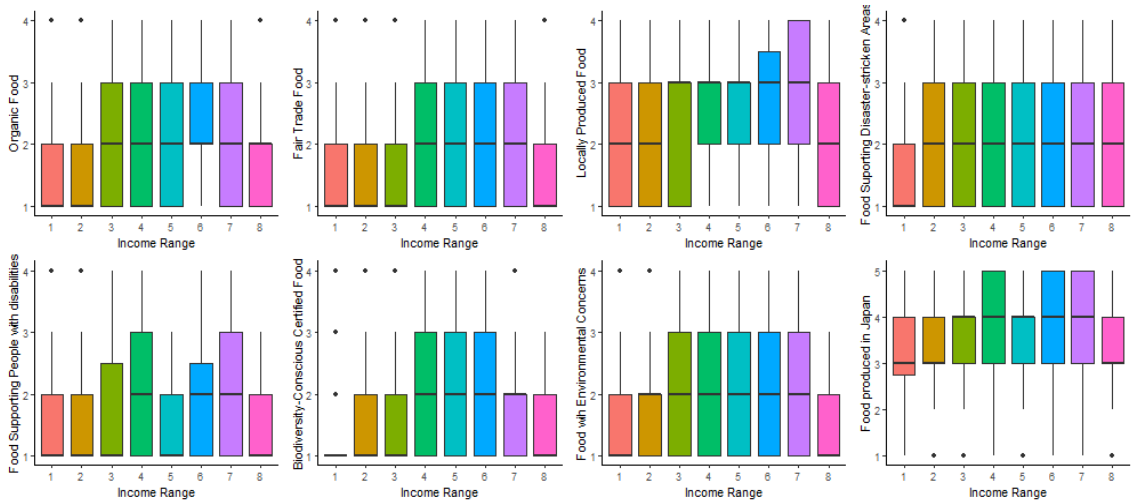

Figure 0.3 Ethical Consumption item's score by income range.

The item regarding food produced in Japan was the one with the highest practice rate, whereas the purchase of items with certification of consideration for the environment (Figure 3.4). These statistics may be a consequence of Japanese government initiatives implemented during the last decade, such as "*Michi no Eki*" (Road Station) and "*Local production for local consumption*" (LPLC) (Miyamoto and Grainger 2005; Hara et al. 2013), to boost the consumption of local products. This is also aligned with the idea of Japanese longing for personal connections (McGreevy and Akitsu 2016).

Apart from purchasing foods produced in Japan, organic food and food which supports disaster areas have the highest rates (Figure 3.4). Japan is constantly assaulted by tumultuous natural disasters, which may justify a higher ascription of people to buy them. Then, by having such propensity, the purchase of local may inherently support disaster areas too. Nonetheless, the

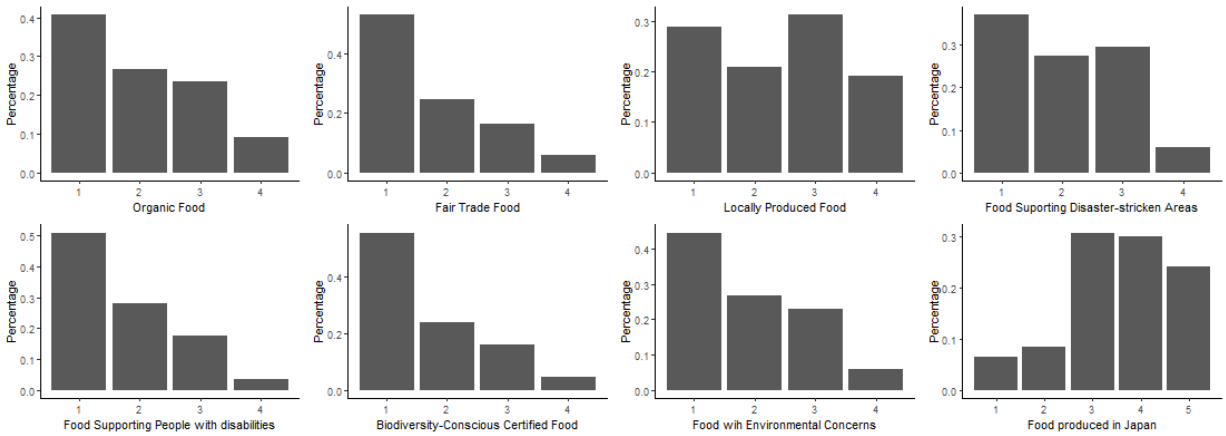

Figure 0.4 Ethical Consumption Items.

present analysis does not have enough information to empirically test such hypothesis. In Figure 3.4, one can see the 8 items concerning Ethical Food Consumption engagement frequency made in the questionnaire. However, in the final decision model the items regarding locally produced food, biodiversity-conscious certified products, and food supporting people with disabilities were not included. Without a concrete definition given in the study, the range of "local" products can be subjective (Hempel and Hamm 2016) and even redundant to the item related with food produced in Japan. Similarly, there may have been the possibility of some respondents considering biodiversity-conscious certified products as a category of environmentally-conscious products. Thus, two broader items were used. Moreover, the questionnaire did not specify what should be considered as disability (physical, sensory, intellectual, etc.). Therefore, as it could contribute to the lack of compositional invariance in the second step of the MICOM invariance test, which would imply that a construct is built differently across groups in an MGA analysis, this item was also excluded. Additionally, despite the item concerning food produced in Japan had been done in a 5-point Likert-Scale whereas the others were done in 4-point scale, the PLS-SEM algorithm is able to deal with it as it always standardizes the data in the algorithm initialization step (Hair Jr. et al. 2021).

As far as PEB are concerned, the majority of the analysed behaviours seem to have a high adoption rate. In fact, one might say that behaviours like recycling or turning off the lights are almost an established common practice (Figure 3.5). On the other hand, growing their own vegetables, using environmentally-friendly products, and avoiding at all costs using private transportation have lower adoption rates (Figure 3.5).

In general, Japanese consumers were price-sensitive (mean value of 4.1 out of 5 on an item about the importance of price when buying food), praised quality (mean value of 4.0 out of 5 on an item about the importance of quality when buying food), and had a somewhat healthy diet (mean values of 3.3 and 3.5 out of 5 on items about the importance of caloric intake and nutrition when buying food). When asked if they considered ethical food products to have a high price,

approximately 62% of the respondents considered green products pricey (4 or 5 scores in the Likert-scale). This seems to be aligned with findings of previous studies (Kurisu and Bortoleto 2011; Dentsu Macromill Insight Inc. 2021). From the displayed labels the two that consumers were more familiar with where Eco Mark and Functional Food Labelling. Around 74% of the

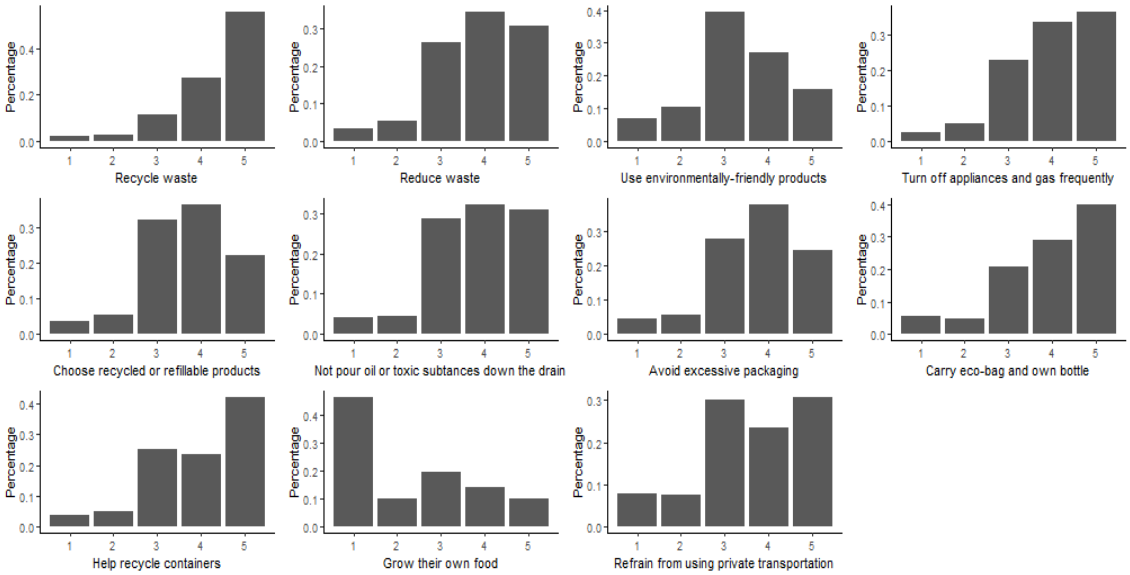

Figure 0.5 PEB adoption rates.

sample had a clear idea of the meaning of Eco Mark (which is a logo attached to products that are certified that help protect the environment), whereas 39.8% was familiar with the Functional Food Labelling. The latter are labels where companies and producers highlight the product's functionality, like health benefits, based on scientific evidence (Maeda-Yamamoto 2021).

3.3.2 Assessment of the measurement (outer) model

The results regarding the outer model are on the tables 3.2, 3.3, and 3.4. All the items' loadings, except for the item EC3, were superior to 0.7. Regardless, as this item's removal did not lead to a large increase in the internal consistency reliability or convergent validity (Hair Jr. et al. 2021), it was kept in the study.

All the HTMT tests and reliability criteria are met. Although INF construct had a Cronbach's α slightly lower than 0.7 (which is the advisable), literature mention values superior to 0.6 as acceptable (Hair et al. 2018). Note that, perceived price and labelling knowledge were measured by a single item thus the values 1. Moreover, as expected, HTMT values between HEALTH and QLT, as well as PRC and QLT were relatively high. Even though they are different concepts, they are somewhat related.

Table 0.2 Constructs' Reliability

Construct	Cronbach's α	Joereskog's rho (ρ_c)	AVE
INF	0.66	0.85	0.75
HEALTH	0.85	0.90	0.63
QLT	0.85	0.90	0.63
KNG	0.91	0.93	0.65
LAB	1.00	1.00	1.00
PRC	0.74	0.85	0.65
BEL	0.90	0.92	0.63
PP	1.00	1.00	1.00
INT	0.93	0.94	0.66
EC	0.89	0.92	0.70

Table 0.3 Heterotrait-monotrait ratio of correlations (HTMT)

Constructs	INF	QLT	KNG	LAB	PRC	HEALTH	BEL	PP	INT	EC
INF	-	-	-	-	-	-	-	-	-	-
QLT	0.63	-	-	-	-	-	-	-	-	-
KNG	0.49	0.49	-	-	-	-	-	-	-	-
LAB	0.30	0.48	0.52	-	-	-	-	-	-	-
PRC	0.44	0.78	0.24	0.30	-	-	-	-	-	-
HEALTH	0.49	0.69	0.49	0.34	0.37	-	-	-	-	-
BEL	0.67	0.72	0.53	0.45	0.55	0.56	-	-	-	-
PP	0.27	0.44	0.24	0.27	0.59	0.26	0.51	-	-	-
INT	0.66	0.77	0.60	0.38	0.37	0.67	0.75	0.18	-	-
EC	0.56	0.68	0.77	0.49	0.25	0.69	0.65	0.25	0.83	-

Table 0.4 Items' loadings, means and standard deviations.

Construct	Item	Loading	Mean (Likert-Scale)	Std.	Skewness	Kurtosis
Health:	HEALTH1: *"To what extent do you usually avoid binge eating and drinking?"*	0.83	3.73 (5)	1.17	-0.79	2.92
	HEALTH2: *"To what extent do you usually pay attention to the nutritional balance of meals?"*	0.91	3.76 (5)	1.15	-0.76	2.87
	HEALTH3: *"To what extent do you usually avoid food high in additives?*	0.88	3.33 (5)	1.18	-0.27	2.37
	HEALTH4: *"To what extent do you usually try to eat fruits and vegetables?"*	0.89	3.83 (5)	1.14	-0.86	3.08
	HEALTH5: *To what extent do you usually choose safe foods?"*	0.91	3.57 (5)	1.14	-0.54	2.70

Price Sensitivity:	PRC1: *"When you purchase food how important is the product's price?"*	0.88	4.52 (5)	1.40	-1.19	3.82
	PRC2: *"When you buy fruits or vegetables how much do you consider the price?"*	0.77	4.08 (5)	1.55	-0.78	2.60
	PRC3: *"When you buy coffee or tea how much do you consider the price?"*	0.79	4.09 (5)	0.91	-0.95	3.88
Quality:	QL1: *"When you purchase food how important is the product's freshness?"*	0.81	4.69 (5)	1.46	-1.32	3.93
	QL2: *"When you purchase food how important is the producer or brand?"*	0.81	3.97 (5)	1.59	-0.66	2.76
	QL3: *"When you buy coffee or tea how much do you consider quality and freshness?"*	0.85	4.13 (5)	1.61	-0.79	2.52
	QL4: *"When you buy coffee or tea how much do you consider the brand type?"*	0.74	3.49 (5)	0.98	-0.36	2.98
	QL5: *"When you buy fruits or vegetables how much do you consider quality and freshness?"*	0.76	4.00 (5)	1.03	-0.90	3.41
Information:	INF1: *"Are your everyday grocery shopping and Ethical Consumption influenced by internet articles or/and social media?"*	0.89	3.20 (5)	1.07	-0.38	2.66
	INF2: *"Are your everyday grocery shopping and Ethical Consumption influenced by your friends and family?"*	0.82	3.21 (5)	1.07	-0.48	2.76
Knowledge:	KNG1: *"Are you familiar with the following concepts: Ethical consumption?"*	0.83	1.66 (4)	0.91	1.18	3.30
	KNG2: *"Are you familiar with the following concept: Organic?"*	0.75	2.60 (4)	0.90	-0.12	2.27
	KNG3: *"Are you familiar with the following concept: Fair Trade?"*	0.81	2.17 (4)	0.99	0.31	1.97
	KNG4: *"Are you familiar with the following concept: Food Mile?"*	0.83	1.64 (4)	0.88	1.19	3.38
	KNG5: *"Are you familiar with the following concept: Food Waste?"*	0.81	1.60 (4)	0.91	1.29	3.44
	KNG6: *"Are you familiar with the following concept: LOHAS?"*	0.81	2.08 (4)	1.05	0. 48	1.95
	KNG7: *"Are you familiar with the following concept: Sustainability?"*	0.81	1.66 (4)	0.95	1.16	3.07
Labelling:	LAB1: *"Indentify with certificates are you familiar with:"*	1.00	3.46 (14)	2.49	-1.67	7.00
Price Perception:	PP1: *"I believe the food produced with consideration for people, societal, and the environment has a high price."*	1.00	3.71 (5)	0.94	-0.68	3.67
Positive Beliefs:	BEL1: *"I believe the food produced with consideration for people, societal, and the environment is ecological?"*	0.82	3.54 (5)	0.95	-0.52	3.42
	BEL2: *"I believe the food produced with consideration for people, societal, and the environment has a good quality?"*	0.82	3.45 (5)	0.91	-0.37	3.55

	BEL3: *"I believe the food produced with consideration for people, societal, and the environment is necessary to the future?"*	0.85	3.60 (5)	0.98	-0.49	3.27
	BEL4: *"I believe the food produced with consideration for people, societal, and the environment is safer?"*	0.80	2.94 (5)	0.94	-0.35	3.38
	BEL5: *"To what extend do you disagree/agree: Ethical consumption can improve or enhance society and the environment?"*	0.82	3.43 (5)	0.95	-0.39	3.30
	BEL6 *"To what extend do you disagree/agree: Products labelled as ethical (e.g., with logos) were really produced with people, society, and the environment in mind."*	0.78	3.33 (5)	0.98	-0.33	3.42
Intentions:	INT1: *"When I buy vegetables or fruits I take in consideration if it is supports disaster-affected areas?"*	0.87	3.74 (5)	1.33	-0.49	2.47
	INT2: *"When I buy vegetables or fruits I take in consideration if it has a certification mark?"*	0.89	3.54 (5)	1.32	-0.29	2.39
	INT3: *"When I buy vegetables or fruits I take in consideration if it supports developing countries?"*	0.87	3.47 (5)	1.27	-0.28	2.44
	INT4: *"I think ethical products are worth paying for, even though they were a little bit expensive."*	0.75	2.96 (5)	1.09	-0.23	2.53
	INT5: *" If the price is lower (or if not different from the other products), you consider purchasing ethical products)."*	0.76	2.94 (5)	1.05	-0.26	2.74
	INT6: *"If it is less expensive, I am compelled to buy it even though it was not an ethical product."*	0.86	3.33 (5)	1.39	-0.21	2.13
	INT7: *"How important to you is know that a product is organic grown when purchasing food?"*	0.76	3.27 (5)	1.04	-0.31	2.88
	INT8: *"How important to you is know that a product is locally grown when purchasing food?"*	0.79	2.99 (5)	1.03	-0.16	2.77
Ethical Consumption:	EC1: *"How often do you purchase organic products (grown without pesticides or chemical fertilizer)?"*	0.89	2.01 (5)	1.00	0.52	2.05
	EC2: *"How often do you purchase fair trade products?"*	0.87	1.76 (5)	0.94	0.94	2.73
	EC3: *"How often do you purchase Japanese (local) produced foods?"*	0.64	3.57 (4)	1.14	-0.52	2.65
	EC4: *"How often do you purchase agricultural products and foods that support disaster-stricken areas?"*	0.85	2.05 (5)	0.95	0.33	1.91
	EC5: *"How often do you purchase agricultural products and food produced considering the environment?"*	0.90	1.91 (5)	0.95	0.61	2.18

3.3.3 Assessment of the structural (inner) model

As far as collinearity is concerned all the constructs showed values inferior to 3 (Table 3.5) and the R^2 > adjusted were 0.68 for intention, and 0.69 to the behaviour. *RMSE* values showed a moderate predictive power, according (Shmueli et al. 2019), with 3 out 5 being inferior to the errors of a naive linear model benchmark (because of the small sample size, the number of cross-validation folds in the code was set to 4). $SRMR$ value was 0.07 (<0.08).

From the hypothesis suggested on the methodology, not all were significant (*p-value* < 0.05). As visible in Table 3.6, Table 3.7, and Figure 3.6, only price sensitivity and recognition of labels were significant explaining high price perception. Overall quality, health, and knowledge seemed to be determinant both on intention and on the purchasing decision. Price had a total effect of -0.11 on Ethical Consumption and intention of -0.07. The total effect of labelling on intention was not significant (Table 3.7) and gender was the only control variable significant on EC.

Table 0.5 Variance Inflation Factor (VIF)

BEL:	INF	QLT	KNG	LAB	PRC	
	1.37	2.19	1.51	1.44	1.60	
PP:	INF	QLT	HEALTH	KNG	LAB	PRC
	1.37	2.73	1.76	1.59	1.44	1.61
INT:	BEL	PP	KNG	QLT	HEALTH	
	2.07	1.33	1.42	2.14	1.78	
EC:	INT	PRC	KNG	LAB	AGE	GENDER
	1.67	1.16	1.81	1.44	1.13	1.08
	CHILD	EDU	SALLOW	SALHIGH		
	1.05	1.10	1.21	1.21		

Table 0.6 Path Coefficients Bootstrapping results.

Path	Original est.	Bootstrap Mean	Bootstrap Std; . T.Stat. 2.5%CI 97.5%CI				Result
H3.1: HEALTH →PP	0.03	0.03	0.05	0.51	-0.07	0.12	*Rejected*
H3.2: HEALTH →INT	0.19	0.19	0.03	5.60	0.12	0.26	*Accepted*[3]
H3.3: PRC →BEL	0.11	0.11	0.04	2.60	0.03	0.19	*Accepted*[2]
H3.4: PRC →PP	0.45	0.45	0.05	9.63	0.35	0.54	*Accepted*[3]
H3.5: PRC →EC	-0.07	-0.07	0.03	-2.95	-0.12	-0.03	*Accepted*[2]
H3.6: QLT →BEL	0.32	0.32	0.05	6.86	0.23	0.41	*Accepted*[3]
H3.7: QLT →PP	0.05	0.05	0.07	0.72	-0.08	0.17	*Rejected*
H3.8: QLT →INT	0.35	0.35	0.04	8.94	0.27	0.42	*Accepted*[3]
H3.9: INF →BEL	0.26	0.26	0.04	6.62	0.18	0.33	*Accepted*[3]
H3.10: INF →PP	0.01	0.01	0.04	0.20	-0.08	0.09	*Rejected*
H3.11: KNG →BEL	0.18	0.18	0.04	5.14	0.11	0.24	*Accepted*[3]
H3.12: KNG →PP	0.06	0.06	0.04	1.29	-0.03	0.14	*Rejected*
H3.13: KNG →INT	0.18	0.18	0.03	6.73	0.13	0.24	*Accepted*[3]
H3.14: KNG→EC	0.38	0.38	0.04	10.70	0.31	0.44	*Accepted*[3]
H3.15: LAB →BEL	0.11	0.11	0.03	3.36	0.04	0.17	*Accepted*[3]
H3.16: LAB →PP	0.09	0.09	0.04	2.55	0.02	0.17	*Accepted*[2]
H3.17: LAB →EC	0.10	0.10	0.03	3.52	0.05	0.15	*Accepted*[3]
H3.18: BEL →INT	0.38	0.38	0.04	10.07	0.31	0.46	*Accepted*[3]
H3.19: PP →INT	-0.24	-0.24	0.03	-8.97	-0.29	-0.19	*Accepted*[3]
H3.20: INT →EC	0.52	0.52	0.03	16.65	0.45	0.57	*Accepted*[3]
HControl: Gender →EC	0.06	0.06	0.03	2.65	0.02	0.11	*Accepted*[2]
significant at 0.05[1] significant at 0.01[2] significant at 0.001[3]							

Knowledge about Ethical Food Consumption was found to be significant throughout the entire system, with exception of price perception. In fact, knowledge was the construct with the highest total effect on consumption and second highest on intention (Table 3.7). The results are consistent with the findings of Vergura et al. (2022) about the effect of knowledge on the organic care industry. They are also consistent with the findings in Dhir et al. (2021a) on the apparel industry, about the relationship between knowledge and environmental attitudes, and about the impact of labelling on the purchase. These results reaffirm the description of Japanese consumers as informed and risk-averse (Synodinos 2001; Tandon et al. 2021; Nakagawa and Zimmerman 2021).

Table 0.7 Model Total Effects

Stimuli →INT:	**Path Coefficient**
INF →INT	0.10[2]
QLT →INT	0.46[2]
KNG →INT	0.24[2]
LAB →INT	0.02
PRC →INT	−0.07[2]
HEALTH →INT	0.18[2]
Stimuli →EC:	**Path Coefficient**
INF→EC	0.05[2]
QLT →EC	0.24[2]
KNG→EC	0.50[2]
LAB →EC	0.11[2]
PRC → EC	−0.11[2]
HEALTH →EC	0.09[2]
GENDER →EC	0.06[1]
significant at 0.01[1] significant at 0.001[2]	

Regarding health consciousness, the results support the findings of Tandon et al. (2021) on its effects on the behaviour. However, as mentioned earlier, the current study had not enough information to verify the mediation through beliefs. Regardless, from a strategic point of view, it is clear health can play a role in the adoption of EC. In fact, when analysing the AIC and BIC values of the hypothesized model with one that does not consider the direct effect of HEALTH on INT nor the direct effects of KNG, PRC, LAB stimuli on EC, one can see the decrease of the model fitness (Table 3.9).

Table 0.8 Models' AIC and BIC

	INT AIC	INT BIC	EC AIC	EC BIC

Hypothesized Model	-667	-641	-686	-638
Simplified Model	-632	-610	-508	-473

Previous research pointed out the higher importance the Japanese give the subjective and descriptive norms. In alignment, the results have shown that information retrieved from third parties was significant to positive beliefs but not to price perception (Ando et al. 2007). Notwithstanding the total effect of information on behaviour was the lowest of all constructs.

Results seem to indicate intention is highly dependent on quality, health, and knowledge stimuli, whereas the purchasing behaviour depends on knowledge, quality, price, and labelling recognition stimuli.

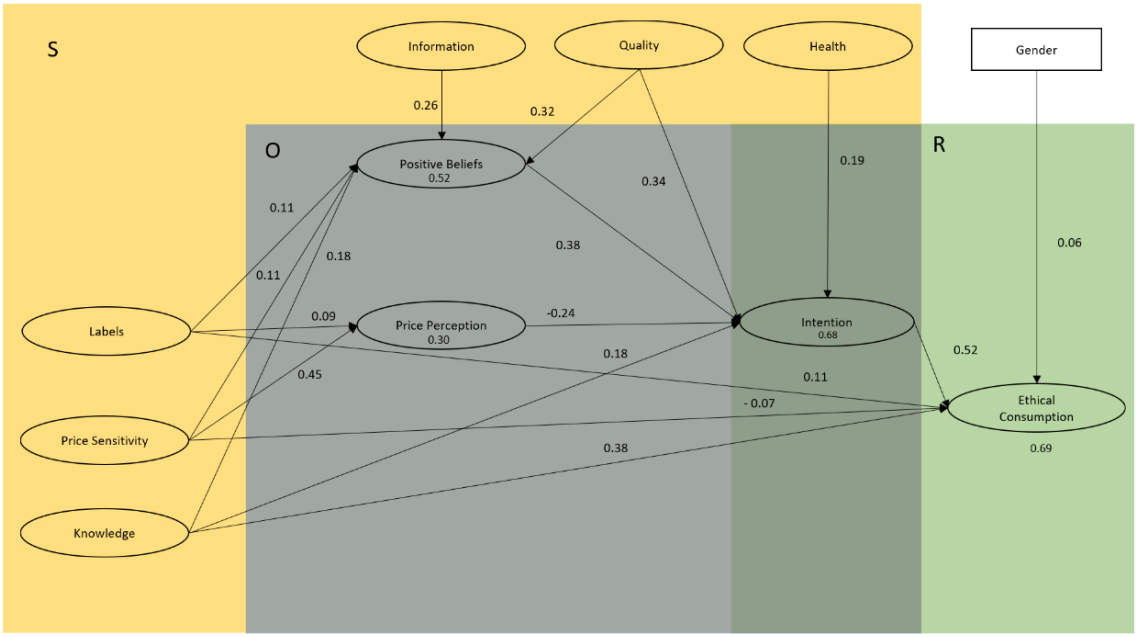

Figure 0.6 Path coefficient results (significant at 0.05); To be aligned with Figure 3.1, LAB and KNG were presented solely in the S area.

3.3.4 Mediation analysis

A mediation analysis was done for the stimuli which had a direct effect on EC (Table 3.9). The proposed model hypothesised that LAB had both a direct effect on ethical food consumption (EC) and an indirect one via BEL and Intention, and via PP and Intention. However, only the direct path was significant. The indirect effect was not significant, as the two mediation paths had opposite signs and approximately the same size. PRC also had a mediation path through positive beliefs and intention, and one passing by price perception and intention. In this case, the mediation

effect, although small, was found significant and complementary to the direct effect. As far as knowledge (KNG) is concerned, three mediation paths were considered. From these three paths, only $KNG \rightarrow BEL \rightarrow INT \rightarrow EC$ and $KNG \rightarrow INT \rightarrow EC$ were significant. This implies a total indirect effect of KNG in EC. Once the direct effect was also significant, it is a case of a partial mediation effect.

Alongside price, labels may act as situational factors, meaning that during the purchasing action, one might feel the direct impulse to buy a product containing a label they recognize as sustainable if happens to be at the same price of an entry-level product. For instance, according to Dentsu Macromill Insight Inc. (2021), one-third of the Japanese inquiries would purchase an organic product if the price was the same as other options, meaning it would be expected that these price sensitive individuals, which do not usually include such products on their shopping list, could be motivated to buy ethical products upon a price promotion. Moreover, people familiar with Ethical Consumption concepts may be more sensitive to campaigns mentioning them.

These results support the idea that considering S-R direct paths can lead to a higher explanation power of the purchasing behaviour model once allows the inclusion of factors that might trigger impulse or unplanned buying behaviour and do not necessarily trigger a planned purchase of those goods. Furthermore, it highlights S-O-R as a powerful and flexible tool capable of providing a holistic view of the decision process behind a behaviour.

Table 0.7 Mediation Effects

Path	Path Coefficient
PRC→BEL→INT→EC	0.021[2]
PRC→PP→INT→EC	-0.055[2]
PRC→EC (direct effect)	-0.073[2]
Tot. Indirect Effect of PRC	**−0.033[2]**
LAB→BEL→INT→EC	0.021[2]
LAB→PP→INT→EC	-0.011[1]
LAB→EC (direct effect)	0.097[2]
Tot. Indirect Effect of LAB	**0.009**
KNG→BEL→INT→EC	0.035[2]
KNG→PP→INT→EC	-0.007
KNG→INT→EC	0.094[2]
KNG→EC (direct effect)	0.378[2]
Tot. Indirect Effect of KNG	**0.122[2]**
Significant at 0.05[1]; significant at 0.01[2]	

3.3.5 Clustering and Profiling

The *Spearmen* correlation within PEB items was considered high. Thus, a PCA prior to Clustering was done. The data passed the tests regarding PCA fitness to the sample, with a KMO = 0.93, a *p-value* = 0 on the Bartlett's test, and a Cronbach's Alpha index of 0.90 (>0.70).

Taking into consideration the eigenvalues, and the graphic disposition of them (elbow method) a 2 factors clustering was chosen (Figure 3.7). The results of the factor analysis are shown on Table 3.10. The factor self-sufficiency (PEB10) named GROW, and consumption PEB (PEB1-9 and PEB11) named PEBG were used to create summated scales (mean value of each factor's items) for the clustering algorithm. PEB3 had a high-cross loading, however, as the first factor has a large number of items and PEB3 is aligned with other recycling items included in the factor, the item was kept.

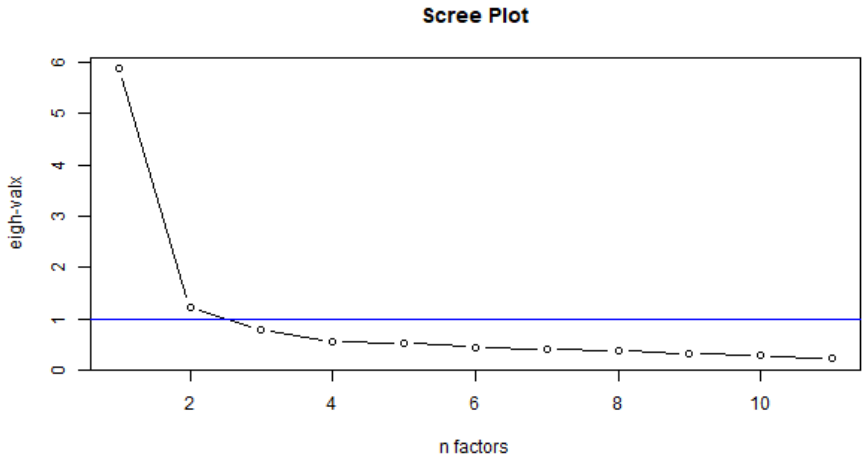

Figure 0.7 PCA Scree Plot

The value of the *Hopkins test* was 0.99, indicating the new factors are suitable for clustering. After the hierarchical clustering run, 12 out of 23 indices available on the package *Nbclust*, indicated 3 as the ideal number of clusters. Such indices are calculated based on heterogeneity changes, and accumulated heterogeneity within groups. Note that, to run the package *Nbclust* the user needs to pick the minimum and the maximum number of divisions that wishes to consider. In this case, the maximum was 4, as after this, there was the possibility of originating really small clusters that would not meet the minimum size for the multi-group comparisons. The details on indices' calculation methods can be found in Halkidi (2001). Once found the ideal number of clusters, the run of the *K-Medoids* algorithm was done for 3 groups. The first group had 158 observations, the second 280, and the last had 161 observations (Table 3.11).

Table 0.8 PCA Results and mean and standard deviation of the PEB.

ITEM	RC1	RC2	H2	U2	Com.	Mean (Likert-scale)	Std.
PEB1: *"Do you usually try to recycle your waste?"*	**0.80**	-0.21	0.69	0.31	1.1	4.31 (5)	0.96
PEB2: *"Do you usually try to recycle your waste?"*	**0.79**	0.21	0.67	0.33	1.1	3.84 (5)	1.03
PEB3: *"Do you usually try to use environmentally-friendly product?"*	**0.63**	0.56	0.71	0.29	2.0	3.35 (5)	1.08
PEB4: *"Do you usually try to turn off appliances and gas frequently?"*	**0.81**	0.04	0.65	0.35	1.0	3.96 (5)	1.01
PEB5: *"Do you usually try to choose recycled or refillable products?"*	**0.77**	0.23	0.65	0.35	1.2	3.68 (5)	1.00
PEB6: *"Do you usually try to not pour oil or toxic substances down the drain?"*	**0.78**	0.16	0.64	0.36	1.1	3.81 (5)	1.05
PEB7: *"Do you usually try to avoid excessive packaging?"*	**0.84**	0.20	0.74	0.26	1.1	3.72 (5)	1.03
PEB8: *"Do you usually try to carry an eco-bag and your own bottle?"*	**0.73**	0.02	0.54	0.46	1.0	3.93 (5)	1.14
PEB9: *"Do you usually try to help recycle containers?"*	**0.81**	0.00	0.66	0.34	1.0	3.95 (5)	1.11
PEB10: *"Do you usually try to recycle to grow your own food (e.g. vegetable garden)?"*	-0.03	**0.93**	0.86	0.14	1.0	2.32 (5)	1.43
PEB11: *"Do you usually try to refrain from using private transportation?"*	**0.50**	0.13	0.27	0.73	1.1	3.61 (5)	1.22
SS loadings	5.69	1.50					
Proportion Var	0.52	0.13					
Cumulative Var	0.52	0.64					
Proportion Explained	0.80	0.20					
Cumulative Proportion	0.80	1.00					

Table 0.9 Cluster's characteristics.

Cluster	GROW Centre (Medoid)	PEBG (Medoid	Size
1	3.0	3.0	158
2	1.0	4.0	280
3	4.0	4.2	161

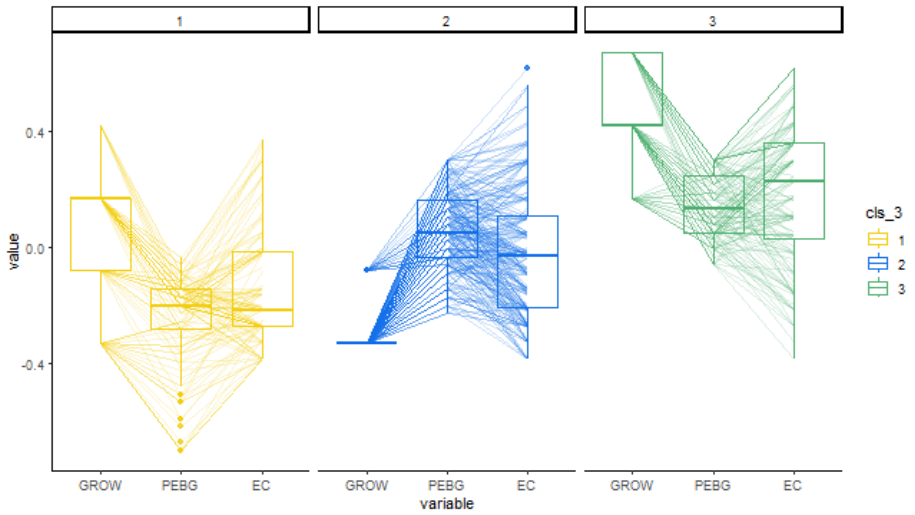

Figure 0.8 Cluster's Boxplots of PCA Factors and a summated EC scale.

To understand if the groups also differed on their EC engagement, a sustainable food consumption summated scale (mean of the items used in the decision model) was included to the clustering data frame. Given on of the item of EC had a different scale from the others, mean value was calculated based on the items standardized values. To facilitate the data visualization, GROW and PEBG were also standardized (Figure 3.8). By looking at Figure 3.8, one can see that the groups appear to have different ethical consumption rates. Note it does not imply that the structure of the behavioural model is different, but it may help on the profiling of the Japanese ethical consumer which is useful for marketing purposes. EC, GROW, and PEBG were found statistically distinct across groups, at a *p-value* < 0.05, via a Kruskal-Wallis' test. Moreover, on the Dunn's test (for pairwise group comparisons) all the null hypotheses were also rejected.

Table 0.10 Cluster's Socio-Demographics

Attribute		Cluster (1)	Cluster (2)	Cluster (3)
Gender	Women (%)	38.6%	49.3%	57.8%
	Men (%)	61.4%	50.7%	42.2%
Region	Saitama	24.7%	16.7%	20.5%
	Chiba	14.6%	18.9%	14.3%
	Tokyo	36.7%	37.9%	44.1%
	Kanagawa	24.1%	26.8%	21.1%
City Type	Tokyo metropolitan Area	25.9%	29.3%	34.8%
	Government-designated Area	22.8%	29.3%	21.1%
	City with a population of 200 000 or more	28.5%	21.1%	23.6%
	City with a population less than 200 00	19.6%	18.9%	17.4%

	Town/Village	3.2%	1.4%	3.1%
Yearly Income (before taxes)	< 2 million yen (%)	12.7%	6.8%	5.6%
	2-4 million yen (%)	12.0%	15.7%	16.1%
	4-6 million yen (%)	19.6%	21.4%	19.9%
	6-8 million yen (%)	14.6%	15.7%	15.5%
	8-10 million yen (%)	10.1%	8.9%	5.7%
	10-12 million yen (%)	5.1%	5.7%	6.8%
	>12 million yen (%)	5.7%	14.3%	12.4%
	Not declared	20.3%	11.4%	10.6%
Marriage (%)		35.4%	58.6%	57.8%
Children (%)		42.4%	34.6%	41.0%
Age (mean)		37.8	49.0	47.5

Regarding the cluster number 1, it is possible to see on Figure 3.8 that is the group with the lowest green consumption rates and standard PEB. Nonetheless they have an average engagement on self-grown vegetables. The consumers of this group have lower wages than the other clusters and a younger sample than group 3 and group 2. The group have more male than females. Considering, they have a lower income than the other clusters buying what is considered by some a gourmet sector food may not be the priority. This is also the group with the largest percentage of people who did not want to declare their income.

Moreover, the biggest group (group 2) is characterized by a regular practice of behaviours such as recycling, bringing its own bag, or trying to reduce waste as well as buying ethical products occasionally. On the other hand, it is the group with the lowest engagement on vegetables gardens and have a lower purchasing power than cluster 3. Around 60% of the people live in Tokyo Metropolitan area or a government-designated city (500 000 people or more). It is the cluster with most balance gender ratio (51% to 49%) and its age distribution are similar to the total sample (around 52% is on their 40's and 50's).

At last, the third cluster contains people who which have a mid-high engagement in all the factors analysed. Among the groups they are the ones which use more vegetable gardens and buy food ethically. According to the measurements evaluated one may say this group is the most environmentally friendly. This cluster has a higher percentage of women, have on average the highest purchasing power among the groups and live in Tokyo Metropolitan area and cities with more than 200 000 inhabitants. As they have the highest income available to them among the groups, the higher price associated with ethical products may have a smaller impact than on cluster 1 and cluster 2. Moreover, in Japan, household shores are still mainly dwelt by women (Qian et al. 2020; Nakamura et al. 2022).

It is interesting to notice both cluster 1 and 3, which have a younger sample and more children than cluster 2, have a higher engagement on gardening and growing its own vegetables. Such may be linked with the fact gardening is considered by some as a good family activity and a way to connect children to nature (Iijima and Egahiro 2014; Coogan 2019). Note that, even though cluster 2 comprises older people than the other groups, they are mostly still in working age. Interestingly, despite having the highest percentage of cohabitation with children, Cluster 1 has the lowest marriage rate. This may indicate that these respondents are young adults still living with their families, as it is an increasing trend in Japan (Nishi, 2017).

Even if it seems to exist a difference between the purchasing rates across groups, such does not imply that the decision-making process is distinct. Hence on the following section an assessment of whether or not PEB practices rates can be a moderation factor on ethical purchasing is done.

3.3.6 PLS multi-group analysis assessment

Using the 3 groups found, the following steps of the multi-group analysis assessment included sample size evaluation, a MICOM assessment, a Klesel et al. (2019)'s NDT, with a Bonferroni correction, and a Non-Parametric permutation-base Test proposed by Chin and Dibbern (2009) to make pairwise comparisons. The NDT was chosen once it evaluates differences across groups based on a complete structural model, and because there is no established knowledge on how the model performs differently across the three clusters (Cheah et al. 2023).

The sample sizes of the sub-populations must be large enough to meet the guidelines regarding statistical power (Matthews 2017). Following the suggestions of Cohen (1992) and Hair et al. (2017), all the groups are large enough (>156) to ensure a statistical power of 80% with a 5% of significance for a minimum R^2 of 0.10. However, it is important to note sample size also influence on the multi-group analysis procedure. Henseler et al. (2016) mentioned small samples may lead to misleading results in the compositional analysis (step 2 of MICOM). Furthermore, Klesel et al. (2019) and Klesel et al. (2022) point out that a sample of 100 observations was not sufficient to NDT consistently identify small to moderate differences across the groups advising groups of least 200 observations. Although two of the groups in the analysis are smaller than 200, Chin and Dibbern (2009) mentioned a minimum size of 150 observations per group for their pairwise Non-Parametric permutation-base test (NPT). Based on the latter, this study proceeded to the next analytical step.

As far as MICOM is concerned, the step which confirms that the model follows the same configuration across groups (step 1) is assured by the fact that all the observations were gathered by the same survey on the same region and time period. Both step 2, which checks composite scores are perfectly correlated (Henseler et al. 2016), and step 3, which tests the composites mean values and the composites equality (Henseler et al. 2016; Cheah et al. 2023), showed that the data is pruned for analysis under a multi-group analysis (Table 3.13).

Table 0.11 MICOM Steps 2 and 3 (p-value > 0.05)

Construct\Pair of Clusters	1-2	1-3	2-3
	p-value	*p-value*	*p-value*
Step 2			
INF	1.00	0.05	0.17
QLT	0.63	1.00	0.74
KNG	1.00	1.00	1.00
LAB	1.00	1.00	1.00
PRC	0.69	1.00	0.70
HEALTH	1.00	1.00	1.00
BEL	1.00	1.00	0.72
PP	1.00	1.00	1.00
INT	0.98	1.00	1.00
EC	0.09	1.00	0.12
STEP 3 Mean			
INF	1.00	1.00	1.00
QLT	0.22	0.42	1.00
KNG	1.00	1.00	1.00
LAB	1.00	0.34	0.76
PRC	0.09	0.14	1.00
HEALTH	0.50	0.12	1.00
BEL	0.11	0.44	1.00
PP	0.16	1.00	0.33
INT	1.00	0.10	0.30
EC	1.00	0.37	0.34
STEP 3 Var			
INF	0.22	0.37	1.00
QLT	0.21	0.06	1.00
KNG	1.00	1.00	1.00
LAB	0.80	1.00	0.85
PRC	0.36	0.13	1.00
HEALTH	1.00	1.00	1.00
BEL	0.37	1.00	0.82
PP	0.58	1.00	1.00

INT	1.00	1.00	1.00
EC	1.00	1.00	1.00

The NDT test (set to 5000 permutations) rejected both null hypothesis (Table 3.14), implying that PEB rates can act as a moderation factor. However, when testing the pairwise comparison via the methodology proposed by Chin and Dibbern (2009) none of the null hypotheses (a certain path is equal across two groups) were rejected. Such may be derived from asymmetric sample sizes, or by the degree of non-normality (Chin and Dibbern 2009).

Although NDT was able to detect overall differences across groups, the results were not conclusive at a pairwise level. Thus, future researchers should further explore this moderation alternative under a bigger sample. By using other pro-environmental rates as a moderator instead of perhaps an abstract concept of environmental concern, researchers can find synergies among environmental behaviour which may bring benefits in respect of practical and social implications and marketing campaigns.

Table 0.12 Non-Parametric Permutation-Based Test (Klesel et al. 2019)

Distance measure	T.Stat.	p-value	Decision
dG	2.56	0.00	*Rejected*
dL	42.04	0.00	*Rejected*
H0:Model-implied indic. cov. matrix is equal across groups.			

3.4 Discussion

The current study successfully achieved its main objective of presenting a comprehensive and holistic model of ethical food purchasing decisions in Japan. The R^2 for intention was 0.68 and 0.69 for the stated buying behaviour, which are moderate values close to the substantial threshold (> 0.75) (Hair Jr. et al. 2021).

In agreement with the results of Vergura et al. (2022) in the organic care products market, the knowledge stimulus was also significant in the green food sector. Not only it was significant, but it was the stimulus with the largest effect on behaviour. Such may be related to the importance that the Japanese put on information (Synodinos 2001).

When analysed in a unique model, all the stimuli remained significant to behaviour, confirming the results of the scholars who analysed them separately. However, on intention, LAB's effect was not significant. This suggests knowledge about labels can act as an important

situational factor to purchase but is not a focal point to create a purchase intention in the food sector. These findings oppose the results of Dhir et al. (2021b) that found organism constructs related to labelling beliefs significant to the intention of buying green apparel. Thus, including a wider range of items about labelling beliefs (Organism) in further ethical food research is advised to clarify the labelling stimulus role.

Previous research in Japan called for the inclusion of QLT and PRC price constructs (Tandon et al. 2021). The present research answers such call and validates its relevance. For instance, quality was the largest stimulus effecting intention. Despite being considered more community driven than other societies (Ando et al. 2007, 2010), the communication construct was the one with the smallest effect within the Japanese residing in Kanto region. This may be related to the importance of personally evaluating the quality and taste of food, but it might also concern the measurement items utilized. This construct was addressed with two items, which may not have been enough to fully capture the role of friends, family and social media in both intention and behaviour. For example, even though is a different behaviour, on the analysis of Chapter 5 the impact of social descriptive and subjective norms was tackled from different angles. Gender was the only significant control variable. Such can derive from the gender distribution of house shores in Japan. According to Nakamura et al. (2022) women are still responsible for many of the house shores including grocery shopping.

In agreement with the findings of Talwar et al. (2021) intention was a significant predictor of behaviour under the S-O-R framework. Although intention as a predecessor of behaviour is often associated with TPB (Ajzen 1991), the results show that its integration on a S-O-R methodology is an important step to address the stated engagement on ethical consumerism.

Nonetheless, while Talwar et al. (2021) considered intention as the only direct effect on behaviour the present analysis successfully tested the direct paths of PRC, LAB, and KNG stimulus. The inclusion of S-R paths on S-O-R contributed to an increase of the explanation power of the model. It is also a way of including situational or impulse stimuli that contribute to the explanation of the attitude-intention-behaviour gaps reported in academia (Kollmuss and Agyeman 2002; Hassan et al. 2016; Sultan et al. 2020; Casais and Faria 2022). For instance, if the direct effect LAB was excluded, this stimulus would have been considered insignificant.

From the objectives established, only the use of pro-environmental behaviours practice as a moderation factor for the multi-group analysis was not supported entirely. Based on the relationship between environmental values and sustainable lifestyles (Biswas 2017) and the PEB hierarchy suggested by Wooliscroft et al. (2014), PEB adoption (small-cluster 1, average-cluster 2, and high-cluster 3) was expected to be a significant moderator. However, while studies like (Kushwah et al. 2019) and Dwivedi et al. (2022), which assessed environmental concern from an

abstract perspective, found a moderation effect, no clear path distinction was found in this analysis (only at an aggregated level). Errors resulting from a misunderstanding of the questions might be reduced if a frequency question is done instead of a conceptual abstract item. Thus, further research is encouraged on the topic. Even if the results were not conclusive on the MGA, the groups found were aligned with the idea that someone engaging in "costly" PEB also had high engagement of other PEB (Wooliscroft et al. 2014). These ideas of PEB hierarchy and different pro-environmental lifestyles, particularly related to food consumption, will be further explored in the following chapter.

3.4.1 Theoretical Contributions

When it comes down to the theoretical contributions of this chapter, this study is one of the few that focus in several aspects of Ethical Food Consumption. Even though, organic, and local food purchasing were the most popular behaviours, the podium was also shared with food that considers disaster areas. Simultaneously, the results supported previous works' decision of focusing only on organic or local production once they seem to be the most mainstream behaviours.

Second, the study contributes to literature using a S-O-R framework and a multi-group analysis application on the field. Among the behavioural theoretical frameworks, most papers seem to be based on TPB or Altruistic Model (Lee and Yun 2015). The proposed methodology used previously explored stimuli like health consciousness, price, labels (Lee et al. 2020), communication (Anisimova et al. 2019), and quality (Konuk 2019), and added knowledge into the same unique model.

Regarding responses, previous S-O-R models, with exception of Talwar et al. (2021), focused either on the behaviour (Lee et al. 2020; Tandon et al. 2021) or on its intention (Lee and Yun 2015). On the other hand, the present research included both internal and external responses. It also included direct relationships between stimuli and response. Although most of the times stimuli are mediated by organic processes, Jacoby (2002) allows the possibility of non-planned, spontaneous responses. The results of the mediation analysis pointed out that price sensitivity and labelling recognition indirect effects were small or not significant, supporting the idea that including S-R paths can improve the explanatory capacity of the models.

Furthermore, multi-group analysis can be an important tool to create effective target campaigns and action plans. Environmental concern (Kushwah et al. 2019), gender (Tandon et al. 2021) or trust (Tandon et al. 2020a) have been used as moderators on ethical consumption studies.

However, to the author's knowledge, this is the first study which attempted to establish a multi-group comparison based on a Pro-Environmental Behaviour clustering. Even though the results were not conclusive at a pairwise level, the overall model test detected differences across groups. More precisely, the findings of the current chapter support, to a certain extent, the idea that looking at PEB practice rates as a moderator can be an effective way of assessing how the environmental concern of an individual (measured in practical terms instead of asking them about it at an abstract realm) impacts green food consumer's decision model. However, to discover which paths are affected, further research is needed on the use of PEB clusters as moderators.

The last point on the theoretical implications, refers to the better understanding of such a unique market as the Japanese one. When compared with countries such India (Paul et al. 2016; Tandon et al. 2020b; Kumar et al. 2021), China (Lee et al. 2020), or European countries (Michaelidou and Hassan 2008; Gonçalves et al. 2016; Rees et al. 2018; Loera et al. 2022), Japanese ethical market is under-explored. The results seem to show that the core characteristics of the contemporary Japanese consumer are aligned with previous portraits done by Synodinos (2001) and McGreevy and Akitsu (2016).

3.4.2 Social and Management Contributions

As far as practical implications are concerned, according to this study's findings, fostering the knowledge about ethical food and its environmental and health benefits seems essential. According to Dentsu Macromill Insight Inc. (2021), many Japanese consumers, highlighted "*when choosing among similar products, it's best to choose those that contribute to society*". Considering the latter, and once price is a significant factor to decision, highlighting the benefits can result in a fairer evaluation of value trade-offs. Awareness campaigns like creating mascots, promotional campaigns and tasting campaigns are some of the examples of possible ways of boosting this awareness and allowing a more educated choice. Given the relevance on behaviour of knowledge and the fact Kanto region is a metropolitan area with well-established and extensive public transportation system, using it as an educational and marketing about environmental issues and pro-environmental behaviours may be an option. In fact, currently is it possible to find some information about SGDs in trains in Japan, so widening the scope of the messages could be relatively straightforward.

Coherent with previous analysis labelling and knowledge about of certification marks influences the purchasing behaviour (Sakagami et al. 2006; Dhir et al. 2021a). Increasing the trust on the certification, and ensure it is well visible on the package can impact the behaviour. The improvement on the trust of the certificate can be achieved by assuring the products quality (which

by itself is relevant on intention formation), and/or by having a clear and transparent production. Technology regarding food-traceability play a role in the latter point as well as local food projects (Kubota et al. 2017) and farm-to-fork initiatives. According to Nakagawa and Zimmerman (2021), more than one third of the organic consumption in Japan are from specialized shops, or food markets. Local markets can bring the feeling of proximity and community and minimize issues about origin or production process of the products. Thus, having an efficient marketing strategy for such markets might foster the sale of these products.

Moreover, people who frequently buy ethical products seems to adopt also other behaviours such recycling, refill products and low packaging. Ensuring ethical product have eco-friendly packing or no packing at all can be a way of fostering the purchase of this product. Recently in countries such as France or Portugal the number of grocery places having bulk food is increasing, such may also be a valid alternative in Japan.

Lastly, although the focus of the work is ethical food consumption, the clustering results pointed out behaviours like growing its own vegetables have space even in a busy Metropolitan area. Buying consciously is not only buying eco-friendly products but also not buying more than necessary and in some cases have some self-production (e.g., herbs, and small vegetables).

3.5 Chapter Conclusion and Future Research

Evidence suggests ethical food consumption in Japan is bound to intention, knowledge, price, and certification recognition. Intention and environmental knowledge (general and about concrete labels and certification) had a positive impact on consumption, whereas price had a negative one. Similarly, the quality and associated benefits of green products were positively related to intention, while price perception and intention had a negative relation. The price sensitivity's indirect effect was small, and the labelling one was not significant. Such findings suggest that an increase on the explanatory power of the model can be achieved by including S-R path to cope with impulse factors.

Overall people who highly engage in growing food and other pro-environmental behaviours also had a higher engagement in ethical food consumption. Moreover, the group with the lowest engagement on ethical consumption had a less frequent practice of general PEB. Such may derive from the different purchasing power and residence place among the clusters. Self-grown vegetables seemed to be more popular among young parents. The multi-group analysis showed that aside differences on the frequency of sustainable purchasing products, these groups had an overall distinct decision-making process.

These findings widened the scope of analysis about ethical food products and successfully identified key drivers to ethical purchase in Japan, using a less commonly applied approach. Some remarks on future developments concerning the range of products analysed and methodology are made on the following paragraph.

First, this analysis was based on a self-reported questionnaire, and only considered consumers from Kanto region. is the most populated area in Japan, but further analysis is needed before generalizing these conclusions to Japanese consumers at large. The data was collected only in one point in time. In order to design effective adoption strategies, it is important consider how habits are created and sustained (Steg and Vlek 2009; Abrahamse 2020). And so, extending the analysis through time, like accompanying a focus group may give resourceful insights. Moreover, based on spillover concepts, further understanding how behaviour family of PEB are expressed by people with different lifestyles can contribute to the design of interventions able to catalyse several behaviours simultaneously. Following this line of thought, the next chapter explores what kind of patterns exist among Japanese consumers related to the moment of purchasing food, how it is used, and how the food is disposed of.

In light of the SEM results, quality seems to have both a direct and indirect effect on intention, nevertheless the scope of beliefs and barriers was limited. Further research including a wider range of behavioural barriers and benefits or including organic constructs like openness to change (Talwar et al. 2021), ethical self-identity (Talwar et al. 2021; Rambabu et al. 2023), and personal norms (Rivas et al. 2022; Fakfare et al. 2023) is needed. For instance, this study did not include availability and convenience issues. Tandon et al. (2021) has reported availability was not a significant predictor, however the study did not include metrics of time and convenience. Japanese society is known by its busy working life and inconvenience besides availability have been reported as barrier to consumption organic and local products in several studies (Chambers et al. 2007; Hjelmar 2011; Chekima et al. 2019). For a pragmatic consumer, which lacks in time, opportunity and end ups buying in a convenient supermarket for their routine (Hjelmar 2011), the reduced shelf space of this products can outweigh potential ethical considerations (Carrigan and Attalla 2001; Chambers et al. 2007).

Given the results of the multi-group analysis, further investigation with a larger sample is necessary to assess in detail how the model changes across the groups of pro-environmental practice. Alternatively, the use of other strategies like FIMIX-PLS or POS-PLS may show interesting results on detecting heterogeneity between groups.

Moreover, Japanese cultural differences such as collectivism or concepts like *"mottainai"* were found significant to pro-environmental behaviours (Ando et al. 2007, 2010; Sirola et al. 2019) and were not included directly on the research. Aspects such as Japanese consumer's

disposition to food which help disaster areas, were interesting finding of the current work and ought to a more detailed analysis.

Finally, to evaluate the robustness of the model, it could be interesting comparing the present model results with the ones obtained by relaxing the assumption Likert-scales are ordinal, and/or using other clustering techniques.

Chapter 4: Ethical Consumption and Food Recovery Hierarchy Behaviours: A Clustering Analysis in Japan.

4.1 Introduction

This chapter is dedicated to identifying how the engagement in food related PEB changes along the purchase, usage, and disposal consumption stages, as well as if the groups with different behavioural patterns also differ in characteristics (e.g. age and gender), eating habits, or perceptions toward pro-environmental behaviours. The main results are available in Morais and Ishida (2024).

As previously mentioned, the way one consumes their food, along with how the dispose of organic waste, can have a deep impact on mitigating climate change. Organic waste has been a predominant portion of the total amount of household waste (Ueta and Koizumi 2001; Okayama 2016; Yamada et al. 2017), increasing the interest of government entities, companies, non-profit organizations (NPO) and academics about food waste generation and ways of preventing it (Boulet et al. 2021; Attiq et al. 2021; United Nations 2022; Rukikaire and Loran 2022; Simões et al. 2022; Nguyen et al. 2022).

Previous literature, especially on the marketing and psychology fields, have looked at the differences in PEB adoption rate from a lifestyle perspective (Plummer 1974; Brunsø et al. 2004, 2021; Savelli et al. 2020; Choi and Feinberg 2021; Aschemann-Witzel et al. 2021; Arenas-Gaitán et al. 2021, 2022). Segmentation using lifestyles and the integration of behavioural spillover ideas can contribute to the development of successful, less punitive interventions to promote a shift for more sustainable lifestyles (Thøgersen and Crompton 2009; Qing et al. 2012; Nash et al. 2019; Savelli et al. 2020; Brunsø et al. 2021). Lifestyles were considered an umbrella concept that comprised a person's activities, interests, and opinions (Plummer 1974; Savelli et al. 2020; Arenas-Gaitán et al. 2022). Recent studies have further described them as being a cognitive mediator between life values and behaviours (Brunsø et al. 2004, 2021; Arenas-Gaitán et al. 2022). Behavioural spillover relates to the idea that engaging in one PEB can influence whether a person adopts other behaviours, implying interventions can have wider impact than solely on the targeted behaviour (Nash and Whitmarsh, 2023).

Motivations for and against ethical food consumption have been used to identify people's heterogeneity towards food products (Burke et al. 2014; Huddart Kennedy et al. 2019). Moreover, scholars have looked for food consumption and food waste behaviour patterns by accessing purchasing motives, quality aspects, cooking methods, consumption circumstances, and ways of

shopping (Brunsø et al. 2004; Aschemann-Witzel 2018; Grunert 2019; Arenas-Gaitán et al. 2022; Szymkowiak et al. 2022). Brunsø et al. (2021) has also proposed a simpler assessment based on three core dimensions: food involvement, food innovativeness, and food responsibility. Besides sustainable food consumption and food waste behavioural nuances (Gaiani et al. 2018; Bravi et al. 2019; Annunziata et al. 2022), scholars have analysed these behaviours alongside health-related lifestyles (Scalvedi et al. 2018; Savelli et al. 2020). With the exception of Kunszabó et al. (2022), little attention has been given to food waste recycling patterns. While Kurisu and Bortoleto (2011) associated composting with people who follow a Lifestyle of Health and Sustainability (LOHAS), an integrative study covering eating habits and all stages of food consumption (purchase, usage, disposal) from a food waste avoidance perspective has not been done yet. Under the pro-environmental behaviours sphere and specifically in regard to food waste, frameworks like the 3R's (Reduce, Reuse, and Recycle) and the Food Waste Recovery have been useful resource to both policy makers and academics (Kurisu and Bortoleto 2011; Diaz-Ruiz et al. 2018; Joshi and Visvanathan 2019; Attiq et al. 2021; Inaba et al. 2022; EPA 2022; Simões et al. 2022; Nguyen et al. 2022).

According to the Food Waste Recovery Hierarchy (FWRH) (Papargyropoulou et al. 2014) food consumption, waste prevention, and disposal, can be seen as interdependent components which contribute for a more sustainable world with different degrees of preference. Therefore, to gain a better understanding of Japanese consumers' eco-friendly behaviour, it is crucial to consider all stages of FWRH together, rather than treating them as separate actions. Instead of focusing solely on food waste prevention (Bravi et al. 2019), food disposal (Kunszabó et al. 2022), or food consumption (Scalvedi et al. 2018; Huddart Kennedy et al. 2019; Brunsø et al. 2021), the current chapter discusses how Japanese people might practice these actions simultaneously or not, and if they happen alongside healthy food choices. Thus, this chapter's analysis was based on the levels of the Food Waste Recovery Hierarchy incorporated with the steps of consumption (purchase, usage, and disposal).

Similarly to the previous a chapter, the present methodology also comprised a two-step clustering approach. However, following the Hierarchical clustering, a *K-Means* technique with a Euclidean distance was used, instead of a *K-Medoids* algorithm with a *Mahalanodis* distance. To further understand the obtained clusters and their ways of living, people were asked to report their gardening interest, cooking, and dietary options, and to rank the behaviours according to their burdensome and positive environmental impact. Respondents' intention on starting/continuing recycling food waste via composting was also used, once from several food disposal methods, it is a primary food recycling process in Japan (Takata et al. 2012). Additionally, composting is a PEB that depending on how the system is designed, may require different degrees of involvement of a household unit. For example, a household can make and use its own compost,

make it and give away the compost, or in a kerbside organic waste collection situation, a household might only provide the waste that is then composted by the community or at a central level. Chapters 5, 6, and 7, will further address composting behaviour and such composting systems.

Nonetheless, the present chapter aims to contribute to food consumption and waste management academia by exploring the patterns and contrasts existent across the Japanese population on the adoption rates of ethical purchasing, waste reduction, and food waste recycling PEB. The aim of this analysis is to identify: 1) which food related PEB are mainstream and which ones have low engagement; 2) what campaigns and incentives can be efficient based on people's behavioural patterns; and finally, 3) if groups with different behavioural patterns also differ in age, gender, income, eating habits, and perceptions towards pro-environmental behaviours.

4.2 Background and Methodology

4.2.1 PEB and Food Waste Recovery Hierarchy

The food recovery hierarchy (Papargyropoulou et al. 2014) is a framework in which behaviours are ordered from the most preferred to the least preferred, by considering environmental, economic, and social sustainability (EPA 2022; Nguyen et al. 2022). The most preferred behaviours are food waste reduction and food waste prevention at the source (EPA 2022). The next most preferred behaviour is, if still nutritious and safe, the food surplus be distributed to groups affected by hunger, or to people in need within the community (Nguyen et al. 2022). The following behaviours include feeding animals with food scraps or leftovers, engaging in nutrient recovery procedures like composting or green bin separation if such collection type is available in the area (Ladele et al. 2021; Nguyen et al. 2022), and using the waste at an industrial level (generation of energy, biofuel). The least preferred option is landfill disposal or incineration. It is important to note that while some countries like the US prioritize energy generation and biofuel over composting, the opposite happens in Europe (Imbert 2017). In Japan, it seems the latter order is being followed (Yoshida 2018; Fujii and Kondo 2018). The food recovery hierarchy is aligned with the 3R's philosophy (Reduce, Reuse, Recycle) (Figure 4.1) and its increasingly popular extension, the 4R's (Reduce, Resue, Recycle, Recover) ideology, which, in turn, has been associated with concept of *"mottainai"* in Japan (Jakimiuk et al. 2023). Despite its Japanese routs this philosophy seems to be gaining traction internationally (Jakimiuk et al. 2023; Mitaka City 2023).

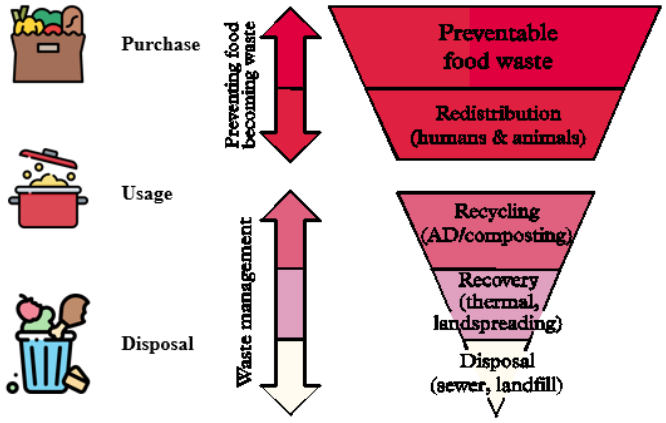

Figure 0.1 Food Recovery Hierarchy (adapted from UK Parliament (2014)*)*

Numerous behaviours can be observed within the realms of food prevention and reduction. Bravi et al. (2020) studied how in-store behaviours, storing practices, and food management in the house impacted the waste produced. Shopping habits and actions like doing a shopping list, meal planning, inventorying supplies (e.g., checking the fridge before shopping), and buying only necessary groceries have also been identified as drivers to waste reduction (Quested et al. 2013; Diaz-Ruiz et al. 2018; Bravi et al. 2019; Sirola et al. 2019; Aydin and Yildirim 2021; Simões et al. 2022; Wu et al. 2023). From a usage perspective, regardless of the proper storing of products or the use of a freezer to extend shelf-life, scholars have often included cooking and/or eating leftovers, using date-labels on food, portioning of rice and pasta (food quantities), cooking skills and overall eating habits as drivers to waste reduction (Quested et al. 2013; Ponis et al. 2017; Bravi et al. 2020; Simões et al. 2022; Wu et al. 2023).

Many of these behaviours are related to everyday routines and to people's relation with food. Scholars have analysed food waste behavioural patterns based on food waste reasons, waste prevention motivations, and attitudes towards food waste (Gaiani et al. 2018; Bravi et al. 2019; Annunziata et al. 2022). Overall, higher food involvement as well as healthy dietary habits have been associated with groups that wasted less food (Savelli et al. 2020; Aschemann-Witzel et al. 2021; Szymkowiak et al. 2022). People with healthier dietary habits also tended to engage more frequently in pro-environmental behaviours like recycling, and ethical consumerism (Scalvedi et al. 2018; Asvatourian et al. 2018; Savelli et al. 2020).

Moreover, Burke et al. (2014) identified three distinct profiles related to the reasons to buy sustainable food in Australia. Consumers with positive views tended to be older women which focused on these products' quality as well as their environmental and health benefits. The ambivalent group also had a larger number of women but also a higher scepticism on what ethical meant. The group with negative views on ethical consumption had more men than women. This group was more impacted by indifference, expense, confusion, and scepticism as reasons not to

buy green products. This association between food quality, health, expense, and ethical food was also seen on the profiles identified by Huddart Kennedy et al. (2019) when studying food aesthetics and ethical food.

Thus, in alignment with the emerging health, well-being, and environmentally sustainable driven lifestyle (LOHAS) (Choi and Feinberg 2021), it would be expected that while shopping, consumers make sustainable decisions beyond the ones which have a direct effect on household food waste. For example, while grocery shopping customers can purchase organic or eco-friendly products (Talwar et al. 2021), avoid highly packaged products, use their own bag while shopping, and look for refillable or easily recyclable products (Kurisu and Bortoleto 2011; Bortoleto et al. 2012). As show by the results of Chapter 3 and previous literature, sustainable food products, although more expensive, are usually seen as of a better quality, safer, and healthier (Chekima et al. 2019; Tandon et al. 2021). Additionally, organic products use natural fertilizers by default, which are less harmful to the environment and can be derived from kitchen waste (Mihai et al. 2023). This use of kitchen waste to produce fertilizer can promote the cycle of resources and a higher involvement of consumers on top of their buyer role. It can also catalyse the engagement on other pro-environmental behaviours. For these reasons, the current analysis also comprised PEB associated with the ways of shopping and cooking that are aligned with a sustainable lifestyle.

4.2.2 Clustering Algorithm

In this chapter, clustering is used to identify differences on the practice rates of ethical consumption behaviours and Food Waste Recovery Hierarchy related PEB. In accordance with the idea that PEB and ethical choices may be presented hierarchically (Wooliscroft et al. 2014) and the clustering results of the previous chapter, it would be expected that individuals who practice time consuming or costly PEB like buying organic food (Sakagami et al. 2006; Chekima et al. 2019; Dorce et al. 2021) or compost (Wu et al. 2019), to also engage in more mainstream practices like recycling, while the contrary does not necessarily hold (Wooliscroft et al. 2014). Eating habits, PEB perceptions, composting intention, and socio-demographics were used to profile the obtained clusters. Based on the profiles gathered in the previous literature, it would be expected to see an association between women, healthy lifestyles, and environmental involvement (Scalvedi et al. 2018; Asvatourian et al. 2018; Savelli et al. 2020; Choi and Feinberg 2021), as well as between gardening interest and composting (Kunszabó et al. 2022).

The present algorithm included a data reduction technique (PCA), a Hierarchical Clustering followed by a *K-Means* method, and a profiling step. During the data reduction, a promax rotation was used to better interpret the obtained factors. Other orthogonal and oblique

rotations were explored, but the promax rotation had the clearest results. Even though oblique rotations allow correlation between the factors, such was not considered a major issue given the purely clustering nature of the analysis. For instance, on the previous chapter, oblique rotations were avoided because of the nature and independence assumption behind a PLS-SEM. A Kaiser-Meyer-Olkin (KMO) test, a Bartlett's test, and a Cronbach's Alpha index were calculated to verify if the data could be factorized. Next, the ideal number of factors was decided and summated scales were calculated. On this chapter's application the distance matrix was calculated based on the Euclidean distance and the selected linkage was the Ward's linkage criteria. Euclidean distance was chosen based on the low correlation values between the PCA factor. The *K-Means* was used due to its simplicity and common pairing with the preferred distance.

4.2.3 Data Collection and Questionnaire

The analyses of this chapter, Chapter 5, and Chapter 6 are based on the data resultant from an online survey which was conducted by a marketing research company between 2022-09-20 and 2022-09-21. Contrary to the dataset used in Chapter 4, which was data from a preexisting questionnaire, this survey was designed to meet the research specifications of this doctoral dissertation. Therefore, the survey included 30 questions concerning pro-environmental behaviours related to both responsible consumerism and waste management. In particular the scope of the survey tried to cover not only frequency rates of the mentioned PEB areas (food purchasing moment, food usage, and food disposal), but also the reason and factors behind food waste reduction and composting decisions. From the whole dataset, this chapter focused only on questions covering food related behaviours aligned with the Food Recovery Hierarchy (Papargyropoulou et al. 2014) and ethical behaviours that can occur while shopping for groceries. When compared the Ethical Food Consumption construct used in Chapter 3, the Ethical Consumption factor of this intended to give a broader perspective about the moment of purchasing food, thus including aspects like packaging too. From the Ethical Food Consumption items of the last chapter, only the purchase of organic food was used, as it one of most commonly studied aspects of Ethical Food Consumption (Baumann et al. 2017) and it can be directly connected with food waste recycling processes. Additionally, questions about the positive impact and convenience of the analysed PEB, intention of engaging in composting, and dietary choices were included on the analyses of this chapter. The latter items will also integrate the analysis of the following chapter.

With exception of the questions about garden/farming interest ("*I am interested farming*", "*I am interested in backyard/community gardening*", "*I am interested in balcony herb garden*", "*I*

have no interest in the above options"), composting behaviour with a given definition (no, used to, yes), cooking ingredients ("*I cook almost everything from fresh ingredients*", "*I use some precooked/frozen ingredients*", "*I do not cook/I rarely eat at home*"), and the awareness of composting support programs ("*I do not know*", "*I know they are available, but I do not know the details*", "*I know whether or not they are available*"), the majority of the items were addressed on 6-point Likert-scales (e.g., 1-never 6-always, 1-strongly disagree 6-strongly agree). A 6-point Likert-scale was preferred to a 7-point Likert-scale once the Japanese people tend to choose "neutral" answers (Kurisu 2015). The survey included two questions on composting/food recycling behaviour: the categorical item mentioned above and a 6-point Likert-scale (1-never; 6-always) regarding whether respondents engage in composting/recycling organic waste. In this chapter, only the 6-point question was addressed. This chapter's analytical approach also considered Likert-scales as continuous.

The sample includes 1500 Japanese adults over 30 years old residing in 9 different prefectures (Aichi, Chiba, Fukuoka, Hyogo, Kanagawa, Kyoto, Osaka, Saitama, and Tokyo). As of first October of 2020, Japanese adult population was 126.146 million people from which around 60% was residing on the prefectures selected on the study. Besides being among the most populated prefectures in Japan, their different policies towards waste management were also considered during selection. For instance, according to Kurisu and Bortoleto (2011) and Hirose (2015), Aichi Prefecture invested earlier in waste reduction campaigns and composting subsidies and at least two towns in Fukuoka have made Zero Waste pledges (Life Hugger and Lee 2023). Within the selected areas, Tokyo is the most populated area followed by Kanagawa, Osaka, and Aichi.

A quota sampling technique was used to ensure a sample that closely matched the general population in terms of age, gender, and prefectures' population density. At the time this survey was designed, new census information was available, thus the quota sampling was based on the 2020 population census rather than the 2015 data (as in Chapter 3). To a better understating of the results three points should addressed. First, as many of the Japanese with ages between 18-30 still live with their parents and the early twenties is a period associated with academic pursuits (Fumihiko 2017; MEXT 2019), the study focused on the population over 30 years old. Second, even though there is a marginal number of elders over 70, similarly to the survey from the last chapter, the quota of the elderly group in proportion to the population composition, was based on the population between 60 and 69. This was preferred given low the percentage of elders registered for the internet surveys. Finally, as the survey was written in Japanese, it only addressed Japanese citizens

.

4.3 Results

The data was analysed with R (4.2.1) coding language via Rstudio (5.5.4). The clustering analysis was based on NbClust 3.0.1 (to find the ideal number of cluster) and Stats 4.2.1 (Hierarchical Clustering and K-Means).

4.3.1 Descriptive Analysis

The original sample size was 1500, however two observations were excluded due to missing data about their education. Female respondents made up 49.7% of the respondents, while 50.3% were men. The sample only included Japanese adults over 30 years old, 22% of them were between 30 and 39 years old, 30% in their 40s, 26% in their 50s, and the other 22% of the sample was over 60 (Table 4.1). Approximately 30% of the respondents had at least one child residing with them, and the most common household had the respondent living with another person (e.g., parent, spouse, or children).

In terms of education and career, 66% of the people held a university degree or equivalent (e.g., vocational school), 30% had completed high school, and 4% had finished junior high school. The most frequently reported household income range was between 4 and 6 million yen a year with approximately 41% of the sample being corporate workers and 20% housewives/husbands. According to the Japanese Ministry of Health, Labour, and Welfare (MHLW) wage report of 2022 (MHLW 2023a), the average salary in Japan was 3.7 million yen/year (311,800 yen/month). Among the analysed prefectures the values ranged from 3.6 million yen/year (296,100 yen/month) in Fukuoka to 4.5 million yen/year (375.500 yen/month) in Tokyo. Despite existing a clear gap between women's and men's wages (MHLW 2023a) and an average of 1.05 income earners per household (Statista 2023), the results of this analysis do not express these issues directly once the survey question was about the total income available in the household. In Japan, the average available income in a household was 5.5 million yen/year in 2021 (MHLW 2023b) which is in accordance with the survey statistics.

From the 17 PEB analysed in this chapter bringing one's own bag when grocery shopping (5.02 out 6), overall recycling (4.96 out 6), and avoiding leftovers (4.89 out 6) were the most frequent behaviours (Table 4.3). On the other hand, using leftovers to feed the animals (1.77 out of 6), composting/reusing organic waste in the garden (1.91 out of 6), and reducing the organic waste volume using an electric machine (1.89 out of 6) were among the least frequent (Table 4.2).

Table 0.1. Socio-Demographics of the sample

Variables	Categories	N	N%
Gender	Male	754	50.3%
	Female	744	49.7%
Age	30s	334	22.3%
	40s	442	29.5%
	50s	392	26.2%
	>60	330	22.0%
Region	Saitama	166	11.1%
	Chiba	143	9.5%
	Tokyo	324	21.6%
	Kanagawa	213	14.2%
	Aichi	167	11.1%
	Kyoto	55	3.7%
	Osaka	195	13.0%
	Hyogo	122	8.1%
	Fukuoka	113	7.5%
Educational Level	Junior High Sch. (or equivalent)	68	4.5%
	High Sch. (or equivalent)	448	29.9%
	College	176	11.7%
	University Degree (Undergraduate and Postgraduate)	806	53.8%
Marital Status	Single	572	38.2%
	Married	926	61.8%
Household Size	1	271	18.1%
	2	685	45.7%
	3	296	19.8%
	4	136	9.1%
	> 4	110	7.3%
Living with Children	Yes	447	29.8%
	No	1051	70.2%
Yearly Income (before taxes)	< 2 million yen	160	10.7%
	2-4 million yen	295	19.7%
	4-6 million yen	355	23.7%
	6-8 million yen	260	17.4%
	8-10 million yen	180	12.0%
	10-12 million yen	94	6.3%
	>12 million yen	154	10.3%
House Type	Apartment	703	46.9%
	House	795	53.1%
Job	Corporate Worker	610	40.7%
	Housewife/husband	296	19.8%

	Part-timer	204	13.6%
	Unemployed	170	11.3%
	Self-Employed	81	5.4%
	Others*	137	9.1%

Note: 1 million yens were approximately 7000 UDS in September of 2022 (the period when the data was collected).

Note: "Others" includes professions like public officer, lawyer, accountant, teacher, designer, and company director.

4.3.2 Data Reduction

The Principal Component analysis was done for a set of 17 PEB, however due to high cross-loadings and low loadings 3 behaviours were excluded during the PCA and the procedure was repeated for the restricted group. The final results are visible in Table 4.2, where the 14 behaviours were divided into 3 factors. The sample passed the tests regarding PCA fitness to the data, with a p-value = 0 on Bartlett's test, a KMO = 0.88, and a Cronbach's Alpha index of 0.88 (> 0.70). As mentioned earlier, according to the Food Recovery Hierarchy the most preferred behaviours relate to preventing waste production, either at a purchase or usage level. As expected, one of the factors comprises waste prevention behaviours in-house (PREV) such as not throwing away food, avoiding leaving leftovers, and planning the meals. The second factor covers other levels of the hierarchy like giving food to neighbours, feeding animals with leftovers, using a machine to reduce the volume of the waste, and composting organic waste. Thus, it was named after diverging waste from landfills (DIV). The last factor covers the prevention of food waste at the in-store level (making a shopping list) and other aspects of ethical consumerism (EC). It includes behaviours which help the reduction of pollution at the moment of purchase like making a shopping list, bringing their own water bottle, choosing products with less packaging, using eco-friendly goods, using recycled or refillable products, and purchasing organic food. Thus, the results support the theoretical categories hypothesized (Figure 4.2).

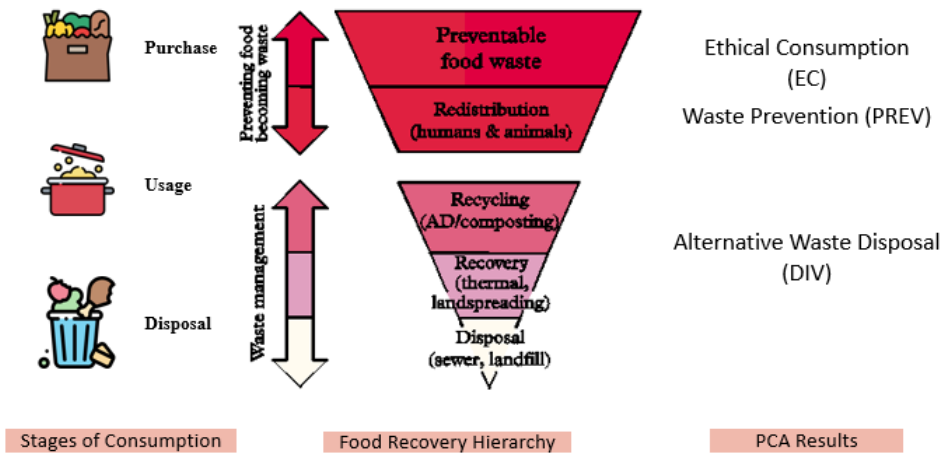

Figure 0.2 Consumption Stages, PCA Results, and Food Recovery Hierarchy (adapted from UK Parliament (2014))

Apart from PEB3 and PEB9, all the items had a loading close to/or superior to 0.7 implying a well-defined structure (Hair et al. 2018). Despite the loadings of PEB3 and PEB9 being lower than the rest of the items, they meet the minimal level for interpretation (+-0.3 to +-0.4) (Hair et al. 2018). It is relevant to mention that item PEB3 had a loading superior to 0.3 on both EC and PREV resulting in a ratio of variance of 1.78 (0.442/0.332). According to Hair et al. (2018), this ratio may imply a potential cross-loading. However, as the item was theoretically aligned with the designated factor (prevention in-house), it was kept. Moreover, as previously mentioned under a clustering analysis the independence of the factors is not a strict assumption as in other multivariate techniques.

Table 0.2 Items' average, standard deviation, Principal Component Analysis' (PCA) factor loadings and explained proportion.

ITEM	Mean	Std.	DIV	PREV	EC
PEB1: Do you avoid throwing away food?	4.79	1.15	0.00	**0.97**	-0.11
PEB2: Do you avoid leftovers?	4.83	1.16	-0.05	**0.96**	-0.14
PEB3: Do you plan your meals?	4.12	1.35	0.11	**0.44**	0.33
PEB4: Do you try to reduce food waste?	4.20	1.44	0.02	**0.75**	0.10
PEB5: Do you usually give food to your neighbours?	2.12	1.50	**0.77**	-0.04	0.14
PEB6: Do you use leftovers or scraps to feed the animals/pets?	1.77	1.53	**0.94**	0.00	-0.11
PEB7: Do you use a volume reducer waste machine?	1.89	1.53	**0.90**	-0.01	-0.05
PEB8: Do you engage in composting/reusing organic waste?	1.91	1.55	**0.80**	-0.01	0.05
PEB9: Do shop with a shopping list?	3.70	1.67	0.17	0.20	**0.42**
PEB10: Do you bring your own water/tea bottle when going out?	3.66	1.86	-0.10	-0.09	**0.74**
PEB11: Do you opt for products with less packaging?	3.60	1.55	-0.03	-0.07	**0.90**
PEB12: Do you use eco-friendly goods?	3.43	1.49	0.01	-0.09	**0.93**
PEB13: Do you opt for recycled or refillable products?	4.20	1.44	-0.23	0.16	**0.69**
PEB14: Do you purchase organic food?	3.09	1.51	0.15	-0.12	**0.80**

PEB15: Do you bring your own bag when shopping?	5.02	1.46	-	-	-
PEB16: Do you avoid water running?	4.43	1.36	-	-	-
PEB17: Do you recycle?	4.96	1.36	-	-	-
SS Loadings	-	-	3.05	2.64	3.60
Proportion Var.	-	-	0.22	0.19	0.26
Cumulative Var.	-	-	0.22	0.41	0.66
Proportion Explained	-	-	0.33	0.28	0.39
Cumulative Proportion	-	-	0.33	0.61	1.00

Notes: DIV: food recycling actions that diverge waste from landfills; PREV: in-house waste prevention; EC: ethical consumption

4.3.3 Clustering and Profiling

The value of the Hopkins test was 0.99 implying a pattern may exist within the observations. Given the low to moderate correlation between factors (<0.6) (Mukaka 2012) (Table 4.3), a Euclidean distance was used during the clustering process. As mentioned on the methodology section, this analysis used a hierarchical clustering technique followed by a K-Means. Based on the indices provided by the Nbclust package (minimum number of clusters was set to 3 and the maximum 12), the suggested number of clusters was either 3 (4 out of 23 indices) or 4 (5 out of 23 indices). Other 4 out the 23 indices suggested 6 clusters, but this option was not considered as it would be harder to interpret than the other 2 options. Therefore, initially, the algorithm was executed for both 3 and 4 cluster options. After running the algorithm with both alternatives, clearer groups were found under 4-cluster approach, and so the analysis proceeded with this setting (Figure 4.3). When 3 clusters were considered, DIV did not differ between the second and third clusters, and both PREV and EC of Clusters 1 and 2 were similar.

Table 0.3 Spearman Correlation Matrix between PCA factors

Spearman Correlation	PREV	DIV	EC
PREV	1.00		
DIV	0.12	1.00	
EC	0.57	0.36	1.00

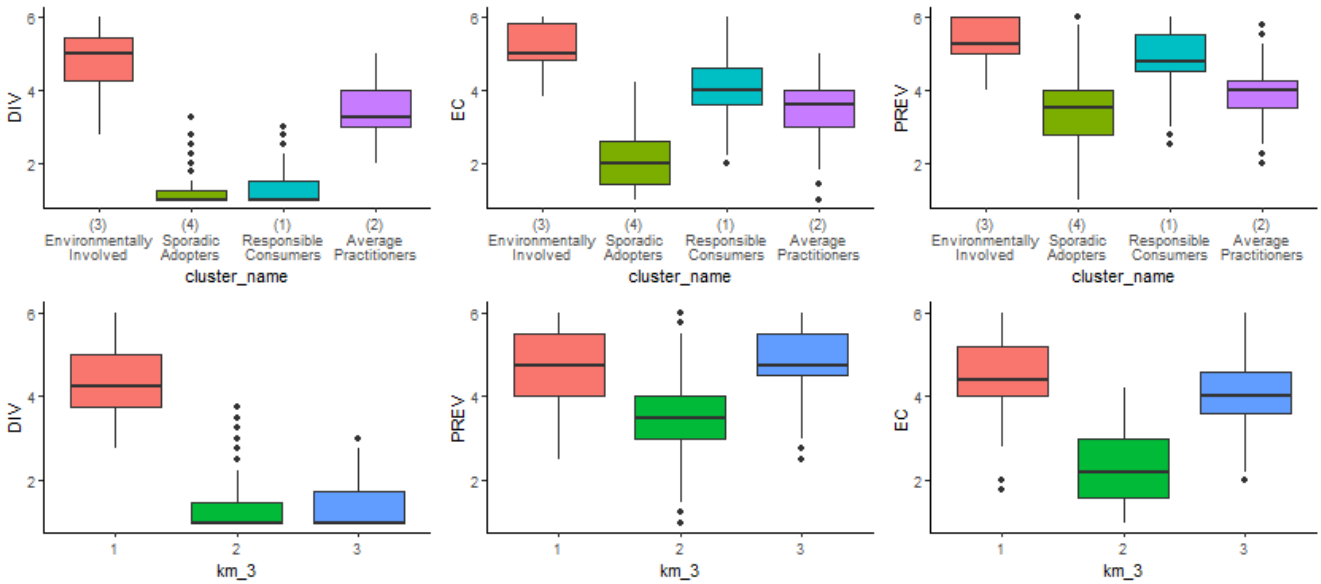

Figure 0.3 Factor's boxplots for a 4 and 3 clusters solution.

Table 4.5 shows the key features of the obtained clusters including their size, centres' coordinates, and major attributes. To evaluate if the factors were significantly different across groups, a Kruskal-Wallis' test followed by Dunn's test with a Bonferroni correction (once there are more than 2 groups) for the pairwise group comparisons were done. All the null hypotheses were rejected at a p-value < 5% implying all the groups have distinct behavioural profiles regarding their ethical consumption, food waste prevention and food recycling habits (Table 4.4). The four clusters were named: Sporadic Adopters, Average Practitioners, Responsible Consumers, and Environmentally Involved. The Environmentally Involved represented 10.3% of the total sample, the Average Practitioners 13.4%, the Sporadic Adopters 25.4%, and finally the Responsible Consumers comprise approximately half of the sample (50.9%).

Table 0.4 Kruskall Wallis' Test and Dunn's Test Results (bold values represent situations where the test hypothesis is rejected).

Variable	Kruskal Wallis' Test	Dunn's Test per pair of clusters (z_score; p_value)					
	(chi_squared; p_value)	1-2	1-3	1-4	2-3	2-4	3-4
DIV	921.55; 0.000	-19.70; 0.000	-22.00; 0.000	4.10; 0.000	-3.56; 0.002	20.87; 0.000	23.05; 0.000
PREV	698.97; 0.000	13.40; 0.000	-5.94;0.000	21.86; 0.000	-14.80; 0.000	3.58; 0.002	19.86; 0.000
EC	940.78; 0.000	7.09; 0.000	-10.3; 0.000	25.52; 0.000	-13.74; 0.000	11.92; 0.000	26.29; 0.000
AGE	85.56; 0.000	6.10; 0.000	6.30; 0.000	6.92; 0.000	**0.68; 1.000**	**-0.57; 1.000**	**-1.28; 1.000**

Compost INT	267.86; 0.000	4.59; 0.000	9.67; 0.000	-9.28; 0.000	4.58; 0.000	-10.85; 0.000	-15.04; 0.000
Balanced Meals	4.12.73; 0.000	7.94; 0.000	-6.94; 0.000	16.17; 0.000	-11.60; 0.000	4.42; 0.000	17.05; 0.000
Eating Vegetables	384.27; 0.000	12.17;0.000	**-2.45; 0.085**	15.62; 0.000	-11.03; 0.000	**0.17; 1.000**	12.53; 0.000
Salty Foods	418.67; 0.000	6.88; 0.000	-7.35; 0.000	15.37; 0.000	-11.16; 0.000	4.81; 0.000	16.90; 0.000
Fatty Foods	418.67; 0.000	5.19; 0.000	-8.65; 0.000	15.77; 0.000	-10.98; 0.000	6.62; 0.000	18.36; 0.000
Additives	448.50; 0.000	5.78; 0.000	-7.95; 0.000	16.96; 0.000	-10.96; 0.000	6.96; 0.000	18.50; 0.000
Vegetarian	257.78; 0.000	-6.11; 0.000	-14.08; 0.000	**2.35; 0.111**	-7.09; 0.000	7.25; 0.000	14.58; 0.000

The Responsible Consumers group (Cluster 1) has respondents that, even though they rarely engage in waste diverging behaviours, frequently try to reduce their waste and leftovers. Moreover, they sometimes (more frequently than not) buy products that have, in principle, a smaller environmental impact than a conventional one. For instance, they regularly tried to buy organic vegetables instead of regular ones or purchase refillable/reusable products instead of single-use packages (products). This group was the only one in which the percentage of women superior to men (63% versus 37%) and where the concentration of housewives/husbands and part-timers was the highest. This could justify the high adoption of prevention behaviours and consumption related PEB, as they are chores related with household duties (Qian et al. 2020; Nakamura et al. 2022). As expected, given the percentage with housewives/husbands, and similarly to what happened in group 2 and group 3, the majority of the cluster was married. Age was found statistically different across the clusters (Kruskal-Wallis' test), as this cluster's respondents were older than in the other groups. Nonetheless, not all the hypotheses of the Dunn's test to age were rejected (Table 4.4).

A person belonging to group 2 (Average Adopters) was characterized by engaging in all PEB somewhat frequently. Mostly men working in a corporate job, had lower practice rates than group 1 both on prevention and ethical consumption PEB rates. On the contrary, the engagement in diverging actions is substantially higher, though not as much as group 3. As the previous literature suggested, sometimes the engagement in one behaviour can have a negative spillover effect in another PEB (Truelove et al. 2014; Nash et al. 2019; Maki et al. 2019; Kumar et al. 2023). For example, recycling may have an adverse effect in which people end up consuming more resources (Ma et al. 2019; Oláh et al. 2022). Similarly, it may be that people who have a recycling

plan for leftovers or spoiled food end up relaxing their prevention actions (Tucker and Farrelly 2016).

Group 3, the Environmentally Involved, was the most balanced in terms of gender, however the percentage of men was slightly higher. It was also the group with the largest households, and the highest percentage of children (Table 4.5). This cluster reported high frequency rates in all PEB. Even though the present study did not assess the waste quantity per se, and it was based on self-reported qualitative data, it seems that this cluster was the one which tried to have the lowest environmental footprint. It was the group that had a higher percentage of people in their 30's (36.8% of the group) when compared with group 1's 15.0%, group 2's 30.8% and the Sporadic Adopters' 26.8%. In fact, while Environmentally Involved respondents accounted for 10.3% of the total sample, they represented 16.8% of the people in their 30's. Interestingly, it was also the group with more people over 70-years-old percentage wise (and absolute wise apart from Cluster 1), resulting in a larger age variance than in the other groups. This is a nuance that may be camouflaged by looking only at the cluster's average age (Table 4.5) or at the results of the age Dunn's test once it is a non-parametric rank test comparing the groups' mean ranks (Table 4.4).

The final cluster, the Sporadic Adopters, had the lowest PEB practice rates. The second largest cluster was composed mostly by men (69%) working in a company (44%) or unemployed (18%). It was the group with the highest percentage of unemployed respondents and with the lowest income available. It also had fewer children and less married people than the other clusters. The age distribution was similar to the Average Practitioners (Table 4.5).

In terms of place of residence, most of the groups seemed to follow the overall sample distribution (Table 4.1, 4.5). However, only 5% of the group 3 lived in Saitama (contrary to the sample total of 11%), while the percentage of people residing in Tokyo, Kanagawa, and Aichi prefectures was slightly higher. The percentage of Tokyo residents within group 2 and 3 was also higher than in the total sample. Groups 1, 2, and 3 second most populated region was one of the prefectures adjacent to Tokyo, whereas after Tokyo, the Sporadic Adopters tended to live in Osaka.

From a factor's perspective, prevention behaviours seemed to be the most adopted, followed by responsible consumerism and finally diverging behaviours (Figure 4.3). Additionally, Figure 4.4 includes frequency rates of water management, waste recycling (plastic, cans, bottles, cardboard), and the use of one's own bag while shopping (these were the behaviours which were excluded on the PCA step) as well as dietary concerns of the respondents. Responsible Consumers seemed to have high practice rates on these PEB, being the "*My bag*" PEB more frequent than on the Environmentally Involved. The latter is not unexpected as housewives/husbands are commonly responsible for chores like grocery shopping. The Average Practitioners kept the trend

of medium to high rates. Finally, Sporadic Adopters had interesting results when compared with the Average Practitioners. Even though the latter group had more average to avid practitioners, the former had a larger fraction of people who try to save as much water as possible and bring their own bag when shopping. These rates on water saving are aligned with the high "eco-friendliness" perception reported by this cluster (Table 4.6), but also with fact that water saving and the use of the own bag (in Japan, many supermarkets charge extra for the plastic bag) can contribute directly for money saving.

Table 0.5. Clustering Results and Clusters' Profiles

Attribute		(1) Responsible Consumers	(2) Average Practitioners	(3) Environmentally Involved	(4) Sporadic Adopters
Cluster Size		762	201	154	381
DIV (Centre)		1.32	3.35	4.85	1.19
PREV (Centre)		4.86	3.94	5.32	3.33
EC (Centre)		4.09	3.51	5.17	2.03
Gender	Women (%)	62.9%	38.8%	45.5%	30.7%
	Men (%)	37.1%	61.2%	54.4%	69.3%
Job	Corporate Worker (%)	31.5%	57.2%	55.8%	44.4%
	Part-Time (%)	17.2%	8.5%	8.4%	11.3%
	Housewife/husband (%)	28.0%	9.5%	14.9%	10.8%
	Unemployed (%)	10.8%	6.0%	5.2%	17.8%
	Self-Employed (%)	4.6%	6.0%	8.4%	5.5%
Yearly Income (before taxes)	< 2 million yen (%)	8.9%	9.5%	7.1%	16.3%
	2-4 million yen (%)	20.6%	19.9%	11.7%	21.0%
	4-6 million yen (%)	27.6%	19.9%	21.4%	18.9%
	6-8 million yen (%)	16.9%	19.9%	14.9%	17.8%
	8-10 million yen (%)	12.5%	13.4%	10.4%	11.0%
	10-12 million yen (%)	5.0%	8.0%	13.6%	5.0%
	>12 million yen (%)	8.5%	9.5%	20.8%	10.0%
Marriage (%)		68.8%	57.7%	65.6%	48.6%
Children (%)		29.3%	32.8%	45.5%	23.1%
Age (mean)		53.1	47.4	47.2	47.9
Household (mean)		2.6	2.7	3.1	2.6
1st Most Populated Prefecture		Tokyo (19.2%)	Tokyo (26.9%)	Tokyo (26.0%)	Tokyo (22.0%)
2nd Most Populated Prefecture		Kanagawa (15.1%)	Kanagawa (12.4%)	Kanagawa (16.2%)	Osaka (16.0%)
3rd Most Populated Prefecture		Saitama (12.3%)	Saitama (12.4%)	Aichi/Osaka (16.0%)	Kanagawa (12.6%)
Notes: Percentages of other jobs (e.g., teachers or self-employed) were omitted from the table					

Moving to the burdensome and positive impact perceptions, it is relevant to mention that the overall ranking of the most eco-friendly PEB within the clusters were calculated as the sum of the following: $3 * N_{ij1} + 2 * N_{ij2} + 1 * N_{ij3}$, being N_{ijg} the number of people in the cluster $i \in I = \{1,2,3,4\}$ that classified the behaviour $j \in J = \{1,2,\dots,11\}$ in the position $g \in G = \{1,2,3\}$.

When asked to pick three out of eleven behaviours (compost, "*My bag*", "*My bottle*", choose eco-friendly goods, recycle, choose refillable products, purchase organic food, reduce food waste, use public transportation, and save water), depending on which they considered the most eco-friendly, all the groups mentioned the reduction of food waste. The Responsible Consumers considered reducing food waste, recycling, separating waste, and bringing one's own bag when shopping the most positive behaviours. The Average Practitioners and the Environmentally Involved pointed out composting, reducing food waste, and bringing one's own bag when going shopping ("*My bag*"). Finally, the Sporadic Adopters' rank included food waste reduction, recycling, and the wise use of water resources (Table 4.6).

Table 0.6. Eco-Friendly and Bothersome Ranking

Position	(1) Responsible Consumers	(2) Average Practitioners	(3) Environmentally Involved	(4) Sporadic Adopters
1st Eco-Friendly	Food waste reduction	Food waste reduction	Compost organic waste	Food waste reduction
2nd Eco-Friendly	Separate and recycle waste	Compost organic waste	Food waste reduction	Separate and recycle waste
3rd Eco-Friendly	*"My bag"*	*"My bag"*	*"My bag"*	Make a wise use of water resources
1st Burdensome	Compost organic waste	Compost organic waste	Compost organic waste	Compost organic waste
2nd Burdensome	Purchase organic food	Purchase organic food	Food waste reduction	Purchase organic food
3rd Burdensome	Use eco-friendly goods	Food waste reduction	Purchase organic food	*"My bottle"*

Regarding burdensome (Tables 4.6 and 4.7), all groups positioned (on a 6-point Likert-scale) composting as the most demanding behaviour. Purchasing organic food was also mentioned across all clusters. Although this study does not specify what kind of burden these PEB have on people's routine, based on previous literature and Chapter 3 model results, it would be expected that on the case of organic food it is related with its price (Sakagami et al. 2006; Chekima et al. 2019; Dentsu Macromill Insight Inc. 2021; Dorce et al. 2021). This chapter's results seem to be aligned with latter, since the Sporadic Adopters were the ones with the lowest available income

and highest reported burden level towards organic food. On the other hand, the burden reported towards organic food by the Responsible Consumers was the lowest. Responsible Consumers, in general, tended to report the lowest burden levels when compared to the rest of the sample. For instance, while Responsible Consumers commonly answered that PEBs were not much of a burden (on a 6-point Likert-scale, the median value of 7 PEB was 2), the other clusters more often reported some kind of burden (3 and 4 in the Likert-scale). Apart from composting and the purchase of organic food, the Environmentally Involved tended to report the highest levels of burden (Table 4.7).

Table 0.7 Bothersome average score per Cluster (bold values are the top 3 highest values)

PEB	Environmentally Involved	Sporadic Adopters	Responsible Consumers	Average Practitioners
Compost	**4.1**	**4.51**	**4.43**	**3.8**
Reduce Food Waste	**3.77**	3.24	2.65	**3.53**
"*My bag*"	3.57	2.92	1.94	3.13
"*My bottle*"	3.69	**3.59**	2.54	3.52
Choose few/no package items*	3.58	3.15	2.34	3.39
Choose eco-friendly goods	3.71	3.55	**2.8**	3.49
Recycle	3.6	3.2	2.43	3.42
Choose refillable goods	3.62	3.2	2.41	3.34
Reduce waste as much as possible	3.61	3.37	2.55	3.42
Purchase organic food	**3.72**	**3.98**	**3.38**	**3.54**
Use public transportation	3.66	3.1	2.75	3.44
Save water	3.58	3.06	2.42	3.4
*this item was not included on the list for the top 3 most eco-friendly behaviours				

Moreover, food waste reduction and compost organic waste were both considered extremely eco-friendly behaviours and quite demanding by the Average Practitioners and the Environmentally Involved. This demonstrates that despite the additional burden, they still decided to practice those PEB, either for environmental reasons or others. Composting has been considered, and atypical PEB highly influenced by non-environmental factors (Edgerton et al. 2009). For example, studies like Tucker and Speirs (2003) and Loan et al. (2019) mentioned gardening and farming as a relevant point for engaging in composting. The present analysis somewhat supports such literature once groups with a higher gardening/farming interest were also the ones adopting more frequently waste diverging behaviours (Figure 4.7). These factors behind composting decisions will be further addressed in the following chapter.

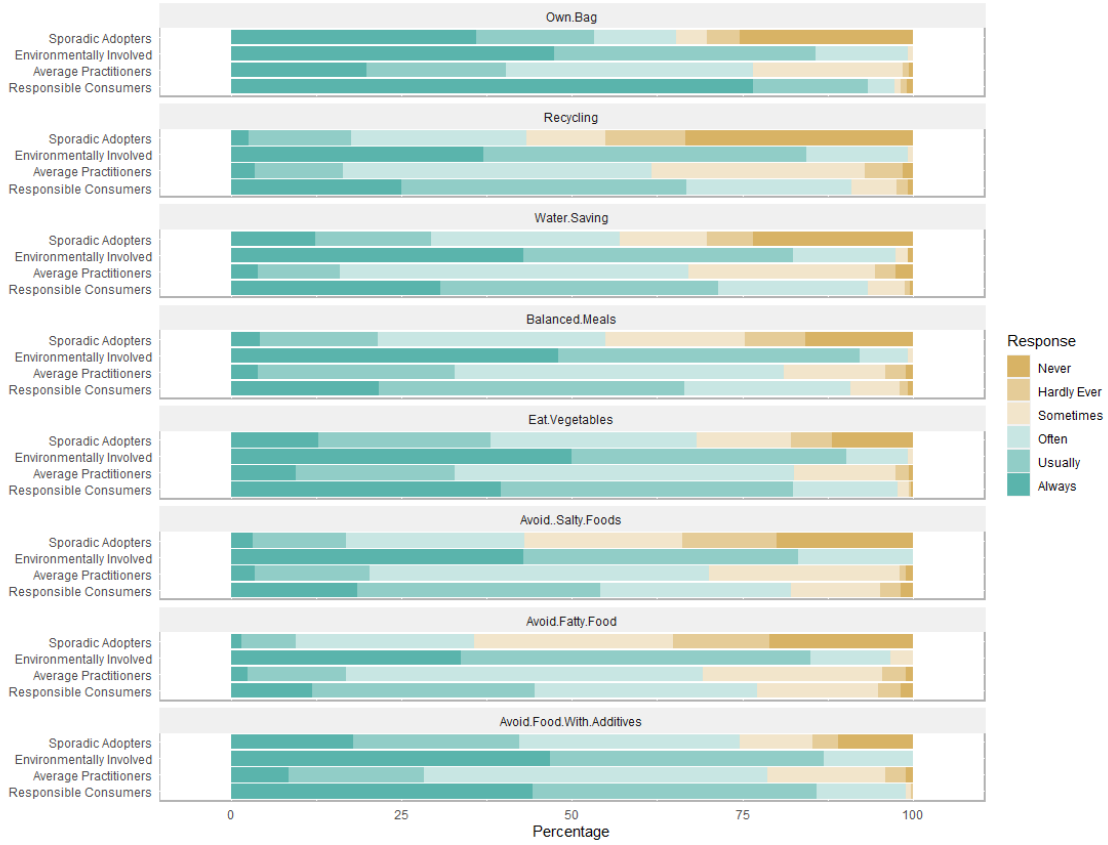

Figure 0.4 PEB excluded during the PCA and Dietary Concerns

Regarding eating habits and dietary concerns, groups with more housewives/husbands were the ones with the highest cooking frequencies (Figure 4.5). The fact Sporadic Adopters ate out less than other groups is congruent with the reported income and unemployed rates. On the other hand, the Environmentally Friendly group, where around 20% of the group declared to receive more than 12 million yen/year, ate out more frequently. Although overall the vegetarian meals frequency was extremely low, the Environmentally Involved and Average Practitioners tended to do it more times than the others (Figure 4.5). Eating vegetables and having balanced meals were the highest dietary concerns across all groups (Figure 4.5). This may be traced back to the traditional dietary culture of Japan ("*washoku*") where the basic set meal ("*teishoku*") is regarded as well-balanced and nutritious (Kumakura et al. 2023; MAFF 2023b). A traditional set meal should include a soup (usually miso soup), a staple dish (e.g., rice), a main dish (rich in protein products like soybeans, meat, or fish) and a vegetable/pickle-based side dish nutritious (Kumakura et al. 2023; MAFF 2023b). To this set seasonal fruits and milk products may be added nutrition (MAFF 2023b). The differences between each group dietary concerns were statistically significant on the Kruskal-Wallis' Test and Dunn's pairwise comparison for all the aspects analysed except for the pairwise comparison between the 1st and 3rd clusters and the 2nd and 4th groups on the attention given to vegetables (Table 4.4). Environmentally Involved and

Responsible Consumers reported higher concerns about making healthy decisions. Sporadic Adopters were the ones that registered less concern on all the aspects analysed.

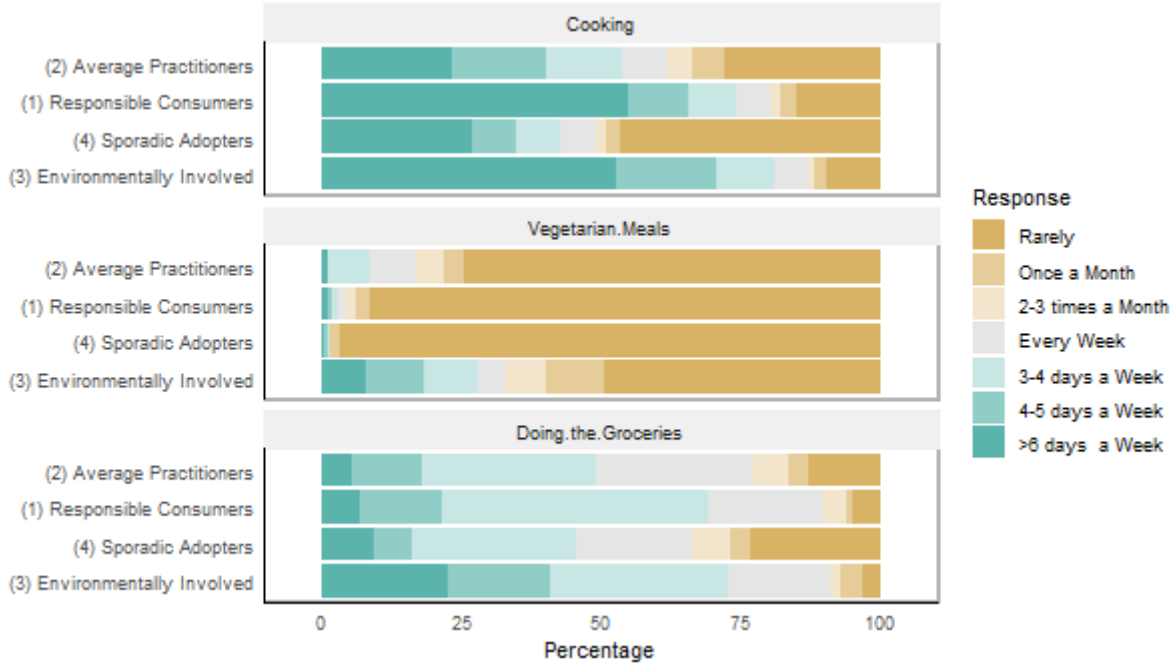

Figure 0.5 Food Related Habits by Cluster

Finally, when asked about their intention on starting/continuing composting organic and kitchen waste the answers portrayed an interesting picture. On the Kruskal-Wallis' test and pairwise Dunn's test, the answers were statically different (Table 4.4) and, as visible in Figure 4.6, the clusters that had been reported doing composting, were the ones with the lowest will to continue/start, whereas the Sporadic Adopters, who tented to have low DIV adoption rates, reported the highest intentions.

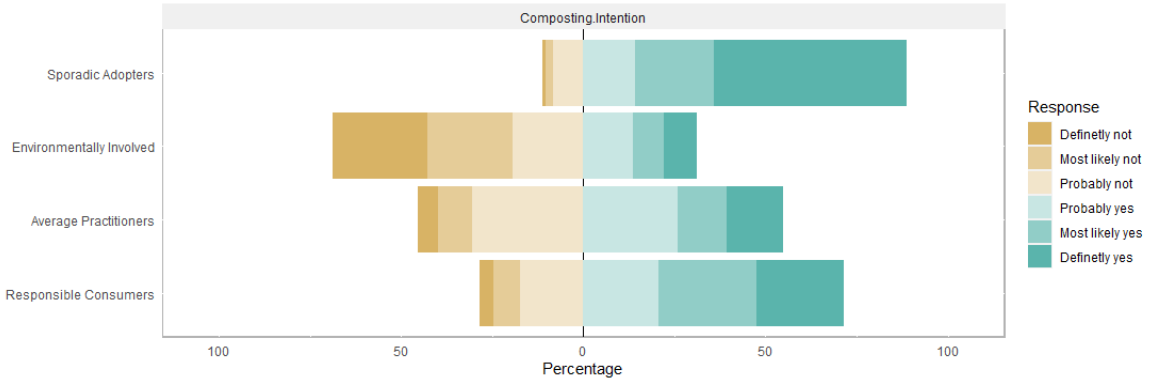

Figure 0.6 Composting Intention

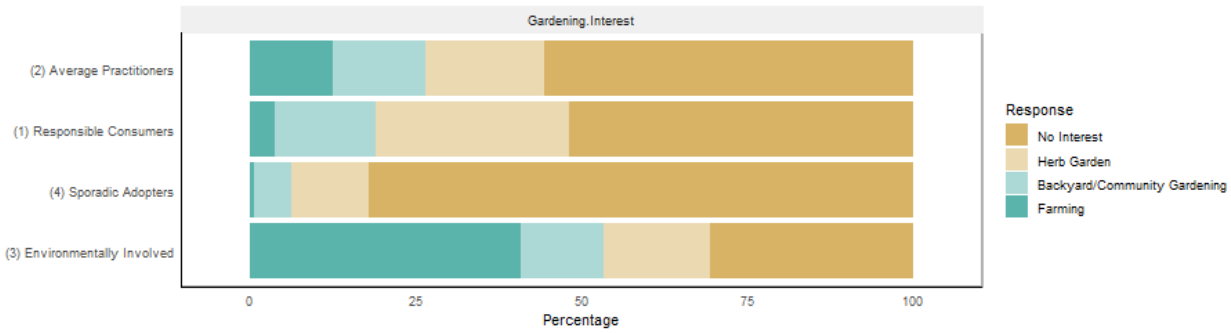

Figure 0.7 Gardening/ Farming Interest

4.4 Discussion

4.4.1 Theoretical Contributions

Starting with the theoretical contributions, this study is one of the few that presents a holistic perspective on the food consumption steps (purchase, usage, and disposal). Contrary to previous works, it not only included prevention measures but also covered other stages of the food recovery hierarchy, such as giving food to neighbours, feeding the animals with scraps, and composting organic and kitchen waste.

4.4.2 Social and Management Contributions

From a social and management perspective, several points should be discussed. The clustering algorithm found 4 distinct clusters given their practice rates of the studied PEB. The first remark relates to the difference in the cluster's size. Only a small part of the sample belongs to the Average Practitioners and even a smaller percentage to the Environmentally Involved cluster. These results are somewhat in agreement with Kurisu and Bortoleto (2011) and Liu et al. (2016), which mentioned low composting adoption rates in Japanese society. Kurisu and Bortoleto (2011) also mentioned differences in PEB adoption rates across Aichi, Osaka, and Tokyo prefectures. Notwithstanding the geographic distribution of the clusters was quite similar to the original sample with the exception of the Sporadic Adopters' concentration in Osaka, and the Environmentally Involved having a slightly higher percentage of respondents living in Tokyo, Kanagawa, and Aichi. Recently, in Chigasaki city (Kanagawa), the waste disposal began being charged by weight with incentives on composting (RareA 2022), and Nagoya city (Aichi) has funding for Non-Profit Organizations (NPOs) working with food waste recycling (Nagoya City Hall 2023). Several other cities within these prefectures have available composting grants and

incentives for households who wish to purchase composters or food drying machines (Island land Co. Ltd 2023), which can be related to the geographic distribution of the latter cluster. Nonetheless, marketing approaches (e.g., direct communication from city officials) often influence the success of the policies (Hotta and Aoki-Suzuki 2014) and such aid or incentives are at the city level. The used dataset did not have enough specificity or information to properly assess the effectiveness of such campaigns and to further explore how they impacted the current analysis. However, in Chapter 7, an exposition of the types of alternatives and marketing strategies being used to promote sustainable lifestyles in Japan is provided.

Both Qian et al. (2020) and Nakamura et al. (2022) stated that, in Japan, women tended to engage more in food waste prevention behaviours. The results of the current chapter are aligned with previous literature, but an interesting nuance was revealed once alternative disposal actions were included. The largest cluster, the Responsible Consumers, were mostly housewives or women with part-time jobs. This was in agreement with the high cooking percentage and the high adoption of behaviours related to consumption, once doing the groceries falls under household chores. They also reported paying attention to their dietary options more often. Similarly, the Environmentally Involved, which was the second group with a higher percentage of housewives, also seemed to cook frequently and report higher practice rates on ethical consumption and waste prevention PEB. On contrary, Average Adopters, which were mainly married men, had lower PREV and EC rates than the latter clusters, but had higher DIV rates than the Responsible Consumers. This may be derived from the relaxation point mentioned previously but can also be related to the gender dichotomy of the house tasks in Japan (Ono 2018). This implies that even if environmentally concerned, they have less chances of engaging in green purchase or waste prevention acts.

Previous literature, including Chapter 3's results, related ethical food consumption and food waste prevention to healthy consciousness (Savelli et al. 2020; Tandon et al. 2021; Dorce et al. 2021) and segmentation works have often found groups that had high PEB engagement also had higher dietary concerns (Burke et al. 2014; Scalvedi et al. 2018; Asvatourian et al. 2018). The present findings confirm such tendencies to a certain extent. It seems that also in Japan, the Environmentally Involved, in accordance with the LOHAS lifestyle, were both health and environmentally conscious in all the aspects analysed. However, the relationship between food disposable alternatives and eating habits does not seem as straight forward and further work on should address this component. While the Average Practitioners did have a higher adoption rate on DIV than the Responsible Consumers, the latter group had a higher food involvement in all the other accessed behaviours. Being the Responsible Consumers group composed by a higher percentage of older women, it showed similar characteristics to food involved groups identified in Italy, Germany, the Netherlands, Denmark, Sweden, and Australia (Burke et al. 2014; Scalvedi

et al. 2018; Asvatourian et al. 2018; Aschemann-Witzel et al. 2021). Aschemann-Witzel et al. (2021) and Burke et al. (2014) also identified groups with low food involvement which seem to share traits with the Sporadic Adopters on regards of income, gender, and behavioural pattern. The profiles identified in these chapter also share some resemblance with the clusters from Chapter 3. For instance, the predominant clusters in both situations were older and showed a relatively high engagement in all factors except with for the ones related to growing their own food (in Chapter 3) and food waste recycling (in this chapter). Although not the same factors, based on previous research, one can pose that the probability of recycling food as fertilizer increases with the engagement in vegetable gardening. Moreover, groups with higher engagement in the latter PEB, also had a higher percentage of children cohabitation and overall lower engagement in PEB seemed was also associated with groups with lower income available in both chapters.

Moreover, the present analysis showed interesting results regarding the perceived burden level of each cluster, as the Responsible Consumers had the lowest stated levels and the Environmentally Involved had the highest. One possible explanation may derive from the higher concentration of housewives/husbands in the Responsible Consumers' group, thus easing burdens associated with inflexible or oversaturated time schedules. Aspects like inconvenience and lack of time have been reported as barriers to PEB engagement (Hjelmar 2011; Wu et al. 2019) and, as previously mentioned in Chapter 2, Japan has a physically and mentally demanding work culture, which has even resulted in death cases ("*karoshi*") (Ono 2018; Kawashukuda 2022). Another explanation for the distinct burden level across groups might be derived from the sense of responsibility or guilt of oneself. The Japanese word used on the survey was "*futan*" which can also be read as bearing a responsibility. Therefore, the burden levels reported by the Environmentally Involved are aligned with literature that has used the sense of guilt and perceived responsibility to explain PEB adoption (Kurisu 2015). Nonetheless, further analysis on the clarification of these burdensome dimensions is needed.

In agreement with scholars like Tucker and Speirs (2003), Loan et al. (2019), and Kunszabó et al. (2022), the interest in gardening/farming was parallel to the adoption levels of food recycling methods. Both Average Adopters and Environmentally Involved mentioned composting as quite demanding, but extremely eco-friendly, and despite currently engaging in such PEB they did not seem particularly enthusiastic about continuing (at least when comparing with other clusters). This reinforces the complexity of the trade-offs related to PEB. These differences in the intention may derive from factors like practical knowledge or by a novelty aspect from the respondents that were not familiar with the concept prior to the survey (on the survey a definition about composting was given). This gap between intention and the actual practice seems to be in agreement with the results of Tanaka et al. (2011). The latter found

differences between the composting intention effect on the actual behaviour among prior composting practitioners and non-practitioners. However, the study was narrowed to Shisō city in Hyogo Prefecture. To extent the research about what drives composting adoption, the next chapter will be further study this PEB based on sample used on this chapter.

This gap also points out that theoretical behavioural modelling of composting data collected only at one point in time should be done carefully. There seems to exist a large gap between intention and the behaviour, the Theory of Planned Behaviour (TPB) (Ajzen 1991), which posed intentions precede behaviour. This may not be the most suitable framework, at least in the Japanese case.

The people from the Environmentally Involved cluster were the ones with larger households and more children. These results are somewhat contradictory with previous research where household size and children were positively related with food waste produced (Boulet et al. 2021; Nakamura et al. 2022). Nevertheless, from a qualitative perspective it can represent that people try harder to prevent waste or diverge waste from incineration (or landfills) despite producing more of it. Aligned with the current results, Iijima and Egahiro (2014), Coogan (2019), Honami et al. (2022), and Yang et al. (2022) did point out how children may contribute to the purchase of organic food and to engagement in gardening and composting. However, the current study did not examine in detail how parenting might have changed throughout the years. For instance, parents of young children may pay more attention to fostering their children's connection with nature, whereas in later years, both the children's and parents' focus may shift to school performance, club activities, and cram school (Ishida et al. 2005).

This chapter results support the PEB hierarchy proposed by Wooliscroft et al. (2014) to a certain extent. While people which engaged "costly" PEB also adopted mainstream practices, it is important to keep in mind what was earlier mentioned about the opportunity of engaging in such behaviours. Additionally, both Average Practitioners and Environmentally Involved ate plant-based meals more frequently. This was in line with idea that reducing meat consumption or adopting plant-based diets have environmental benefits (Chai et al. 2019; Cheah et al. 2020). It seems, nonetheless, that despite recent increasing trends on plant-based diets in countries like UK (Alae-Carew et al. 2022), this is not the case in Japan yet.

Across the groups, the burden of both composting and purchasing organic food was unanimous. According to Kurisu and Bortoleto (2011) and Dentsu Macromill Insight Inc. (2021) price can be a relevant barrier to the purchase of organic products. Thus, having efficient marketing strategies, relying on promotional campaigns, mascots, celebrities, or tasting campaigns are some of the examples of possible ways to boost the awareness about these products' pros and cons. This allows for a more educated choice, and a better understanding of the trade-

off between the price paid and product quality. Such campaigns might be especially effective for Average Practitioners, who seem to have an interest in eco-friendly products but not to the same extent as both Environmentally Involved and Responsible Consumers. Some of these points were already mentioned in the previous Chapter's implications.

Kim et al. (2019) and Sewak et al. (2021) discussed different social marketing components to boost waste reduction, waste-sorting, and composting. The present research contributes to the segmentation component. From a general perspective, taking into consideration the clusters' dimensions, the profile of the Responsible Consumers and Sporadic Adopters should be prioritized. Responsible Consumers were mostly housewives in their 50s and 40s who did not compost but consumed in an ethical way. Thus, using the purchasing moment to foster food recycling and showing the link between organic food and food recycling can be an effective way to promote composting to this group. Promoting it as a community activity may also be beneficial. As the Sporadic Adopters seem to be more sensitive to money and convenience issues, waste charges, composting incentives, or organic waste collection policies should be prioritized. For example, cities like Nagai in Japan (Okayama et al. 2020, 2021; Kawai et al. 2020), Porto in Portugal (Weidner et al. 2020), and Seattle in the US (Pai et al. 2019), have organic waste collection programs, Chigasaki city has a waste charge policy (RareA 2022), and cities like Hamamatsu (Shizuoka Prefecture) in Japan subsidize the purchase of several types of composting containers (Hamamatsu City Hall 2023).

Moreover, as the Environmentally Involved and the Average Practitioners showed low intention to continue composting, having different focus groups and programs to see what strategies are more effective to easing the sustained adoption of those PEB might be beneficial. For instance, while many towns give incentives to purchase a composter container, not many finance the materials needed to sustain this activity. Additionally, the Environmentally Involved had a higher percentage of children cohabitation than the other groups, so programs targeting children's education may boost the PEB adoption of the whole family. Despite some papers on children's education and PEB adoption (Zsóka et al. 2013; Hirose 2015; de Leeuw et al. 2015; Izumi et al. 2020), more research on the field is needed especially due to nuances between countries' education systems and cultural values (e.g., *"mottainai"*).

4.5 Chapter Conclusion and Future Research

The present analysis extended previous segmentation studies on food consumption to comprise food recycling behaviours. The results showed that health concern, and high adoption

rates on ethical consumption and food waste prevention are not necessarily associated with high engagement on alternative food waste disposal in Japan. Prevention, and to a certain extent ethical consumerism seem to be more common practices, while the adoption of alternative disposal methods is rarer. And so, even though the biggest group, the Responsible Consumers, frequently tried to prevent waste, had healthy eating habits, and purchased in a sustainable way, they rarely composted or recycled their food waste in any way. Four clusters were found: Sporadic adopters; Average Practitioners; Responsible Consumers; and Environmentally Involved. Approximately 51% of the sample was allocated to the Responsible Consumers cluster, which was characterized as older than the other clusters and with more women in part-time jobs or in-house duties. Environmentally Involved tended to be young respondents with children and gardening/farming interest. They were also the ones who ate plant-based meals more frequently and often paid attention to the healthiness of their meals. Thus, they seem to live under a lifestyle of health and sustainability.

The nuance of the reported intention to engage on composting shows the importance of understanding how habits are created and sustained to design effective adoption strategies (Steg and Vlek 2009; Abrahamse 2020). Its findings and limitations set ground for further research on food waste management specially in the Japanese Market.

Firstly, this analysis relied on self-reported qualitative data, and only considered respondents over 30 years old and from 9 of the 47 prefectures. The prefectures included are among the most populated in Japan, but further analysis is needed before generalizing these conclusions to all Japanese spheres, especially to younger generations. According to the results, the Environmentally Involved respondents belonged to the younger generations or the oldest in the sample. Hence, understanding whether the clustering profiles still hold on a wider age spectrum could be relevant for designing effective interventions. This latter point also suggests that if researchers wish to focus on an older sample, other collection alternatives, such as mail survey or interviews, might be preferable, as older people are not as prevalent in survey agencies' databases. Additionally, once the data was qualitative, there was no indication of what kind of food waste was thrown away (opened, leftover, expired date) (Okayama et al. 2021) and how much was thrown away. It may occur that people who reported high engagement on PEB produce more waste than people who reported smaller rates. For example, it might be a numerous household (Nakamura et al. 2022).

This research had a mostly exploratory scope, and further analysis regarding the decision-making process food recycling behaviours is needed. These behaviours are still under-explored from a psychological and behavioural theory perspective (Sewak et al. 2021), especially when compared to both ethical consumption and preventing behaviours. Thus, aligned with this gap,

and as the main goal of this doctoral research is presenting a comprehensive and holistic view on the role of the consumer in building a more sustainable food systems, the next two chapters will explore in detail food waste recycling drivers, particularly household composting engagement and dropout factors. In the Japanese market, to the author's knowledge, the only paper looking at composting from a theoretical behaviour model perspective was Tanaka et al. (2011).

The current findings also call for the importance of better understanding possible facilitators for adoptions of these behaviours (Bernstad 2014; DiGiacomo et al. 2018; Leeabai et al. 2022), the relevance of assessing how marketing campaigns worked in different regions (Aoki et al. 2010; Hotta and Aoki-Suzuki 2014; Zheng et al. 2017; Duque-Acevedo et al. 2022), and the urgency of discussing alternative ways to treat organic waste (both at a central and decentralized level) that are socially, legally, economically and environmentally viable given the unique characteristics of the area (Takata et al. 2012; Okayama 2016; Pai et al. 2019; Babalola 2020). As mentioned earlier, Chapter 7 will explore the latter topic to a certain extent.

Finally, although the food recovery framework mentions collective and community-based actions like food banks (Liu et al. 2016) or the use of food waste-reducing (digital) platforms (de Almeida Oroski and da Silva 2022), those were not included. Thus, similar to works like Ando et al. (2010), Bamberg et al. (2015), Christie and Waller (2019), Baumann et al. (2017), and Roseira et al. (2022), further exploration of ethical consumption, waste prevention, and food recycling methods from a collective and community perspective could show interesting results.

Chapter 5: Composting Behaviour in Japan: An application of the Theory of Consumption Value and look on drop out reasons.

5.1 Introduction

This chapter is dedicated to the last step of food consumption, the disposal. Based on the findings of the previous chapters alternative disposal options do not seem a mainstream behaviour among Japanese. Thus, besides understanding the profile of such adopters (Chapter 4), identifying what are the main factors that lead to the engagement of these behaviours can result in an increasing effectiveness of food waste recycling promotional strategies, which in turn contributes to climate change mitigation. As mentioned in Chapter 2, a significant portion of the produced food is wasted without ever being consumed. Only in 2021, Japanese households wasted approximately estimated that 2.44 million tons food (almost half of the total amount wasted by the food industry) (MAFF 2023a). As organic waste is a major source of garbage, composting can play an important role in waste reduction (Tanaka 1999; Takata et al. 2012; Vázquez and Soto 2017; Kopaei et al. 2021; Mihai et al. 2023)

Despite the possibility of the occurrence of strong odours, adverse effects on human health, or the presence of heavy metals if not properly managed (Cerda et al. 2018; Kopaei et al. 2021; Kunszabó et al. 2022; Mihai et al. 2023), composting has the potential to reduce landfill emissions of greenhouse gases (GHGs) (Cerda et al. 2018; Kunszabó et al. 2022; Mihai et al. 2023). It can also promote local entrepreneurship, raise the awareness of food waste produced, and provide nutrient-rich compost that can be used in gardens, agricultural land, and eroded soils (Cerda et al. 2018; Christie and Waller 2019; Pai et al. 2019; Kunszabó et al. 2022; Mihai et al. 2023). So, countries like Japan have considered it a primary food recycling process (Takata et al. 2012).

Composting systems can be large-scale, complex centralized operations, or decentralized systems consisting of a network, or standalone processes at a community, neighbourhood, or household level (Pai et al. 2019; Bruni et al. 2020). Moreover, composting programs can vary deeply depending on its setup (e.g., drop-off, collection, etc.), used process (e.g., windrows, aerated static piles, tunnel composting, and in-vessel composting), integrated IoT (e.g, composting 4.0 (Monteiro et al. 2021)). Thus, depending on the set-up, it may require different degrees of involvement of a household unit. From a waste provider role to a stakeholder that is responsible for providing, producing, and consuming the compost, respectively. These different

set-ups will be further addressed in Chapter 7. Information about process specifications can be found in works like Zhou et al. (2022) and Ayilara et al. (2020).

In 2020, Japan had 100 central composting facilities (Kawai et al. 2020). Nevertheless, only about 17% of the municipalities had implemented some kind of food waste segregation system, and the actual percentage of waste delivered to composting facilities corresponded to less than 1% of the total waste generated (Kawai et al. 2020; MOE 2021, 2023b). On the other hand, more than 50% of the municipalities have available financial assistance to the purchase of electrical composting machines (Island land Co. Ltd 2023). Many of those also offer assistance on other type of composters, and cities like Kobe (Hyogo), Fukuoka (Fukuoka), or Edogawa (Tokyo) have available monitoring programs and training sessions (Loan et al. 2019; Edogawa City 2022; RareA 2022; Go Green Kobe 2023; Fukuoka City 2024a). Notwithstanding, when looking at practice rates of different Pro-Environmental Behaviours (PEB) across Asian cities (including major Japanese cities), Phuphisith et al. (2020), Lee et al. (2013), Kurisu and Bortoleto (2011), and Aoki et al. (2010), found that kitchen waste composting was among the least popular PEB. Moreover, previous findings suggested that composting is mostly expressed by individuals who have high environmental concerns and try to lead healthy and sustainable lifestyles (Kurisu and Bortoleto 2011; Lee et al. 2013; Kunszabó et al. 2022). The findings of the Chapter 4's clustering analysis were also aligned with this idea, as the Environmental Involved were the ones engaging more frequently in food waste disposal alternative PEB.

Literature have pointed out the inclusion of social norms or psychological factors such as beliefs on the framing and messaging of a behavioural intervention and direct and personal contact from local entities can have an impact on its success rates (Hotta and Aoki-Suzuki 2014; Abrahamse 2020). Such resulted in a call for further efforts to understand the mechanisms of behaviour change, particularly at the consumer level (Liu et al. 2016; Wei et al. 2017; Kawai and Huong 2017). In response to this gap, the present chapter intends to clarify what are the main drivers to engage in this pro-environmental behaviour in Japan.

Despite the growing literature about food waste generation and its prevention, it seems research about the factors pondering the adoption of alternative ways of refusing food waste, such as household composting or food waste segregation schemes is increasing at a slower pace (Wu et al. 2019; Kopaei et al. 2021; Sewak et al. 2021; Ladele et al. 2021; Nguyen et al. 2022), particularly in Japan. Previous papers were mostly based in the U.S. (Waliczek et al. 2016; Wu et al. 2019; Niles 2020), Canada (Taylor and Todd 1995; Taylor et al. 1997; Mckenzie-Mohr 2000; Sussman and Gifford 2013; DiGiacomo et al. 2018; Pickering et al. 2020; Ladele et al. 2021), or European countries like Sweeden (Sterner and Bartelings 1999; Bernstad 2014; Linder et al. 2018) and the U.K. (Tucker and Speirs 2003; Tucker et al. 2003; Edgerton et al. 2009; Nomura et al.

2012). Besides Tanaka et al. (2011), which focused on a specific town in Hyogo, no research could be found about the drivers to household composting in Japan.

The present work used as theoretical framework the Theory of Consumption Values (TCV) (Sheth et al. 1991). TCV is a widely known marketing framework that relies in five consumption values (functional value, social value, emotional value, epistemic value, and conditional value) to understand consumers' choices (Sheth et al. 1991; Tanrikulu 2021). By using this framework, factors commonly associated with composting like knowledge and gardening interest (Loan et al. 2019) were analysed alongside less explored aspects such as one's self-image (Nguyen et al. 2022) or project awareness and descriptive norms (Pickering et al. 2020). Descriptive norms have been mentioned as relevant to the decision by intervention-based studies (Mckenzie-Mohr 2000; Nomura et al. 2012; Sussman and Gifford 2013; Bernstad 2014; Geislar 2017; Linder et al. 2018), but to the author's knowledge, this is one of the few composting behavioural models composting that has considered such effects. Additionally, although TCV's success in explaining and predicting behaviours across several sectors (e.g., food consumption, smoking, apparel, education, and tourism) (Tanrikulu 2021), there is no previous research on household composting involvement. To test the model hypothesis the current analysis used the Ordinal Partial Least Squares Structural Equation Modelling (OrdPLS) (Cantaluppi 2012; Cantaluppi and Boari 2016), which is an extension to the Partial Least Squares Structural Equation Modelling (PLS-SEM) that can cope with categorical indicators (Schuberth et al. 2018). While recently, the use of PLS-SEM rocketed (Hair et al. 2018; Sarstedt et al. 2022b), literature using OrdPLS is still limited. Thus, the present chapter also contributes to extending the applications of this statistical tool.

This chapter aims to: 1) identify the main drivers to household composting decisions in Japan; 2) provide relevant information about household composting to support the design of future composting interventions in Japan; 3) determine if the Theory of Consumption Values be used to explain household composting; and 4) extend the literature on OrdPLS applications.

5.2 Background and Methodology

5.2.1 Theory of Consumption Values: Model Hypotheses

Previous behavioural works on food waste recycling have focused either on household composting or kerbside segregation schemes. In recent years there has been an increase on the number of cities adopting collection schemes (Pai et al. 2019). However, in Japan the food waste segregation schemes are still scarce (MOE 2023b). The reference literature included decision-making models and intervention-based studies on both household composting and food waste

segregation, as they both tackle food waste recycling and have been studied together in studies like Widyatmika and Bolia (2023), Nguyen et al. (2022), Kala and Bolia (2021), Ladele et al. (2021), and Niles (2020). Despite possible differences on adoption reasons (Nguyen et al. 2022), these behaviours can be seen as complementary measures to reduce the waste that ends up in the landfills (Pai et al. 2019). Food waste recycling (composting, feeding animals with scraps, etc.) has also been used as part of models to explain overall food waste behaviour (Parizeau et al. 2015; Abdelradi 2018; Diaz-Ruiz et al. 2018; Pham et al. 2019; Attiq et al. 2021; Wu et al. 2023). For instance, Wu et al. (2023) found composting routines as well as using leftovers to feed pets can contribute to higher food waste rate. Such findings are aligned with the idea that having a recycling option may result in a relaxation of prevention behaviours (negative spillover) and that an increase on recycling rates may simply reflect a higher production rate (Ueta and Koizumi 2001; Tucker and Farrelly 2016; Ma et al. 2019; Oláh et al. 2022).

Household composting and food waste kerbside segregation have often been associated to attitudes and perceptions towards behaviour, knowledge, convenience and lack of control, socio-demographics, and gardening (Table. 5.1). Despite case study evidence, only Pickering et al. (2020) has considered programs awareness and messaging in a behavioural decision-model. Similarly, only Nguyen et al. (2022) has included environmental self-image when studying food recycling behaviours.

Table 0.1 Literature on models and interventions about household composting and food waste segregation schemes

Paper/Country	***Theoretical Framework***	***Independent Variables (1)***	***Dependent Variable***	***Methodology***
Widyatmika and Bolia (2023); India and Indonesia	No	Socio-demographics; Laws; Environmental Concern; Monetary Incentives; Composting site.	Home Composting (Yes/No) Sorting (Yes/No)	Self-Reported Survey; Logit Model
Kunszabó et al. (2022); Hungary	No	Socio-Demographics; Composting; General PEB; Gardening; House type; Place of living; Household size; Children; Benefits; Barriers; incentives.	-	Self-Reported Survey; Clustering
Leeabai et al. (2022); Thailand	No	Design, Visual prompts, Past experience.	Sorting Rate	Experimental Design; Self-Reported Survey; ANOVA; Welch's t-test
Nguyen et al. (2022); Australia	No	Socio-Demographics; Situational factors, Psychological factors; Household characteristics.	Sustainable Food Waste Disposal (Yes/No)	Self-Reported Survey; Factor Analysis; Logit Model
Rahman et al. (2022); Bangladesh	TPB + DPM*	ATC*; Subjective Norms; PBC*; Harmonious Passion; Obsessive Passion.	Composting Intention	Self-Reported Survey to Home Gardens; PLS-SEM/ANN

Sayara et al. (2022); Palestine	No	Socio-Demographics; KNG*; Environmental concern; Incentives; Barriers; Organic Farming.	Composting Intention	Self-Reported Survey; Descriptive and Graphical Analysis
Fernando (2021); Sri Lanka	No	Reason to and against Compost.	Home Composting (Yes/No)	Interview; Qualitative Research
Kala and Bolia (2021); India	No	Socio-Demographics; House type; Gardening; Collection System satisfaction; Sorting incentives; Composting incentives.	Sorting (Yes/No), Composting (Yes/No)	Self-Reported Survey; Binomial logistic regression
Kopaei et al. (2021); Iran	TPB+NAM*	ATC*; Subjective Norms; PBC*; Personal Norms; Ascription of responsibility; Awareness of the consequences; KNG*.	Home Composting Intention	Face-to-face questionnaire; Clustering; PLS-SEM; PLS-MGA
Ladele et al. (2021); Canada	No	Socio-Demographics; House type; ATC*; Situational factors, Food Waste rate; Planning habits; Environmental concern; KNG*, Sorting perception; Household size; Housing tenure.	Sorting Support (7-point Likert Scales)	Self-Reported Survey; Univariate means standard deviation; t-test; Bivariate correlation; Linear regression
Niles (2020); U.S.	No	Socio-Demographics; ATC* Knowledge and Perceptions of Act 148*; Household characteristics.	Food Waste Management Behaviour	Self-Reported Survey; Telephone Survey; chi-square test; Kruskal Wallis test; Ordered Logistic Regression
Pickering et al. (2020); Canada	No	Socio-Demographics; NEP*; Climate Change Uncertainty and Scepticism; Anthropologic origin; KNG*; Benefits; Messaging; Framing.	Organic waste-diversion programs participation likelihood	Self-Reported Survey; Logistic Regression; ANCOVA
Christie and Waller (2019); Australia	No	Composting Experience.	Awareness of waste, green thinking, connection, community building	Focus Group; Interviews; Qualitative Analysis
Loan et al. (2019); Vietnam	No	Socio-demographics; ATC*; KNG* ; Gardening; Training; Food Waste Reduction Habit; PEB Adoption.	Home Composting (Yes/No), Level of Participation (1,2,3)	Self-Reported Survey; Interviews; Logit Model
Wu et al. (2019); U.S.	No	Socio-Demographics ;Time Perception; Children; Disabilities; Household size; Working hours.	Sorting (Yes/No)	Self-Reported Survey; Logit Model
DiGiacomoc et al. (2018); Canada	No	Convenience (Bin Location).	Food Waste sorting (Kg)	Experimental Design; Descriptive and Graphical Analysis
(Linder et al. 2018)	No	Descriptive norms; messaging.	Food Waste sorting (Kg)	Experimental Design; Descriptive and Graphical Analysis; Linear regression
Nsimbe et al. (2018); Uganda	No	Socio-Demographics; KNG*; Perceptions; Gardening; Waste Sorting at Home;	Home Composting (Yes/No)	Semi-Conducted Interview; Logit Model
Li et al. (2017); China	No	Composting incentives and barriers.	Sorting Participation Rate	Interview; Qualitative Research; Descriptive Statistics

Karkanias et al. (2016); Greece	No	Composting incentives and barriers.	Composting (frequency 5-point Likert Scale)	Longitudinal Self-Reported Survey; Interview; Descriptive and Graphical Analysis
Waliczek et al. (2016); US	No	Socio-demographics; Composting School Program (Yes/No).	KNG*; ATC*; Environmental Concern; Locus of Control	Self-Reported Survey; ANOVA; Pearson product-moment correlation test
Bernstad (2014); Sweeden	No	Convenience; Leaflet distribution.	Food Waste Qt. (Kg)	Experimental Design; Descriptive and Graphical Analysis
Karim Ghani et al. (2013); Malaysia	TPB*	Socio-Demographics; ATC*; Subjective Norm; PBC*; Situational factors; Composting intention.	Food waste sorting (5-point Likert Scale)	Self-Reported Survey; Cronbach's alpha test; T-tests; Multiple regression
Sussman and Gifford (2013); Canada	Theory of Normative Conduct	Messaging; Role Model Person.	Sorted Properly (Yes/No)	Design Experiment & Interviews; Log-linear Model
Nomura (2011); UK	No	Social norms, intervention feedback.	Program Participation Rate	Design Experiment; Regression analysis
Tanaka et al. (2011); Japan	Two-Phased Decision-Making Model	Perceived seriousness; Responsibility; Effectiveness; Feasibility; Cost-benefit; Social-norm; Composting intention.	Composting Behaviour (Yes/No)	Self-Reported Survey; Factor Analysis, Covariance Analysis
Edgerton et al. (2009); UK	No	Environmental Concern, PEB Adoption, ATC*, KNG*, Social diffusion, Social norms, Gardening, Household constitution, Age.	Home Composting (Yes/No)	Self-Reported Survey; Logit Model
Tucker and Speirs (2003); UK	No	Gardening, ATC*, Social norms, KNG*.	Home Composting (Composter, Drop-Out, Never Composter)	Self-Reported Longitudinal Survey; Chi-Squared Test on Contingency Tables
Tucker et al. (2003); UK	No	Gardening, ATC*, Social norms, KNG*; Drop-out reasons; Adoption reasons.	Home Composting (Composter, Drop-Out, Never Composter)	Self-Reported Longitudinal Survey; Descriptive Analysis; Chi-Squared Test on Contingency Tables
Sterner and Bartelings (1999); Sweeden	No	Socio-demographics; ATC*; Gardening; Time.	Home Composting (Waste %)	Self-Reported Survey; Linear, Exponential and Logit Model
Mckenzie-mohr (2000); Canada	No	Social Norms; Composting Barriers.	Home Composting	Case study exposition
Taylor and Todd (1995); Taylor et al. (1997); Canada	TPB	ATC* (personal advantages, social advantages, complexity); Subjective norms (internal and external); PBC* (Self Efficacy, Resource Facilitation Conditions); Composting Intention.	Home Composting	Longitudinal Self-Reported Survey and Diaries; CFA (Structural Equation Model).

(1) independent variables included in previous literature, regardless of final significance * DPM: Dualistic Passion Model; ATC: attitudes towards composting; PBC: Perceived Behaviour Control; KNG: knowledge: NAM: Norm Activation Model; NEP: New environmental paradigm; Act 148 is Vermont's food waste law (place where the study took place)

From the studies mentioned in Table 5.1., only a small number of them are based on theoretical behavioural frameworks. Such supports the call for further applications of theoretical frameworks on the understanding of household-level food waste recycling (Sewak et al. 2021). When a framework was used, most articles applied integrated models based on the Theory of Planned Behaviour (TPB) (Ajzen 1991; Taylor and Todd 1995; Taylor et al. 1997; Karim Ghani et al. 2013; Kopaei et al. 2021; Ladele et al. 2021; Rahman et al. 2022). Nonetheless, instead using an extension of TPB or the Two-Phase Decision Model (Tanaka et al. 2011), TCV was used.

The Theory of Consumption Values (TCV) (Sheth et al. 1991) is a practical tool that can be used by policy makers to define, reinforce, or modify strategies that address social and environmental issues (Tanrikulu 2021). It relies on five values (functional value, social value, emotional value, epistemic value, and conditional value) to explain consumers decision towards a particular product/service. TCV is a robust approach that comprises both utilitarian and hedonic aspects of consumer behaviour (Kaur et al. 2020; Tanrikulu 2021). Thus, it allows a straightforward inclusion of economical, psychological, situational, and social variables found relevant in previous papers in a single model. On the other hand, despite remaining one of the most prominent models to predict human behaviour, TPB has been criticized, including by its own authors, on its limited to captor factors like emotions, measurement context, irrationality, affect, emotions, habits, or past behaviour (Ajzen 2011; Kumar et al. 2023).

Another reason for choosing TCV was because it does not depend on intention. The time span between intention and behaviour measurements has been pointed out as a limitation of frameworks like TPB (LaMorte 2022). While authors such as Taylor and Todd (1995), Taylor et al. (1997), and Davies et al. (2002) have coped with this limitation by using data from different points in time, the present research uses data from a single point in time. Moreover, despite intention being considered an important predictor to the adoption of a behaviour (Ajzen 1991; Bamberg and Möser 2007), intention-behaviour relationship may not always be perfect (Boldero 1995). The intention-behaviour gap has been reported by several scholars (Kollmuss and Agyeman 2002; Hassan et al. 2016; Sultan et al. 2020; Casais and Faria 2022), and its "size" can vary upon the analysed behaviour (Barr 2003). In some cases, intention-behaviour relationships were found weak or even non-significant (Davies et al. 2002; Karim Ghani et al. 2013). In Japan, Tanaka et al. (2011) found intention to be non-significant to the action of people who were not engaging in composting previously. This intention incongruity was also seen in Chapter 4, as people of stated not engaging in compost also stated higher intention rates than the ones

composting. For such reasons, authors like Bortoleto et al. (2012) have excluded intention from the analysis of waste prevention behaviours. Thus, the current analysis used a framework which did not include intention towards behaviour.

On its simpler form TCV has 5 main independent values, however scholars often applied the framework using sub-dimensions within the values, especially with the functional value (Tanrikulu 2021). The current analysis also assumed sub-dimensions within the values.

5.2.1.1 Functional Value

The Functional Value relates to the perceived utility acquired from the features and physical performance of a certain product/service (Kaur et al. 2020). Researchers have often included under this value sub-dimensions such as price and quality (Sweeney and Soutar 2001; Lin and Huang 2012; Gonçalves et al. 2016; Talwar et al. 2023), but factors like efficiency (Peng et al. 2014), perceived convenience (Yang and Lin 2017), and choice's positive and negative features (Sheth et al. 1991) have also been analysed (Tanrikulu 2021).

As the situation under analysis involves engaging in a behaviour or not, the approach used by Sheth et al. (1991) on the choice of whether or not to smoke was followed, and the positive and negative features of composting were included under the functional value. In the present case, the measurements of both positive (POS) and negative (CONS) attributes were adapted from previous composting literature (Table 5.4). More precisely, concerning positive attributes of composting, four items were included covering the perceptions that household composting can lower environmental impact than the mainstream disposal option, leave a better environment to the future generations, reduce the amount of waste that is incinerated or ends up in the landfills, and the fact that compost can be used on gardening and agriculture (Loan et al. 2019; Pai et al. 2019; Fernando 2021; Kopaei et al. 2021; Sewak et al. 2021; Kunszabó et al. 2022; Mihai et al. 2023).

On the other hand, previous studies on household composting have identified bad smell, attracts vermin and other animals, lack of space, lack of organic waste, and necessary effort and time as barriers to household composting adoption (Tucker and Speirs 2003; Tucker et al. 2003; Edgerton et al. 2009; Karkanias et al. 2016; Nsimbe et al. 2018; Fernando 2021; Sayara et al. 2022). Seven items were included regarding the latter barriers to engagement.

The current model also tested the significancy of composting perceived convenience (CONV) and lack of control. Convenience, or the lack of it, was found a significant factor to backyard composting and food waste segregation (Taylor et al. 1997; Tucker and Speirs 2003;

Edgerton et al. 2009; Bernstad 2014; DiGiacomo et al. 2018; Ladele et al. 2021; Nguyen et al. 2022). The 4 measurements used were based on Yang and Lin (2017), which tested convenience factors within the TCV framework, and convenience and lack of control items from Bortoleto et al. (2012), and Kopaei et al. (2021).

As aspects like time, space, and effort have been often associated with composting convenience and lack of control perceptions (Taylor et al. 1997; Tucker and Speirs 2003; Nguyen et al. 2022), besides the direct effect of positive and negative attributes on household composting, their indirect effect through convenience was also hypothesized. When applying TCV to over-the-top media services, Talwar et al. (2023) incorporated concepts from the means-end chain framework (Gutman 1982) and hypothesized different levels to TCV values. Under such layout the indirect effect of functional value (quality) through functional value (price) was tested (Talwar et al. 2023). Similarly, indirect effects were also hypothesized in the current model. Nevertheless, contrary to Talwar et al. (2023) and given the majority of sustainable marketing research assumed values independency (Tanrikulu 2021), the present analysis kept such assumption and only considered the indirect paths within a specific value.

- H5.1: PROS→CONV: perceived positive features impact composting perceived convenience.
- H5.2: CONS→CONV: perceived negative features impact composting perceived convenience.
- H5.3: PROS→COMP: perceived positive features impact composting adoption.
- H5.4: CONS→COMP: perceived negative features impact composting engagement.
- H5.5: CONV→COMP: perceived convenience impacts composting involvement.

5.2.1.2 Social Value

Social Value (SOC) measures the perceived utility acquired from product/service's association with one or more social groups (Sheth et al. 1991). It is related to aspects such as social approval and self-image improvement. Taylor and Todd (1995) and Taylor et al. (1997) mentioned that once composting happens indoors, the effect of social factors such as the perceived pressures and opinions from family, colleagues, or the community (subjective norms) may be weakened. On the other hand, comparison studies between Western countries and Japan emphasized the importance of community and social cohesion in Japanese culture (Ando et al. 2007, 2010). Previous behavioural models on household composting have mostly included subjective norms measurement like "*people think I should compost*" (Taylor and Todd 1995; Taylor et al. 1997; Edgerton et al. 2009; Tucker and Farrelly 2016; Kopaei et al. 2021), but only

Nguyen et al. (2022) has included a construct addressing a person's self-identity. Under TCV's social value, both perspectives can be captured. This analysis included 4 measurement items based on Bortoleto et al. (2012), Khan et al. (2017), and Kopaei et al. (2021). The items are related to one's self-image as an eco-friendly person as well as pressures from peers suggestions. By including several social perspectives based on previous literature, this chapter's analysis also aims to address one of the points made in Chapter 3 about the possibility that the use of few items contributed to the weak connection found between friends/media retrieved information and Ethical Food Consumption.

- H5.6: SOC→COMP: social value is significant to composting adoption.

5.2.1.3 Emotional Value

The emotional value (EMT) of an alternative is associated with its capacity of arousing or perpetuating feelings or affective states (Sheth et al. 1991). These emotions may be affirmative, destructive, or both (Kushwah et al. 2019). Scholars have included items like anxiousness, angriness, confidence, personal/moral obligations, playfulness, enjoyment, and satisfaction (Sheth et al. 1991; Lin and Huang 2012; Khan and Mohsin 2017; Yang and Lin 2017; Teng 2018).

Previous literature on composting and food waste behaviours found variables such as ascription of responsibility, environmental concern, harmonious and obsessive passion, and personal norms significant to behaviour (Bortoleto et al. 2012; Kopaei et al. 2021; Ladele et al. 2021; Rahman et al. 2022). When studying drivers to backyard composting intention, Kopaei et al. (2021) and Rahman et al. (2022) found ascription of responsibility, personal norms, and feelings of excitement were significant to composting intention. Additionally, Ladele et al. (2021) mentioned that environmental concern as driver to waste diversion behaviours.

Based on both previous research on household composting and TCV application (Sheth et al. 1991; Lin and Huang 2012; Bortoleto et al. 2012; Teng 2018; Kopaei et al. 2021), this model's emotional construct covered environmental concern, satisfaction, and personal norms with 5 items.

- H5.7: EMT→COMP: emotional value has an impact on composting adoption.

5.2.1.4 Epistemic Value

Epistemic Value relates to the ability of composting of arousing curiosity, infuse newness and/or fulfil the desire for knowledge (Sheth et al. 1991; Kushwah et al. 2019; Tanrikulu 2021).

Measurements related to this value have comprised items concerning knowledge acquisition, willingness to learn, curiosity, visibility (advertisement, friends example), as well as novelty and current knowledge status (Sheth et al. 1991; Lin and Huang 2012; Wen and Noor 2015; Khan and Mohsin 2017; Kaur et al. 2020). The present chapter focused on the visibility (VIS) and knowledge status (SKNG) dimensions.

Researchers have often pointed out that monetary assistance and training as good strategies to increase the composting engagement (Loan et al. 2019; Wu et al. 2019; Pai et al. 2019; Kunszabó et al. 2022). Nevertheless, despite many Japanese municipalities providing incentives like financial support (Island land Co. Ltd 2023), household composting is among the least common pro-environmental behaviours (Aoki et al., 2010; Kurisu and Bortoleto, 2011; Lee et al., 2013; Phuphisith et al., 2020). This low adoption rate was once again confirmed by the results of the last Chapter.

An initiative framing and messaging can influence its success (Abrahamse 2020). Based on the latter premise, previous composting intervention-based studies explored the impact on engagement of messaging based on know-how and descriptive norms (information about the behaviour of others) (Mckenzie-Mohr 2000; Nomura et al. 2012; Sussman and Gifford 2013; Bernstad 2014; Geislar 2017; Linder et al. 2018). Nonetheless, when it comes to decision models, to the author's knowledge, besides Pickering et al. (2020), there is no paper testing descriptive norms and program's awareness within a decision-making model. The visibility construct of the present model addresses how visible are composting programs to the respondent, tackling both perceptions about the behaviour of the community and their awareness of on-going programs. The measurements used were adapted from Kaur et al. (2020) and Sheth et al. (1991).

Moreover, in PEB research, knowledge have been often considered an important driver to adoption (Kurisu 2015). Knowledge about and how to compost is commonly recognized as significant to composting adoption (Edgerton et al. 2009; Nsimbe et al. 2018; Loan et al. 2019; Pickering et al. 2020). It has been even pointed out as a possible reason for people preferring backyard composting over food waste segregation schemes (Ladele et al. 2021). Thus, besides the visibility construct, a variable about current composting knowledge status was tested. It comprised two items about composting's process and definition based on Wen and Noor (2015) and Loan et al. (2019).

- H5.8: VIS→COMP: composting incentives visibility is significant to household composting involvement.
- H5.9: SKNG→COMP: knowledge about composting impacts composting adoption.

5.2.1.5 Conditional Value

The conditional value is associated with the utility of a product/service as the consequence of a set of circumstances or specific situations of the choice maker (Sheth et al. 1991; Tanrikulu 2021). It comprises aspects like time, place and context that enhance its functional or social value (Sheth et al. 1991; Kushwah et al. 2019; Tanrikulu 2021). Under the conditional value two sub-dimensions were tested.

Composting, contrary to other PEB, has been pointed out as a behaviour that can be highly influenced by non-environmental factors (Edgerton et al. 2009). In particular, when analysing simultaneously food waste segregation and household composting, Nguyen et al. (2022) and Niles (2020) mentioned that the presence of a garden as one of the factors for individuals to pick the household composting over food waste segregation schemes. Moreover, several scholars have highlighted the connection between gardening/farming and the choice of composting, including Chapter 4 findings (Tucker and Speirs 2003; Tucker et al. 2003; Edgerton et al. 2009; Nsimbe et al. 2018; Loan et al. 2019; Sayara et al. 2022; Kunszabó et al. 2022). Thus, in the present analyses, one of the sub-dimensions associated with the conditional value concerns the farming/gardening (GDN) interest of the respondents. The item used in the model was the same used in previous chapter.

The second sub-dimension addresses time and financial availability (AVB) of the people of the sample. The perception of lack of time, regardless of the actual free time of a person or of the process' required time has been pointed as constraint to engagement (Edgerton et al. 2009; Wu et al. 2019). Acquisition costs were also pointed as a barrier by Pickering et al. (2020). Thus, based on the latter authors, the present analysis tested three items regarding weather or not the respondents have financial and time conditions to engage composting if they wish to do so. In a first instance, a material (food waste) availability item was also added, however the item showed a low loading when assessing the outer model, so it was excluded from the final model. This item (if respondents cooked with a lot of fresh products or not) was initially considered since when asked about composting difficulties, some people have mentioned not having enough organic waste (Fernando 2021).

- H5.10: GDN→COMP: gardening/farming interest impacts composting engagement.
- H5.11: AVB→COMP: availability impacts composting engagement.

5.2.1.6 Control Variables

Gender (GENDER), house type (HOUSE), and household size (SIZE) were used as control variables. The role of socio-demographics like gender, or education towards PEB adoption has not been consistent in literature (Kurisu 2015). Such extends to composting and segregation schemes academia. For instance, some pointed out gender, house type, income, household size, and children to be significant to composting and green bin schemes (Edgerton et al. 2009; Pickering et al. 2020; Kala and Bolia 2021). On the other hand, Nsimbe et al. (2018), Sterner and Bartelings (1999), and Loan et al. (2019) found none of the latter socio-demographics and house characteristics impactful (at a 5% significancy level) to household composting. In Chapter 4, clusters varied both on socio-demographics and on the engagement in alternative disposal behaviours. For instance, larger household tended to engage more frequently alternative disposal methods. Nonetheless, as it was mentioned in Chapter 3, the latter does not imply that the decision-model behind composting is different among socio-demographics/clusters. Contrary to the analysis on Ethical Food Consumption, the clusters from the previous chapter were not used as a basis to a multi-group assessment. The decision was based in three major aspects: 1) The was size of the clusters of the Chapter 4 were quite unbalanced, with one cluster representing approximately half of the total sample. Literature pointed out that extremely unbalanced samples may not show trustworthy results (Cheah et al. 2023). 2) The clusters that were found were also based on the dependent variables of this analysis. 3) Finally, the statistical tool used on the current analysis was the OrdPLS, which is still not a widespread method. Therefore, it makes it more difficult to make sure that the multi-group assessment would be mathematically coherent.

Despite previous studies mentioning residential area (urban, rural) and age (Edgerton et al. 2009; Wu et al. 2019; Niles 2020) as important factors to food waste recycling, these two variables were not included in this study. The percentage of respondents living in rural areas was approximately 4% of the total sample which is lower than the national percentage in recent years (8%) (World Bank 2024). Thus, it was considered that the inclusion of this variable would not show trustworthy conclusions about its impact on composting decision. Moreover, age was not included as it did not present a linear relation with the main dependent variable. Considering that having children directly contributes to a larger household, only the latter variable was analysed in the model.

- H5.12: GENDER→COMP: gender is significant to composting engagement.
- H5.13: HOUSE→COMP: the house type (apartment or house) affects composting involvement.
- H5.14: SIZE→COMP: the household size is significant to composting adoption.

5.2.1.7 Household Composting Engagement

Composting engagement has been commonly accessed either by the yes or no categorical items (Edgerton et al. 2009; Tanaka et al. 2011; Nsimbe et al. 2018; Widyatmika and Bolia 2023), or frequency measurement like Likert-scales (Taylor et al. 1997; Karim Ghani et al. 2013; Karkanias et al. 2016), but some studies have used a three-level categorical variable (yes, dropout, no) instead (Tucker et al. 2003; Tucker and Farrelly 2016). Moreover, Loan et al. (2019) analysed, in separate models, both backyard composting adoption (yes, no) and adoption frequency (minimal, moderate, frequent). Taking advantage of the OrdPLS analytical capabilities the current analysis used as measurements of composting involvement a categorical question based on Tucker and Speirs (2003) and Tucker et al. (2003), and a food waste composting frequency scale (6-point Liker-scale). The latter item was the one used in the previous Chapter.

5.2.2 Statistical Tools: Ordinal PLS-SEM

This analysis as well as the one from the previous chapter are based on the same dataset. However, once the dataset has non-equidistant categorical indicators, including an item related to the composting dependent variable, the model hypothesises were tested using an Ordinal Partial Least Squares Structural Equation Modelling (OrdPLS). As mentioned in Chapter 2, OrdPLS is an extension of the Partial Least Squares Structural Equation Modelling (PLS-SEM) that can cope with categorical data by using the polychoric correlation matrix (Cantaluppi 2012; Schuberth et al. 2018).

Academics pointed out PLS is more adequate when the research has a predictive side, the goal goes beyond testing established theoretical frameworks and the analysis comprises formative variables (Hair and Alamer 2022). While this analysis is based on the Theory Consumption Values, it presents some modifications to the original framework presented by Sheth et al. (1991), thus adding an exploratory side to this research.

Regarding the assessment of the inner model, the present analysis assessed the standardized root mean square residual (SRMR) to address the explanatory side of the method (Schuberth et al. 2023) and compared the model prediction errors, using the *MAE* indices of the items of dependent variable, to the ones of a naive linear model benchmark (Shmueli et al. 2019; Hair Jr. et al. 2021). At least half of errors should be inferior to the benchmark model (Shmueli et al. 2019) and the SRMR should be no bigger than 0.08 (Cho et al. 2020; Dash and Paul 2021). It

is important to note, however, that under the presence of composite variables and categorical items such cut-off values may not be accurate (Schuberth 2022; McNeish 2023).

5.2.3 Data Collection

This analysis is based on the sample described on the previous chapter. However, given the different nature of the analyses the items included in the current chapter differ from Chapter 4. Besides questions mentioned in the previous chapter, items addressing the conditional, emotional, epistemic, social, and functional values related with the composting decision-making process were included in the survey. In coherence with Chapters 3 and 4, Likert-scales items were assumed to be continuous. Nevertheless, questions of a non-equidistant categorical nature were considered as categorical.

Prior their usage in the model, the values regarding the items about gardening/farming and the knowledge about the composting support (from different institutions) were transformed. The categorical question about gardening was done as in away respondents could choose more than on type of gardening/farming depending in what types they were interested in. The variable used in the model numbered (1,2,3,4) the respondents according to the largest gardening/farming scale they choose. For instance, if a respondent had interest in farming and herb gardening their final score was 4. People who said not having interested were classified with 1. Regarding the support awareness, the variable was simplified from 4 ("*I do not know"*, *"I know it is not available"*, "*I vaguely know about it"*, and "*I know that it is available"*) categories to 3 ("*I do not know"*, "*I vaguely know about it"*, and "*I know whether or not it is available"*), so it would better fit the definition of the Epistemic Value.

5.3 Results

The data was analysed with R (4.2.1) coding language via Rstudio (5.5.4). As far as the analytical package is concerned, the OrdPLS results were obtained with the cSEM (0.5.0). The bootstrapping was set to 5000 times.

5.3.1 Descriptive Results

The socio-demographic attributes such age, income, household size, residence area are summarized in the previous chapter, namely in Table 4.1. Moreover, approximately 13% of the respondents stated having previous composting experience, but only 6.1% is currently making it. When it comes to engagement frequency, the average score was 1.91 (6-always and 1-never). It is important to note that the frequency item asked if people used organic waste as a fertilizer, whereas a composting definition was given to those who were unfamiliar with the concept on the experience item. Therefore, if a person uses eggshells, seaweed, or coffee grounds directly on the garden as fertilizer, it is possible they answered no on the direct composting question and but that they reported to use organic matter as fertilizer/stabilizer sometimes. The latter indicator was the one used in the clustering analysis of the 4th Chapter.

5.3.2 Assessment of the measurement (outer) model

The results regarding the outer reflective model are available on Table 5.2, Table 5.3, and Table 5.4. All the items' loadings, except for the item CONV1, were superior to 0.7. Regardless, the item was kept in the study once removing it did not lead to a large increase in the internal consistency reliability or convergent validity (Hair Jr. et al. 2021). All the AVE values were superior to 0.50 and the Cronbach's α and ρ_c, bigger than 0.70. The ρ_c of the composting and knowledge constructs were bigger than 0.95 which could imply some redundancy (Ringle et al. 2023). However, once the Joereskog's rho (ρ_c) is seen as an upper boundary and the Cronbach's α of these variables were inferior to 0.95, it was considered that there were no reliability issues.

All HTMT values were smaller than the maximum recommended by academia. Nonetheless, when running the model, a warning regarding the HTMT/HTMT2 assumption that all intra-block and inter-block correlations between indicators must be either all-positive or all-negative (Schuberth 2022; Ringle et al. 2023) appeared. That is an issue already identified and addressed in academia (Ringle et al. 2023), but despite some software having updated versions of both HTMT and HTMT2, it is not yet the case of the cSEM package. According to Ringle et al. (2023), negative correlation patterns among indicators may often occur when measuring emotion or personality traits. However, once the goal of the HTMT is to determine the indicators' empirical overlap, their signs are not decisive (Ringle et al. 2023). HTMT2 also has the tendency to show inadmissible solutions when the construct correlations are low (Ringle et al. 2023). In turn, small construct correlations favour the occurrence of negative indicator correlations (Ringle et al. 2023). The latter, nonetheless, also implies discriminant validity issues are less likely to emerge (Ringle et al. 2023). After checking the correlation values of the indicators of the constructs that triggered

the warning Table 5.5, it was concluded that the model did not present discriminant validity issues (no correlation was bigger than modulus 0.23).

Table 0.2 Reliability Measurements

Construct:	AVE	Cronbach's α	Joereskog's rho (ρ_c)
PROS	0.74	0.88	0.92
CONS	0.73	0.94	0.95
CONV	0.65	0.82	0.82
AVB	0.76	0.84	0.91
VIS	0.76	0.92	0.94
SKNG	0.93	0.92	0.96
EMT	0.59	0.83	0.88
SOC	0.72	0.87	0.91
COMP	0.93	0.93	0.97

Table 0.3 Discriminant Validity: HTMT

Construct:	PROS	CONS	VIS	SOC	AVB	EMT	SKNG	CONV	COMP
PROS	1.00								
CONS	0.63	1.00							
VIS	0.18	0.14*	1.00						
SOC	0.41	0.03*	0.71	1.00					
AVB	0.46	0.09*	0.48	0.63	1.00				
EMT	0.74	0.26	0.40	0.67	0.60	1.00			
SKNG	0.39	0.05*	0.45	0.39	0.51	0.49	1.00		
CONV	0.24	0.63	0.28	0.05*	0.02*	0.02*	0.16	1.00	
COMP	0.35	0.05*	0.64	0.59	0.57	0.52	0.69	0.29	1.00
*HTMT2 was null									

Table 0.4 Items' loadings, means and standard deviations.

TVC Value	Indicator	Loading	Mean	Std.	Skewness	Kurtosis	Reference Literature
Functional Value	PROS1: "*Do you think composting can reduce food waste?*"	0.89	4.32	1.26	-0.91	3.74	Fernando, (2021); Kopaei et al. (2021); Kunszabó et al. (2022); Loan et
	PROS2: "*Do you think composting is useful for farming/gardening*?"	0.89	4.18	1.26	-0.74	3.43	

	PROS3: "*Do you think composting reduces the impact on landfills?*"	0.75	3.95	1.25	-0.46	3.09	al. (2019); Sheth et al. (1991)
	PROS4: *"Do you think composting can help leaving a better environment for future generation?"*	0.90	4.02	1.22	-0.62	3.39	
	CONS1: *"Do you think composting is smelly?"*	0.89	4.52	1.22	-0.84	3.67	Sayara et al. (2022); Fernando (2021); Nsimbe et al. (2018); Karkanias et al. (2016); Edgerton et al. (2009); Tucker and Speirs (2003); Sheth et al. (1991)
	CONS2: *"Do you think composting needs too much space?"*	0.87	4.58	1.23	-0.93	3.84	
	CONS3: *"Do you think composting attracts verminous and animals?"*	0.90	4.56	1.22	-0.85	3.71	
	CONS4: *"Do you think composting is not worth doing unless there are a lot of organic waste?"*	0.73	3.99	1.28	-0.46	2.96	
	CONS5: *"Do you think composting is time consuming?"*	0.87	4.52	1.18	-0.93	4.08	
	CONS6: *"Do you think composting takes a lot of effort?"*	0.89	4.57	1.21	-0.96	3.94	
	CONS7: *"Do you think composting is not worth doing, if there is no garden?"*	0.81	4.41	1.31	-0.76	3.26	
	[a]CONV1: *"Is composting a burden?"*	0.68	2.67	1.28	0.73	3.28	Bortoleto et al. (2012); Kopaei et al. (2021); Yang and Lin (2017)
	[a]CONV2: *"To what extent do you agree: Composting does not fit my routine."*	0.77	3.09	1.47	0.29	2.28	
	[a]CONV3: *"To what extent do you agree: I do not have enough knowledge to compost."*	0.87	2.58	1.48	0.67	2.55	
	[a]CONV4: *"To what extent do you agree: I do not have the necessary tools to compost."*	0.88	2.50	1.47	0.78	2.73	
Epistemic Value	VIS1: *"To what extent do you agree: Many people where I live compost."*	0.83	2.14	1.35	1.02	3.19	Kaur et al. (2020); Sheth et al. (1991)
	VIS2: *"To what extent do you agree: I have relatives or friends who are currently engaged in composting."*	0.84	2.24	1.42	0.91	2.82	
	[o]VIS3: *"Do you know if you can receive any assistance from your municipality/prefecture?"*	0.89	1*	-	-	-	
	[o]VIS4: *"Do you know if you can receive any assistance from your*	0.90	1*	-	-	-	

	community/neighbourhood association?"						
	ºVIS5: "Do you know if you can receive any assistance from an NPO or university? "	0.90	1*	-	-	-	
	SKNG1: *"To what extent do you understand the meaning of composting?"*	0.96	2.90	1.76	0.22	1.53	Loan et al. (2019); Wen and Noor (2015)
	SKNG2: *"Do you know how to make compost?"*	0.97	2.40	1.60	0.71	2.15	
Conditional value	ºGARDEN: *"Are you interested in farming/gardening activities?"*	1	1*	-	-	-	Edgerton et al. (2009)
	AVB1: *"To what extent do you agree: I could afford the time to compost if I wanted to."*	0.91	3.15	1.46	0.11	2.10	Wu et al. (2019); Edgerton et al. (2009); Pickering et al. (2020)
	AVB2: *"To what extent do you agree: I am financially capable of composting, if I wanted to."*	0.84	3.02	1.43	0.16	2.21	
	AVB3: *"To what extent do you agree: I could afford the time to reduce food waste if I wanted to."*	0.86	3.45	1.40	-0.16	2.28	
Social Value	SOC1: *"To what extent do you agree: If I do not recycle or do other ecofriendly behaviours my family members or relatives will think less of me."*	0.87	2.43	1.38	0.66	2.54	Bortoleto et al. (2012); Khan and Mohsin (2017); Kopley et al. (2021)
	SOC2: *"To what extent do you agree: I like people to think of me as being eco-friendly."*	0.87	2.66	1.39	0.39	2.30	
	SOC3: *"To what extent do you agree: I believe is my social obligation to make efforts to reduce household food waste."*	0.76	3.25	1.45	-0.16	2.12	
	SOC4: *"To what extent do you agree: My family members living with me think I should reduce food waste."*	0.89	2.55	1.38	0.46	2.27	
Emotional Value	EMT1: *"To what extent do you agree: I worry how my actions affect the environment"*	0.79	3.65	1.18	-0.34	3.06	Bortoleto et al., (2012); Kopaei et al. (2021); Lin and Huang (2012); Sheth et al. (1991); Teng (2018)
	EMT2: *"To what extent do you agree: I think it is wrong do not recycle food waste at home"*	0.80	3.43	1.19	-0.06	2.99	
	EMT3: *"To what extent do you agree: I feel bad for throwing away food waste."*	0.74	3.97	1.26	-0.45	3.00	
	EMT4: *"Do you think is good to promote composting?"*	0.78	3.74	1.31	-0.49	2.90	
	EMT5: *"Do you think composting is fun?"*	0.72	3.27	1.37	-0.10	2.32	

Composting Involvement	ºCOMP1: *"Do you make compost?"*	0.98	1*	-	-	-	Taylor et al. (1997); Tucker and Speirs (2003)
	COMP2: *"Do you engage in composting/reusing organic waste?"*	0.95	1.91	1.55	1.45	3.61	
ªQuestions' scale was reversed;ºcategorical question; *mode value instead of the mean value for the items considered categorical.							

Table 0.5 Polychor Correlation Matrix Between Items with a null HTMT2

		CONS							CONV			
		CONS 1	CONS 2	CONS 3	CONS 4	CONS 5	CONS 6	CONS 7	CONV 1	CONV 2	CONV 3	CONV 4
VIS	VIS1	-0.09	-0.13	-0.13	0.07	-0.08	-0.13	-0.11	0.18	0.01	0.17	0.18
	VIS2	-0.07	-0.12	-0.10	0.03	-0.03	-0.11	-0.10	0.17	0.03	0.18	0.17
	VIS3	-0.11	-0.14	-0.12	-0.02	-0.07	-0.12	-0.10	0.18	0.10	0.25	0.23
	VIS4	-0.09	-0.15	-0.11	-0.01	-0.07	-0.12	-0.10	0.18	0.10	0.29	0.26
	VIS5	-0.14	-0.19	-0.16	-0.03	-0.11	-0.15	-0.11	0.18	0.08	0.27	0.24
SOC	SOC1	-0.03	-0.07	-0.06	0.07	0.01	-0.06	-0.08	0.13	0.00	0.09	0.12
	SOC2	0.02	0.00	-0.01	0.07	0.06	0.02	-0.01	0.13	-0.02	-0.02	-0.01
	SOC3	0.13	0.13	0.13	0.06	0.13	0.10	0.06	0.09	-0.04	-0.15	-0.15
	SOC4	-0.01	-0.04	-0.04	0.08	0.00	-0.04	-0.05	0.13	-0.01	0.06	0.08
AVB	AVB1	0.04	0.04	0.02	0.03	0.09	0.03	-0.01	0.16	-0.02	-0.04	-0.01
	AVB2	0.05	0.04	0.03	0.08	0.07	0.02	0.00	0.13	-0.08	-0.03	-0.02
	AVB3	0.11	0.10	0.09	0.09	0.14	0.10	0.04	0.09	-0.06	-0.13	-0.12
EMT	EMT1	0.21	0.22	0.19	0.10	0.19	0.19	0.12	0.04	0.02	-0.11	-0.13
	EMT2	0.15	0.12	0.14	0.10	0.15	0.11	0.08	0.10	0.05	-0.05	-0.05
	EMT3	0.23	0.27	0.24	0.12	0.23	0.22	0.19	-0.04	-0.06	-0.21	-0.23
	EMT4	0.15	0.17	0.15	0.02	0.18	0.15	0.07	0.11	0.07	-0.08	-0.09
	EMT5	0.12	0.11	0.10	0.09	0.14	0.09	0.08	0.18	0.17	0.07	0.05
SKNG	SKNG 1	0.08	0.11	0.08	-0.01	0.10	0.06	0.06	0.08	0.00	0.13	0.05
	SKNG 2	0.03	0.03	0.02	-0.03	0.05	0.00	-0.01	0.15	0.06	0.24	0.16
COMP	COMP 1	0.05	0.05	-0.01	-0.06	0.08	-0.01	-0.06	0.27	0.09	0.23	0.26
	COMP 2	-0.06	-0.12	-0.10	-0.02	-0.06	-0.10	-0.12	0.23	0.08	0.19	0.23

5.3.3 Assessment of the structural (inner) model

The variables used on the structural model had VIF values inferior to 3 (Table 5.6). The R^2adj were 0.32 for convenience and 0.68 for composting behaviour (Figure 5.1). One of the composting items showed a smaller *MAE* value than the naive linear benchmark model and the other was larger. Thus, implying a moderate predictive power (Shmueli et al. 2019). Note, that one of the limitations of OrdPLS is that the predictive values of the categorical items are dependent on the calculation method used ("mean" or "median") (Cantaluppi 2012; Schuberth et

al. 2018; Schuberth 2022). On this analysis the approach chosen was the “mean”. Moreover, the naive linear benchmark model considers all the variables continuous. The SRMR value was 0.077 (<0.08), implying a good model fit.

Not all the hypotheses were significant (p-value<0.05) to explain/predict composting involvement. None of the control variables were significant to COMP at a 5% p-value. Nevertheless, assuming a 10% significance, the house type would be included into the model, suggesting that living in a house rather in an apartment has a positive impact on the composting decision. Within the Functional Value neither PROS or CONS had a direct impact, but both had a significant indirect impact on composting through convenience, being fully mediated by the latter variable (Table 5.7 and Table 5.8). Social and Epistemic Values hypotheses were accepted (Table 5.7, Figure 5.1). The model results suggest that the latter values have a high impact on composting adoption. From the sub-dimensions of the Conditional Value both gardening and availability were found significant. The Emotional Value was not found significant to the choice of behaviour (Table 5.7).

Table 0.6 VIF Table

VIF	CONV	COMPOST
PROS	1.49	2.78
CONS	1.49	2.23
CONV	-	1.61
AVB	-	1.73
GDN	-	1.87
SKNG	-	1.79
SOC	-	2.50
EMT	-	2.55
SIZE	-	1.17
GENDER	-	1.13
HOUSE	-	1.16

Table 0.7 Path Coefficients

	Path Estimate	t-stat	p-value	Confidence Interval (95%)	Hypothesis
H5.1: PROS→CONV	0.17	4.97	0.000	[0.10;0.23]	Accepted***
H5.2: CONS→CONV	-0.65	-23.11	0.000	[-0.71;-0.60]	Accepted***
H5.3: PROS→COMP	0.04	1.03	0.302	[-0.03;0.11]	Rejected
H5.4: CONS→COMP	0.00	0.11	0.914	[-0.07;0.07]	Rejected
H5.5: CONV→COMP	0.14	3.99	0.000	[0.07;0.20]	Accepted***
H5.6: SOC→COMP	0.11	2.90	0.004	[0.03;0.18]	Accepted***
H5.7: EMT→COMP	0.04	0.98	0.325	[-0.03;0.11]	Rejected

H5.8: VIS→COMP	0.20	5.43	0.000	[0.13;0.27]	Accepted***
H5.9: SKNG→COMP	0.36	10.72	0.000	[0.30;0.43]	Rejected
H5.10: GDN→COMP	0.18	5.00	0.000	[0.11;0.25]	Accepted***
H5.11: AVB→COMP	0.10	3.47	0.001	[0.04;0.16]	Accepted***
H5.12: GENDER→COMP	-0.05	-1.62	0.106	[-0.12;0.01]	Rejected
H5.13: HOUSE→COMP	0.06	-1.67	0.096	[-0.01;0.12]	Rejected*
H5.14: SIZE→COMP	0.04	1.26	0.208	[-0.02;0.10]	Rejected
*accepted at p-value<10%; ** accepted at p-value<5%; *** accepted at p-value<1%					

Table 0.8 Indirect Effects

	Estimate	t-stat	p-value	Confidence Interval (95%)	Hypothesis
PROS→CONV→COMP	0.02	2.86	0.004	[0.01;0.04]	Accepted***
CONS→CONV→COMP	-0.09	-3.86	0.000	[-0.13;-0.05]	Accepted***
*accepted at p-value<10%; ** accepted at p-value<5%; *** accepted at p-value<1%					

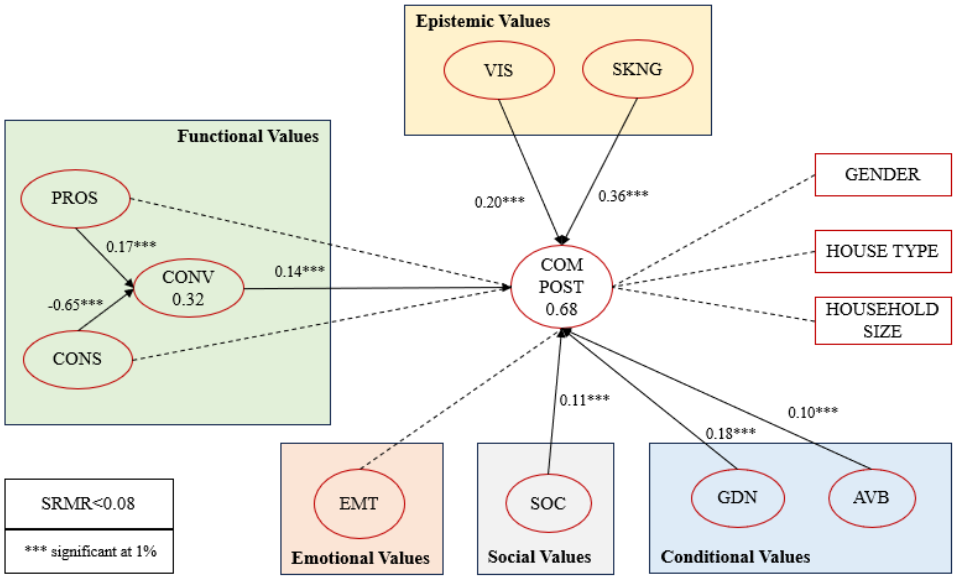

Figure 0.1 TCV Model Results

5.4 Discussion

5.4.1 Theoretical Implications

The use of TCV to model consumer choices has been increasing in recent years (Tanrikulu 2021). Notwithstanding, this is the first analysis which has applied it to the choice of composting. The results suggest that the Theory of Consumption Values can be a resourceful tool when studying composting, widening the scope of behaviours modelled by this theory. The present research also extended previous theory uses by including sub-dimensions within the values, and assuming they can be related. While relations between sub-dimensions of the same value were hypothesized, no relation between values was assumed in this study. Value independence is a primary assumption of TCV, which have been held on the majority of the studies on sustainable marketing (Tanrikulu 2021). Nevertheless, this assumption has been criticized by some scholars and studies using some of the values as moderators or mediators can be found in academia (Khan and Mohsin 2017; Tanrikulu 2021; Talwar et al. 2023).

By using TCV, it was possible to test under the same model, multiple social components such as subjective norms, descriptive norms, and one's self-image. Thus, giving a robust picture about the social importance to composting engagement in Japan. To the author's knowledge this is the first study on household composting including items on all these factors in a single model. The findings of the current model suggest that including measurements regarding one's self-image and descriptive norms can increase the explanatory power of a composting model.

The current analysis found meaningful results that are coherent with previous work in the composting field using OrdPLS. Given the advantages of using PLS instead CB-SEM (Hair and Alamer 2022; Ringle et al. 2023), an increase in the adoption of this technique in the future would be expected. OrdPLS was first proposed by Cantaluppi (2012) and Cantaluppi and Boari (2016), but despite its ability to cope with categorical data its use on social sciences is scarce. Its low adoption rate may derive from some of the difficulties encountered on the present model, namely: 1) Concerning R packages, OrdPLS is currently only available on the cSEM R package, which does not have a HTMT index that can deal with different signs in the inter/intra-block correlation of the constructs (Ringle et al. 2023); 2) There is more literature available for its covariance-based counterpart, facilitating results assessment and methodology understanding; 3) There are still some limitations on its predictive modes (Schuberth et al. 2018); 4) The inclusion of categorical variables resulted in a considerable increase on the running time of the model when using cSEM. For a 5000 times bootstrapping, the model running time was approximately 1 hour and 23 minutes (with computer with an Intel (R) Core (TM) i7-7600U CPU @ 2.80GHz 2.90 GHz processor and a 12GB RAM). The present analysis assumed the 6-point Likert-scales continuous and only modelled as categorical the items which had a few and non-equidistant options. If the whole model were to be considered categorical a longer running time would be expected.

5.4.2 Social and Management Implications

This present model results confirm the idea can be highly influenced by non-environmental factors (Edgerton et al. 2009). From all the values included in the research not all were significant at a 5% significance level. Previous authors stated that depending on the analyses some values may not be relevant for the consumer choice (Sheth et al. 1991). That seems to be the case of the emotional value on composting behaviour. Even though previous research on composting found personal norms, harmonies passion, and obsessive passion significant (Kopaei et al. 2021; Rahman et al. 2022), that was not the case on the current analysis. A possible cause for this difference is that the latter studies did not address the behaviour adoption but composting intention instead. As previously mentioned, based on the intention-behaviour gap identified by previous authors (Davies et al. 2002; Tanaka et al. 2011; Bortoleto et al. 2012) and the fact that the data was collected in a single point in time, intention was not included in the model. However, in a longitudinal study/intervention, analysing such variable may show interesting findings.

Functional aspects were directly and indirectly impactful to composting engagement. The negative attributes of composting seemed to have a stronger effect on convenience than the positive attributes. Such suggests that finding ways of alleviating these negative barriers can increase convenience perceptions which in turn will reflect on household composting engagement. For instance, Kurniawan et al. (2013), mentioned the importance of recommending the appropriate composting technology based on regional characteristics.

A relevant finding of this model is the importance of the social value and composting visibility to home composting in Japan. Aligned with the idea that the Japanese are more collective oriented and sensitive to social norms (Ando et al. 2007, 2010), and contrary to previous findings about the weak effect of subjective norms (Taylor and Todd 1995; Taylor et al. 1997), social value which comprised subjective norms and self-image items, had a significant effect on composting adoption. This results also support (Nguyen et al. 2022) findings about the importance of environmental self-identity to compost choice of behaviour. Thus, marketing relying on one's self-image as an eco-friendly individual or one connected with nature can be an effective strategy to foster this behaviour and possibly lead to positive spillover effects in other behaviours, such as food waste prevention, or waste recycling (Whitburn et al. 2020). Behavioural spillover implies that adopting one behaviour may catalyse or reduce (in case it is a negative effect) engagement in others (Truelove et al. 2014; Nash et al. 2019; Abrahamse 2019; Maki et al. 2019)

The significant effect of the composting visibility construct also calls for a raise on the awareness of the existing composting support programs as well as the visibility of community efforts to reduce and recycle waste. Besides having assistance available it is important to develop

effective marketing strategies, so people know that such support exists. One way may pass precisely by using descriptive norms about the community engagement as part of interventions' messaging.

Naturally, depending on the kind of support available, the messaging might change. To the author's knowledge, there are not extensive literature on waste reduction interventions nor an overview on the strategies adopted by local governments in Japan. Having such understanding and fomenting "*know-how*" sharing among municipalities might be important for the effectiveness of future campaigns. For example, a food waste segregation scheme in Tsushima (Nagasaki) is being developed with the support of Osaki (Kagoshima), which is an internationally recognized success case of food waste segregation (Morita 2017; ISHES News 2023; Osaki Town SDGs Council 2024; Tsuruda 2024).

Aligned with the idea that monetary support can be used as a strategy to foster composting (Niles 2020; Pickering et al. 2020; Kunszabó et al. 2022), it seems that many municipalities in Japan offer some kind of monetary assistance on the moment of purchase of the bin (Island land Co. Ltd 2023). Based on the current chapter results, framing this monetary assistance alongside technology/process information, or building a network around people who were granted financial support might increase the popularity and long-term engagement of these schemes. In fact, several researchers have put emphasis on the importance of practical training and continuous monitoring throughout the process (Tucker and Farrelly 2016; Kawai and Huong 2017; Loan et al. 2019; Pai et al. 2019; Jamal et al. 2019; Kala and Bolia 2021; Sayara et al. 2022). Tucker et al. (2003) mentioned that unsuccessful production of compost was one of the main reasons for dropping out the behaviour. A high dropout rate was also one of the reasons to Edogawa (Tokyo) stop financing composting bins purchase and investing on training and knowledge build up instead (Edogawa City 2022).

However, it is noteworthy, that social influence may be stronger when the programs are relatively new, whereas it may not be the case once they are well-established programs and strong ideas towards the behaviour have been formed (Pickering et al. 2020). Such suggest that adapting the messaging to the intervention stage should also be considered.

Financial and time availability was found significant to behaviour, confirming Wu et al. (2019) findings on how the lack of time perception can act against composting/segregation adoption. Moreover, in agreement with other previous scholars, gardening interest was proven to be an important condition for adopting composting (Tucker and Speirs 2003; Tucker et al. 2003; Edgerton et al. 2009; Nsimbe et al. 2018; Loan et al. 2019; Kunszabó et al. 2022). Using compost in the garden/farm can reduce costs associated with soil amendments and avoid the usage of

chemical products (Mihai et al. 2023). On the other hand, it poses the question of how should municipalities boost home composting when there is no gardening interest?

One solution might pass by increasing the integration between home composting projects and urban farms, owned community gardens, or public parks (Pai et al. 2019). For instance, in Japan, there are NPOs and municipalities that allow composters to give back their compost to farmers or municipal gardens (Kuchiba 2022; Sapporo City 2024a). Another possibility may pass by implementing locality/colony level decentralized the system (Kala and Bolia 2021), or a centralised food waste collection programs as cities like Nagai City or Seattle have (Kawai 2019; Pai et al. 2019; Kawai et al. 2020). These types of systems can also alleviate the convenience constraints associated with home composting. On the other hand, by levelling up the systems, the role of the local authorities might become more prominent (Jamal et al. 2019). It also poses additional challenges such as quality of the input and output material, system characteristics, logistics, demand/usage of the compost, associated costs, and overall long-term sustainability of the programs (e.g., depopulation of certain region of Japan) (Tsurumi et al. 2005; Nigussie et al. 2015; Cerda et al. 2018; Kawai 2019; Jamal et al. 2019; Paes et al. 2019; Inaba et al. 2022; Iacovidou and Zorpas 2022; Rathore et al. 2022; Fang et al. 2023). These points will be addressed once again with a higher detail in Chapter 7.

5.5 Chapter Conclusion and Future Research

The model results suggest that home composting in Japan is bound to social approval, behaviour visibility, knowledge about the process, gardening/farming interest, convenience, and a person's availability to do it. Positive and negative functional aspects of the composting process were significant the convenience perception that a person holds towards composting. Thus, they were found to have an indirect effect on the choice of behaviour. Fomenting community project and continuous training and support can be important pillars of successful composting programs. Moreover, improving the convenience of the process (Bernstad 2014; DiGiacomo et al. 2018), and fostering circular systems by increasing the integration between home composting projects and urban farms, owned community gardens, or public parks (Pai et al. 2019) might raise adoption rates even when people do not have gardening interest.

The present work widened the scope of analysis of the TCV and successfully identified key drivers to home composting in Japan, while using a categorical PLS-SEM model. Nevertheless, discussing food waste disposal alternatives is a topic of emerging importance that

should be further addressed by scholars and entrepreneurs. Future research developments as well as some of the limitations of this analysis are mentioned on the following paragraphs.

Firstly, this analysis relied on self-reported qualitative data from 9 of the 47 prefectures and only considered individuals over 30 years old. While the prefectures included are among the most populated in Japan, the sample percentage of people living in rural regions was smaller than the national average. Previous works pointed out differences between urban and rural areas food waste generation, composting incentives, and composting adoption rates (Niles 2020; Inaba et al. 2022; Nakamura et al. 2022). Therefore, further analyses on these nuances are needed.

Moreover, only the socio-demographics direct effect was studied, and age was not included in the model. According to Kala and Bolia (2021) and Widyatmika and Bolia (2023), different countries and social groups might prioritize incentives of distinct natures. Testing socio-demographics as a multigroup factor or a moderator may be helpful for future targeting of composting campaigns.

While engagement rates can vary depending on the promotional approach (Abrahamse, 2020, 2019; Hotta and Aoki-Suzuki, 2014), it is important to understand how to sustain that engagement (Steg and Vlek 2009). Only a small number of studies have looked deeper on composting drop-out reasons and how people engagement changes over time (Tucker and Speirs 2003; Tucker et al. 2003; Karkanias et al. 2016). Thus, the following chapter, Chapter 6, will contribute to academia by analysing this sample's dropout profiles and dropout reasons.

Finally, adding quantitative information and understanding the current state of ongoing Japanese programs is crucial for the development of sustainable composting systems being those decentralised or central ones. This will be partially addressed in Chapter 7.

Chapter 6: A closer look on composting dropout reasons in Japan

6.1 Introduction

Based on the findings of the previous chapter gardening interest, social pressures, knowledge, and convenience are important to composting involvement. Nonetheless, Chapter 5 did not provide detailed information regarding dropout reasons. Often decentralised such as household composting has been associated with high dropout and low adoption rates (Pai et al. 2019; Bruni et al. 2020; Edogawa City 2022; Iacovidou and Zorpas 2022). Thus, the present chapter contributes to waste management research field by, instead of focusing on engagement reasons (like the previous chapter), focusing on identifying the profile and reasons mentioned by people which have been involved in composting but do not do it anymore.

Decentralized food recycling such as household composting has been associated with low adoption rates when compared with other pro-environmental behaviours, including in Japan (Aoki et al. 2010; Kurisu and Bortoleto 2011; Phuphisith et al. 2020). For instance, the Japanese municipality of Edogawa (Tokyo) has inclusively taken into consideration this high dropouts' rate when deciding between investing in educating consumers toward composting or giving monetary incentives to engagement (Edogawa City 2022). According to Chapter 4's findings, people engaging in food waste recycling PEB showed less motivation in sustaining their composting behaviour than the trying motivation shown by who stated have never composted before. Inconvenience, odours, pest attraction, and time needed to properly compost have been often pointed as barriers keeping adoption rates low (Karkanias et al. 2016; Iacovidou and Zorpas 2022). This is also aligned with the findings of the previous chapter.

While literature has pointed out how different promotional strategies impact people's engagement in pro-environmental behaviours (PEB) interventions (Mckenzie-Mohr 2000; Hotta and Aoki-Suzuki 2014; Abrahamse 2020), scholars have also highlighted the importance of understanding how these changes can be sustained and durable (Steg and Vlek 2009; Abrahamse 2020). Notwithstanding, only a small number of studies have looked into composting dropping out reasons or made longitudinal studies to better understand how people's engagement changed over time (Sterner and Bartelings 1999; Tucker et al. 2003; Karkanias et al. 2016; Dai et al. 2016; Linder et al. 2018). Similarly, few follow-up studies on projects implemented in the past, such as the Rainbow project implemented in Nagai City in 1997 (Tsurumi et al. 2005; Ohashi 2008; Kawai 2019), or the food waste collection projects of the Vietnamese cities of Hanoi and Da Nang (Kawai and Huong 2017; Kato et al. 2020) can be found in literature. To the author's knowledge,

this is the first study looking at composting lapsing reasons in Japan, thus representing an opportunity to find important clues for long-term effective PEB interventions in the country.

This study includes the following analyses: 1) A comparison between the reasons why people who have never tried composting and the reasons why dropouts stopped composting; 2) A comparison between the reasons why current adopters compost and the reasons for dropouts having had engaged in composting; and 3) Profiles of dropouts, including which clusters from Chapter 4 they belong to is presented.

6.2 Background and Methodology

6.2.1 Dropout background

When studying dropping out reasons, Tucker et al. (2003) mentioned that moving to a new house, unsuccessful/inefficient compost production, and lack of waste and time were the most recurrent reasons to stop adopting this PEB. Population migration was also mentioned as a main reason to the decrease in the food waste collected in Nagai city's (Niigata, Japan) segregation scheme (Kawai 2019). Alongside the trend of depopulation in smaller, more rural areas occurring in Japan (Koizumi 2022), Kawai (2019) highlighted the importance of ensuring the knowledge about the city's waste separation rules are being clearly diffused to the newcomers. Thus, in agreement with scholars stating the importance of providing conditions to sustain PEB engagement throughout time (Steg and Vlek 2009; Waite et al. 2015; Abrahamse 2020).

The reasons for and against included in this chapter were aligned with difficulties and incentives identified in previous household composting and food waste segregation research. Particularly, reasoning related to functional, emotional, social, epistemic, and conditional values of the previous chapter's decision model, as well as the Food Waste Recovery Hierarchy (Papargyropoulou et al. 2014) used in were included in the survey. Thirteen motives for having had stopped composting/have never composted were included, namely: 1) Time Consuming (Tucker et al. 2003; Tucker and Farrelly 2016; Wu et al. 2019); 2) Bed Smell (Karkanias et al. 2016; Pickering et al. 2020; Sayara et al. 2022; Iacovidou and Zorpas 2022); 3) Verminous (Tucker and Speirs 2003; Karkanias et al. 2016; Pickering et al. 2020); 4) Cost (Pickering et al. 2020); 5) No use for the compost (e.g., no garden) (Edgerton et al. 2009; Loan et al. 2019); 6) Family Objection (Sayara et al. 2022); 7) Neighbourhood nuisance. 8) No space (Tucker and Speirs 2003; Sayara et al. 2022); 9) Failure (Tucker et al. 2003; Fernando 2021); 10) Did not know about compost (Pickering et al. 2020; Fernando 2021); 11) Bothersome and required effort (Tucker and Speirs 2003; Tucker et al. 2003; Pickering et al. 2020; Sayara et al. 2022); 12) Not enough food waste (Tucker and Speirs 2003; Tucker et al. 2003; Karkanias et al. 2016; Fernando

2021); 13) Give the leftovers to animals/pets (Papargyropoulou et al. 2014; Karkanias et al. 2016; Sayara et al. 2022);

Neighbourhood nuisance was included as a barrier based on the results found on the previous chapter regarding social pressure and norms effect on household composting. Thus, implying that besides family objections neighbourhood resistance and the necessity to conform may also lead to dropping out.

Moreover, moving out was not included as a reason to stop composting, despite Tucker et al. (2003) having considered it the most important reason to drop out household composting. This decision was done based on the ideas of habit discontinuity and mental inertia (Verplanken et al. 2008; Marechal and Lazaric 2010). Based on the latter, interruptions on someone's daily life such as moving out, travelling, retiring, or starting a family, can give a person a chance of reassessing their habitual behaviours. These trigger moments have often been seen as an opportunity to increase eco-friendly behaviour adoption (Marechal and Lazaric, 2010; Nash et al., 2019; Russell et al., 2017; Verplanken and Holland, 2002), but sometimes, they can also lead to negative spillover effects (Ratay et al. 2024). For instance, under the scope of this study, if people were already feeling demotivated because they did not have enough waste or other reasons, will be likely to use the move as a motive to stop. For this reason, the analysis focused on which functional, emotional, and social factors would be more likely to be behind people stopping with a moving out and did not include trigger moments to the cessation. Moreover, motives such as lack of space, or no garden can be associated with new living conditions and not necessarily with the act of moving out.

Reasons for engaging/having had engaged in composting covered 10 aspects, mentioned by previous researchers: 1) Acquaintance/Neighbour's recommendation (Edgerton et al. 2009; Jamal et al. 2019); 2) Family member's recommendation (Edgerton et al. 2009); 3) Eco-Friendliness (Tucker and Farrelly 2016; Pickering et al. 2020; Fernando 2021; Sayara et al. 2022); 4) Use it as fertilizer and soil amendment in gardening and farming (Edgerton et al. 2009; Tucker and Farrelly 2016; Fernando 2021; Sayara et al. 2022); 5) Waste Reduction (Pickering et al. 2020); 6) Monetary Incentive (Fernando 2021); 7) A lot of people in the area do it (community norms) (Mckenzie-Mohr 2000); 8) Health (Fernando 2021); 9) Enjoyment; 10) Children's Education.

Christie and Waller (2019) mentioned the important role composting and gardening can have in children's connection with nature. Some cities in Japan seem to be following this narrative. For example, Kobe City (Hyogo Prefecture) has promoted composting as an option for children summer school project in 2023, and Gifu City (Gifu Prefecture) has implemented composting and gardening projects in some schools (Go Green Kobe 2023; Gifu City 2024). Moreover, gardening related activities have been rising as recreation and leisure activity as they can reduce a person's

stress levels (Iijima and Egahiro 2014; Egerer et al. 2022). Researchers have also looked at passion and interest items when studying composting engagement (Karim Ghani et al. 2013; Rahman et al. 2022)

6.2.2 Statistical Tools

The analysis of this chapter is mostly descriptive. Thus, on a first instance, it relied in descriptive and visualisation tools such boxplots, sample distributions, and frequency rates. Following, to understand if there were significant behavioural differences between dropouts, practitioners, and people without previous composting experience, behavioural differences between dropout, practitioners, people without previous composting experience, as well as among dropout respondents from different clusters (Chapter 4's clusters), Mann-Whitney-U, Kruskal Wallis, and pairwise Dunn's significancy tests were used. Details about these significance tests can be found in Chapter 2.

6.2.3 Data Collection

This Chapter's analysis is based on same dataset of Chapter 4 and Chapter 5. However, it focuses on different aspects from the previous analysed. One of the constructs used on the composting engagement decision model (Chapter 5) was a categorical question based on a given composting definition, in which the respondents could choose from three options (I compost, I used to compost but stopped, I have never composted). Contingent upon the answers to this question, respondents were either asked about their reasons for composting/having had composted, or their reasons for not composting. Similarly to other items of the questionnaire, the questions concerning the reasons in favour and against composting were done in a 6-point Likert-scale and assumed continuous.

6.3 Results

Out of 1498 respondents, 102 (6.8%) respondents mentioned that they had composted in the past, but no longer do. From the dropouts' sub-sample 50% were female (51) and 50% were male (51) (Table 6.1). The average age was 53 years old, and the most common household size was of 2 people. The age group distribution of dropouts had a more uniform shape compared to

the distributions of the entire sample and the subgroup of current composters (Figure 6.1). Particularly, when compared with the entire sample, the dropouts had a higher concentration of people over 60 years old (Figure 6.1). There were more dropouts living in houses than in apartments (63.7% vs 36.4%) (Table 6.1). The income distribution was similar to the overall sample, with most of the respondents stating an average household income (from 4 million yens to 8 million yens) (Table 4.1, Table 6.1). Most of the dropouts a lived in Tokyo (18.6%), Saitama (15.7%), Aichi (12.7%), and Kanagawa (12.7%).

Table 0.1 Socio-demographics of the dropouts sub-sample

Variables	Categories	N	N%
Gender	Male	51	50.0%
	Female	51	50.0%
Age	30s	23	22.5%
	40s	24	23.5%
	50s	18	17.6%
	>60	37	36.2%
Region	Saitama	16	15.7%
	Chiba	8	7.8%
	Tokyo	19	18.6%
	Kanagawa	13	12.7%
	Aichi	13	12.7%
	Kyoto	4	3.9%
	Osaka	8	7.8%
	Hyogo	10	9.8%
	Fukuoka	12	10.8%
Educational Level	Junior High Sch. (or equivalent)	3	2.9%
	High Sch. (or equivalent)	24	23.5%
	College	13	12.7%
	University Degree (Undergraduate and Postgraduate)	62	60.8%
Marital Status	Single	30	29.4%
	Married	72	70.6%
Household Size	1	15	14.7%
	2	34	33.3%
	3	31	30.4%
	4	15	14.7%
	> 4	7	6.9%
Living with Children	Yes	27	26.5%
	No	75	73.5%
Yearly Income (before taxes)	< 2 million yen	4	3.9%
	2-4 million yen	25	24.5%
	4-6 million yen	25	24.5%

	6-8 million yen	18	17.6%
	8-10 million yen	14	13.7%
	10-12 million yen	10	9.8%
	>12 million yen	6	5.9%
House Type	Apartment	37	36.4%
	House	65	63.7%
Job	Corporate Worker	46	45.1%
	Housewife/husband	21	20.6%
	Part-timer	14	13.7%
	Unemployed	6	5.9%
	Self-Employed	10	9.8%
	Others*	5	4.9%

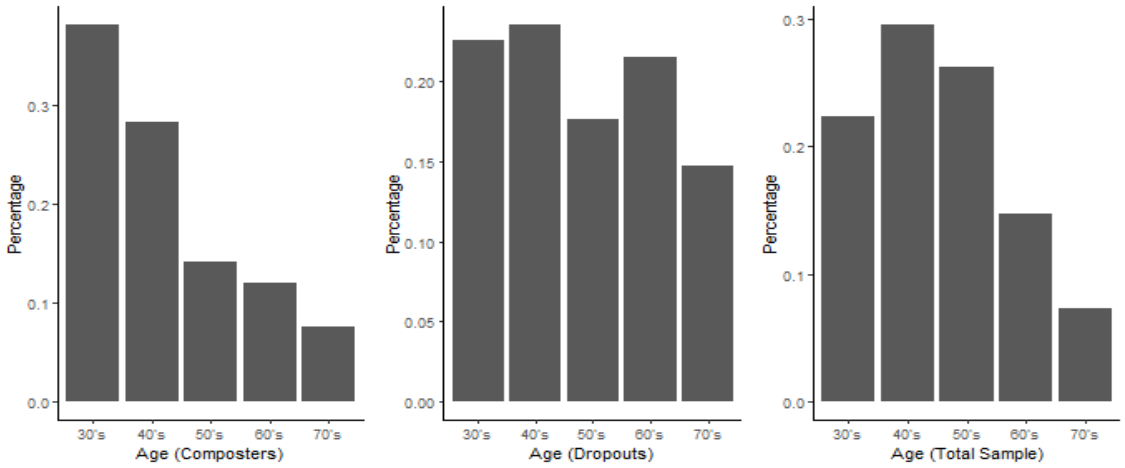

Figure 0.1 Respondents distribution per age group (10 years)

When it comes to their cluster distribution (groups found in Chapter 4), almost half of the dropouts (48%) belonged to the Responsible Consumers, 28.4% to the Average Practitioners, 18.6% to the Environmentally Involved, and 4.9% to the Sporadic Adopters (Table 6.2). The highest concentration of dropouts was among Responsible Consumers, characterized by having a higher proportion of female respondents engaged in household duties and an older sub-sample compared to other clusters. Responsible Consumers, which represent approximately 50% of both the entire sample and the dropouts' sub-sample, were the respondents who showed high engagement in waste reduction and ethical consumption PEB but had low adoption of alternative waste disposal methods. This implies that in the past, around 15% of the Responsible Consumers could have been characterized as Environmentally Involved. Additionally, aligned with Chapter 4's results, many of the women dropouts were Responsible Consumers and the largest number of the dropout men were part of the Average practitioners (Table 6.2).

Table 0.2 Cross-table of the dropouts per cluster and gender

Cluster Name	Male	Female	Total Dropouts
(1) Responsible Consumer	14	35	49 (48%)
(2) Average Practitioners	23	6	29 (28.4%)
(3) Environmentally Involved	11	8	19 (18.6%)
(4) Sporadic Adopters	3	2	5 (4.9%)
Total Dropouts	51 (50%)	51 (50%)	102 (100%)

Concerning gardening interest (Figure 6.2), 30.4% of people that were once involved in composting reported having interest in vegetable and herb gardens on balconies and small spaces, 29.4% had interest in gardening in a backyard/community garden, 21.6% had interest in farming, and 18.6% had no interest in gardening/farming activities. Thus, despite the majority of the dropouts showing gardening interest, it seems they are more interest in smaller scale styles of gardening than the current composters (Figure 6.2). This, findings are aligned with Chapter 5 and previous literature associating composting behaviour and gardening (Edgerton et al. 2009; Tucker and Farrelly 2016; Loan et al. 2019; Niles 2020; Kunszabó et al. 2022; Nguyen et al. 2022).

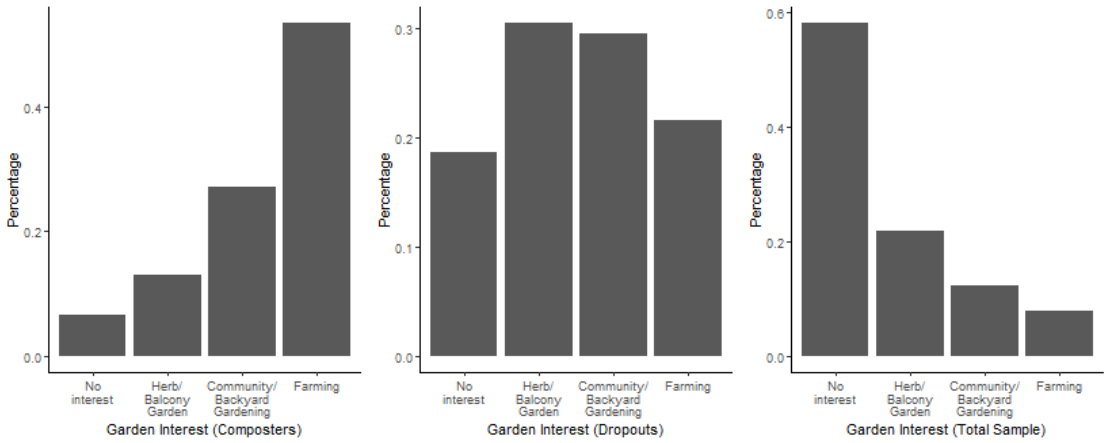

Figure 0.2 Respondents' gardening/farming interest distributions.

Moreover, as mentioned in previous chapters, intention to compost did not seem to reflect actual behaviour (Figure 6.3). Many of the current composters reported not being motivated to continue, while a large proportion of the respondents who have never been involved in composting stated having interest in starting it. When it comes to dropouts' intention distribution, although skewed to the left, the data approximates a normal distribution's shape (Figure 6.3). This

might indicate some remorse or delayed guilt from having stopped composting, or even that some of these people are considering adopt another recycling method.

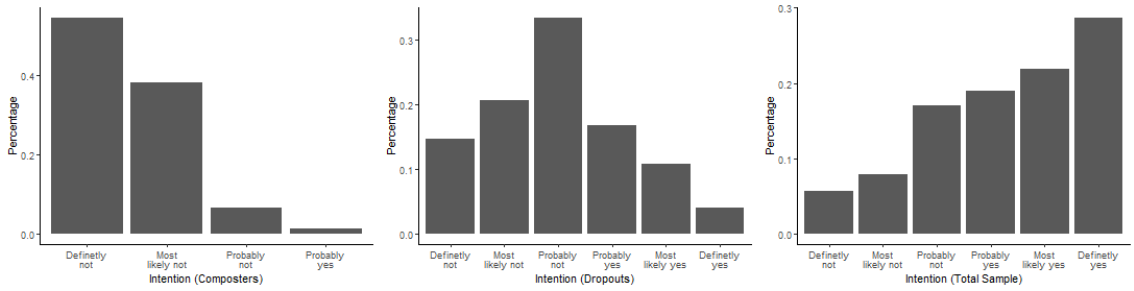

Figure 0.3 Respondents' composting intention distributions.

Besides the categorical question about composting based on a given definition, the frequency of food waste recycling through composting and its usage as fertilizer was addressed in more general lines with a 6-point Likert-scale. This allowed the capture of respondents who might have changed slightly their food recycling process (e.g., to an anaerobic process, vermicomposting, community-based composting), and thus did not think their food recycling process to match the definition given in the survey. It also enabled the capture of information about respondents that might, for instance, apply directly coffee grounds or eggshells to the soil. Some dropout respondents seemed to identify themselves with the latter cases, especially the ones who were Average Practitioners and Environmentally Involved (Figure 6.4). On the other hand, people who were both Responsible Consumers and dropouts seemed to have ceased completely their composting/food recycling activities. Overall, most of the dropouts completely ceased recycling their food waste. These results support the decision of having used two items in the composting engagement construct in Chapter 5's decision model.

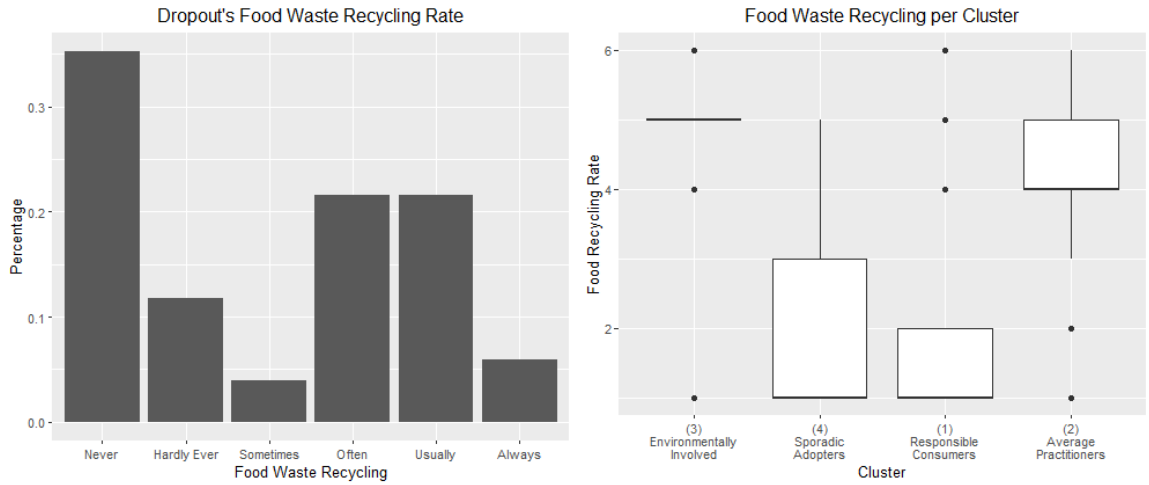

Figure 0.4 Dropouts' Food Waste Recycling (composting) frequency.

Dropouts' top reasons for stopping were functional aspects such as the required time, malodours, vermin, bothersome, incurred costs and required space (Figure 6.5). The least important dropping out reasons were the use of food waste to feed animals, no knowledge about compost, and neighbourhood nuisance. As for the main reasons for having tried composting, they included composting environmental benefits (such as reducing waste and being eco-friendly) and its gardening applications.

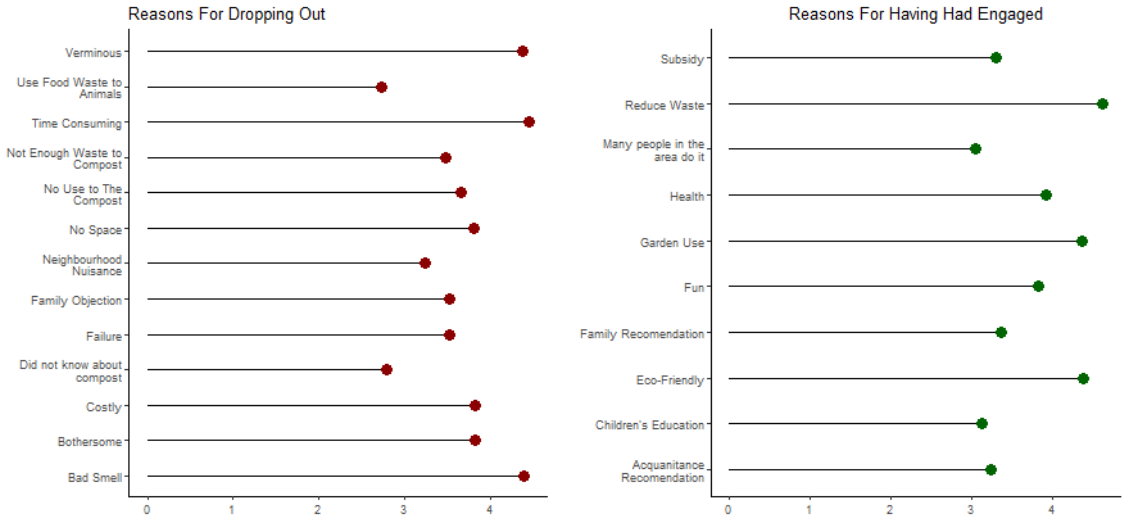

Figure 0.5 Dropout respondent's reasons for and against composting.

When looking at the differences between the reasons for having engaged in composting across the dropouts of different clusters, all the items were statistically different in a Kruskal Wallis' test. However, regarding reasons for dropping out, while the top reasons (in bold in Table 6.3) mentioned earlier were found statistically different across groups, not all the hypotheses were rejected. Note that the number of dropouts belonging to the Sporadic Adopters' cluster is five, which has been the minimum value advised to Kruskal Wallis' test (Lomuscio 2021).

Table 6.3 Krukall Wallis' test results

Reason (To/Against) / Mean Value	(1) Responsible Consumers	(2) Average Practitioners	(3) Environmentally Involved	(4) Sporadic Adopters	Kruskal Wallis' Test (p-value)
Acquaintance Recommendation	2.65	**3.86**	4.05	2.4	0.000*
Family Recommendation	2.71	3.83	**4.63**	2.4	0.000*
Eco-Friendly	**4.43**	**4.10**	**5.00**	3.2	0.005*
Fun	3.69	3.62	**4.79**	2.6	0.001*
Healthy	3.96	3.66	4.58	2.6	0.022*
Garden Use	**4.78**	3.59	4.58	**4.2**	0.001*
Reduce Waste	**5.12**	**4.00**	4.37	**4.4**	0.000*
Available Subsidy	2.71	3.48	4.52	**3.4**	0.001*

Many people in the area do it	2.35	3.45	4.37	2.6	0.000*
Children's Education	2.49	3.59	4.42	1.8	0.000*
Time Consuming	**4.47**	**4.28**	**4.68**	**4.40**	0.638
Bad Smell	**4.47**	**4.21**	**4.73**	3.40	0.058
Vermin	**4.41**	**4.14**	**4.84**	**3.60**	0.069
Costly	3.53	3.83	**4.68**	3.40	0.001*
No Use to The Compost	3..29	3.76	4.58	3.20	0.004*
Family Objection	3.18	3.66	4.42	2.60	0.005*
No Space	3.76	3.72	4.26	3.00	0.252
Failure	3.10	3.76	4.26	3.40	0.008*
Did not know about compost	1.98	3.31	4.21	2.40	0.000*
Bothersome	3.67	3.72	4.31	**3.80**	0.300
Not Enough Waste to Compost	3.18	3.52	4.42	2.40	0.001*
Use Food Waste to Animals	1.78	3.62	4.00	2.00	0.000*
Neighbourhood Nuisance	2.65	3.62	4.37	2.40	0.000*
*significant at 5%					

Comparing the reasons why people who dropped out with those who have never tried composting, the results seem to point out that respondents who have never tried it, tended to have stronger feelings about the barriers to engagement. Particularly, in concerns related to epistemic values such as knowledge and failure, functional barriers such as required space, and the fact of not having a way of using the produced compost (Figures 6.6). With the exception of time, bad smell, vermin, and family objection reasons, the intensity of the reasons to not compost was found statistically significant between these two groups in the Mann-Whitney-U test (Table 6.4). Note that, the reasons in which the null hypotheses were not rejected were the top reasons from dropouts having had stopped.

Table 6.4 Mann-Whitney-U test results

Reason For (Adopter vs Dropouts)	Mann-Whitney-U test (p-value)	Reason Against (No Experience vs Dropouts)	Mann-Whitney-U test (p-value)
Acquaintance Recommendation	0.023*	Time Consuming	0.748
Family Recommendation	0.002*	Bad Smell	0.874
Eco-Friendly	0.009*	Verminous	0.234
Fun	0.000*	Costly	0.002*
Healthy	0.000*	No Use to The Compost	0.000*
Garden Use	0.000*	Family Objection	0.795
Reduce Waste	0.000*	No Space	0.000*

Available Subsidy	0.002*	Failure	0.000*
Many people in the area do it	0.022*	Did not know about compost	0.000*
Children's Education	0.003*	Bothersome	0.000*
		Not Enough Waste to Compost	0.004*
		Use Food Waste to Animals	0.013*
		Neighbourhood Nuisance	0.014*
*significant at 5%			

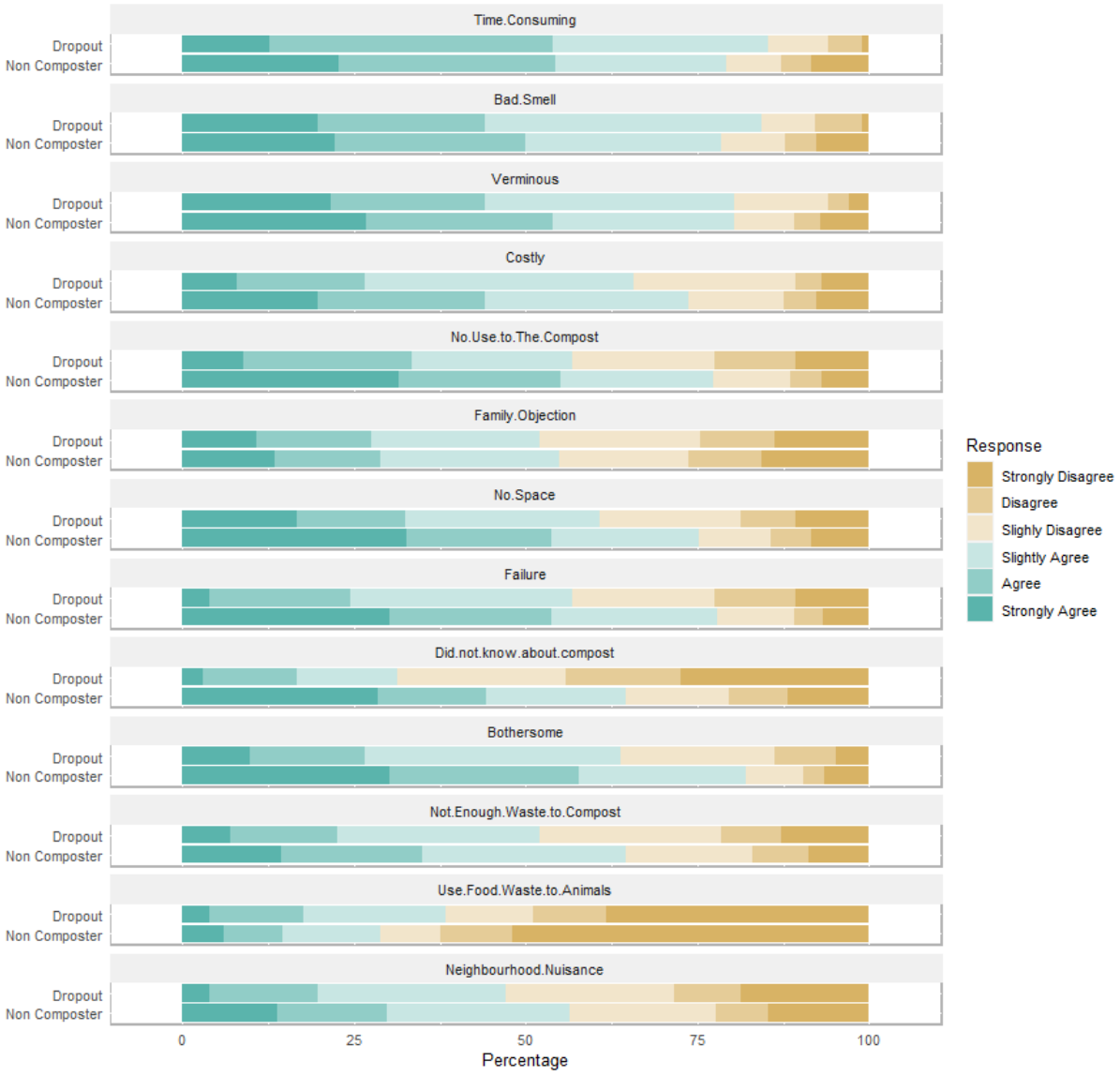

Figure 0.6 Reasons for Have Never Composting/Having Had Stopped

Moreover, the dropouts' reasons for having had engaged in composting and current practitioners main factors in favour of composting seemed to be the same (Figure 6.7). Nevertheless, the results of Mann-Whitney-U test suggested that there are significant differences

on the intensity of positive composting aspects between these two groups. Composters presented stronger beliefs towards the reasons to compost (Table 6.3). Such does not come as surprise, taking into consideration that the composters are still adopting the behaviour.

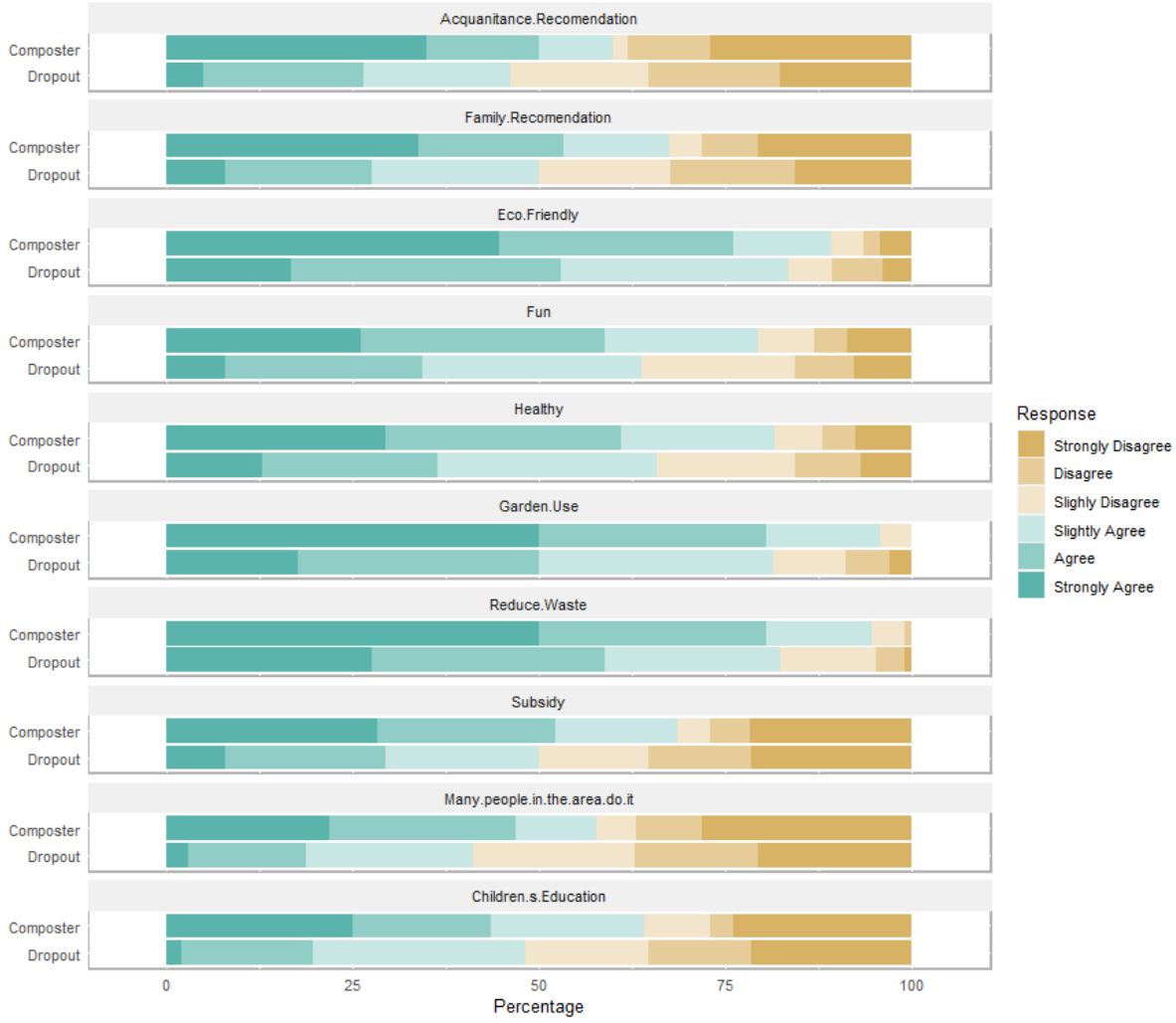

Figure 0.7 Reasons for Composting/Having Tried Composting

6.4 Discussion

6.4.1 Theoretical Implications

As this is the last chapter based on the data from the survey designed for this dissertation, some overall remarks about the questionnaire's structure should be done. First, based on the findings of this chapter and Chapter 4, it seems that the higher the involvement in composting is, the lower is the intention to continue. However, the questions related to reasons for stopping/not making compost were only done to people who currently do not compost, and not to practitioners. Thus, an opportunity to further address ways of maintaining the engagement in composting

throughout time was lost, by not asking composters why they reported such lack of motivation to continue and what would be the main reasons for them wanting to stop. Similarly, a chance to identify what would be the main reasons for prospect adopters to start composting, was also missed. To increase the understanding about persons motivations an option "*other*" could also have been included.

Secondly, the reasons to and against included in the survey were aligned with the functional, emotional, social, epistemic, and conditional values of the previous chapter's decision model and the Food Waste Recovery Hierarchy), while factors such as moving out were not analysed. However, when further exploring compost dropping out reasons, research might want to consider the mediation effect of these points in time, not only moving out (to a new house, city, or prefecture), but also other trigger such as retirement, eco-campaigns at someone's work, and travels. Additionally, the inclusion of items concerning different food recycling processes and what kind of failure they encountered may be included for a more detailed analysis. One of the questions of the questionnaire was done in a more general way about if people recycle/compost their food waste and use it as a fertilizer/soil amendment, however the categorical question was done based on a given definition (the complete question stands as: "*Compost is made by fermenting organic matter such as food waste, food scraps and fallen leaves from households with the help of micro-organisms. Do you compost?*"). As result, some people, who have possibly shifted to an alternative recycling process of compost, did not consider that their recycling method matched the given definition, or participate in kerbside systems, were considered composting dropouts. Many cities worldwide are starting to adopt circular economy policies and kerbside programs, and in presence of both options people, who do not have prior experience, tend to prefer participating in kerbside models (Niles 2020; Widyatmika and Bolia 2023). Despite kerbside food collection not being widespread in Japan (MOE 2023c), Herrador et al. (2024) mentioned an increase in Circular Economy policies and programs.

Thirdly, the survey used self-reported Likert-scales which can bring some measurement uncertainty, as the items' related concepts and frequency notions can change among respondents (Lange and Dewitte 2019). A way to overcome this issue could have passed by, when possible, using more tangible measurements like Nguyen et al. (2022) did. When asking respondents about how much waste they produced, the latter authors used ice-cream and water bottles as reference measures (Nguyen et al. 2022). Having such tangible items can also be useful when implementing behavioural change interventions (Izumi et al. 2020). Likewise, in the questionnaire of this doctoral dissertation, the gardening/farming item was designed to give a more concrete idea on the "scale" of the interest of the respondents. Future researchers may try to use more this kind of scales.

Fourthly, as mentioned in Chapter 4, the only item included in the survey about Ethical Food Consumption was related to organic products. Nonetheless, based on Chapter 3's results, and specially in Japan, including local/national foods (with a clear definition of the covered range) and food supporting disaster-stricken areas could have given a more in-depth portrait of the Japanese behavioural patterns throughout the food consumption stages. Similarly, the inclusion of more concrete measures about food lifestyles and the usage of food resources in a way that prevents waste (Brunsø et al. 2004, 2021; Simões et al. 2022) could have contributed to a more complete profiling.

Finally, as the analyses made in Chapter 5 is, to the author's knowledge, the first applying TCV to household composting, the survey not only contained pre-existing TCV survey scales, but also included items from other previous literature on the analysed PEB. This allowed some exploratory flexibility if needed, but at the same time resulted in some questions (items about general environmental knowledge and items related with New Environmental Paradigm (NEP) (Dunlap and Van Liere 2008)) not being used in any of the analyses of the chapters. Based on the relevant results found about composting engagement using the TCV framework, future researchers might want to test more traditionally used items of this framework.

6.4.2 Social and Management Implications

According to the results, more than one third of the dropouts were people over 60 years old. Depending on the technology used for composting, some can require more manual work than others, which in turn, may become harder as a person gets older. Moreover, sometimes elders move in with your familiars or to a homecare facility, which may also imply the cessation of their composting activities.

Busy schedules and long working hours are associated with the Japanese Laboral market (Ono 2018). Thus, the fact one of top reasons to stop composting was related to time restrictions is aligned with many dropouts having corporate jobs. Moreover, approximately 50% of the dropouts were Responsible Consumers, which tend to often engage in PEB related with the purchase and usage of food products. Therefore, and given that dropouts seemed keener to restart composting than the current practitioners to continue, an improvement in the conditions and support offered to who wishes to engage in composting may result in a re-adoption of the behaviour. This moderate intention to restart might derive from the idea that, sometimes, the interruption can result in a reinvigoration of someone's environmental awareness and consequently promote PEB adoption (Nash et al. 2019).

Dropouts expressed gardening interest, but to a smaller extent than the current composters. In particular, they showed more interest in activities such as having balcony herb balcony gardens rather than community farming or backyard gardening. The formers have smaller necessity of soil amendments in comparison with farming or backyard gardening of larger scales, which can result in a feeling of not having use for the remaining compost. As expected, dropouts expressed less intense reasons to compost than current composters. On the other hand, their barriers to compost were less intense than the people who have never tried.

Some Average Practitioners and Environmentally Involved that ceased their composting activities shifted to a different recycling method. Moreover, the percentage of Aichi residents among the dropout was superior to the overall sample percentage. According to Kurisu and Bortoleto (2011) and Hirose (2015), Aichi invested in food waste policies since an early age, but it seems that some people, who may have been early adopters of composting technologies, have ceased their activities by the time this survey was done. This highlights the importance of finding the best technology to ones' lifestyle and having ways of keeping the consumers engaged throughout time. For instance, when a composting technology that fitted better the climate conditions of the region than the one being used started being promoted in an Indonesian city, the composting adoption rates of the population increased (Kurniawan et al. 2013).

6.5 Chapter Conclusions and Future Research

Vermin, malodours, and lack of time were the most common reasons for dropping out household composting in Japan. All the clusters found in Chapter 4 reported the same top dropout reasons. Composting's eco-friendliness and its usage in gardening/farming were the main reasons to people tried this PEB. However, the reasons to have had engaged in composting were less homogenous across clusters than the cessation factors. Many dropouts were Responsible Consumers and Average Practitioners. the intention of the dropouts towards making compost was higher than the intention shown by the current practitioners, which may imply that if their surrounding infrastructure and conditions to recycle improve, they might restart composting. A small number of dropouts seemed to have shifted to an alternative method of food recycling.

Despite the decision of not including them in the present analysis, future research covering this topic may ponder the inclusion of variables about moving to another residential area and assess their role as moderators to other reasons. As dropping out factors are not often explored, it could also be interesting to run semi-conducted interviews or focus group to better understand what led to the dropout, as well as if there are specific incentives that can be implemented to motivate people to re-start their food recycling practices. Additionally, in order to optimize

Japanese food waste management systems and how their advertised to the citizens, understanding which is connection between long-term engagement and the different approaches municipalities use to promote food waste recovery, may be relevant. For instance, Edogawa City (Tokyo) decided to invest into building citizens' knowledge about composting instead of giving monetary incentives, but, to the author's knowledge, there is no actual study measuring the impact of this decision. The following chapter will the address this point to a certain extent, as it explores different Japanese food waste recovery systems and how they are being promoted to the consumers. Nevertheless, no direct connection with differences on adoption rates or the long-term engagement on the behaviour is established, so future research focusing on establishing such connection is needed.

Chapter 7: Ethical Consumption and Composting Facilitators in Japan: A case study household/community incentives

7.1 Introduction

Throughout the previous chapters important drivers to food related PEB were pointed out and adoption profiles were identified. In this chapter, the objective is to understand what kind of local initiatives exist in Japan to foster these behaviours along the food systems, what their main differences and similarities are, and which the previously identified profiles are being targeted how. Under the scope of this dissertation, no interventions or experiments were designed nor implemented. However, this chapter intends to explore how some organizations, communities, and local governments have been enacting the government normative guidelines about food waste recycling and the promotion of sustainable lifestyles.

Collaboration between all stakeholders of the food chain, including the consumers is fundamental. Literature has pointed out that building public awareness and consensus, taking into account the preferences and demands of the stakeholders, as well as direct and personal contact by local governments, are decisive for a successful and sustained behavioural change (Vicente and Reis 2008; Kawai et al. 2020). Nevertheless, the way this communication is designed should not be disregarded once research about information campaigns has shown contradictory results on its effectiveness (Dai et al. 2016; Abrahamse 2020). For instance, Abrahamse (2020) mentioned the way the information is framed (e.g. inclusion of social norms, environmental values, or the use of a nudging approach) can impact the success of the communication strategy (Abrahamse 2020). For example, citizens' participation level of involvement in local and governmental projects can vary deeply from non-participation (manipulation, therapy), to tokenism (information, consultation, placation), and citizen control (partnership, delegated power, citizen control), which might impact the project's effectiveness and receptiveness (Arnstein 1969; Gaber 2019).

Depending on how they were designed, food recycling systems may require different degrees of involvement of a household unit. From a waste provider role to a stakeholder that is responsible for providing, producing, and consuming the compost, respectively. Contingent on the food recycling process, the waste, and in some cases sewage too, can be turned into fertilizer, animal feed, bio-gas, or bio-mass among others (Hata 2021; MAFF 2021). Food recovering systems can also be a large-scale, complex centralized operations, or a decentralized one consisting of a network, or standalone processes at a community, neighbourhood, or household level (Pai et al. 2019; Bruni et al. 2020). Within compost production systems there are also a

variety of processes such as windrows, aerated static piles, tunnel composting, in-vessel composting (Cerda et al. 2018; Zhou et al. 2022).

The number of case studies about the implementation and/or interventions about centralized, and decentralized composting/food recovering systems (in some cases both systems have been compared or analysed in parallel) has been increasing across the world in recent years (Nomura et al. 2012; Hotta and Aoki-Suzuki 2014; Waite et al. 2015; Dai et al. 2016; Kawai and Huong 2017; Oliveira et al. 2017; Bong et al. 2017; DiGiacomo et al. 2018; Linder et al. 2018; Bonoli et al. 2019; Pai et al. 2019; Jamal et al. 2019; Paes et al. 2019; Niles 2020; Bruni et al. 2020; Monteiro et al. 2021; Kala and Bolia 2021; Sewak et al. 2021; Marcello et al. 2021; Iacovidou and Zorpas 2022; Leeabai et al. 2022; Rathore et al. 2022; Eghbali et al. 2022; Mihai et al. 2023; Widyatmika and Bolia 2023). However, Japanese-based literature is scarcer in comparison with U.S or European-based research, especially studies focusing on providing a broad review on which are the most common strategies adopted by local authorities, being them centralized, decentralized, or hybrid. Thus, this chapter will address such research gaps and be the first presenting a SWOT analysis on compost return systems (hybrid systems), a food recovery cycle that seems to be gaining traction in Japan.

In the first instance, an overview of central food recycling systems across Japan is provided, identifying common and distinctive traits of their setups and promotional approaches. Following, the same is done for decentralized household composting initiatives. Finally, the strengths, weaknesses, threats, and opportunities (SWOT) of hybrid systems, where composting happens at a household level, but the compost is used at a community or central level, are presented. This is, to author's knowledge, the first academic study on such hybrid settings.

7.2 Background and Methodology

7.2.1 Food Recycling Systems and Interventions Data Collection

Interventions can be of several natures and address many aspects of behaviour. Regarding food related behaviours, interventions have often relied on mechanism such as nudging, change to default, changes on the food environment, environmental labelling, visual prompts, provision of information, and social norms (Abrahamse 2020). Moreover, while some initiatives target specific behaviours (Sussman and Gifford 2013), others can have a more general scope like fostering pro-environmental identity (Whitburn et al. 2023). For instance, connection with nature has been found to be positive and significant to pro-environmental behaviour (Whitburn et al. 2020), implying that fostering this connection, may result in the adoption of several pro-

environmental behaviours. Literature concerning this idea that engagement in a specific behaviour may also catalyse the adoption of others (spillover effect) has been growing recently (Maki et al. 2019; Kumar et al. 2023). These effects, however, are not always positive. Researchers have identified positive, negative (e.g., recycling possibility leading to a higher consumption of resources (Ma 2019)), contextual (e.g., a PEB that is performed in one context, spreads to another context), and temporal (the engagement in a PEB causes a subsequent change in the frequency or intensity of that same behaviour adoption) spillover effects (Nash et al. 2019; Capstick et al. 2022). Such synergies between PEB, as well as the fact that some PEB have faster decision-making processes then others, should also be taken into consideration when designing the interventions, as they can contribute to the project's (in)effectiveness (Abrahamse 2020). Moreover, besides its initial implementation stage, it is important to develop support mechanisms to ensure that stimuli to adoption are kept throughout time (Steg and Vlek 2009; Kawai and Huong 2017; Abrahamse 2020).

When studying central food waste segregation schemes, previous studies have mentioned the following engagement strategies: 1) raising the education and awareness through seminars, conferences, local medias (social media, radio, newspaper, television); 2) having convenient equipment and infrastructure; 3) continuous monitoring and support; 4) implementing monetary incentives or reward programs (e.g. pay by weight of residual waste) 5) taxing the amount garbage; 6) having practical example on how to make segregation; 7) having a community or neighbourhood liaison; 8) and being transparency about the use of the final product (e.g. promote food products that used compost derived from the segregated food waste) (Evison and Read 2001; Sussman and Gifford 2013; Bernstad 2014; Moh and Abd Manaf 2014; Dai et al. 2016; Kawai and Huong 2017; Jamal et al. 2019; Niles 2020; Kawai et al. 2020; Widyatmika and Bolia 2023). In Japan, cities with central systems seem to be following some of these approaches.

As far as decentralized systems are concerned, Pai et al. (2019) divided their incentives into top down and bottom-up approaches. Top-down strategies include providing technical assistance or training and local ordinances to promote composting, whereas collection systems at community level and setting up community composting in public garden, schools or parks are bottom-up approaches (Pai et al. 2019). These strategies to be aligned with part of the information dissemination methods mentioned by Dai et al. (2016), being some currently in use across Japan.

7.2.2 Data Collection

The data about composting initiatives around Japan was mostly collected online. This analysis crossed information from reports and datasets from the Ministry of Environment of Japan

(MOE) (MOE 2021, 2022, 2023b, a), an online dataset about food waste drying machines' subsidy available by prefecture from a company that sells these machines (Island land Co. Ltd 2023), and from municipalities' official websites.

Additionally, information about Kobe city's (Hyogo) composting monitoring program and a compost collecting system was gathered through in person interviews and emails exchange with the projects' coordinators and a farmer involved in a compost collection project. Kobe city is one of the largest cities in Japan and has since an early stage been a place focused on consumer-farmer relations, being the birthplace of Japanese consumer co-operative movement (JCCU 2024). Despite having now expanded to business areas such supermarkets, consumer co-operative movement initial goal was to support and improve the livelihood Kobe citizens (JCCU 2024). By interviewing different stakeholders of these programs, a multi-dimensional perspective of the attributes of each project could be given. The emails and interviews were done in Japanese.

7.3 Food Waste Recycling Schemes in Japan

7.3.1 Central Food Waste Recycling Alternatives and Incentives in Japan

During the 1980s there was a revival in the Japanese composting industry with an increase in the number of composting plants (Kawai et al. 2020). Almost 40 years later, Japan summated 100 central composting facilities which were responsible of processing 0.5% of the total waste produced in 2021 (Table 7.1) (Kawai et al. 2020; MOE 2021, 2023c). Not all of these facilities treat household waste, nor all municipalities have separate collection systems for food waste. According to MOE's report on food loss, only 212 municipalities (12.4% from 1704 that answered the survey) stated to collect separately food waste in all their wards and 80 have a separate food waste collection system in some of their wards (4.7%) (MOE 2021). The latter report is missing some municipalities of Hokkaido, Okinawa prefectures, and two municipalities of Kyoto prefecture (MOE 2023b).

Table 0.1 Waste quantity in Japan in 2021

Unit	Total Waste (tons)	Total Waste Recycled (tons)	Waste Composting Facilities (tons)	Animal Feed Conversion Facilities (tons)	Methane Fermentation Facilities (tons)
Tons	39 359 760	8 156 991	183 548	9 633	105 199
% total	100%	20.72%	0.47%	0.02%	0.27%

% recycled	-	100%	2.25%	0.12%	1.29%

Back in 2008, Ohashi (2008) presented an overview on 58 municipalities that started composting projects back in the 90's and early 2000's. From the analysed cities, 8 did not include households as a source of waste, and by the time of the latter paper was published, 11 of the analysed projects (19%) have ceased their operations (Ohashi 2008). The main factors associated with the end of those operations were: low demand for compost, inconsistent compost quality, contamination of the source waste, and mechanical failures (Ohashi 2008). Low compost demand has also been pointed out as a reason for metropolitan areas like Kyoto not considering regional composting (Matsuda et al. 2012). Quality of the final output (Ohashi 2008; Madusanka et al. 2017; Guo et al. 2018; Kawai et al. 2020; Iacovidou and Zorpas 2022; Fang et al. 2023), constant quantity and quality of the waste (Li et al. 2017; Jamal et al. 2019; Okayama et al. 2020; Kawai et al. 2020; Torrijos et al. 2021), as well as initial costs (Madusanka et al. 2017; Kawai et al. 2020), have also been mentioned as struggles of central segregation systems by scholars from diverse countries.

Both Kawai et al. (2020) and Iacovidou and Zorpas (2022) have summarized some pre-requisites to successful central composting systems concerning social, economic, technological, environmental, and political aspects. In particular, Kawai et al. (2020) identified necessary conditions concerning the project's social context, cooperation and understanding of residents, institutional aspects, governance capability, financial aspects, and technical aspects (Figure 7.1). This section will give some examples of citizens cooperation approaches as well as financial, social, and technical aspects of central food recycling initiatives in Japan.

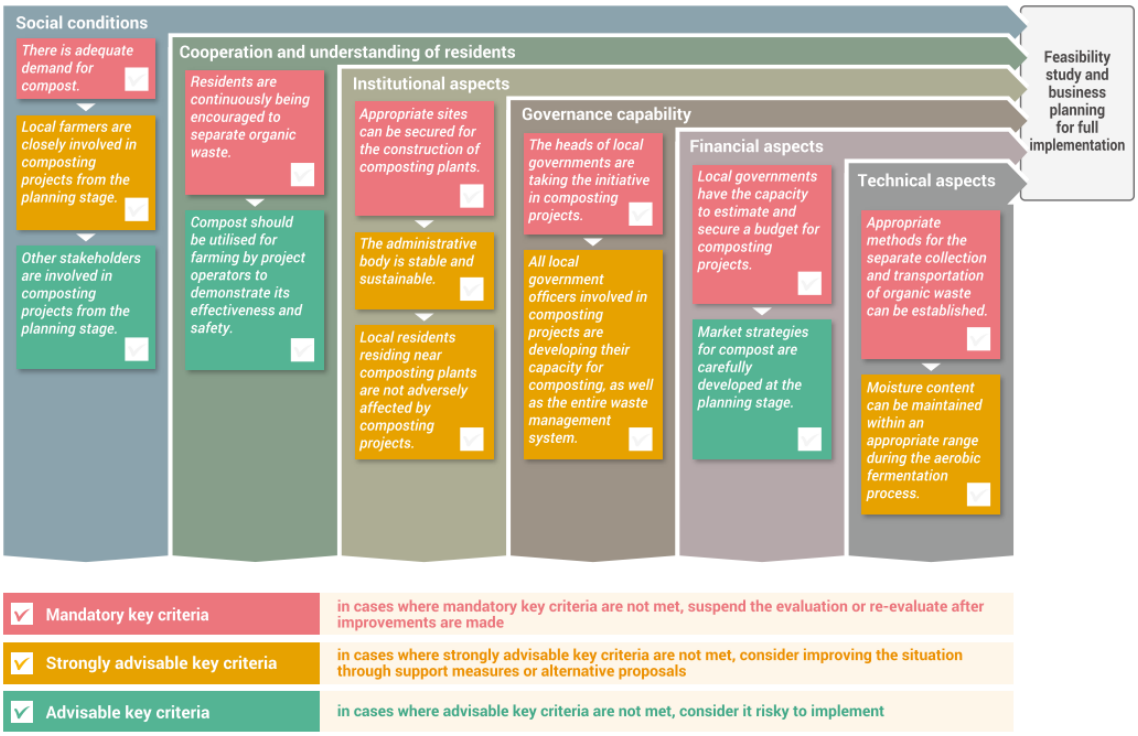

Figure 0.1 Central Composting systems requirement (retrieved from Kawai et al. (2020)*)*

7.3.1.1 Technical Aspects

In Japan, technical aspects of centralized food recycling systems seem to vary in attributes such as packing used for collection (e.g., plastic bags, paper bags, plastic bucket), collection location (e.g., kerbside or drop-off station), frequency of collection, transportation method (e.g., different truck types) (Kawai et al. 2020) and, as it was already mentioned, the final output and composting process. From the analysed sample, cities with larger populations tended to adopt more often plastic bags as a packing material, which in turn were associated with the use of compactor trucks (Table 7.2, Figure 7.3 (b)). Cities which used plastic buckets for collection tended to use flatbed trucks (Figure 7.3 (a)). In Ikeda town (Fukui Prefecture), the food waste is collected in paper bags and the project is ran in collaboration with an NPO (Ikeda Town 2021). Also, in Shibata city (Niigata), food waste collection is available in some areas of the city through a partnership between the city and an NPO (Shibata City 2023; You&Me NPO 2024). From the sample, only Koshimizu town in Hokkaido prefecture used a compostable bag to package the food waste, as the bag is also composted on the city's composting process (Koshimizu Town 2024). Also in the same prefecture, in Niseko town, citizens use plastic bags to segregate the waste, but after they put them the kerbside bucket stations (Niseko Town 2024a, b). Drop-off systems seem to have greater flexibility in collection frequency. However, it is relevant to mention that

the drop-off bucket itself has designated collection days. Cities usually make that information available too (Satsuma Town 2023).

Table 0.2 Municipalities running food waste collection schemes.

Prefecture	City	Packing of Collection	Location	Frequency	Final output	Population (2020 Census)
Ibaraki	Tsuchiura	plastic bag	kerbside	designated day	compost; biogas	142 074
Aichi	Obu	plastic bag	kerbside	designated day	biogas	93 123
Kagoshima	Satsuma	plastic bag and bucket	drop-off	everyday	compost	20 243
Okayama	Maniwa	plastic bucket	drop-off	everyday	compost	42 725
Ishikawa	Kaga	plastic bucket	drop-off	designated day	compost	63 220
Aichi	Toyohashi	plastic bag	kerbside	designated day	biogas; coal	371 920
Shizuoka	Fujieda	plastic bag	kerbside	designated day	compost	141 342
Yamagata	Nagai	plastic bag and bucket	drop-off	everyday	compost	26 543
Aomori	Towada	plastic bag and bucket	kerbside	everyday	compost; energy	60 378
Hokkaido	Kutchan	plastic bag	kerbside	designated day	compost	15 129
Tottori	Yazu	plastic bucket	drop-off	everyday	compost	15 937
Nagasaki	Tsushima	plastic bucket	drop-off	everyday	compost	28 502
Nagano	Shimosuwa	plastic bag	kerbside	designated day	compost	19 155
Hokkaido	Koshimizu	compostable bag	-	-	compost	4 623
Hokkaido	Niseko	plastic bag and bucket	drop-off	designated day	compost	5 074
Fukui	Ikeda	paper bag	drop-off	designated day	compost	9 382
Kagoshima	Osaki	plastic bucket	-	-	compost	12 385
Niigata	Shibata	-	-	collection	compost	94 927



Figure 0.2 (1) Plastic Bag (Tsuchiura City 2024)*; (2) Plastic Bucket* (Maniwa City 2019)*; (3) Ikedas's Paper Bag (retrieved from* Kawai et al. (2020)



Figure 0.3 (1) Compactor Truck retrieved from Tsuchiura City (2024)*; (2) Flatbed Truck* (Osaki Town 2020)

7.3.1.2 Planning and Budgeting

Another important factor in central systems concerns the budgeting of construction, operational, and marketing activities (Kawai et al. 2020). To do so, it is essential to have an adequate estimation of compost demand and balance point between raw materials and final output (Kawai et al. 2020). Raw materials in a food recycling/composting system can be food waste, but also garden and farm waste, and in some cases, like in Toyohashi city (Aichi), sewage waste (Toyohashi City 2024). Thus, having an accurate estimation of the food loss and food waste rates at a city level can be of interest during a project's planning stage. Food waste represents a heavy parcel of the total waste in Japan (Liu et al. 2016; Yamada et al. 2017). Nevertheless, the actual conditions of the waste panorama can change across municipalities (Suthar and Singh 2015; Pai et al. 2019). Understanding these variations in the waste quantity and composition is not only a resourceful information to plan food recycling systems but also to design effective overall food waste reduction strategies.

Ueta and Koizumi (2001) and Yamada et al. (2017) presented in detail the waste composition of Neyagawa city (Osaka) and Kyoto city (Kyoto), respectively. In 2022, the cities of Sano (Tochigi), Fujioka (Gunma), Okegawa (Saitama), Ito (Shizuoka), and Ibara (Okayama) also examined their waste composition and calculated their food loss rates (MOE 2022). Based on the latter cities' reports, as well as other regions previous assessments, more populated areas

are associated with smaller and less disperse rates of food loss per person/day (MOE 2022). This kind of waste examination, however, does not seem to be a common practice among local governments yet. Only around 23% of the municipalities stated knowing the amount of food waste generated by households (MOE 2023b). This percentage becomes even smaller when it comes to towns/cities that have an understanding of the composition of the food waste (leftovers, cooking scraps, or packed goods) (MOE 2023b). Distinct data collection methods were used across cities that conducted such assessments (MOE 2023b). Within these collection methods, three municipalities conducted monitoring programs with the cooperation of citizens (MOE 2023b). This is an example of citizens' involvement in a planning stage, which can possibly foster a higher engagement in subsequent initiatives related to the survey topic, motivate the participants to look for more information about the respective issues, and increase a person's awareness about their own behaviour.

7.3.1.3 Promotional Strategies

This support and involvement of waste generators (citizens, restaurants, hotels, farms) is crucial to assure that food recycling systems are sustainable (Jamal et al. 2019; Kawai et al. 2020; Iacovidou and Zorpas 2022). Local governments should ensure the waste reduction initiatives are clearly explained to all the stakeholder, including residents (Yamada et al. 2017). As mentioned previously, different Japanese municipalities seem to rely on different approaches.

7.3.1.3.1 Reward Programs:

In certain the municipalities where food waste segregation was adopted, residents who participate in the program are eligible to receive free compost. This is the case of Tsushima city (Nagasaki), Shimosuwa town (Nagano), and Koshimizu town (Hokkaido) (Koshimizu Town 2024; Tsushima City 2024a, b; Shimosuwa Town 2024). In Tsushima city the possibility of receiving free compost is well visible on the project's promotional flyer (Figure 7.4). In Shimosuwa town, the compost is distributed free of charge twice a year (Shimosuwa Town 2024). According to Ohashi (2008), compost availably (if it is available to the public or not) and price (free or not) are two of the characteristics the varies a considerably from project to project.



Figure 0.4 Free compost opportunity in Tsushima city's Promotional Flyer (Tsushima City, 2024)

7.3.1.3.2 Composting Liaisons:

Another way to promote engagement is through liaisons (Jamal et al. 2019; Kawai et al. 2020). Project liaisons can be NPOs/NGOs, companies, leaders of community groups, women's unions, or neighbourhood associations that act as a bridge between the waste generators and central management (Kurniawan et al. 2013; Dai et al. 2016; Kawai et al. 2020; Kuchiba 2022). Liaisons can encourage residents to participate in separation at the source, as well as assure the proper disposal of the organic waste (Kawai et al. 2020). Both in Ikeda town (Fukui) and Shibata city (Niigata), food waste collection is done through NPOs (Ikeda Town 2021; Shibata City 2023), allowing a closer proximity between stakeholders and facilitating the support and assistance in the separation process. Furthermore, based on Chapter 5 findings as well as previous research (Postmes and Swaab 2005; Abrahamse and Steg 2013; Dai et al. 2016), these personal interactions can facilitate PEB adoption by making social norms more prominent and building group identity. These mediators can also facilitate direct links between waste generators and farmers.

In cities such as Osaki town (Kagoshima) and Shimosuwa town (Nagano), neighbourhood leaders and women's unions inspect the contents of household food waste buckets before they are taken to the composting facilities (Figure 7.5) (Morita 2017; Osaki Town 2020; Osaki Town SDGs Council 2024). Moreover, in Koka city (Shiga) and Shimosuwa town (Nagano) new groups of participants need to fill a form listing all the members and assign a group leader (Koka City 2023; Shimosuwa Town 2024). In Shimosuwa town, the group leader is responsible for a maximum of 8 households and ensures the proper storage of the group's containers, alongside passing down information to the households (and vice versa) (Shimosuwa Town 2024).



Figure 0.5 Waste Inspection (Osaki Town 2020)

7.3.1.3.3 Transparency about the use of the final product:

Showing citizens the possibilities that can arise from their actions and give concrete example in which compost is being used, can not only promote the segregation of waste but also foster the consumption of ethical food (Kawai et al. 2020). Upon composting production some cities (Nagai, Motegi, Ikeda, Kaga) have created special labels for compost grown vegetables and antenna shops where these products are being sold (Figure 7.6) (Ikeda Town 2015; Kaga City 2021). In the case of Ikeda town, some antenna shops are located in other cities of the prefecture, thus promoting the relationship between cities within the same region and the consumption of local goods (Ikeda Town 2015). Nagai city (Yamagata) has also implemented a program in which the school lunches are made with compost grown products (Kawai et al. 2020). These kinds of strategies are aligned with the Ethical Food Consumption drivers identified in Chapter 3.



Figure 0.6 (1) Nagai city's compost label; (2) Motegi town's compost label; (3) Ikeda town's antenna shop; (4)(5)(6) Ikeda town's compost labels; (7) Kaga city antenna shop (Kawai et al. 2020; Kaga City 2021; Ikeda Town Agricultural Corporation 2024).

Other cities give concrete examples of compost applications or details about the process's final output (e.g., Toyohashi city, Maniwa city) (Maniwa City 2019; Toyohashi City 2024). Moreover, despite not being free, in Yahaba town in Iwate Prefecture, the purchase of the compost made from household waste is promoted directly on the waste separation calendar of the town (Figure 7.7).



Figure 0.7 Yahaba city's waste collection calendar (Yahaba City 2024).

7.3.1.3.4 Explanatory videos and leaflets, and knowledge sharing

Towada city (Aomori), Tshushima city (Nagasaki), and Nishiizu town (Shizuoka) are municipalities which are now on their project's launch/trial stage (Towada City 2024; Tsushima City 2024a; Osaki Town SDGs Council 2024; Tsuruda 2024). Thus, similarly to other cases (Bernstad 2014; Kawai et al. 2020), collection trials were first done in specific locations of the municipalities (Towada City 2024; Osaki Town SDGs Council 2024). These trials involved sensitization and promotional campaigns within the neighbourhood associations of those locations, which included workshops and seminars. Under the "ALL COMPOST" project, Nishiizu and Tsushima cities' segregation scheme and educational meetings are being developed in a city-to-city cooperation with Osaki city (Kagoshima), which has already a well-established food waste recycling system (Morita 2017; Osaki Town SDGs Council 2024; Tsuruda 2024). Having access to expertise of stablished projects can be an efficient strategy to increase the success rate of new interventions (Kurniawan et al. 2013).

Besides this knowledge sharing factor, another point to be highlighted is the use of English words on the advertising of the latter initiatives. Leung and Chan (2016) and Holmquist and Cudmore (2013) mentioned that the use of English words by non-English speaking countries in marketing campaigns can increase the appeal of the product/service that is being advertised. In this case, the project is called "ALL COMPOST" and Tsushima's promotional flyer used in the first page the words "A LITLE EFFORT" (Figure 7.8). These are short and easy words that target two of the composting drivers identified in Chapter 5. The unity and collective aspect of Japanese culture, and the composting required effort (often seen as a barrier), respectively. Additionally, in Towada city (Aomori), a Q&A file was put together based on the most common questions from

the seminars, and after the experiment, the households were invited to fill a feedback survey received from the households (Towada City 2024). The latter highlights the importance of collecting and taking into consideration the feedback of the waste generators.

Many cities include in their messaging illustrative figures, waste flow charts, visual cues of the food waste segregation rules, examples of which kind of collection container (bag, bucket) should be used, and/or main advantages of the system (Figure 7.8). Tsuchiura city, for example, also has an explanatory video on how to properly segregate the food waste on their website (Tsuchiura City 2024).

Figure 0.8 Satsuma town's food waste flow; Tsushima city's flyer; Maniwa city's food waste separation rules (Maniwa City, 2019; Satsuma Town, 2024, 2023; Tsushima City, 2024)



The messaging style seems to differ depending on the stage of implementation of the project. For instance, in Yahaba town (Iwate), the food waste separation process was simplified and included into town waste collection calendar (Figure 7.7). In Nagai city (Yamagata) and Kunitomi town (Miyazaki), which started their programs in 1997 and 1985 respectively (Ohashi 2008), information regarding food waste segregation passes by telling the residents in which day of the week this type of waste is collected (Nagai City 2024). Although in these cities food waste collection is most likely part of people's routines, Kawai (2019) have called for the importance of ensuring that new residents are aware of how to properly segregate the food waste. Note that, in Japan, waste categories have often assigned collection day within the week. These waste categories and collections days vary across municipalities. Within a city, wards often have different collection days for each of the city's waste categories. Recently, besides the physical copy of the calendar, some municipalities have a phone app version of it (Kunitomi Town 2023).

7.3.2 Decentralized Household Composting Incentives in Japan

7.3.2.1 Technical Aspects

An alternative to central collection of food waste, are decentralized systems. In these systems, composting happens at the household or community levels. There are a variety of household composting alternatives that can be incentivised by local entities. In Japan, the most frequently advertised technologies seem to be EM bokashi composters, electric drying machines and composters, cardboard box composters, manual gallon/bucket composters, and in some cases, Japanese alternative manual technologies such as Kiero composters and composting bags. Each technology has its pros and cons. For instance, Voběrková et al. (2020) have expressed concerns about the quality of the fertilizer resultant from electric automatic composters.

Household or community composting can have benefits at a logistical, ecological, economical, and social levels (Pai et al. 2019).Moreover, when compared with centralized alternatives, it has lower transportation and treatment costs, fewer contamination issues, and can stimulate local entrepreneurship and community spirit (Pai et al. 2019; Bruni et al. 2020). On the other hand, as mentioned by Pai et al. (2019) and seen in Chapter 5 and 6, these systems tend to have low engagement rates.

7.3.2.2 Promotional strategies

Decentralized alternatives can be incentivized in parallel with central food collection systems. In fact, they can be an important complement to centralized schemes (Pai et al. 2019). In Japan, Fujieda in Shizuoka Prefecture has available monetary assistance to the purchase of electric composters even though it has a food waste segregation scheme, and it is not an exclusive case (Fujieda City 2022, 2023). However, financial assistance is not the only possible promotional strategy.

7.3.2.2.1 Monetary Incentives and Information Sharing (seminars, leaflets, videos)

The most common incentive to household composting adoption in Japan is financial assistance. Approximately 56% of the municipalities offer financial to the purchase of at least one composting technology (food waste dryers or electric food waste composters) (Island land Co. Ltd 2023). Despite the author not having had the means to verify all 1718 municipalities and 23 special wards of Tokyo, it seemed that many of the cities that offered financial support to the acquisition of electric composting technologies also had financing available to EM bokashi composters and composting gallons/buckets. Among the 47 prefectures, more than 85% of the municipalities in Tochigi, Mie, Ishikawa, and Nagano offer financial assistance. On the other hand,

in Aomori, Fukui, and Hokkaido less than 20% of the municipalities have available these monetary incentives. In the U.S., Niles (2020) noticed that many people in rural areas were already composting on their backyard. Given Aomori, Fukui, and Hokkaido prefectures have a lot of rural areas within their boundaries, a similar situation might be occurring. If that is the case, offering subsidies to purchase composting equipment might be redundant. Another reason may be that some municipalities on these prefectures have adopted central approaches. However, further research is needed to understand such financing nuances.

Besides, the type of technology financed, other applications conditions vary across municipalities (Table 7.3). For example, the covered percentage can range from 25% on electric composters in Sakura (Chiba), Isahaya (Kyushu), Katsuyama (Fukui), Aizuwakamatsu (Fukushima), Tajimi (Gifu), Misato (Kumamoto), Marumori (Miyagi), and Hino (Shiga) to almost a full refund of the purchase amount in places like Ayase (Kanagawa) and Daisen (Tottori) (Island land Co. Ltd 2023). In some cities the percentage covered changes depending on the type of technology. As the electric composter have a higher cost than the other technologies (e.g., EM Bokashi, gallons, and buckets), some cities cover a higher percentage of the latter. Moreover, in Hamamatsu (Shizuoka), designated types of composting buckets can be obtained free of charge (Hamamatsu City Hall 2023).

While the majority of programs target all citizens, some municipalities have small nuances depending on if a person lives in the suburb or in the central area of the town (Table 7.3). Overall, the programs work in a first come first served system until the yearly budget is achieved. Usually, a household has limit of times and number of equipment that can apply for.

Table 0.3 Financial Assistance Conditions

Application parameter	Conditions
Technology Type	Electric; Manual; EM Bokashi; Cardboard Box
Equipment Type	Some cities/towns provide a list of all the models that are covered by the monetary program.
Tax	Included or not in the covered cost.
Eligible People	All residents; city centre; suburbs.
Participation Type	Fixed amount; Percentage of the equipment cost.
Participation Value	Participation percentage/amount changes across cities.
Application Timming	Before or after the purchase of the equipment; Designated application window.
Price celling	Maximum value that is covered by programs
Application Requirements	Previous participation; Yearly allocated budget

Purchase Place	Designated place of purchase or not.

In order to make available the information about subsidies' conditions to communities, cities have to have at least one communication channel. This channel is often the cities' websites. Besides such information, local governments provide information on pros and cons of each process/equipment, on how to make the compost, or previous users feedback (e.g, Hayama town in Kanagawa (Hayama Town 2023) and Ogaki city in Gifu (Ogaki City 2024a)). Having such information can foster the long-term engagement in composting and help new users to evaluate which technology better suits their lifestyle. However, the detail and way this information is passed down to the citizens changes deeply across local governments. Based on the previous chapters findings many people are not aware of whether or not this financing is available, implying that the information was made available to people who had prior interest in engaging on the behaviour, rather than with the goal of attracting new adopters.

Thus, more than having or not available such monetary incentives, having direct and personal contact via workshops, seminars, using social media, local media (like journals) or didactic content to share knowledge may raise the engagement in composting. In fact, cities like Edogawa (Tokyo) have opted just for providing resources and educational seminars rather than funding the purchase of equipment (Edogawa City 2022). As the basis of the decision the city mentioned the high dropout rate of household composting, which seems to be aligned with the findings of Chapter 5 and Chapter 6. Cities such as Sapporo (Hokkaido), Fukuoka (Fukuoka), Sendai (Tohoku), Sakai (Osaka), Odawara (Kanagawa), and Gifu (Gifu) also provide courses on composting and ways of using the compost in a home gardening regularly (Figure 7.9) (Sakai City 2022; Sendai City 2024a; Gifu City 2024; Sapporo City 2024b; Odawara City 2024). In the case of Fukuoka city (Fukuoka) these training sessions are run by an NPO (Fukuoka City, 2024a). Moreover, in Nagoya city (Aichi), the financing happens at the association/group level and not at the household level. In other words, to foster decentralized community level composting, neighbourhood associations and environmental groups are eligible to receive monetary assistance if they intend to tackle food loss and food waste recycling issues (Nagoya City Hall 2023).



Figure 0.9 Composting/Gardening Seminars in the cities of Odawara, Fukuoka, and Sapporo

7.3.2.2.2 Monitoring Programs

One alternative/complementary option to monetary incentives are monitoring programs. Monitoring programs differ from seminars and workshops as instead of happening in a single point in time, the monitoring happens throughout a certain period of time (e.g., 3 months). Under this promotional format, cities open application windows and once the vacancies are full, they distribute, sometimes free of charge, the necessary composting equipment to the participants (Go Green Kobe 2023). Following, during a determined amount of time, they are supposed to take notes of the progress, or to fill a feedback survey at the end of the designated time.

These programs are often associated with a specific type of composting technology. From 61 monitoring programs, some studied cardboard box composting as the base technology (e.g., Kakogawa city in Hyogo) or composting bags (e.g., Amakusa city in Kumamoto) (Amakusa City, 2023; Kakogawa City, 2024a). However, the most commonly examined equipment was electric composters (e.g., Ono town in Fukushima and Suwa city in Nagano) and, in partnership with the Kiero NPO, the Kiero composting method (e.g., Kobe city in Hyogo, Higashimurayama city in Tokyo, Arakawa city in Tokyo, Chiba city in Chiba, Ikoma city in Nara) (Ono Town 2017; Higashimurayama City 2021; Go Green Kobe 2023; Suwa City 2023; Chiba City 2023; Arakawa City 2024; Ikoma City 2024). More than a half of the 61 programs analysed used the latter method. Moreover, some cities ran monitoring programs in more than one composting process (e.g, Myazaki city in Myazaki and Oizumi town in Gunma) (Miyazaki City 2023; Oizumi Town 2024).

The “Kiero” method is a Japanese composting alternative that has been a focal part in food waste recycling in Zero-Waste towns like Kamikatsu and Minamata (Jakimiuk et al. 2023). It uses only natural soil as a base material and requires less mixing and overall maintenance than other techniques (Jakimiuk et al. 2023). Once it is supported by an NPO, besides local government support, there is also the chance of building a community among people who adopted this technology through the NPO. For example, in the summer of 2023, which in Japan is a time associated with festivals, the Kiero NPO promoted an online “festival” in which people, regardless of their location, were invited to share their stories and experiences with the “Kiero” method (Kiero Official 2023). This can foment community spirit, knowledge sharing, and increase the motivation of a person to continue composting, thus promoting composting engagement (Chapter 5) and preventing dropout situations (Chapter 6). It can also act as a show case for future adopters.

Also in the summer of 2023, Kobe city (Hyogo) started a Kiero monitoring program for adults and as a part of children's summer school project (Figure 7.10). Since the summer, a second application window opened to adults around the winter holidays season (Go Green Kobe 2023). Similarly to Kiero’s online festival, the city embedded the project within the Japanese cultural landscape by using the Summer Research School project for elementary school children as an engagement vehicle. As visible on Figure 7.10, the messaging of each booklet was targeted to the specific audience (parents/adults and children). Information meant for the younger participants had simpler explanations and used words such as “challenge” and “hint” passing the idea of gamification of the composting process. Additionally, the composting tasks on the children’s book often included the image of a children in it.

According to staff members, the project took a year to prepare, and it was advertised through social media platforms such as Facebook, Line, and Instagram. It was also advertised on local newspapers, in adds inside trains, and in schools. Promotional events and workshops were also held in more than one occasion during summer. The monitoring workshops covered information about the Kiero composting method (its origin, how it works, how it is made, and how to use it), as well as an introduction to Kobe city's waste reduction goals. Feedback surveys were to be given to participants, approximately one month and three months after the start. Following the monitoring period, the organization members highlighted that more important than tracking participants’ future engagement, they wished to encourage people to continue by posting the results’ of their efforts on the program’s official website. Civic scientists have mentioned that sharing stories, feedback, and ideas with fellow participants and local communities on social medias can help catalyse the projects’ development and expansion (Krug et al. 2022; The Land Institute 2024). These strategies seem to be being used by NPOs to promote composting, as the

Kiero example given above, and by cities like Odawara city which has a local newsletter about food waste (Odawara City 2024).

Among the most commonly asked questions at monitoring workshops, the Kobe Kiero organizers mentioned aspects such as decomposition time, the type and amount of food waste that can be put in the composters, how frequently can waste be added, how to use the final output, what to do in case of insect infestation, and how to increase the speed of the decomposition process. These seem to be aligned with the functional barriers studied in Chapter 5 and Chapter 6.

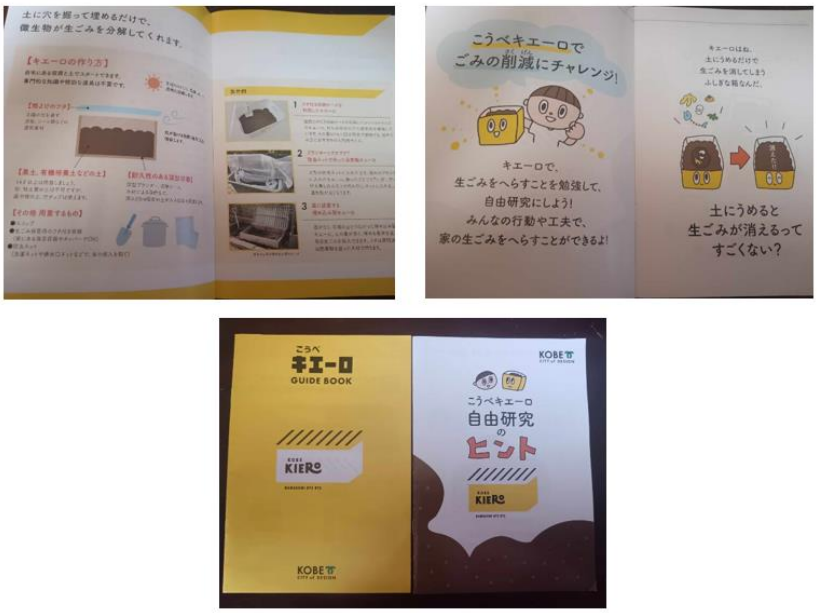

Figure 0.10 Kobe city monitoring program guidelines booklets

7.3.2.2.3 Trial Programs

Prior to the purchase of a composting technology some cities give the citizens the possibility of having a trial period in which the city council lands a composter to the interested household. The price of the composting equipment can vary deeply depending on its features. In particular, electric/automatic composters or waste drying machines, can be quite costly. Therefore, municipalities like Kihoku town (Mie), Yanagawa city (Fukuoka), and Komatsu city (Ishikawa) have trial programs (Kihoku Town 2023; Komatsu City 2024; Yanagawa City 2024). Such systems allow households to make a more robust choice, save money, and prevent additional waste from units that could be discarded in a dropout situation. In other words, it decreases the chance of a premature dropout. Trial programs can vary on length, with some places offering a rental up to 3 months (e.g., Komatsu city).

7.3.2.2.3 Reward Programs

In cities such as Odawara (Kanagawa), Anjo (Aichi), Tahara (Aichi), and Sapporo (Hokkaido) the use of electric composters, drying machines or composters are not being incentivized exclusively by monetary assistance on the purchase of the equipment but also through rewards given to citizens that return the dried food waste/compost surplus (Anjo City 2023b, a; Sapporo City 2024a; Odawara City 2024). In Odawara city (Kanagawa), people that want to start composting are eligible to receive cherry tomatoes (Odawara City 2024). In Anjo (Aichi) and Tahara (Aichi), citizens are eligible to receive paper bags, toilet paper, tissue boxes, or garbage bags (for other waste categories) in turn of dried food waste (Tabela 7.4). These cities based their rewards programs on essential goods of one's daily life, such as toilet paper. Similarly, in Sapporo city (Hokkaido), Kurume city (Fukuoka), and Yamagata city (Yamagata), people who return their dried waste/compost are eligible to receive vegetables (in Sapporo a regional type of onion is being given) (Yamagata City 2020; Kurume City 2022; Sapporo City 2024a). Besides fomenting food recycling these initiatives are also fostering local food consumption.

Moreover, in Niigata city (Niigata), people can receive the resultant compost free of charge (as happen in some cities who collect household food waste separately) and in both Sendai (Miyagi) and Ogaki cities (Gifu), consumers can accumulate points to later exchange them not only for garbage bags vegetables, or compost, but also chopsticks and other kinds of merchandise with the city's waste management mascot (Figure 7.11) (Niigata City 2020; Ogaki City 2022, 2024a, b; Sendai city 2024). Kitakyushu city (Fukuoka) and Kakogawa city (Hyogo) have point systems that can me latter used, for instance, in commuting cards (IC cards) (Kitakyushu City 2024; Kakogawa City 2024b). In cities where people can collect points, besides composting related activities, residents can often win them by participating in several environmental initiatives aligned with SDGs.



Figure 0.11 Sendai city's Waste Mascot Merchandize

These rewards programs are based on a food recycling setup that seems to be increasing in popularity in Japan. However, to the author's knowledge there is no international studies about it. Under this setup composting is done at the household level but it is not necessarily used by the consumers. Instead, it can be partially or fully returned to farmers, community associations, community farms, or cleaning centres. The next sub-section will further explore the flow of these alternative systems via a SWOT analysis.

Table 0.4 Reward Programs Weight System

Compost Weight	Anjo	Tahara
200 g/250 g	1 toilet paper roll/1 paper bag	paper bag
400 g	-	1 toilet paper roll
500 g	-	1 box of tissues
1kg	10 garbage bags/100-yen vegetable coupon	-
>3 kg	-	-

7.3.3 A point in between. Composting Collection Systems. A SWOT Analysis

When talking about the scale of composting systems previous literature mentioned that composting setups can be centralised ones, decentralized at a community/network level, or decentralized at a household level (Figure 7.12) (Pai et al. 2019; Bruni et al. 2020; Mihai et al. 2023). Nonetheless, in Japan, a hybrid solution can be found. Under this hybrid solution, the responsible for the composting process (or in some cases the food drying process) is the household, but the usage of the process' output can be local gardens, farmers, or a secondary treatment facility. As a mixed solution, these systems have benefits of both central and decentralized systems. Consequently, it also shares negatives points with both setups.

Besides the cities mentioned above, which run these kind of return systems alongside reward programs, Kumamoto city (Kumamoto), Fukuoka city (Fukuoka), Gifu city (Gifu), and Zama city (Kanagawa) also have compost/dried waste return programs (Gifu City 2024; Zama City 2024; Kumamoto City 2024; Fukuoka City 2024b). Moreover, a one yearlong pilot project on this hybrid layout was ran in Kawasaki city (Kanagawa) during 2021/2022 (Kuchiba 2022). To better understand the liabilities and benefits of this composting layout the SWOT framework explained in Chapter 2 was used.

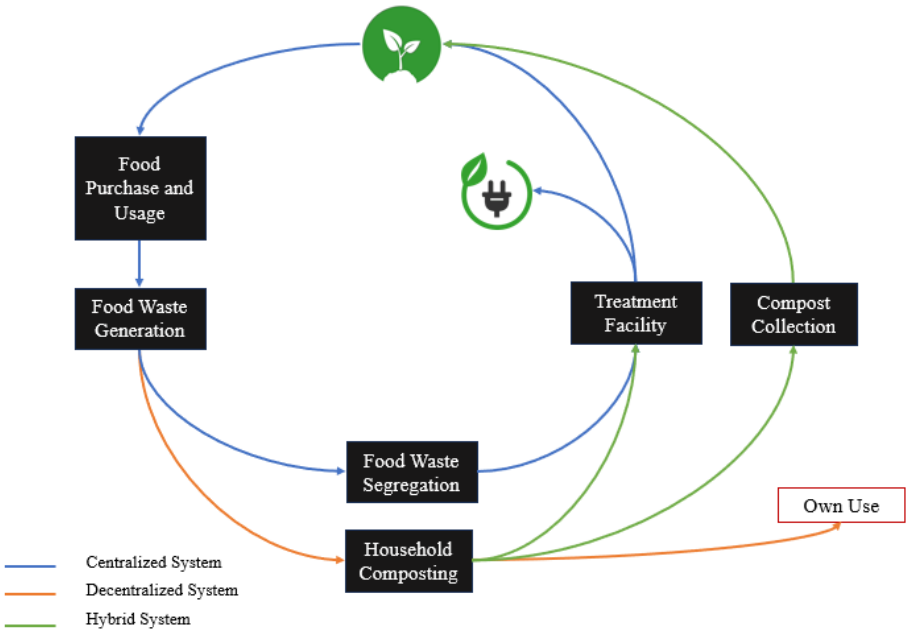

Figure 0.12 Food System Flow

7.3.3.1 Strengths:

These programs tend to target composting technologies customized to be kept in small spaces. This the case of electric composters, composting bags (Figure 7.13), or even cardboard box composting (as it happens in Gifu city, Gifu). Specially in Japan, where many houses in metropolitan areas are of small dimensions, having a technology able to fit the routine and life in smaller spaces, can attract people who are environmentally concerned but do not have a backyard or gardening interest. In particular, composting bags are a mobile and energy free solution. They are also made domestically out of recycled materials (Chikyu-Labo 2024; LFC 2024).

The second strength of these business model is related to its lower initial and running costs when compared with central alternatives. Despite having transportation costs associated, they do not necessarily need a central treatment facility as the composting process is done by the consumers. Once having a treatment facility is not a necessary condition of these setups their implementation period can also be faster than a pure central alternative.

Moreover, there is an optimization of the use of the compost resources. According to a member of one of the composting bag companies, people tend to use entirely the first batch of composting and return the second one or use part of the produced batch and return the surplus amount. At the same time, the collected compost usually already has a designated destiny. For instance, in Gifu city the compost is used in gardens of schools and the students are involved in

application of the compost to the gardens (Gifu City 2024). The compost can also be used on community gardens or being directly returned to the farmers, thus promoting Farm to Fork direct links (Kuchiba 2022). According to Bruni et al. (2020), the more central a system is the higher the possibility of the contamination is. In a hybrid system and given the households can also be users of the produced compost the contamination level is expected to be smaller than in central layouts. Similarly to other recycling processes, hybrid layouts contribute to a reduction of the food waste that is incinerated or end up in landfills.



Figure 0.13 Different models of composting bags and an example of an electric composter (retrieved from Komatsu City (2024)*,* LFC (2024)*,* Ibuki Farm (2024)*, and* Chikyu-Labo (2024)*)*

7.3.3.2 Weaknesses:

One of the weaknesses of decentralized composting systems is their low adoption rate (Pai et al. 2019). Such tendencies were seen in previous chapters as well as in previous research (Aoki et al. 2010; Kurisu and Bortoleto 2011). Composting return systems share this weakness. According to a composting bag staff, some people dropout due to lifestyle changes, re-locating to a different city, or because they failed making compost. This is in accordance with the findings of Chapter 6 and Tucker et al. (2003). Thus, similarly to other decentralized systems, a big challenge is to understand effective ways of both attracting new adopters and keeping the long-term engagement and motivation of the current participants. As previously mentioned, helplines, workshops, reward programs, and achievement sharing may be helpful to foster engagement. Moreover, despite not having as many associated costs as a centralized composting process, hybrid systems still have transportation costs, which do not occur at the household composting level.

Another weakness of the system is the inaccurate composition of the compost. According to a farmer who for the past 2 year has been participating in a household compost return system, as the organic waste constitution can change depending on the household it is difficult to know exactly the constitution of each compost batch. Additionally, the received compost needs an additional maturation period when it gets to farming plot, which requires having a stocking place.

In comparison with traditional fertilizers, its application on the field is also a more time intensive activity said the farmer.

7.3.3.3 Opportunities:

One of the opportunities of hybrid systems relate to distribution channels these systems offer. Depending on how or who is operating the collection system, opportunities for cooperation between NPOs, companies, farmers' associations, local government and communities may arise. It can also be an opportunity to integrate composting systems with ICT technologies, like apps (Kuchiba 2022). Moreover, there is the possibility of spillover effects on the purchase of organic products, gardening, and the awareness of the amount of waste produced, leading to a decrease in food waste. For example, as previously mentioned, in Gifu, compost is used as an educational resource in schools (Gifu City 2024). Cities as well as composting bag companies also often offer gardening workshops on how to use the compost. These presential events are opportunities to create descriptive and social norms and build human connections that can further foster the shift to these behaviours.

When managed by or in partnership with a company/NPO it can also link farmers beyond a specific city's boundaries, thus expanding the territorial coverage of these systems. Moreover, as mentioned by a farmer using household compost, due to the recent steep increase in the prices of chemical fertilizers, household composting can alleviate the economic pressures famers face, besides increasing their selling channels. Thus, "traditional" farming increasing costs can foster the adoption or at least the trial of this hybrid systems by farmers.

7.3.3.4 Treats:

As there is not a clear idea of the constitution of the compost received from the households, farmers that are part of these programs are not eligible for the Japanese certification for organic products JAS, said a participating farmer. Moreover, this uncertainty about the components can make more difficult the engagement of farmers who are more risk adverse, he added. The farmer also mentioned that this is not an issue exclusive to this type of fertilizer but also, and probably to a bigger extent, to fertilizer made out sewage.

Another concern regards the scalability of these programs and the unstable supply and demand of the compost. Before applying food waste composting, it is usually necessary to have

a last maturation step. This requires time, space, and manual labour, which a participating farmer mentioned as barriers to expanding the use of this type of fertilizer. Moreover, once household composting is more susceptible to dropout cases and the amount of compost is dependent on the number of consumers/businesses returning it, the expansion of these schemes may have slower pace than a "traditional" fertilizer. The need of having a compost receiver (farmer, garden, or other) also contributes to the latter issue. Additionally, while high prices of chemical fertilizers are an opportunity for household composting, if the current market trend reverts, farmers will have less incentives to use this kind of fertilizers.

7.4 Discussion

Throughout this chapter the layouts of Japanese composting schemes, as well as some of their promotional strategies were presented. Despite cities choosing to promote food recycling at different scales, some marketing approaches were common to the different schemes, namely: the usage of food labels and food markets as a promotional vehicle; the usage of community liaisons; messaging using English words; videos and explanatory images; workshops; visits; the use of social media and local newspapers as promotional vehicles; and finally, the availability of helplines via LINE or other social media.

Hybrid Systems:	**Decentralized Systems:**	**Centralized Systems:**
(+) Positive impact on waste production awareness.	(-) Compost making failures.	(+) Less issues with smell and verminous.
(-) Compost composition	(+) Positive impact on waste production awareness.	(+) Positive impact on waste production awareness.
(-) System scalability	(+) Personal/Garden usage	(-) Implementation requirements such as initial costs, compost demand and trust, citizens receptiveness.
(+/-) Less fixed costs when compared to centralized systems but higher transportation costs than decentralized systems	(-) Low adoption rates.	(-) Source contamination.
(+) Source contamination.	(+) Increase the community spirit and involvement.	(+) Variety of final output possibilities.
(-) Low adoption rates.	(+) Low implementation costs.	(+) Possible spillover effect on the demand of organic food.
(+) Variety of final output possibilities.	(+) Source contamination.	(+) Responsibility of the consumers (waste provider role).
(+) Possible spillover effect on the demand of organic food and other pro-environmental behaviours.	(+) Variety of final output possibilities.	
(+) Gardening and community entrepreneurship	(+) Possible spillover effect on the demand of organic food and other pro-environmental behaviours.	

None of these approaches is free of drawbacks so it is important, prior implementation, to access the social, economic, geographical, and environmental conditions of the target location/s. Currently Japan is facing depopulation of rural areas and the shrinkage of population (Koizumi 2022; Kawai et al. 2022). Consequently, food recycling alternatives developed by cities should take this into consideration too. Moreover, given recent central governmental directives. This is the case of cities like Kobe (Hyogo) or Sendai (Miyagi) which have separate social media for their environmental initiatives and organize events like city cleaning days or have available eco-friendly recipes (Kobe city 2024; Sendai City 2024). These initiatives can foster citizens connection with both nature and their local community.

In Osaki town (Kagoshima) and Kamikatsu town (Tokushima), this eco-friendly facet became a trade-mark of the towns, attracting inclusively eco-tourism or national and international partnerships with cities that which to adopt eco-friendly measure. Moreover, in some cities, point collecting reward systems cover several SDGs. This gamification as incentive can be especially attractive to younger generations. Many cities have specific mascot for their environmental waste reduction initiatives too. Although this chapter did not directly target community actions, these also have a role on the promotion of sustainable lifestyles and food waste recycling.

7.5 Chapter Conclusion and Future Research

Japanese municipalities seem to always have some type of food waste recycling strategy being advertised to their residents, being that a central, a decentralized, or a hybrid system. Central segregation schemes are a rarer approach, with only 17% of the municipalities offering this type of food recycling setup (MOE 2023b), being the most common approach the promotion of decentralized food recycling at a community or household level. While some cities only provide suggestions on how to engage in food recycling, more than a half of the municipalities subsidizes the purchase of a composting technology. The way the messaging of information about food waste recycling alternatives is passed down to the citizens, the characteristics of the system, and the number of promotional vehicles used by local governments, varies deeply within the country. Hybrid solutions in which consumers compost and return the final output can be a compromise solution between central and decentralized schemes with possible positive spillover effects in other consumers' pro-environmental behaviours. The latter setup seems to be a unique setup found in Japan.

To increase the circularity of the consumed resources and create robust recycling networks, collaboration and involvement of several stakeholders within the food systems

(companies, NPOs, farmers and neighbourhood associations, local governments, producers, and consumers) should occur more often. When developing and designing food recycling systems taking into consideration the geographic specificity of the place is also essential.

While the present work presented existing composting layouts and its promotional vehicles, it did not analyse which vehicle or type of messaging was more effective in Japan. One could expect that fostering practical knowledge, and providing ways of promoting gardening interest may be effective. However, more interventions and experimental based cases are needed.

Given that the number of cities collecting feedback about monetary subsidies and composting experiences seems to be increasing, identifying the similarities and differences across the different cities' feedback can also be helpful to design or restructure Japanese food recycling systems.

Chapter 8: Conclusions

This doctoral dissertation's main research objective was to present a holistic perspective on incentives and drivers to consumers/households' climate actions associated to food consumption in Japan. Through behavioural modelling, consumers' profiling, information about governmental promotional programs, and the main drivers to engagement in pro-environmental throughout the stages of consumption (purchase, usage, disposal) were identified. The document can be divided into the following research questions: 1) What are the main drivers to ethical food consumption in Japan? 2) Which patterns and contrasts exist across the Japanese population on the adoption rates of ethical purchasing, waste reduction, and food waste recycling pro-environmental behaviours? 3) What are the main drivers for household composting in Japan? 4) What are the main reasons for composting drop out? 5) How is food recycling being incentivized? What are the alternatives?

Chapter 3 focused on the first step of consumption, the purchase. More precisely it focused on understanding the profile and the decision-making process of ethical food consumers in the Japanese market. To determine the main drivers of behaviour, a Stimulus-Organism-Response (S–O-R) model with Stimulus-Response (S–R) direct paths was tested via a Partial Least Squares Structural Equation Modelling (PLS-SEM). Next, the groups resultant of a two-step clustering technique between Pro-Environmental Behaviours (PEB) like recycling and reducing waste were used as a basis of a multi-group analysis. Evidence suggests ethical food consumption in Japan is bound to intention, knowledge, price, and certification recognition. The multi-group analysis implied an overall difference across the three groups defined, but the results were not conclusive at a pairwise level.

The following chapter, Chapter 4, looked at the nuances on practice rates of food related PEB adoption profiles throughout consumption (purchase, usage, disposal). To do so, a two-step clustering analysis was done. The scope of the evaluated PEB covered the purchase, usage, and disposal of food products. Ethical consumption behaviours (the purchase of little packaging, organic, eco-friendly and/or refillable goods), food waste prevention actions (leftovers avoidance, meal planning, and food waste reduction/avoidance), and alternative disposal measures (feeding animals, composting, giving food to neighbours) were analysed. Four significantly distinct clusters were found, namely: sporadic adopters, average practitioners, responsible consumers, and environmentally involved. Approximately 51% of the sample was allocated to the responsible consumers cluster, which was characterized by having more women in part-time jobs or in-house duties and older respondents than the other groups. The Environmentally involved group tended

to be young respondents with children and gardening/farming interest. They were also the ones who ate more frequent plant-based meals and had healthier eating habits.

Chapter 5 focused on food waste disposal, the last step of consumption. By using the Theory of Consumption Values (TCV) framework with a OrdPLS algorithm, the main household composting drivers in Japan were identified. The model results suggest that home composting in Japan is bound to social approval (social value), behaviour visibility and current knowledge about the process (epistemic value), convenience (functional value), gardening/farming interest, and a person's availability (conditional value). Positive and negative functional aspects of composting were significant to the convenience perception that a person holds towards the behaviour. Therefore, they were found to have an indirect effect on the choice of composting.

Chapter 6 further explores household composting behaviour, but instead of focusing on engagement factors, it concentrates on identifying the major reasons for why households drop out of composting. Approximately 7% of the respondents stated having composting experience, but mostly due to vermin, malodours, and lack of time stopped them. Composting's eco-friendliness and its usage in gardening/farming were among the main factors why people have tried this pro-environmental behaviour in the first place. Future policies should pass by increasing the convenience of food waste recycling systems as well as giving mechanisms to improve functional aspects of the process.

Next, in Chapter 7, some of the on-going Japanese solutions to encourage sustainable lifestyle were analysed. An overview on the centralized, decentralized, and compost return systems was given, and examples of promotional strategies municipalities are using to boost these behaviours such as monitoring programs, reward systems, and financial assistance. This chapter also includes a SWOT analysis on compost return systems, and a food waste recovering solution that seems to be exclusive to Japan at the time of writing.

Based on the results and cases presented through Chapters 3 to 7, the following major conclusions can be drawn: Firstly, Food Waste prevention seems to be a concept embedded in Japanese society, especially through the spread of ideologies like "3R" and "*mottainai*". On the other hand, this does not necessarily reflect on Ethical Consumption and even to a lesser extent on Food Waste Recycling behaviours. In fact, while the most common consumer tried reducing waste and buy in an ethical way sometimes, only a few tried to follow a sustainable lifestyle throughout all the consumption stages (purchase, usage, and disposal). However, it's important to keep in mind that the data used in this document relies on self-reported measurement which, may not reflect in the same proportions on the actual amount of waste produced. Another limitation of this research is the lack of representation in younger demographics and rural areas. Additional

research regarding the food usage stage and interventions addressing the effectiveness of different behavioural change promotional approaches is also needed in Japan.

A key factor to ensure the difference between the image one holds about themselves, and their actual behaviour is minimized, might be promoting education about these topics. Knowledge was an important driver for the adoption of both Ethical Food Consumption and Household Composting. Nonetheless, kind of knowledge and the method that it is transmitted should not be disregarded. Information vehicles should clarify the connection between food recycling and ethical food consumption and explain how to deal with vermin, bad smells, and minimize "lost time" to prevent dropouts. Based on the results, relying on communication vehicles that allow building social norms, may be particularly effective to boost PEB engagement in Japan.

Solutions for both people with and without gardening interests should be provided. One of the food waste recycling solutions, which seems to tackle the connection between purchase, usage, and disposal consumption stages, is a system in which consumers compost but then return the final output to a community or central entity. In this manuscript, they were referred as Hybrid solutions. These solutions can be a compromise option between central and decentralized schemes with possible positive spillover effects in other areas of a consumer's life. Many municipalities subsidize the purchase of composting equipment but do not offer much more support. Moreover, people do not seem to be particularly aware of these incentives. Approximately 17% of the municipalities have some kind of food waste segregation scheme.

Besides its policy implications, the current manuscript extends the previous applications of the Stimulus-Organism-Response (S-O-R) and the Theory of Consumption Values (TCV) (Sheth et al. 1991) frameworks. The latter theoretical frameworks were used to explain green food consumption and household composting behaviour. On statistical grounds, less commonly applied algorithms such as clustering using a *Mahalanodis* distance, a Partial Least Squares Structural Equation Modelling (PLS-SEM) with a multi-group assessment (MGA) with more than 2 groups, and the categorical extension of the PLS-SEM (OrdPLS) were also used as analytical tool, which present meaningful analytical results.

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Appendix

R code:

```
"
tittle: Circularity of Food Resources in Japan: Consumers' Incentives for Ethical Consumption and Food Recycling
date: 2024
@author: ana_catarina_thomaz_moura_morais
university: Kobe University, Graduate School of Agricultural Sciences
goal: This a compilation code of the algorithms used in all the chapters of this doctoral research.
The main goal of this dissertation is to identify the main factors to adopt food related PEB throughout the consumption flow (purchase, usage, disposal)
This compilation code is divided into 4 main sections.
1) Chapter 3: Ethical Food Consumption Drivers in Japan. A S-O-R framework application using PLS-SEM with a MGA assessment based on clustering
2) Chapter 4: Ethical Consumption and Food Recovery Hierarchy Behaviours: A Clustering Analysis in Japan.
3) Chapter 5: Composting Behaviour in Japan: An application of the Theory of Consumption Value
4) Chapter 6: Why do the Japanese dropout household composting?
"
#---------------------------- Packages ----------------------------------
#SEM
library(lavaan) #cb-sem package
library(seminr) #PLS-SEM package (based on SmartPLS)
library(cSEM) #PLS-SEM package (Based on ADANDO), OrdPLS can be used
library(plspm)
#clustering & Data Reduction
library(cluster)
library(flexclust)
library(ClusterR) #K-Medoids with Mahalanobis
library (stats) #Hierarchical clustering
library(clustMixType)
library(NbClust) #ideal number of clusters indices
library(psych) #cluster analysis, PCA, FA, etc.
library(GPArotation) #Factor rotation
library(hopkins) # assess is the clusters can be made
library(factoextra) #PCA, analyses and visualisation
library(dendextend) #hierarchical cluster dendrograms
library(KScorrect) #Kolmogorov-Smirnov
library(ivreg)
#Visualisation
library(tidyverse)
library(ggplot2)
library(summarytools) #data crosstables
library(corrplot) #correlation-based plots
library(ggfortify)
library(GGally)
library(scatterplot3d)
library(ggradar)
library(gridExtra)
library(RColorBrewer)
library(ggfortify)
library(geomtextpath)
theme_set(theme_classic())
#others
library(moments) #skewness kurtosis
library(data.table)
library(haven) #read dta files
library(readxl) #read excel
library(polycor) #polycor matrix
library(car) #ANOVA
library(stringr)
library(writexl)
library(caret)
library(likert)
library(fastDummies) #separates a categorical variable in multiple dummy columns
library(Hmisc)
library(MASS)
library(dplyr) #dataframe manipulation
```

```
library(misty) #statistical tests, descriptive analysis
library(FSA)
library(fmsb) #cronchalpha test

#----------------------------- General Functions --------------------------
#change the Likert-scales orders (1->5; 5->1)
reverseCode <- function(data, rev){

  # get maximum value per desired col: lapply(data[rev], max)
  # subtract values in cols to reverse-code from max value plus 1
  #ma=lapply(df[,v],max,na.rm = TRUE)
  #data[, rev] = mapply(data[, rev], function(x) ifelse(!is.na(x), ma[rev]-x + 1, x))
  data[, rev] = mapply("-", lapply(data[rev], max,na.rm = TRUE), data[, rev]) + 1

  return(data)
}

#Mahalanobis Distance Fuction (Chapter 3):

#retrived from https://stackoverflow.com/questions/18658961/mahalanobis-distance-in-r
# x df, cx (cov matrix)/
mah <- function(x, cx = NULL) {
  if(is.null(cx)) cx <- cov(x)
  out <- lapply(1:nrow(x), function(i) {
    mahalanobis(x = x,
                center = do.call("c", x[i, ]),
                cov = cx)
  })
  return(as.dist(do.call("rbind", out)))
}

#------------------------------- Chapter 3 Ethical Food Consumption S-O-R -------
"
Goal:
1) Find what are the main factors relevant for ethical consumption (survey based)
2) Cluster ethic and PEB guys
3) Assess the significance of the demographics
Data and AI techniques:
1) This analyses uses the S-O-R as the theoretical framework (Jacoby 2002)
2) PLS-SEM;
3) Clustering (K-Medoids)
"

#-------------------------------- CH3 Data Cleaning & Preparation ----------
#read file
df_ch3 <-  read_dta('C:/Users/xxx/Documents/xxxx/ethical_consumption.dta') #change the path if necessary
head(df_ch3)

# DESCRIPTIVE DATA: item name <,item number, invalid, mean, sd,
# median, mad, min, max, skew, kurtosis, se
describe(df_ch3)

#apply(X, MARGIN, FUN)
#transform in a dummy 0 and 1
df_ch3['marry']<-ifelse(df_ch3$marry != 3, df_ch3$marry-1, df_ch3$marry-2)  #check the 3 cases with sensei!
df_ch3['gender']<- df_ch3$gender-1
df_ch3['pet']<-ifelse(grepl("13",df_ch3$q1), 1, 0) #contains function
df_ch3['alone']<-ifelse(grepl("15",df_ch3$q1), 1, 0)
df_ch3['kids']<-ifelse(grepl("4",df_ch3$q1)|grepl("5",df_ch3$q1)|grepl("6",df_ch3$q1)|grepl("11",df_ch3$q1), 1, 0)
df_ch3['others']<-ifelse(df_ch3$q1fa == "", 0, 1)

#household size
house_function<- function(df) {
  # Initialize the result vector
  result <- numeric(nrow(df))

  # Loop through each row of the data frame
  for (i in 1:nrow(df)) {
    q1 <- df$q1[i]

    if (grepl("15", q1)) {
```

```
      result[i] <- 1
    } else if (grepl("13", q1) & str_count(q1, ",") == 0) { #people living alone + a pet
      result[i] <-  1
    }  else if (grepl("13", q1)) {
      result[i] <- str_count(q1, ",")  + 1 #people living with other people and a pet
    } else {
      result[i] <- str_count(q1, ",")  + 2 #people living with another person
    }
  }
  return(result)
}

df_ch3$housesize <- house_function(df_ch3)

#Q11 question is "Do you usually look for information on these words on the internet? (the words are related with sustainability)
#Ethical Consumption; Organic; Faire Trade; Local production for local consumption; Food Mile; Global Warming.
#SDGs: Food Loss; Animal Welfare; Recycle; LOHAS; Sustainability; Eco; Eco-friendly; Child Labor; Consumer Civil Society
#count the number of Concepts which people look for:
df_ch3['q11_n']<-ifelse(df_ch3$q11!="", str_count(df_ch3$q11, ",")+1, 0)

#Q9/ma question: "please select from the certification marks bellow the ones which you are familiar with:"
#count the number of certificates which people are familiar with:
df_ch3['q_certificates']<-ifelse(df_ch3$ma!="", str_count(df_ch3$ma, ",")+1, 0)


#reversed data frame Likert-scales so the 1 means less and the 4/5/6 means more
v<-c('q63','q61','q62','q64','q65','q66','q71','q72','q73','q74','q75','q76','q77'
     ,'q81','q82','q83','q84','q85','q86','q87','q88','q89','q810','q811'
     ,'q101','q102','q103','q104','q105','q106','q107','q108','q109','q1010'
     ,'q1011','q1012','q1013','q1014','q1015'
     ,'q12','q131','q132','q133','q134','q135','q136','q137'
     ,'q18','q141','q142','q143','q144','q145','q146','q147','q148'
     ,'q151','q152','q153','q154','q155','q156','q157','q158'
     ,'q161','q162','q163','q164','q165','q166','q167'
     ,'q168','q169','q1610'
     ,'q171','q172','q173','q174','q175','q176','q177','q178','q179','q1710','q1711','q1712','q1713','q1714','q1715'
     ,'q211','q22','q213','q214','q215','q216','q217','q218','q219','q2110')

df2_ch3<-reverseCode(df_ch3,v)


#summated scale for ethical food consumption quick checks (added q77 in the compilation version)
dc<- c('q131','q132','q133','q134','q135','q136','q137','q77')
df2_ch3['q_test']<-rowSums(df2_ch3[,dc])

#exclude others on education (just 1 observation)
df2_ch3<-df2_ch3[!(df2_ch3$q2==7),]

#some people also did not reported their income but I did not exclude them as income was not used in the model

#create dummies for the demographics and control variables
#city size (1: Tokyo Metropolitan; 2: Government-designated city; 3: city with more than 200 000 people; 4: city with less than 200 000 people; Town/Village)
df2_ch3<-dummy_cols(df2_ch3, select_columns = c("q4"),
                    remove_first_dummy = TRUE)

#income dummy
df2_ch3<-dummy_cols(df2_ch3, select_columns = c("q3"), remove_first_dummy = TRUE)

#earnings boxplot
boxplot(df2_ch3$q_test ~ df2_ch3$q3,main="Earnings")
#create two dummies sumup (low, mid, high income)
#2 and 3 are below 6 million year, 8 is not declared but they seem to follow a lower income relation
#6 and 7 is 10 million and more
#average in 2021 in Tokyo was 723 Million month (apx 8 million year), in Chiba 4.9 million year
#so categories from 4 to 10 mil where considered mid
df2_ch3['q3_low']<-ifelse((df2_ch3$q3 == 1)|(df2_ch3$q3 == 8)|(df2_ch3$q3 == 2), 1, 0)
df2_ch3['q3_high']<-ifelse((df2_ch3$q3 == 6)|(df2_ch3$q3 == 7), 1, 0)

```

```
#education
df2_ch3['q2_2']<-ifelse(df2_ch3$q2 != 1, 1, 0) #high school
df2_ch3['q2_3']<-ifelse(df2_ch3$q2 == 3 , 1, 0) #vocational school
df2_ch3['q2_4']<-ifelse(df2_ch3$q2 == 4,1, 0) #college
df2_ch3['q2_5']<-ifelse((df2_ch3$q2 == 5)|(df2_ch3$q2 == 6), 1, 0) #uni
df2_ch3['q2_6']<-ifelse(df2_ch3$q2 == 6, 1, 0) #graduate

#Simple dummies just with high education or not (college is included in university like)
df2_ch3['q2_sum']<-ifelse((df2_ch3$q2 == 5)|(df2_ch3$q2 == 6)|(df2_ch3$q2 == 4), 1, 0)

#mean and std
#normalized data (not used as PLS-SEM algorithm standardizes the data and so the cluster distance selected)
df2s_ch3<-df2_ch3 %>% mutate(across(where(is.numeric), scale))

df2s_ch3<-as.data.frame(scale(df2_ch3[c('q101','q102','q103','q105','q109','q1012','q1015'
    ,'q162','q163','q164','q165','q166','q2110','q219','q161','q144','q154','q171'
   ,'q216','q211','q22','q213','q72','q73','q74','q75','q76','q77','q177', 'q178'
                              ,'q145','q153','q155','q179','q1712'
             ,'q81','q82','q83','q84','q85','q86','q87','q88','q89','q810','q811'
                 ,'q146','q147','q148','q214','q215','q157','q1713', 'q1714'
                 ,'q131','q132','q133','q134','q135','q136','q137'
)]), scale(4))

#------------------------ CH3 Descriptive Analysis----------------------

par(mfrow = c(2,4))
g1<-ggplot(df2_ch3, aes(x = q131)) + geom_bar(aes(y = (..count..)/sum(..count..))) +
  xlab("Organic Food") + ylab("Percentage")
g2<-ggplot(df2_ch3, aes(x = q132)) + geom_bar(aes(y = (..count..)/sum(..count..))) +
  xlab("Fair Trade Food") + ylab("Percentage")
g3<-ggplot(df2_ch3, aes(x = q133)) + geom_bar(aes(y = (..count..)/sum(..count..))) +
  xlab("Locally Produced Food") + ylab("Percentage")
g4<-ggplot(df2_ch3, aes(x = q134)) + geom_bar(aes(y = (..count..)/sum(..count..))) +
  xlab("Food Suporting Disaster-stricken Areas") + ylab("Percentage")
g5<-ggplot(df2_ch3, aes(x = q135)) + geom_bar(aes(y = (..count..)/sum(..count..))) +
  xlab("Food Supporting People with disabilities") + ylab("Percentage")
g6<-ggplot(df2_ch3, aes(x = q136)) + geom_bar(aes(y = (..count..)/sum(..count..))) +
  xlab("Biodiversity-Conscious Certified Food") + ylab("Percentage")
g7<-ggplot(df2_ch3, aes(x = q137)) + geom_bar(aes(y = (..count..)/sum(..count..))) +
  xlab("Food wih Environmental Concerns") + ylab("Percentage")
g8<-ggplot(df2_ch3, aes(x = q77)) +  geom_bar(aes(y = (..count..)/sum(..count..))) +
  xlab("Food produced in Japan") + ylab("Percentage")
grid.arrange(g1, g2,g3,g4,g5,g6,g7,g8, nrow = 2, ncol=4)
par(mfrow = c(1,1))

#PEB adoption graphs
par(mfrow = c(3,4))
g1<-ggplot(df2_ch3, aes(x = q81)) + geom_bar(aes(y = (..count..)/sum(..count..))) +
  xlab("Recycle waste") + ylab("Percentage")
g2<-ggplot(df2_ch3, aes(x = q82)) + geom_bar(aes(y = (..count..)/sum(..count..))) +
  xlab("Reduce waste") + ylab("Percentage")
g3<-ggplot(df2_ch3, aes(x = q83)) + geom_bar(aes(y = (..count..)/sum(..count..))) +
  xlab("Use environmentally-friendly products") + ylab("Percentage")
g4<-ggplot(df2_ch3, aes(x = q84)) + geom_bar(aes(y = (..count..)/sum(..count..))) +
  xlab("Turn off appliances and gas frequently") + ylab("Percentage")
g5<-ggplot(df2_ch3, aes(x = q85)) + geom_bar(aes(y = (..count..)/sum(..count..))) +
  xlab("Choose recycled or refillable products") + ylab("Percentage")
g6<-ggplot(df2_ch3, aes(x = q86)) + geom_bar(aes(y = (..count..)/sum(..count..))) +
  xlab("Not pour oil or toxic subtances down the drain") + ylab("Percentage")
g7<-ggplot(df2_ch3, aes(x = q87)) + geom_bar(aes(y = (..count..)/sum(..count..))) +
  xlab("Avoid excessive packaging") + ylab("Percentage")
g8<-ggplot(df2_ch3, aes(x = q88)) +  geom_bar(aes(y = (..count..)/sum(..count..))) +
  xlab("Carry eco-bag and own bottle") + ylab("Percentage")
g9<-ggplot(df2_ch3, aes(x = q89)) +  geom_bar(aes(y = (..count..)/sum(..count..))) +
  xlab("Help recycle containers") + ylab("Percentage")
g10<-ggplot(df2_ch3, aes(x = q810)) +  geom_bar(aes(y = (..count..)/sum(..count..))) +
  xlab("Grow their own food") + ylab("Percentage")
g11<-ggplot(df2_ch3, aes(x = q811)) +  geom_bar(aes(y = (..count..)/sum(..count..))) +
  xlab("Refrain from using private transportation") + ylab("Percentage")
grid.arrange(g1, g2,g3,g4,g5,g6,g7,g8,g9,g10,g11, nrow = 3, ncol=4)
par(mfrow = c(1,1))
```

```
273.
274. #PEB means and std
275. sapply(df2_ch3[,c(
276.   'q81','q82'
277.   ,'q83','q84'
278.   ,'q85','q86','q87'
279.   ,'q88','q89', 'q810'
280.   ,'q811'
281. )], function(x) c("Mean"= mean(x),"Std."= sd(x))
282. )
283.
284. #price sensitive, healthy diet, and quality items:
285. sapply(df2_ch3[,c(
286.   'q171','q172','q177','q178'
287. )], function(x) c("Mean"= mean(x),"Std."= sd(x))
288. )
289.
290. #Income relation with EFC
291. par(mfrow = c(8,1))
292. g1<-ggplot(df2_ch3, aes(y= q131, x = as.character(q3))) + geom_boxplot(aes(fill=as.character(q3)), show.legend =
FALSE) +
293.      labs(x = "Income Range", y="Organic Food")
294. g2<-ggplot(df2_ch3, aes(y= q132, x = as.character(q3))) + geom_boxplot(aes(fill=as.character(q3)), show.legend =
FALSE) +
295.   labs(x = "Income Range", y="Fair Trade Food")
296. g3<-ggplot(df2_ch3, aes(y= q133, x = as.character(q3))) + geom_boxplot(aes(fill=as.character(q3)), show.legend =
FALSE) +
297.   labs(x = "Income Range", y="Locally Produced Food")
298. g4<-ggplot(df2_ch3, aes(y= q134, x = as.character(q3))) + geom_boxplot(aes(fill=as.character(q3)), show.legend =
FALSE) +
299.   labs(x = "Income Range", y="Food Suporting Disaster-stricken Areas")
300. g5<-ggplot(df2_ch3, aes(y= q135, x = as.character(q3))) + geom_boxplot(aes(fill=as.character(q3)), show.legend =
FALSE) +
301.   labs(x = "Income Range", y="Food Supporting People with disabilities")
302. g6<-ggplot(df2_ch3, aes(y= q136, x = as.character(q3))) + geom_boxplot(aes(fill=as.character(q3)), show.legend =
FALSE) +
303.   labs(x = "Income Range", y="Biodiversity-Conscious Certified Food")
304. g7<-ggplot(df2_ch3, aes(y= q137, x = as.character(q3))) + geom_boxplot(aes(fill=as.character(q3)), show.legend =
FALSE) +
305.   labs(x = "Income Range", y="Food wih Environmental Concerns")
306. g8<-ggplot(df2_ch3, aes(y= q77, x = as.character(q3))) + geom_boxplot(aes(fill=as.character(q3)), show.legend =
FALSE) +
307.   labs(x = "Income Range", y="Food produced in Japan")
308. grid.arrange(g1, g2,g3,g4,g5,g6,g7,g8, nrow = 2, ncol=4)
309. par(mfrow = c(1,1))
310.
311. #overal means, std, kurtosis, and skewness
312. ch3_means<-data.frame(sapply(df2_ch3[c('q101','q102','q103','q105','q109','q1012','q1015'
313.             ,'q162','q163','q164','q166','q2110','q219','q161','q144','q154','q171'
314.             ,'q216','q211','q22','q213','q72','q73','q74','q75','q76','q77','q177', 'q178'
315.             ,'q145','q153','q155','q179','q1712'
316.             ,'q81','q82','q83','q84','q85','q86','q87','q88','q89','q810','q811'
317.             ,'q146','q147','q148','q214','q215','q157','q1713', 'q1714'
318.             ,'q131','q132','q133','q134','q135','q136','q137', 'q_certificates'
319.             ,'q144','q154','q171'
320. )], function(x) c("Mean"= mean(x),"Std."= sd(x), "Skew"=moments::skewness(x),"kurtosis"=moments::kurtosis(x)))
321.       )
322.
323. "As a general guideline, a skewness value between −1 and +1
324. is considered excellent, but a value between −2 and +2 is generally considered acceptable.
325. Values beyond −2 and +2 are considered indicative of nonnormality.
326. (Hair et al., 2022, p. 66). Aburumann et al. 2023 mentions -3/+3 as nonnormality"
327.
328. #---------------------- CH3 Clustering Step 0: Info & Primary Tests----------
329. "There are several types of clustering methods, partitional, density based and hierarchical and combinatorial;
330. On a 1st approach this study applies a Hierarchical flowed by partitional one (k-medoids).
331.
332. Research Problem:
333. 1) Find clusters given they PEB (Q8) practice rates, so I  check if they have influence on EC decision-making model.
334. 2) See if the clusters differ on socio-demographics
```

```
3) Non-metric variables will be used on a later cluster profiling stage and their difference between groups is to be tested.

Clustering Methodology:
Step 1) Data reduction (PCA analysis to the items of Q8)
Step 2) Hierarchical Clustering: Ideal number of clusters, overall visualization and plot profiling
Similarity Measure choice (used in Hierarchical and partitional clustering):
Among several (Manahathan, Euclidean, City-Block, Mahalanodis)
and despite Euclidean being the most commonly adopted, this study utilizes the Mahalanodis distance.
According to Hair 2020, such distance is adequate for situations where the variables are highly correlated
Step 3) K-medoids: the algorithm uses, the number of clusters discovered in step 2: and using those centroid has beginning seeds.
A k-medoids was used instead of a k-means, once is it possible to use the Mahalanodis distance without initialization problems.
Step 4) Visualization and profiling:
Silhouette, Clustering size, plot 2d &3d, Kruskal Wallis and  Dunn's tests. The latter were preferred due to their assumption
towards normality.

Assumptions:
->Assumption (on Multicollinearity): In cluster analysis the effect is different because
multicollinearity is actually a form of implicit weighting. In the presence of collinearity, a FA may be performed, as well as summated scale,
or only use some of the items as representatives. The similarity measure used also can be more or less sensible to it. Mahalanodis is the best
option.
 "

#data to be used
df_clust_ch3=df2_ch3[,c('q81','q82','q83','q84','q85','q86','q87','q88','q89','q810','q811'
                ,'q131','q132','q133','q134','q135','q136','q137', 'q77')] #q77 added on the compilation
df_clt2_ch3=df2_ch3[,c('q81','q82','q83','q84','q85','q86','q87','q88','q89','q810','q811')]
df_demo_ch3=df2_ch3[,c('gender','kids','pet','age10',"age5",'q2','q3','q4','age','residence','marry')]

#correlation matrix:
par(mfrow = c(1,1))
res_ch3 <- round(cor(df_clust_ch3[,c('q81','q82','q83','q84','q85','q86','q87','q88','q89','q810','q811'
)], method='spearman'), digits=2) #once spearman correlation does not assume normality

#color scheme
col<- colorRampPalette(c("blue", "white", "red"))(20)

# correlation heatmap
heatmap(x = res_ch3, col = col, symm = TRUE)

#correlation plot #2
corrplot(res_ch3, type = "upper", order = "hclust",
         tl.col = "black", tl.srt = 45)
par(mfrow = c(1,1))

#plot for each "bigger" question separated
ggpairs(data.frame( scale(df_ch3[,c('q131','q132','q133','q134','q135','q136','q137','q77')])))
ggpairs(data.frame( scale(df_ch3[,c('q81','q82','q83','q84','q85','q86','q87','q88','q89')])))

'NOTE: All the items Q13 are highly correlated and Q77 is moderately correlated with them.
The Q8 have a high correlation but lower when compared with the ones found within Q13/Q77.
Moreover, while Q8 have overall high practice rates, that not the case on Q13 items, Q77 has and average engagement rate.
Given this last two factors a principal component analysis is performed to achieve items reductions
'

#KMO test to see if data can be reduced:
#KMO(df_clust) #0.95>0.8 -> OK
KMO(df_clt2_ch3) #Overall 0.93 -> OK

#bartlett test to confirm is we can process with the reduction:
bartlett.test(df_clt2_ch3) #ok p_value smaller than 5%

#cronbachalpha to test the reliability:
CronbachAlpha(df_clt2_ch3) #0.8992 > 0.7 -> Ok
```

```
#Determine the number ideal number of Factors to be used
pca_ch3<- principal(res_ch3,11,rotate="varimax")

#Ideal Number Criterion:
#screee plot:
plot(pca_ch3$values, type="b", col="black",  xlab="n factors", ylab="eigh-valx", main="Scree Plot")
abline(h=1, col="blue") #eignvalues = 1
par(mfrow = c(1,1))

#according wiht Hair 2020: 1) the eignvalues 1> it should be 2 Factors
#2) By the scree plot 3 factors seem also reasonable

#---------- CH3 Clustering Step 1: PCA with a varimax rotation and 3 factors------
pca_2_ch3<- principal(res_ch3,2,rotate="varimax")
'the 2 interpretable items and were: Q81-Q89+Q811 and  Q810'

#Given the results of the PCA, is reasonable to create summated scales (mean based) for the factors
df_sum2_ch3<-as.data.frame(df_clust_ch3[,c('q810')])
df_sum2_ch3$PEBG<-rowMeans(df_clust_ch3[, c('q81', 'q82','q83','q85','q86','q87','q88','q89','q811')], na.rm=TRUE)
df2s_ch3<-df2_ch3 %>% mutate(across(where(is.numeric), scale))
#these EC indicators are the ones used for the final version of the S-O-R Model
colnames(df_sum2_ch3)[1]  <- "GROW"
#because of 77 I used the standardized version of EC
df_sum2_ch3$EC<-rowMeans(df2s_ch3[,c('q131','q132','q77','q134','q137')], na.rm=TRUE)


#correlation of the new factors
res2_ch3 <- cor(df_sum2_ch3, method='spearman') #once spearman does not assume normality
heatmap(x = res2_ch3, col = col, symm = TRUE)
ggpairs(data.frame( scale(df_sum2_ch3)))


"standardization:
The final clustering was done without EC (because it was the point below is not as important)
#as mentioned by Hair 2020 clustering is sensitive to the scales: if the factors
#have different scale the data should be normalized."

#------------------------ CH3 Clustering Step 2: HC Clustering ------------
'Hopkins test (allows to test is clustering may be applied or not):
->If the value is between {0.01, ...,0.3}, the data is regularly spaced.
->If the value is around 0.5, it is random.
->If the value is between {0.7, ..., 0.99}, it has a high tendency to cluster.'

hopkins(df_sum2_ch3[c("GROW", "PEBG")]) #0.991 we can proceed


# Compute the Mahalanobis distance matrix
d_ch3 <- mah(df_sum2_ch3[c("GROW", "PEBG")])

# Check the best method:
m <- c( "average", "single", "complete", "ward")
names(m) <- c( "average", "single", "complete", "ward") #different methods

# compute coefficients
ac <- function(x) {
  agnes(d_ch3,diss=TRUE, method = x)$ac
}

map_dbl(m, ac) #ward has the highest coefficient (0.99998), so it is the one to be used
hc_ch3 <- hclust(d_ch3, method = 'ward.D2')

#Optimal number of clusters
#the max number of clusters is 4 because the total sample size is 600 and more clusters
#could originate cluster that did not have a valid sample size for a MGA analysis
nb_all_ch3 <- NbClust(df_sum2_ch3[c("GROW", "PEBG")], diss=d_ch3, distance=NULL,min.nc=2, max.nc=4,
method="ward.D2", index ="all")
#the ideal number was 3 and after 2

#hierarchical with 3
hc3_ch3 <- hclust(d = mah(df_sum2_ch3[c("GROW", "PEBG")]), method = "ward.D2") #the best is 3
h3_ch3 <- cutree(hc3_ch3, k=3)
```

```
#hierarchical with 2 to confirm
hc2_ch3 <- hclust(d = mah(df_sum2_ch3[c("GROW", "PEBG")]), method = "ward.D2") #the best is 2
h2_ch3 <- cutree(hc2_ch3, k=2)

#find number of observations in each cluster
table(h2_ch3)
table(h3_ch3)

df_sum2_ch3$h2<-h2_ch3
df_sum2_ch3$h2<- sapply(df_sum2_ch3$h2, as.character)

df_sum2_ch3$h3<-h3_ch3
df_sum2_ch3$h3<- sapply(df_sum2_ch3$h3, as.character)

#hierarchical cluster plot
par(mfrow = c(1,1))
plot(hc_ch3)
rect.hclust(hc_ch3 , k = 3, border = 2:6)
abline(h = 3, col = 'red')

#---------- CH3 Clustering Step 3: K-Medoids ----------
clus_med_3=Cluster_Medoids(
  df_sum2_ch3[c("GROW", "PEBG")],
  3,
  distance_metric = "mahalanobis")


clus_med_3$medoids
clus_med_3$clustering_stats

#---------- CH3 Clustering Step 4: Visualization and Profiling ------
#Visualizations:
#2D
fviz_cluster(list(data = df_sum2_ch3[c("GROW", "PEBG")], cluster = clus_med_3$clusters))

# Parallel coordinate plots allow us to put each feature on seperate column and lines connecting each column
df_sum2_ch3$cls_3<-clus_med_3$clusters
df_sum2_ch3$cls_3<- sapply(df_sum2_ch3$cls_3, as.character)

df_sum2_ch3<-df_sum2_ch3%>% mutate(across(where(is.numeric), scale))
#Graphics:

#ggpairs
ggpairs(df_sum2_ch3, 1:3, mapping = ggplot2::aes(color = cls_3, alpha = 0.5),
        diag = list(continuous = wrap("densityDiag")),
        lower=list(continuous = wrap("points", alpha=0.9)))

#boxplots per cluster
ggparcoord(data = df_sum2_ch3
           , columns = 1:3
           , alphaLines = 0.2
           , groupColumn = "cls_3"
           , boxplot = TRUE
           , showPoints = FALSE
           , scale = "center"
) + scale_colour_manual(values=c("#F3CD0E","#116EE8","#4CAF6D")) +
  facet_wrap(~ cls_3)


#boxplot of the variables
#note: EC is on the graph  for reference it was not used for clustering
par(mfrow = c(1,3))
g1<-ggplot(df_sum2_ch3, aes(x = cls_3, y = GROW)) +
  geom_boxplot(aes(fill = cls_3))
g2<-ggplot(df_sum2_ch3, aes(x = cls_3, y = PEBG)) +
  geom_boxplot(aes(fill = cls_3))
g3<-ggplot(df_sum2_ch3, aes(x = cls_3, y = EC)) +
  geom_boxplot(aes(fill = cls_3))
grid.arrange(g1, g2,g3, nrow = 1, ncol=3)
par(mfrow = c(1,1))
```

```
540.
541. #significance of the groups:
542.
543. #Kruskal
544. "the data on the groups is not normal distributed,
545. Citation: While Kruskal-Wallis does not assume that the data are normal, it does assume that the different groups have the same distribution, and groups with different standard deviations have different distributions. If your data are heteroscedastic, Kruskal–Wallis is no better than a Between Groups ANOVA, and may be worse. Instead, you should use Welch's ANOVA for heteroskedastic data (which is not discussed in this textbook).
546. The only time I recommend using Kruskal-Wallis is when your original data set actually consists of one nominal variable and one ranked variable.
547. (https://stats.libretexts.org/Courses/Taft_College/PSYC_2200%3A_Elementary_Statistics_for_Behavioral_and_Social_Sciences_(Oja)/Unit_2%3A_Mean_Differences/11%3A_BG_ANOVA/11.08%3A_Non-Parametric_Analysis_Between_Multiple_Groups)
548. "
549. #the groups are statically different -> They were all smaller than the p_value
550.
551. kruskal.test(GROW ~ cls_3, data = df_sum2_ch3)
552. kruskal.test(PEBG ~ cls_3, data = df_sum2_ch3)
553. kruskal.test(EC ~ cls_3, data = df_sum2_ch3)
554.
555. #perform Dunn's Test with Bonferroni correction for p-values
556. dunnTest(as.numeric(EC) ~ as.character(cls_3), data=df_sum2_ch3, method="bonferroni")
557. dunnTest(as.numeric(GROW) ~ as.character(cls_3), data=df_sum2_ch3, method="bonferroni")
558. dunnTest(as.numeric(PEBG) ~ as.character(cls_3), data=df_sum2_ch3, method="bonferroni")
559.
560.
561. #joining demographics
562. df_prof_ch3<-merge(df_sum2_ch3, df_demo_ch3,by.x = 0, by.y = 0, all.x = TRUE, all.y = TRUE)
563.
564. df_prof_ch3 %>%
565.   group_by(cls_3) %>%
566.   summarise(mean_value = mean(age))
567.
568. #age per decades
569. ctable(
570.   y = as.character(df_prof_ch3$age10),
571.   x = df_prof_ch3$cls_3
572. )
573.
574. #city size
575. ctable(
576.   y = as.character(df_prof_ch3$q4),
577.   x = df_prof_ch3$cls_3
578. )
579.
580.
581. #children
582. ctable(
583.   y = as.character(df_prof_ch3$kids),
584.   x = df_prof_ch3$cls_3
585. )
586.
587. #gender
588. ctable(
589.   y = as.character(df_prof_ch3$gender),
590.   x = df_prof_ch3$cls_3
591. )
592.
593. #---------- CH3 S-O-R Model/PLS-SEM ----------
594. "Some indicators were excluded in the final model, namely:
595. Q143 which was related to the brand type for vegetables was excluded because had high cross-loading with intention
596. On Knowledge more general items about sustainability such as recycle (q1011), global warning (Q106), sustainability (Q1013)
597. and SDGs (Q107) were excluded
598. Subjective influence did not have a significant impact on INT but had it on QLT
599. When assessing the MICOM the model needed to be slightly changed. The changes almost did not changed the results
600. "
601.
602. #---------- CH3 Model Using SEMINR ----------
```

```
#join the clustering results to the main data frame that is going to be used in the S-O-R
df3_ch3<-merge(df_sum2_ch3, df2_ch3,by.x = 0, by.y = 0, all.x = TRUE, all.y = TRUE)
colnames(df3_ch3)[1]  <- "row_name"    # change column name for x column


#outer model
model_ch3<-constructs(
  composite("KNG",multi_items("q",c(101,102,103,105,109,1012,1015))), #q1010, qn_11, q_certificates, q1015 had low loadings
  composite("BEL",multi_items("q", c(162,163,164,166,2110,219))), #Q165 low Q161 had a low loading
  composite("PP",multi_items("q", c(161))),
  composite("PRC",multi_items("q", c(144,154,171))),
  composite("INF",multi_items("q", c(22,213))),
  composite("HEALTH",multi_items("q",c(72:76))),
  composite("QLT",multi_items("q", c(145,153,155,179,1712))),
  composite("INT",multi_items("q", c(146:148,214,215,157,1713:1714))),
  composite("EC",multi_items("q", c(131,132,77,134,137))),
  composite('LAB',single_item('q_certificates')),
  #demographics
  composite('PET',single_item("pet" )),
  composite('MARRY',single_item("marry" )),
  composite('ALONE',single_item("alone" )),
  composite('CHILD',single_item("kids" )),
  composite('GENDER',single_item("gender" )),
  composite('AGE',single_item("age" )),
  composite('EDU',single_item("q2_sum" )),
  composite('SALL',single_item("q3_low" )),
  composite('SALH',single_item("q3_high"))
)

#inner model
st_model_ch3 <- relationships(
  paths (from=c('INF','QLT','KNG','LAB','PRC'), to='BEL'),
  paths (from=c('INF','QLT','HEALTH','PRC','KNG','LAB'), to='PP'),
  paths (from=c('BEL','PP','KNG','QLT','HEALTH'), to="INT"),
  paths(from = c('INT','PRC','KNG','LAB','AGE', 'GENDER','CHILD','EDU','SALL','SALH'), to = "EC")
)

#model result with the SeminR
pls_ch3 <- estimate_pls(
  data = df3_ch3,
  measurement_model = model_ch3,
  structural_model = st_model_ch3
)
summary(pls_ch3)
sum_ch3<-summary(pls_ch3)

predict_ch3<- predict_pls(
  model =pls_ch3,
  technique = predict_DA,
  noFolds = 4) #the number of folds were 4 because of the sample is small



sum_predict_ch3 <- summary(predict_ch3)
sum_predict_ch3$PLS_out_of_sample[,c('q131','q132','q77','q134','q137')]
sum_predict_ch3$LM_out_of_sample[,c('q131','q132','q77','q134','q137')]

#assessment of the inner and the outer models
sum_ch3$validity$htmt
sum_ch3$vif_antecedents

#bootstrapping results:
#the recommend bootstrap number is min 1000, ideally 5000 or more
boot_ch3 <- bootstrap_model(pls_ch3,
                            nboot = 5000,
                            cores = parallel::detectCores(),
                            seed = 10
                            )
sum_boot_ch3_5 <- summary(boot_ch3, alpha = 0.05) #different intervals of confidence 5%
sum_boot_ch3_1 <- summary(boot_ch3, alpha = 0.01) #different intervals of confidence 1%
```

```
673. sum_boot_ch3_01 <- summary(boot_ch3, alpha = 0.001) #different intervals of confidence 0.01%
674. sum_boot_ch3_10 <- summary(boot_ch3, alpha = 0.10) #different intervals of confidence 10%
675. sum_boot_ch3_1$bootstrapped_paths
676. sum_boot_ch3_01$bootstrapped_paths
677. sum_boot_ch3_5$bootstrapped_paths
678. #reliability plot available in SeminR
679. plot(sum_ch3$reliability)
680.
681.
682. #Contruct scores
683. boot_scores_ch3=data.frame(boot_ch3$construct_scores)
684.
685. #check construct scores
686. write_xlsx(boot_scores_ch3, "C:/Users/xxxx/Documents/xxx/ch3_construct_scores.xlsx")
687.
688. #------------------------------------------------------------------------------ CH3 Mediation - SEMINR----------
689. df_boot_ch3<-data.frame(boot_paths_df(boot_ch3))
690.
691. #FOLLOW THE PAPER: Cepeda et.all 2017 -> Mediation Analyses in Partial Least Squares Structural Equation
Modelling. Guidelines and Empirical Examples
692. #CHANGE PATH ON THE LOCAL PC
693. today=format(Sys.time(), "%Y%d%b")
694. path= paste0("C:/Users/xxxx/Documents/xxx/",today,"_mediation_an.xlsx")
695. write_xlsx(df_boot_ch3,path)
696.
697. # Inspect total indirect effects
698. sum_ch3$total_indirect_effects
699.
700. #the mediation effects that should be analysed are:
701. #1) Labelling; 2) Price; 3)KNG
702.
703. #1) Labelling:
704. # Inspect indirect effects (LAB)
705. specific_effect_significance(boot_ch3,
706.                            from = "LAB",
707.                            through = c("PP","INT"),
708.                            to = "EC",
709.                            alpha = 0.05)
710. "significat at 5% but not at 1%"
711.
712. specific_effect_significance(boot_ch3,
713.                            from = "LAB",
714.                            through = c("BEL","INT"),
715.                            to = "EC",
716.                            alpha = 0.05)
717. specific_effect_significance(boot_ch3,
718.                            from = "LAB",
719.                            through = c("BEL","INT"),
720.                            to = "EC",
721.                            alpha = 0.05)
722. "significant at 5% and 1%"
723.
724. specific_effect_significance(boot_ch3,
725.                            from = "LAB",
726.                            #through = c("PP","INT"),
727.                            to = "EC",
728.                            alpha = 0.05)
729. "significant at 5%, 1% and 0.1%"
730.
731. #2) Price
732. # Inspect indirect effects (PRC)
733. specific_effect_significance(boot_ch3,
734.                            from = "PRC",
735.                            through = c("PP","INT"),
736.                            to = "EC",
737.                            alpha = 0.05)
738. specific_effect_significance(boot_ch3,
739.                            from = "PRC",
740.                            through = c("BEL","INT"),
741.                            to = "EC",
742.                            alpha = 0.05)
```

```
specific_effect_significance(boot_ch3,
                             from = "PRC",
                             #through = c("PP","INT"),
                             to = "EC",
                             alpha = 0.05)

#------------------------- CH3 Model using CSEM ------------------------------


csem_model_ch3<-"
# Structural Model
BEL ~ INF + QLT + KNG + LAB + PRC
PP ~ INF + QLT + HEALTH + KNG + LAB + PRC
INT ~ BEL + PP + KNG + QLT + HEALTH
EC ~ INT + PRC + KNG + LAB + AGE + GENDER + CHILD + EDU + SALL + SALH

# Composite model
KNG <~ q101 + q102 + q103 + q105 + q109 + q1012 + q1015
BEL <~ q162 + q163 + q164  + q166 + q2110 + q219 #+ q165
PP <~  q161
PRC <~ q144 + q154  + q171
INF <~   q213 + q22
HEALTH <~ q73 + q74 + q75 + q76  + q72
QLT <~ q145 + q153 + q155 + q179 + q1712
INT  <~ q146 +  q147 + q148 + q214 + q215 + q157 + q1713 + q1714
EC <~ q131 + q132 + q77 + q134 + q137  #+ q136 # q135  + q133
LAB <~ q_certificates

#control variables
CHILD <~ kids
GENDER <~ gender
AGE <~ age
EDU <~ q2_sum
SALL <~ q3_low
SALH <~ q3_high
"


# Perform estimation
csem_pls_ch3<- csem(.data = df3_ch3,
                    .model = csem_model_ch3,
                    .PLS_modes = 'modeA')
# summary
csem_sum_ch3=cSEM::summarize(csem_pls_ch3)


# Reliability
#common factors = False so it calculates all the reliability indices even if the version of PLS-SEM used is the normal and nor the PLSc
#because of this, on the assessment, a warning will be always generated
csem_as_ch3=cSEM::assess(csem_pls_ch3 ,.only_common_factors = FALSE )

# Bootstrapping
csem_boot_ch3 <- csem(df3_ch3, csem_model_ch3
                      ,.resample_method = "bootstrap"
                      ,.R = 5000
                      , .seed = 10
                      ,.PLS_modes = 'modeA'
)

csem_boot_sum_ch3<-cSEM::summarize(csem_boot_ch3)

#------------------------ CH3 Model using CSEM (Health Non Direct) ----------------
#Multi-group analysis with more than 2 groups is not available in the SeminR.
#First, the general results were reproduced with the cSEM package

csem_model_h_ch3<-"
# Structural Model
BEL ~ INF + QLT + KNG + LAB + PRC
PP ~ INF + QLT + HEALTH + KNG + LAB + PRC
```

```
INT ~ BEL + PP + KNG + QLT
EC ~ INT + AGE + GENDER + CHILD + EDU + SALL + SALH

# Composite model
KNG <~ q101 + q102 + q103 + q105 + q109 + q1012 + q1015
BEL <~ q162 + q163 + q164  + q166 + q2110 + q219 #+ q165
PP <~  q161
PRC <~ q144 + q154  + q171
INF <~   q213 + q22
HEALTH <~ q73 + q74 + q75 + q76  + q72
QLT <~ q145 + q153 + q155 + q179 + q1712
INT  <~ q146 +  q147 + q148 + q214 + q215 + q157 + q1713 + q1714
EC <~ q131 + q132 + q77 + q134 + q137  #+ q136 # q135  + q133
LAB <~ q_certificates

#control variables
CHILD <~ kids
GENDER <~ gender
AGE <~ age
EDU <~ q2_sum
SALL <~ q3_low
SALH <~ q3_high
"


# Perform estimation
csem_pls_h_ch3<- csem(.data = df3_ch3,
                      .model = csem_model_h_ch3,
                      .PLS_modes = 'modeA')
# Get summary
csem_sum_h_ch3=cSEM::summarize(csem_pls_h_ch3)


# Reliability
csem_as_h_ch3=cSEM::assess(csem_pls_h_ch3 ,.only_common_factors = FALSE )

#comparison with a simplified model
csem_as_ch3$AIC
csem_as_ch3$BIC
csem_as_h_ch3$AIC
csem_as_h_ch3$BIC

#------------------- CH3 MULTI-GROUP (MGA) USING THE CLUSTERS-----------------
as.factor(df3_ch3$cls_3)

#--------------------------- CH3 MGA Step 1: MICOM -------------------------
#multigroup test
out2<- csem(df3_ch3, csem_model_ch3
            ,.resample_method = 'bootstrap'
            ,.R = 5000
            ,.PLS_modes = 'modeA'
            ,.id = 'cls_3'
)

s1=cSEM::summarize(out2$`1`)
s2=cSEM::summarize(out2$`2`)
s3=cSEM::summarize(out2$`3`)


#there are more than 2 groups so it's necessary to apply a correction
outMICOMN2 = testMICOM(out2,
                       .R = 5000 ,
                       .approach_p_adjust =  'bonferroni',
                       .seed = 10 #added on the compilation
                     )
outMICOMN2

#--------------------------- CH3 MGA Step 2: NDT (Klesel) ---------------------

outMGD2 = testMGD(out2,
                  .R_permutation = 5000,
```

```
                .approach_mgd = 'Klesel',
                .approach_p_adjust =  'bonferroni',
                .seed = 10) #added on the compilation


"In contrast, if researchers want to compare the complete structural model, they should rely on the NDT, which was
specifically designed for that purpose and showed the highest power in most of the situation. This is particularly
apparent, in case of small group differences and a large total sample size and in case of smaller total sample sizes
if the group differences are moderate and large, i.e., small-medium to large. Subsequently, they can use the NPT
in combination with a correction for multiple comparison to examine which parameters differ. This procedure
resembles the approach commonly used in the context of ANOVA, where first a F-test is conducted and
subsequently, multiple comparison procedures are employed to investigate which means actually differ significantly -
Klesel 2022"

#---------------------- CH3 MGA Step 3: NPT Pairwise (Chin) ----------------------
#Pairwise analysis NPT (CHIN 2010)
outchin = testMGD(out2,
                .R_permutation = 5000,
                .approach_mgd = 'Chin',
                .approach_p_adjust ='bonferroni',
                .seed = 10) #added on the compilation


# Have a look at the help file of the testMGD function, it has various test
# that you can use but we focused on NDT by Klesel et al. (2019)

#--------------- Chapter 4 & Chapter 5 & Chapter 6 Data Preparation (Python) -------
"
The data set for the analysis of Chapter 4, 5, and 6 is the same. Thus, data preparation step and data retrieval is shared
by all these chapters
Some of the data preparation was done in Python, using Spyder and Anaconda an IDE and packages compilation,
respectively. The python code will be pasted here
as a comment, but if someone wishes to run it, they should use an appropriate Python IDE.
"



"
##-----------------------------PACKAGES----------------------------------
import pandas as pd
import datetime as dt
import unicodedata

#%matplotlib inline
#matplotlib.style.use('ggplot')

#major setups
today= (dt.datetime.today().strftime('%Y-%m-%d')).replace('-','')

#read each prefecture file
df_1=pd.read_csv('C:/Users/catar/Documents/01.PhD/Compost/Aichi.csv', encoding='Shift-JIS')
df_2=pd.read_csv('C:/Users/catar/Documents/01.PhD/Compost/Chiba.csv', encoding='Shift-JIS')
df_3=pd.read_csv('C:/Users/catar/Documents/01.PhD/Compost/Fukuoka.csv', encoding='Shift-JIS')
df_4=pd.read_csv('C:/Users/catar/Documents/01.PhD/Compost/Hyogo.csv', encoding='Shift-JIS')
df_5=pd.read_csv('C:/Users/catar/Documents/01.PhD/Compost/Kanagawa.csv', encoding='Shift-JIS')
df_6=pd.read_csv('C:/Users/catar/Documents/01.PhD/Compost/Kyoto.csv', encoding='Shift-JIS')
df_7=pd.read_csv('C:/Users/catar/Documents/01.PhD/Compost/Osaka.csv', encoding='Shift-JIS')
df_8=pd.read_csv('C:/Users/catar/Documents/01.PhD/Compost/Saitama.csv', encoding='Shift-JIS')
df_9=pd.read_csv('C:/Users/catar/Documents/01.PhD/Compost/Tokyo.csv', encoding='Shift-JIS')

#change col names
def change_col(x):
    if x[0]=='Q':
        x=x.replace('-','')
        x=x.replace('.','')
        if len(x)>2 and unicodedata.category(x[2])=='Lo':
            return x[:2]
        elif len(x)>3 and unicodedata.category(x[3])=='Lo':
            return x[:3]
        elif len(x)>4 and unicodedata.category(x[4])=='Lo':
            return x[:4]
        elif len(x)>5 and unicodedata.category(x[5])=='Lo':
```

```
            return x[:5]
        elif len(x)>6 and unicodedata.category(x[6])=='Lo':
            return x[:6]
        else:
            return x
    elif x=='#SEQ' or x=='SEQ' :
        return 'seq'
    elif x=='案件 ID' or x=='ID':
        return 'id'
    elif x=='SAMPLEID':
        return 'sample_code'
    elif x=='回答日時':
        return 'time'
    elif x=='性別':
        return 'gender'
    elif x=='年齢':
        return 'age'
    elif x=='年代（10 歳刻）':
        return 'age_10'
    elif x=='年代（5 歳刻）':
        return 'age_5'
    elif x=='未既婚':
        return 'marriage'
    elif x=='居住地域':
        return 'loacation'
    elif x=='割付':
        return 'allotment'
    else:
        return x

df_1.rename(columns=lambda c: change_col(c), inplace=True)
df_2.rename(columns=lambda c: change_col(c), inplace=True)
df_3.rename(columns=lambda c: change_col(c), inplace=True)
df_4.rename(columns=lambda c: change_col(c), inplace=True)
df_5.rename(columns=lambda c: change_col(c), inplace=True)
df_6.rename(columns=lambda c: change_col(c), inplace=True)
df_7.rename(columns=lambda c: change_col(c), inplace=True)
df_8.rename(columns=lambda c: change_col(c), inplace=True)
df_9.rename(columns=lambda c: change_col(c), inplace=True)

#concat all the prefectures
df=pd.concat([df_9,df_8,df_7, df_6,df_5, df_4,df_3,df_2,df_1])

#2 people on Q2 (ocupation) answered other being on 無職 and the other 大学（休学中） which I'll consider unemployed (index 49 and 15)
#4 people on Q5 (type) of house chose others with 実家, じっかにいそうろう, 親族所有, 親と同居 (which is pretty much family home/ self-owned)

df=df.loc[:, (df.isnull().sum(axis=0) <= 1480)]

#age from 30 to 50; from 50 to 60; 60 on
df['age_young']=df['age_10'].apply(lambda x: 1 if x==3 or x==4 else 0)
df['age_mid']=df['age_10'].apply(lambda x: 1 if x==5 or x==6 else 0)
df['age_old']=df['age_10'].apply(lambda x: 1 if x!=3 and x!=4 and x!=5 and x!=6 else 0)


#income
df['income_low']=df['Q7'].apply(lambda x: 1 if x==1 or x==2 else 0)
df['income_mid']=df['Q7'].apply(lambda x: 1 if x==3 or x==4 else 0)
df['income_high']=df['Q7'].apply(lambda x: 1 if x==5 or x==6 or x==7  else 0)

def money(x):
    if x['income_low']==1:
        return 1
    elif x['income_mid']==1:
        return 2
```

```
    elif x['income_high']==1:
        return 3
    else:
        return 0
df['income']=df.apply(lambda x: money(x),axis=1)

#change gender from (1=male 2=female) to (0=male 1=Female) no neutral gender questions
df['gender']=df['gender'].apply(lambda x: float(x)-1)


#change marriage to dummy 1=single 2=married 3=divorced/widow(?) if that's the case I will assume them 0 (non-married)
df['marriage']=df['marriage'].apply(lambda x: x-1 if x==1 or x==2 else 0 )

#if there is in the household children with
def children(x):
    #from preschool children/grand-children to junior high-school
    if x['Q34']==1 or x['Q35']==1 or x['Q36']==1 or x['Q37']==1 or x['Q310']==1 or x['Q311']==1 or x['Q312']==1 or x['Q313']==1 or x['Q316']==1:
        return 1
    else:
        return 0

df['children']=df.apply(lambda x: children(x), axis=1)


#if the household has a pet (Q2 is about the number of people in the house)
df['pet']=df.apply(lambda x: 1 if x['Q2']==1 else 0, axis=1)

#if the person lives alone
df['alone']=df.apply(lambda x: 1 if x['Q31']==1 else 0, axis=1)

#job categories (just was 4 working, part-time, unemployed, hhousewife:

#full timers that are not “kaishain”
#the number of composters is higher in self-employed people
df['job_fulltime']=df.Q6.apply(lambda x: 1 if (x!=9 and x!=10 and x!=11 and x!=12 and x!=5 and  x!=1 and x!=2 and x!=3) else 0)
#parttimers
df['job_partime']=df.Q6.apply(lambda x: 1 if  x==5 else 0)

#housewives/husbands
df['job_housewife']=df.Q6.apply(lambda x: 1 if x==10  else 0)

#this one will be silent during the analysis; I'm creating it just for the sake of visualization
#there was only one student on the sample so that was included in the 'unemployed'
df['job_unemployed']=df.Q6.apply(lambda x: 1 if (x==11 or x==9) else 0)

#people who have a corporate (boss or regular) or public officer job
df['job_kaishain']=df.Q6.apply(lambda x: 1 if x==1 or x==2 or x==3 else 0)

df['job_full']=df.Q6.apply(lambda x: 1 if (x!=9 and x!=10 and x!=11 and x!=12 and x!=5) else 0)

def jobs(x):
    if x['job_kaishain']==1:
        return 5
    elif x['job_fulltime']==1:
        return 4
    elif x['job_partime']==1:
        return 3
    elif x['job_housewife']==1:
        return 2
    elif x['job_unemployed']==1:
        return 1

#there was only one student on the sample so that was included in the 'other'
df['job']=df.apply(lambda x: jobs(x), axis=1 )


#5 people don't have high school so it will be ignores
# guys with all 0 had none of this education levels
```

```
df['edu_highschool']=df['Q1'].apply(lambda x: 1 if (x == 6)|(x == 2) | (x == 3) | (x == 4)|(x == 7) else 0) #high
#college or college equivalent
df['edu_college']=df['Q1'].apply(lambda x: 1 if (x == 3) else 0) #college
#uni or equivalent
df['edu_university']=df['Q1'].apply(lambda x: 1 if (x == 4)|(x== 7) else 0) #uni #there are 2 people with other that are not worth it

#function for commercial areas
def edu_level (x):
  if x['edu_highschool']==1:
     return 1
  elif x['edu_college']==1:
     return 2
  elif x['edu_university']==1:
     return 3
  else:
     return 0

df['edu']=df.apply(lambda x: edu_level(x), axis=1)

#function for simplifying the subsidy to only 3 layers:
def subs(x):
    if (x==3) or (x==4): #not available or don't know
       return 3
    elif x==2: #doesn't know the details
       return 2
    elif x==1: #knows
       return 1

def subsc(x):
    if (x==3) or (x==4): #don't know
       return 0
    else: #available
       return 1

def epistemic_1(x):
    if x==4: #don't know
       return 3
    elif x==2: #vaguely knows
       return 2
    elif (x==1) or (x==3): #knows properly
       return 1

def epistemic_2(x):
    if x==4: #don't know
       return 0
    elif (x==1) or (x==2) or (x==3): #knows properly
       return 1

df['Q261b']=df['Q261'].apply(lambda x: subs(x))
df['Q262b']=df['Q262'].apply(lambda x: subs(x))
df['Q263b']=df['Q263'].apply(lambda x: subs(x))
df['Q264b']=df['Q264'].apply(lambda x: subs(x))
df['Q261c']=df['Q261'].apply(lambda x: subsc(x))
df['Q262c']=df['Q262'].apply(lambda x: subsc(x))
df['Q263c']=df['Q263'].apply(lambda x: subsc(x))
df['Q264c']=df['Q264'].apply(lambda x: subsc(x))

df['Q261_epi']=df['Q261'].apply(lambda x: epistemic_1(x))
df['Q262_epi']=df['Q262'].apply(lambda x: epistemic_1(x))
df['Q263_epi']=df['Q263'].apply(lambda x: epistemic_1(x))
df['Q264_epi']=df['Q264'].apply(lambda x: epistemic_1(x))


df['Q261_epi2']=df['Q261'].apply(lambda x: epistemic_2(x))
df['Q262_epi2']=df['Q262'].apply(lambda x: epistemic_2(x))
df['Q263_epi2']=df['Q263'].apply(lambda x: epistemic_2(x))
df['Q264_epi2']=df['Q264'].apply(lambda x: epistemic_2(x))

#living areas rural, habitatiunal areas or commercial
df['rural_area']=df['Q4'].apply(lambda x: 1 if x==5 else 0)
```

```
#mainly a residencial area of living
df['residencial_area']=df['Q4'].apply(lambda x: 1 if (x == 3) or (x == 4) else 0)
#includes factories
df['insdustrial_area']=df['Q4'].apply(lambda x: 1 if (x== 1) else 0)
#includes  stores/commercial districts and offices
df['comercial_area']=df['Q4'].apply(lambda x: 1 if (x== 2) else 0)

#function for commercial areas
def hloc (x):
  if x['rural_area']==1:
      return 1
  elif x['insdustrial_area']==1:
      return 2
  elif x['residencial_area']==1:
      return 3
  elif x['comercial_area']==1:
      return 4
  else:
      return 0

df['living_area']=df.apply(lambda x: hloc(x), axis=1)

#merge intention of the ones that were doing or were not participating in composting
def ints(row):
    if row['Q15']==1:
        return row['Q18'] #continue
    else:
        return row['Q19'] #start
df['intention']=df.apply(lambda row: ints(row), axis=1)

#house type
#the others found here were pretty much parents/family owned house
df['house_mine']=df['Q5'].apply(lambda x: 1 if x== 1 else  0)
df['house_rent']=df['Q5'].apply(lambda x: 1 if x== 3 else 0) #uni #there are 2 people with other that are not worth it
df['apart_mine']=df['Q5'].apply(lambda x: 1 if x== 2 else 0)
df['apart_rent']=df['Q5'].apply(lambda x: 1 if (x== 8)| (x== 4) else 0)
#shared house, company house, others
df['house_other']=df['Q5'].apply(lambda x: 1 if (x == 5)|(x == 6)|(x == 7)|(x == 9) else 0)

df['house']=df['Q5'].apply(lambda x: 1 if x== 1  or x== 3 or x == 5 or x == 6 or x == 7 else  0)
df['apartment']= df['Q5'].apply(lambda x: 1 if x== 2  or x== 8 or x == 4 else  0)
df['rent']=df['Q5'].apply(lambda x: 1 if x== 3 or x == 5 or x == 6 or x == 7 or x == 9 else  0)
df['owner']=df['Q5'].apply(lambda x: 1 if x== 1  or x== 2 else  0)


#dummy more general about gardening and farming
df['garden']=df.apply(lambda x: 1 if (x['Q131'] == 1) | (x['Q132'] == 1) | (x['Q133'] == 1)  else 0, axis=1)

def garden_simple(x):
    a=1
    if (x['Q131'] == 1):
        a=4
    elif (x['Q132'] == 1):
        a=3
    elif  (x['Q133'] == 1):
        a=2
    else:
        a=1
    return (a)

df['garden3_degree'] = df.apply(lambda x: garden_simple(x), axis=1)

#people o farm have an 'higher' interest than the ones in balconies
#they could state if they liked farming, community gardening/backyard or balconies
#we assume that farming or a community farm requires more commitment hence more interest
#the utility chosen was linear
df['garden_degree']=df.apply(lambda x: x['Q131']*3+x['Q132']*2+x['Q133']*1, axis=1)

df['garden2_degree']=df.apply(lambda x: x['Q131']*4+x['Q132']*2+x['Q133']*1, axis=1)

#reverse the other of the rank score for the PEB positive environmental
```

```
#impact if it was the thrid best now it will score one, easier to analyse later
def rank_score(x):

    if x==3:
        return 1
    elif x==2:
        return 2
    elif x==1:
        return 3
    else:
        return 0

#from Q221 to Q2211
df.iloc[:,113:124]=df.iloc[:,113:124].applymap(lambda x: rank_score(x))


#exclude col that I don't need
df=df.drop('Q3', axis=1)

#the question number 9 is about the type of ingredients. I will merge the level of
#not cooking or rarely eating at home once for the ingredients effect mean the same
df['Q9_new']=df['Q9'].apply(lambda x: x if (x!=4 and x!=5) else 4)

#compost dummy where the people who dropped are merged with the ones who are not doing it rn
df['compost_dummy']=df['Q15'].apply(lambda x: 1 if x==1 else 0)
df['compost_cat']=df['Q15'].apply(lambda x: 2 if x==1 else 1)

#ranking top compost
df['top_compost']=df['Q221'].apply(lambda x: 4 if x==0 else x)

#separate them
df_not=df[df['Q15']==3]
df_comp=df[df['Q15']==1]
df_drop=df[df['Q15']==2]

#profilling page uncomment if which to run it
#profile=pp.ProfileReport(df, minimal=True)
#profile.to_file(output_file='C:/Users/xx/Documents/x/{0}_compost_tot.html'.format(today))

df.to_excel('C:/Users/xx/Documents/xx/{0}_data_compost_tot.xlsx'.format(today), index=False)
"

#---------- Chapter 4 & Chapter 5 Data Preparation (R)----------

#read files
df_comp <-  read_excel('C:/Users/xxx/Documents/xxxx/20240429_data_compost_tot.xlsx')
head(df_comp)

# DESCRIPTIVE DATA: item name <,item numbers, mean, sd,
# median, mad, min, max, skew, kurtosis, se
describe(df_comp)

#create an additional wage dummy
df_comp<-dummy_cols(df_comp, select_columns = c("Q7"), remove_first_dummy = TRUE)

#I am excluding to obs who answered others to education
df_comp=df_comp[df_comp$Q1!=8,]

#chapter 4 use the non-reversed version of the burden item
burden_nonreverse<-
df_comp[,c('seq','id','sample_code','Q231','Q232','Q233','Q234','Q235','Q236','Q237','Q238','Q239','Q2310','Q2311','Q2312')]

#reorder the columns to have 6/7 as the highest
#all questions until Q8 are about demographics
#Q9 is a categorical variable, however I will order it from 1 to 5 in which 5 it's less processed food
#Q13 are dummies about farming and gardening which can stay like that. Q134 is no interest so that the only one I
reversed
#Q15 is the category in composting which I want 3 to be the highest
# I will duplicate Q23: as for the clustering it is already in the order I want because 6 is not burden at all
#however for the decision model I'll need burden as the highest thing
#Q24 is a categorical and should be treated like, however it would be nicer to re-order it
```

```
v<-c('Q81','Q82','Q83','Q84','Q85','Q86'
    ,'Q9'
    ,'Q9_new'
    ,'Q101','Q102','Q103','Q104','Q105','Q106','Q107'
    ,'Q111','Q112','Q113','Q114','Q115'
    ,'Q121','Q122','Q123','Q124','Q125','Q126','Q127','Q128','Q129','Q1210','Q1211','Q1212'
    ,'Q134'
    ,'Q141','Q142'
    ,'Q15'
    ,'Q161','Q162','Q163','Q164','Q165','Q166','Q167','Q168','Q169','Q1610'
    ,'Q171','Q172','Q173','Q174','Q175','Q176','Q177','Q178','Q179','Q1710','Q1711','Q1712','Q1713'
    ,'Q201','Q202','Q203','Q204','Q205','Q206','Q207','Q208','Q209','Q2010','Q2011','Q2012','Q2013'
    ,'Q21'
    ,'top_compost'
   ,'Q2312'
    ,'Q231','Q232','Q233','Q234','Q235','Q236','Q237','Q238','Q239','Q2310','Q2311'
    ,'Q241','Q242','Q243','Q244','Q245'
    ,'Q251','Q252','Q253','Q254','Q255','Q256','Q257','Q258'
    ,'Q261','Q262','Q263','Q264'
    ,'Q261b','Q262b','Q263b','Q264b'
    ,'Q261_epi','Q262_epi','Q263_epi','Q264_epi'
    ,'Q271','Q272','Q273','Q274','Q275','Q276','Q277','Q278','Q279'
    ,'Q281'
    #,'Q282' #question made in the negative
    ,'Q283'
    #,'Q284' #question made in the negative
    #,'Q285'
    ,'Q291','Q292','Q293'
    ,'Q301','Q302','Q303','Q304','Q305','Q306','Q307','Q308','Q309'

)

df_comp2<-reverseCode(df_comp,v)
#Q16, Q17, Q22 have NA that are now 7 and 4 values think about those....
df_comp2<-replace(df_comp2, is.na(df_comp2), 0)

#merge the non-reversed burden -> the suffix [_nr]  means they are the non-reversed version
df_comp2<-merge(df_comp2, burden_nonreverse, by=c('seq','id','sample_code'), all.x = TRUE, all.y = TRUE,
suffixes = c("","_nr"))
df_comp2$Q134<-df_comp2$Q134-1

#------------------ CH4 Clustering Step 0: Primary Tests ----------------------
#Q123, Q127, Q1211 were excluded because had low loadings/high cross-loadings
df_clust_ch4=df_comp2[,c(
  'Q102','Q106'
  ,'Q111','Q112'
  ,'Q113','Q114','Q115'
  ,'Q121','Q122', 'Q123'
  ,'Q124'
  ,'Q125','Q126', 'Q127'
  ,'Q128','Q129', 'Q1211'
)]


res_tot_ch4 <- round(cor(df_clust_ch4, method='spearman'), digits=4) #once is does not assume normality

res_ch4 <- round(cor(df_clust_ch4 [,c('Q102','Q106','Q111','Q112' ,'Q113','Q114','Q115'
                                      ,'Q121','Q122'#, 'Q123'
                                      ,'Q124','Q125','Q126'#, 'Q127'
                                      ,'Q128','Q129'#, 'Q1211'
                                     )]
                 , method='spearman'), digits=4) #once is does not assume normality


col<- colorRampPalette(c("blue", "white", "red"))(20)

#heatmap
heatmap(x = res_tot_ch4, col = col, symm = TRUE)
heatmap(x = res_ch4, col = col, symm = TRUE)
```

```
#KMO:
KMO(df_clust_ch4) #0.91>0.80 -> OK
KMO(df_clust_ch4 [,c('Q102','Q106','Q111','Q112' ,'Q113','Q114','Q115'
                    ,'Q121','Q122'#, 'Q123'
                    ,'Q124','Q125','Q126'#, 'Q127'
                    ,'Q128','Q129'#, 'Q1211'
                     )]) #0.88>0.80 -> OK

#bar
bartlett.test(df_clust_ch4) #Ok
bartlett.test(df_clust_ch4 [,c('Q102','Q106','Q111','Q112' ,'Q113','Q114','Q115'
                               ,'Q121','Q122'#, 'Q123'
                               ,'Q124','Q125','Q126'#, 'Q127'
                               ,'Q128','Q129'#, 'Q1211'
                    )]) #Ok
#cronbachalpha:
CronbachAlpha(df_clust_ch4)  #0.90 > 0.70 reliability OK
CronbachAlpha(df_clust_ch4 [,c('Q102','Q106','Q111','Q112' ,'Q113','Q114','Q115'
                               ,'Q121','Q122'#, 'Q123'
                               ,'Q124','Q125','Q126'#, 'Q127'
                               ,'Q128','Q129'#, 'Q1211'
                    )])  #0.88 > 0.70 reliability OK

#---------- CH4 Clustering Step 1: PCA Data Reduction ----------
#Determine the number ideal number of Factors to be used
pca_tot_ch4<- principal(res_tot_ch4,17)
pca_ch4<- principal(res_ch4,14)

#A prior analysis was done with all behaviours.
#However due to low loadings or high cross-loadings 3 were excluded

#total try:
#scree plot
plot(pca_tot_ch4$values, type="b", col="black",  xlab="n factors", ylab="eigh-values", main="Scree Plot")
abline(h=1, col="blue")
par(mfrow = c(1,1))
#eigenvalues
pca_tot_ch4$values


#reduced version:
#scree plot
plot(pca_ch4$values, type="b", col="black",  xlab="n factors", ylab="eigh-values", main="Scree Plot")
abline(h=1, col="blue")
par(mfrow = c(1,1))
#eigenvalues
pca_ch4$values

#according to the scree plot and the eigenvalues the number of factor should be 3 (for both total and redecud/final version)
final_pca_tot_ch4<- principal(res_tot_ch4,3,rotate="promax")
psych::fa.diagram(final_pca_tot_ch4, error = TRUE, side = 3)
#Q1211 ratio is 1.23 < 1.5 which is problematic according with Hair Multivariate Analysis Book
#Q127  ratio is 1.08 (abs) <1.5 which is problematic according with Hair Multivariate Analysis Book
#Q123 ration is 1.12 (abs) <1.5  which is problematic according with Hair Multivariate Analysis Book
#Q111  ratio was 1.5 that the cut off limit so it was kept to further investigation


final_pca_ch4<- principal(res_ch4,3,rotate="promax")

#mean based summated scale
df_sum_ch4<-as.data.frame(df_comp2[,'Q85']) #added the vegetarian meals just for reference not used on the clustering
colnames(df_sum_ch4)[1]  <- "VEG"
df_sum_ch4$PREV<-rowMeans(df_clust_ch4[,c('Q102','Q106','Q122','Q112')], na.rm=TRUE)
df_sum_ch4$DIV<-rowMeans(df_clust_ch4[,c('Q121','Q113','Q114','Q115')], na.rm=TRUE)
df_sum_ch4$EC<-rowMeans(df_clust_ch4[,c('Q125','Q126','Q129','Q128','Q124')], na.rm=TRUE)
df_sum_ch4$seq<-df_comp2[,'seq']
df_sum_ch4$id<-df_comp2[,'id']
df_sum_ch4$sample_code<-df_comp2[,'sample_code']
```

```
1433.
1434. #correlation of the frame
1435. res2_ch4 <- cor(df_sum_ch4, method='spearman') #once is does not assume normality
1436. heatmap(x = res2_ch4, col = col, symm = TRUE)
1437. ggpairs(data.frame( scale(df_sum_ch4)))
1438.
1439.
1440. 'hopkkins test (allows to test is clustering may be applied or not):
1441. ->If the value is between {0.01, ...,0.3}, the data is regularly spaced.
1442. ->If the value is around 0.5, it is random.
1443. ->If the value is between {0.7, ..., 0.99}, it has a high tendency to cluster.'
1444.
1445. hopkins(df_sum_ch4[2:4]) #0.98 ok
1446.
1447. #------------------------ CH4 Clustering Step 2: HC Clustering ----------------
1448. # distance matrix: Mahalanobis
1449. d_mah_ch4 <- mah(df_sum_ch4[2:4])
1450.
1451. #distance matrix: Euclidean
1452. d_ed_ch4<-dist(df_sum_ch4[2:4], method = "euclidean",
1453.           diag = TRUE, upper = TRUE)
1454.
1455. # Check which method is stronger:
1456. m <- c( "average", "single", "complete", "ward")
1457. names(m) <- c( "average", "single", "complete", "ward") #different methods
1458.
1459. # compute coefficient
1460. ac <- function(x) {
1461.   agnes(d_ed_ch4,diss=TRUE, method = x)$ac
1462. }
1463.
1464. #ward has the highest coefficient (0.998), so it is the one to be used
1465. ac_ed_ch4<-map_dbl(m, ac)
1466.
1467. #after assessing the different results with different distance matrices I used the Euclidean for the final results
1468. #Euclidean is the most widespread and easy to implement technique and the results were clear.
1469.
1470. #As the sample size is 1498, so I chose the max number of clusters as 12 (so each would have at least apx 125)
1471. #I set the min value as 3 as on the last EC analyses the ideal recommended number of was 3
1472. #sum up of all the indices for Euclidean
1473. nb_all_ch4 <- NbClust(df_sum_ch4[2:4], diss=d_ed_ch4, distance=NULL,min.nc=3, max.nc=12,
method="ward.D2", index ="all")
1474.
1475. #Euclidean
1476. hc_ed_ch4<- hclust(d_ed_ch4, method = 'ward.D2')
1477.
1478. #eucliean cut
1479. hc_ed_3_ch4 <- cutree(hc_ed_ch4, k = 3)
1480. hc_ed_4_ch4 <- cutree(hc_ed_ch4, k = 4)
1481.
1482. #--------------------------- CH4 Clustering Step 3: K-Means -------------
1483.
1484. set.seed(200) #the results are reproduced
1485. km_4_ch4<- kmeans(df_sum_ch4[2:4], 4, nstart = 25)
1486. km_3_ch4<- kmeans(df_sum_ch4[2:4], 3, nstart = 25)
1487.
1488.
1489. #addition of the cluster columns
1490. #3 cluster: hierarchical clusters and k-means
1491. df_sum_ch4$km_3<-km_3_ch4$cluster
1492. df_sum_ch4$hc_ed_3<-hc_ed_3_ch4
1493.
1494. #3 cluster: hierarchical clusters and k-means
1495. df_sum_ch4$km_4<-km_4_ch4$cluster
1496. df_sum_ch4$hc_ed_4<-hc_ed_4_ch4
1497.
1498. #convert the cluster to category
1499. df_sum_ch4$km_4<-sapply(df_sum_ch4$km_4, as.character)
1500. df_sum_ch4$hc_ed_4<-sapply(df_sum_ch4$hc_ed_4, as.character)
1501. df_sum_ch4$km_3<-sapply(df_sum_ch4$km_3, as.character)
1502. df_sum_ch4$hc_ed_3<-sapply(df_sum_ch4$hc_ed_3, as.character)
```

```
1503.
1504.
1505. #merge with the general dataframe
1506. df_prof_ch4<-merge(df_sum_ch4, df_comp2,by=c('id','seq','sample_code'), all.x = TRUE, all.y = TRUE)
1507.
1508. #------------------- CH4 Clustering Step 4.1: Visualization & Profiling -----
1509. #clusters' name when running it's necessary to confirm if the clusters came in the same order
1510. df_prof_ch4["cluster_name"] <- cut(as.numeric(df_prof_ch4$km_4), 4, labels=c('(3) Environmentally Involved'
1511.                                     ,'(4) Sporadic Adopters'
1512.                                     ,'(1) Responsible Consumers'
1513.                                     , '(2) Average Practitioners'
1514.                                                         ))
1515.
1516. #3D plot
1517. par(mfrow = c(1,2))
1518. scatterplot3d(df_sum_ch4[2:4], pch=20, color=rainbow(4)[km_4_ch4$cluster])
1519. scatterplot3d(df_sum_ch4[2:4], pch=20, color=rainbow(3)[km_3_ch4$cluster])
1520. par(mfrow = c(1,1))
1521.
1522. #boxplot of the each Factor (4 clusters)
1523. par(mfrow = c(1,3))
1524. g1<-ggplot(df_prof_ch4, aes(x = cluster_name, y = DIV)) +
1525.   geom_boxplot(aes(fill = cluster_name), show.legend = FALSE) +
1526.   scale_x_discrete(labels = function(x) stringr::str_wrap(x, width = 10))
1527. g3<-ggplot(df_prof_ch4, aes(x = cluster_name, y = PREV)) +
1528.   geom_boxplot(aes(fill = km_4), show.legend = FALSE) + scale_x_discrete(labels = function(x) stringr::str_wrap(x,
width = 10))
1529. g2<-ggplot(df_prof_ch4, aes(x = cluster_name, y = EC)) +
1530.   geom_boxplot(aes(fill = km_4), show.legend = FALSE) +
1531.   scale_x_discrete(labels = function(x) stringr::str_wrap(x, width = 10))
1532.
1533. g4<-ggplot(df_prof_ch4, aes(x = km_3, y = DIV)) +
1534.   geom_boxplot(aes(fill = km_3), show.legend = FALSE) +
1535.   scale_x_discrete(labels = function(x) stringr::str_wrap(x, width = 10))
1536. g5<-ggplot(df_prof_ch4, aes(x = km_3, y = PREV)) +
1537.   geom_boxplot(aes(fill = km_3), show.legend = FALSE) + scale_x_discrete(labels = function(x) stringr::str_wrap(x,
width = 10))
1538. g6<-ggplot(df_prof_ch4, aes(x = km_3, y = EC)) +
1539.   geom_boxplot(aes(fill = km_3), show.legend = FALSE) +
1540.   scale_x_discrete(labels = function(x) stringr::str_wrap(x, width = 10))
1541. grid.arrange(g1,g2,g3,g4,g5,g6, nrow = 2, ncol=3)
1542. par(mfrow = c(1,1))
1543.
1544. #PEB per cluster
1545. ggparcoord(data = df_sum_ch4
1546.           , columns = 2:4
1547.           , alphaLines = 0.2
1548.           , groupColumn = "km_4"
1549.           , boxplot = TRUE
1550.           , showPoints = FALSE
1551.           , scale = "globalminmax" #std
1552. ) + scale_colour_manual(values=c("#F3CD0E","#116EE8","#4CAF6D","#8B0000")) +
1553.   facet_wrap(~ km_4)
1554.
1555. ggparcoord(data = df_sum_ch4
1556.           , columns = 2:4
1557.           , alphaLines = 0.2
1558.           , groupColumn = "km_3"
1559.           , boxplot = TRUE
1560.           , showPoints = FALSE
1561.           , scale = "globalminmax" #std
1562. ) + scale_colour_manual(values=c("#F3CD0E","#116EE8","#4CAF6D")) +
1563.   facet_wrap(~ km_3)
1564.
1565. #The Euclidean distance showed clearer clusters both in 3 and 4 groups
1566. #The results of the 4 clusters' approach are clearer than 3 clusters' approach
1567.
1568. #------------------------------------------------------------------------------ CH4 Clustering Step 4.2: Significance Tests:------
1569. #Kruskal Wallis
1570. #the groups are statically different -> ok (both cases)
1571. kruskal.test(PREV ~ cluster_name, data = df_prof_ch4)
```

```r
kruskal.test(DIV ~ cluster_name, data = df_prof_ch4)
kruskal.test(EC ~ cluster_name, data = df_prof_ch4)

kruskal.test(PREV ~ km_3, data = df_prof_ch4)
kruskal.test(DIV ~ km_3, data = df_prof_ch4)
kruskal.test(EC ~ km_3, data = df_prof_ch4)

#perform Dunn's Test with Bonferroni correction for p-values
dunnTest(EC ~ cluster_name, data = df_prof_ch4, method="bonferroni")
dunnTest(DIV ~ cluster_name, data = df_prof_ch4, method="bonferroni")
dunnTest(PREV ~ cluster_name, data = df_prof_ch4, method="bonferroni")

#with 3 groups the difference between DIV and PREV to groups 2-3 and 1-3 is not significant
#with 4 groups all the differences are significant at 5%
dunnTest(EC ~ km_3, data=df_prof_ch4, method="bonferroni")
dunnTest(DIV ~ km_3, data=df_prof_ch4, method="bonferroni")
dunnTest(PREV ~ km_3, data=df_prof_ch4, method="bonferroni")

#dietary concerns test
#the groups are statically different -> ok
kruskal.test(Q81 ~ cluster_name, data = df_prof_ch4) #cooking frequency
kruskal.test(Q83 ~ cluster_name, data = df_prof_ch4) #eating out frequency
kruskal.test(Q86 ~ cluster_name, data = df_prof_ch4) #eating breakfast
kruskal.test(Q85 ~ cluster_name, data = df_prof_ch4) #vegetarian meals
kruskal.test(intention ~ cluster_name, data = df_prof_ch4)
kruskal.test(age ~ cluster_name, data = df_prof_ch4)
kruskal.test(Q101 ~ cluster_name, data = df_prof_ch4) #balaced
kruskal.test(Q103 ~ cluster_name, data = df_prof_ch4) #vegetables
kruskal.test(Q104 ~ cluster_name, data = df_prof_ch4) #salty
kruskal.test(Q105 ~ cluster_name, data = df_prof_ch4) #fatty
kruskal.test(Q107 ~ cluster_name, data = df_prof_ch4) #additives
kruskal.test(VEG ~ cluster_name, data = df_prof_ch4) #vegetarian

# Dunn's Test with Bonferroni correction for p-values
dunnTest(Q81 ~ cluster_name, data = df_prof_ch4, method="bonferroni")
dunnTest(Q83 ~ cluster_name, data = df_prof_ch4, method="bonferroni")
dunnTest(Q86 ~ cluster_name, data = df_prof_ch4, method="bonferroni")
dunnTest(Q85 ~ cluster_name, data = df_prof_ch4, method="bonferroni")
dunnTest(intention ~ cluster_name, data = df_prof_ch4, method="bonferroni")
dunnTest(age ~ cluster_name, data = df_prof_ch4, method="bonferroni")
dunnTest(Q101 ~ cluster_name, data = df_prof_ch4, method="bonferroni") #balaced
dunnTest(Q103 ~ cluster_name, data = df_prof_ch4, method="bonferroni") #vegetables
dunnTest(Q104 ~ cluster_name, data = df_prof_ch4, method="bonferroni") #salty
dunnTest(Q105 ~ cluster_name, data = df_prof_ch4, method="bonferroni") #fatty
dunnTest(Q107 ~ cluster_name, data = df_prof_ch4, method="bonferroni") #additives
dunnTest(VEG ~ cluster_name, data = df_prof_ch4, method="bonferroni") #vegetarian

#----------------------- CH4 Clustering Step 4.3: Likert Scales + Graphs------
#intention labels for frequency plot
df_prof_ch4["int"] <- cut(df_prof_ch4$intention, 6, labels=c('Definitely not'
                                                             , 'Most likely not'
                                                             , 'Probably not'
                                                             ,'Probably yes'
                                                             ,'Most likely yes'
                                                             , 'Definitely yes'))

#gardening labels for frequency plot
df_prof_ch4["gard"] <- cut(df_prof_ch4$garden3_degree, 4, labels=c('No Interest'
                                                           ,'Herb Garden'
                                                           ,'Backyard/Community Gardening'
                                                           ,'Farming'
                                                           ))

#Likert-scale Graph for composting intention
likt_i <- likert(data.frame("Composting Intention" = df_prof_ch4[,c("int")]), grouping = df_prof_ch4$cluster_name)
plot(likt_i, centered=TRUE,
     legend.position="right",
     plot.percent.neutral=FALSE,
     plot.percent.low=FALSE,
     plot.percent.high=FALSE,
     reverse=FALSE)
```

```
1643.
1644. #intention boxplot per cluster
1645. ggplot(df_prof_ch4, aes(x = cluster_name, y = intention)) +
1646.   geom_boxplot(aes(fill = km_4)) +labs(x = "Cluster", y="Composting Intention")+ guides(fill="none")
1647.
1648. #Likert-scale Graph for gardening intention
1649. likt_g <- likert(data.frame("Gardening Interest" = df_prof_ch4[,c("gard")]), grouping = df_prof_ch4$cluster_name)
1650. plot(likt_g, centered=FALSE,
1651.      legend.position="right",
1652.      plot.percent.neutral=FALSE,
1653.      plot.percent.low=FALSE,
1654.      plot.percent.high=FALSE,
1655.      reverse=FALSE)
1656.
1657. #Likert-scale Graph for the excluded behaviours cooking/food consumption habits
1658. df_extrad <- data.frame("Cooking" = cut(df_prof_ch4[,c("Q81")], 7, labels=c("Rarely","Once a Month" ,"2-3 times a
Month"
1659.                                                   , "Every Week" , "3-4 days a Week"
1660.                                                   , "4-5 days a Week", ">6 days  a Week"))
1661.                          ,"Vegetarian Meals" = cut(df_prof_ch4[,c("Q85")], 7, labels=c("Rarely","Once a Month" ,"2-3 times a
Month"
1662.                                                             , "Every Week" , "3-4 days a Week"
1663.                                                             , "4-5 days a Week", ">6 days  a Week"))
1664.                          , "Doing the Groceries" = cut(df_prof_ch4[,c("Q82")], 7, labels=c("Rarely","Once a Month" ,"2-3
times a Month"
1665.                                                               , "Every Week" , "3-4 days a Week"
1666.                                                               , "4-5 days a Week", ">6 days  a Week"))
1667.
1668.                          ,"cluster" = df_prof_ch4$cluster_name
1669. )
1670. likt_d <- likert(df_extrad[1:3], grouping = df_extrad$cluster)
1671. plot(likt_d,
1672.      centered=FALSE,
1673.      legend.position="right",
1674.      plot.percent.neutral=FALSE,
1675.      plot.percent.low=FALSE,
1676.      plot.percent.high=FALSE,
1677.      reverse=FALSE)
1678.
1679.
1680. #Likert-scale Graph for the excluded behaviours and dietary concerns
1681. df_food <- data.frame( "Own Bag" = cut(df_prof_ch4$Q123, 6, labels=c("Never","Hardly Ever" ,"Sometimes"
1682.                                                       , "Often" , "Usually"
1683.                                                       , "Always")),
1684.                        "Recycling" = cut(df_prof_ch4[,c("Q128")], 6, labels=c("Never","Hardly Ever" ,"Sometimes"
1685.                                                     , "Often" , "Usually"
1686.                                                     , "Always")),
1687.                        "Water Saving" = cut(df_prof_ch4[,c("Q1211")], 6, labels=c("Never","Hardly Ever" ,"Sometimes"
1688.                                                       , "Often" , "Usually"
1689.                                                       , "Always")),
1690.                        "Balanced Meals" = cut(df_prof_ch4[,c("Q101")], 6, labels=c("Never","Hardly Ever" ,"Sometimes"
1691.                                                       , "Often" , "Usually"
1692.                                                       , "Always"))
1693.                        ,"Eat Vegetables" = cut(df_prof_ch4[,c("Q103")], 6, labels=c("Never","Hardly Ever" ,"Sometimes"
1694.                                                       , "Often" , "Usually"
1695.                                                       , "Always"))
1696.                        ,"Avoid  Salty Foods" = cut(df_prof_ch4[,c("Q104")],  6, labels=c("Never","Hardly
Ever" ,"Sometimes"
1697.                                                         , "Often" , "Usually"
1698.                                                         , "Always"))
1699.                        ,"Avoid Fatty Food" = cut(df_prof_ch4[,c("Q105")],  6, labels=c("Never","Hardly Ever" ,"Sometimes"
1700.                                                       , "Often" , "Usually"
1701.                                                       , "Always"))
1702.                        ,"Avoid Food With Additives" = cut(df_prof_ch4[,c("Q106")],  6, labels=c("Never","Hardly
Ever" ,"Sometimes"
1703.                                                             , "Often" , "Usually"
1704.                                                             , "Always"))
1705.
1706.                        ,"cluster" = df_prof_ch4$cluster_name
1707. )
1708. likt_ff <- likert(df_food[1:8], grouping = df_food$cluster)
```

```
plot(likt_ff,
     centered=FALSE,
     legend.position="right",
     plot.percent.neutral=FALSE,
     plot.percent.low=FALSE,
     plot.percent.high=FALSE,
     reverse=FALSE)

#---------------------- CH4 Clustering Step 4.4: Cross Tables-----------------

#gender, age, household size, residence, place of living, intention, health, cooking, vegetarian

ctable(
  y = as.character(df_prof_ch4$marriage),
  x = df_prof_ch4$cluster_name
)

ctable(
  y = as.character(df_prof_ch4$Q4),
  x = df_prof_ch4$cluster_name
)

ctable(
  y = as.character(df_prof_ch4$age_10),
  x = df_prof_ch4$cluster_name
)

ctable(
  y = as.character(df_prof_ch4$children),
  x = df_prof_ch4$cluster_name
)

ctable(
  y = as.character(df_prof_ch4$Q2),
  x = df_prof_ch4$cluster_name
)

ctable(
  y = as.character(df_prof_ch4$loacation),
  x = df_prof_ch4$cluster_name
)

ctable(
  y = as.character(df_prof_ch4$house),
  x = df_prof_ch4$cluster_name
)

ctable(
  y = as.character(df_prof_ch4$pet),
  x = df_prof_ch4$cluster_name
)

ctable(
  y = as.character(df_prof_ch4$gender),
  x = df_prof_ch4$cluster_name
)


ctable(
  y = as.character(df_prof_ch4$Q7),
  x = df_prof_ch4$cluster_name
)

ctable(
  y = as.character(df_prof_ch4$job),
  x = df_prof_ch4$cluster_name
)

#--------- CH4 Clustering Step 4.5: RANKS of Eco-Friendliness and Bothersome-------
#get the mean values of the main indices per cluster
sapply(df_comp2[,c(
```

```
  'Q102','Q106'
  ,'Q111','Q112'
  ,'Q113','Q114','Q115'
  ,'Q121','Q122', 'Q123'
  ,'Q124'
  ,'Q125','Q126' ,'Q127'
  ,'Q128','Q129', 'Q1211' #Q1210, #Q1211
)], function(x) c("Mean"= mean(x),"Std."= sd(x))
)

# Select the columns to count
columns_to_count <- c("Q221", "Q222", "Q223","Q224","Q225","Q226","Q227","Q228","Q229","Q2210","Q2211")
#this is the reversed burden metric which means that 6 is  "a lot of burden" and 1 is  "not a burden"
columns_to_mean <- c("Q231", "Q232",
"Q233","Q234","Q235","Q236","Q237","Q238","Q239","Q2310","Q2311","Q2312")

#ranking of the most eco-frienadly
df_prof_ch4[,c(columns_to_count,"cluster_name")] %>%
  group_by(cluster_name) %>%
  summarise(across(where(is.numeric), sum))


#Ranking Eco Friendly
agg_tbl_ch4 <- df_prof_ch4[,c(columns_to_count,"cluster_name")] %>%
  group_by(cluster_name) %>%
  summarise(across(where(is.numeric), sum))

#average burden among the clusters
agg_tb2_ch4 <- df_prof_ch4[,c(columns_to_mean,"cluster_name")] %>%
  group_by(cluster_name) %>%
  summarise(across(where(is.numeric), mean))

#eco-friendly ranking to the entire sample
# Count the values in the selected columns
df_eco_ch4 <- sapply(columns_to_count, function(x) table(df_comp2[,x]))
df_top_ch4 <- data.frame(t(df_eco_ch4))
df_top_ch4<- cbind(df_top_ch4, rank1=df_top_ch4[,2]*1)
df_top_ch4<- cbind(df_top_ch4, rank2=df_top_ch4[,2]*2)
df_top_ch4<- cbind(df_top_ch4, rank3=df_top_ch4[,4]*3)
df_top_ch4<- cbind(df_top_ch4, rank=df_top_ch4[,'rank1']+df_top_ch4[,'rank3']+df_top_ch4[,'rank2'])

# Order the data frame by the specified column
df_top_ch4 <- df_top_ch4[order(df_top_ch4[, 'rank'], decreasing=TRUE), ]
df_top_ch4 <- cbind(peb = rownames(df_top_ch4), df_top_ch4)

#ranking of econess
df_top_ch4 %>%
  arrange(rank) %>%    # First sort by val.
  mutate(peb=factor(peb, levels=peb)) %>%   # update the factor levels
  ggplot( aes(x=peb, y=rank)) +
  geom_segment( aes(xend=peb, yend=0)) +
  geom_point( size=4, color="orange") +
  coord_flip() +
  theme_bw() +
  xlab("")

#Order Burden rates
df_burden <- data.frame(Date=as.Date(character()),
                        File=character(),
                        User=character(),
                        stringsAsFactors=FALSE)


peb_1<-c("Q231", "Q232", "Q233","Q234","Q235","Q236","Q237","Q238","Q239","Q2310","Q2311","Q2312")
means <- colMeans(df_comp2[,c("Q231", "Q232",
"Q233","Q234","Q235","Q236","Q237","Q238","Q239","Q2310","Q2311","Q2312")])
df_burden_ch4<- data.frame(peb_1,means)
df_burden_ch4 <- df_burden_ch4[order(df_burden_ch4[, 'means'], decreasing=TRUE), ]

#ranking of Burden
df_burden_ch4 %>%
```

```
  arrange(means) %>%    # First sort by val.
  mutate(peb=factor(peb_1, levels=peb_1)) %>%   #update the factor levels
  ggplot( aes(x=peb_1, y=means)) +
  geom_segment( aes(xend=peb, yend=0)) +
  geom_point( size=4, color="orange") +
  coord_flip() +
  theme_bw() +
  xlab("")


#Order The Practices rates
peb_2<-c("Q111","Q112","Q113","Q114","Q115","Q121", "Q122",
"Q123","Q124","Q125","Q126","Q127","Q128","Q129","Q1210","Q1211")
means<-colMeans(df_comp2[,c("Q111","Q112","Q113","Q114","Q115","Q121", "Q122",
"Q123","Q124","Q125","Q126","Q127","Q128","Q129","Q1210","Q1211")])
df_pratice_ch4 <- data.frame(peb_2,means)
df_pratice_ch4 <- df_pratice_ch4[order(df_pratice_ch4[, 'means'], decreasing=TRUE), ]

#ranking of PEB practice rates
df_pratice_ch4 %>%
  arrange(means) %>%    # First sort by val.
  mutate(peb=factor(peb_2, levels=peb_2)) %>%   #update the factor levels
  ggplot( aes(x=peb, y=means)) +
  geom_segment( aes(xend=peb_2, yend=0)) +
  geom_point( size=4, color="orange") +
  coord_flip() +
  theme_bw() +
  xlab("")

#------------------ CH5 TCV Model of Composting Step 0: Information -------
"
Title: Composting Behaviour Model in Japan
Data: Online survey (Sept 2022) in 9 Japanese (1500 entries) including questions on Ethical Consumption, Waste
Reduction and Composting
Goal: Try to find a theoretical model that holds a satisfactory explanatory power on composting behaviours.

Novelty points: 1) There are not theoretical based composting models, mostly are exploratory or case study based
(Sewak 2021).
2) 2nd study in Japan regarding composting decision models ( fist is an article Japanese in a city in Hyogo using
Hirose's
two phased model, study has more than 10 years), but first using several prefectures.
3) Fist study using Theory of Consumption Value (TCV) on composting. TCV has been used in eco-tourism,
sustainable apparel and ethical food consumption but not composting.
4) Explores OrdPLS-SEM which a relatively new approach of PLS-SEM which does not have many studies published
yet.
"


#------------------------------ CH5 Step 1.1: Data Preparation --------------------

#Dataframe version that is partially categorical
df_comp_par_ch5=df_comp2

#Dataframe version that is partially categorical
df_comp_par_ch5=df_comp2
df_comp_par_ch5$Q15= as.ordered(df_comp_par_ch5$Q15)  #composting
#the frequencies are not exactly equidistant
df_comp_par_ch5$Q81= as.ordered(df_comp_par_ch5$Q81) #cooking 1
df_comp_par_ch5$Q82= as.ordered(df_comp_par_ch5$Q82) #cooking 2
df_comp_par_ch5$Q83= as.ordered(df_comp_par_ch5$Q83) #cooking 3
df_comp_par_ch5$Q84= as.ordered(df_comp_par_ch5$Q84) #cooking 4
df_comp_par_ch5$Q85= as.ordered(df_comp_par_ch5$Q85) #cooking 5
df_comp_par_ch5$Q86= as.ordered(df_comp_par_ch5$Q86) #cooking 6

df_comp_par_ch5$Q261= as.ordered(df_comp_par_ch5$Q261) #subsidy 1
df_comp_par_ch5$Q262= as.ordered(df_comp_par_ch5$Q262) #subsidy 2
df_comp_par_ch5$Q263= as.ordered(df_comp_par_ch5$Q263) #subsidy 3
df_comp_par_ch5$Q264= as.ordered(df_comp_par_ch5$Q264) #subsidy 4

df_comp_par_ch5$Q261b= as.ordered(df_comp_par_ch5$Q261b) #subsidy 1
df_comp_par_ch5$Q262b= as.ordered(df_comp_par_ch5$Q262b) #subsidy 2
df_comp_par_ch5$Q263b= as.ordered(df_comp_par_ch5$Q263b) #subsidy 3
```

```
df_comp_par_ch5$Q264b= as.ordered(df_comp_par_ch5$Q264b) #subsidy 4

df_comp_par_ch5$Q261c= as.ordered(df_comp_par_ch5$Q261c) #subsidy 1
df_comp_par_ch5$Q262c= as.ordered(df_comp_par_ch5$Q262c) #subsidy 2
df_comp_par_ch5$Q263c= as.ordered(df_comp_par_ch5$Q263c) #subsidy 3
df_comp_par_ch5$Q264c= as.ordered(df_comp_par_ch5$Q264c) #subsidy 4

df_comp_par_ch5$Q261_epi= as.ordered(df_comp_par_ch5$Q261_epi) #subsidy 1
df_comp_par_ch5$Q262_epi= as.ordered(df_comp_par_ch5$Q262_epi) #subsidy 2
df_comp_par_ch5$Q263_epi= as.ordered(df_comp_par_ch5$Q263_epi) #subsidy 3
df_comp_par_ch5$Q264_epi= as.ordered(df_comp_par_ch5$Q264_epi) #subsidy 4

df_comp_par_ch5$Q261_epi2= as.ordered(df_comp_par_ch5$Q261_epi2) #subsidy 1
df_comp_par_ch5$Q262_epi2= as.ordered(df_comp_par_ch5$Q262_epi2) #subsidy 2
df_comp_par_ch5$Q263_epi2= as.ordered(df_comp_par_ch5$Q263_epi2) #subsidy 3
df_comp_par_ch5$Q264_epi2= as.ordered(df_comp_par_ch5$Q264_epi2) #subsidy 4

df_comp_par_ch5$top_compost= as.ordered(df_comp_par_ch5$top_compost) #top_compost
#df_comp_par_ch5$Q222= as.ordered(df_comp_par_ch5$Q222) #top_reduce

df_comp_par_ch5$garden_degree= as.ordered(df_comp_par_ch5$garden_degree)
df_comp_par_ch5$garden2_degree= as.ordered(df_comp_par_ch5$garden2_degree)#garden keeness metric
df_comp_par_ch5$garden3_degree= as.ordered(df_comp_par_ch5$garden3_degree)
df_comp_par_ch5$garden= as.ordered(df_comp_par_ch5$garden) #garden dummmy
df_comp_par_ch5$compost_dummy =as.ordered(df_comp_par_ch5$compost_dummy)
df_comp_par_ch5$compost_cat= as.ordered(df_comp_par_ch5$compost_cat)
df_comp_par_ch5$Q9=as.ordered(df_comp_par_ch5$Q9) #cook with fresh ingredients level
df_comp_par_ch5$Q9_new=as.ordered(df_comp_par_ch5$Q9_new)
df_comp_par_ch5$rural_area=as.ordered(df_comp_par_ch5$rural_area)
df_comp_par_ch5$gender=as.ordered(df_comp_par_ch5$gender)
df_comp_par_ch5$job_full=as.ordered(df_comp_par_ch5$job_full)
df_comp_par_ch5$house=as.ordered(df_comp_par_ch5$house)
df_comp_par_ch5$Q7=as.ordered(df_comp_par_ch5$Q7)
df_comp_par_ch5$age_young=as.ordered(df_comp_par_ch5$age_young)
df_comp_par_ch5$age_old=as.ordered(df_comp_par_ch5$age_old)
df_comp_par_ch5$income=as.ordered(df_comp_par_ch5$income)
df_comp_par_ch5$Q131=as.ordered(df_comp_par_ch5$Q131)
df_comp_par_ch5$Q132=as.ordered(df_comp_par_ch5$Q132)
df_comp_par_ch5$Q133=as.ordered(df_comp_par_ch5$Q133)
df_comp_par_ch5$Q134=as.ordered(df_comp_par_ch5$Q134)
df_comp_par_ch5$Q221=as.ordered(df_comp_par_ch5$Q221)
df_comp_par_ch5$Q222=as.ordered(df_comp_par_ch5$Q222)


df_comp_par_ch5$Q15= as.ordered(df_comp_par_ch5$Q15)  #composting categorical question
#the frequencies are not exactly equidistant
df_comp_par_ch5$Q81= as.ordered(df_comp_par_ch5$Q81) #cooking 1
df_comp_par_ch5$Q82= as.ordered(df_comp_par_ch5$Q82) #cooking 2
df_comp_par_ch5$Q83= as.ordered(df_comp_par_ch5$Q83) #cooking 3
df_comp_par_ch5$Q84= as.ordered(df_comp_par_ch5$Q84) #cooking 4
df_comp_par_ch5$Q85= as.ordered(df_comp_par_ch5$Q85) #cooking 5
df_comp_par_ch5$Q86= as.ordered(df_comp_par_ch5$Q86) #cooking 6
df_comp_par_ch5$Q261= as.ordered(df_comp_par_ch5$Q261) #subsidy 1
df_comp_par_ch5$Q262= as.ordered(df_comp_par_ch5$Q262) #subsidy 2
df_comp_par_ch5$Q263= as.ordered(df_comp_par_ch5$Q263) #subsidy 3
df_comp_par_ch5$Q264= as.ordered(df_comp_par_ch5$Q264) #subsidy 4
df_comp_par_ch5$Q261b= as.ordered(df_comp_par_ch5$Q261b) #subsidy 1
df_comp_par_ch5$Q262b= as.ordered(df_comp_par_ch5$Q262b) #subsidy 2
df_comp_par_ch5$Q263b= as.ordered(df_comp_par_ch5$Q263b) #subsidy 3
df_comp_par_ch5$Q264b= as.ordered(df_comp_par_ch5$Q264b) #subsidy 4
df_comp_par_ch5$Q261c= as.ordered(df_comp_par_ch5$Q261c) #subsidy 1
df_comp_par_ch5$Q262c= as.ordered(df_comp_par_ch5$Q262c) #subsidy 2
df_comp_par_ch5$Q263c= as.ordered(df_comp_par_ch5$Q263c) #subsidy 3
df_comp_par_ch5$Q264c= as.ordered(df_comp_par_ch5$Q264c) #subsidy 4
df_comp_par_ch5$garden_degree= as.ordered(df_comp_par_ch5$garden_degree)
df_comp_par_ch5$garden2_degree= as.ordered(df_comp_par_ch5$garden2_degree)#garden keeness metric
df_comp_par_ch5$garden3_degree= as.ordered(df_comp_par_ch5$garden3_degree)
df_comp_par_ch5$garden= as.ordered(df_comp_par_ch5$garden) #garden dummmy
df_comp_par_ch5$compost_dummy =as.ordered(df_comp_par_ch5$compost_dummy)
df_comp_par_ch5$compost_cat= as.ordered(df_comp_par_ch5$compost_cat)
df_comp_par_ch5$Q9=as.ordered(df_comp_par_ch5$Q9) #cook with fresh ingredients level
```

```
df_comp_par_ch5$Q9_new=as.ordered(df_comp_par_ch5$Q9_new)
df_comp_par_ch5$rural_area=as.ordered(df_comp_par_ch5$rural_area)
df_comp_par_ch5$gender=as.ordered(df_comp_par_ch5$gender)
df_comp_par_ch5$job_full=as.ordered(df_comp_par_ch5$job_full)
df_comp_par_ch5$house=as.ordered(df_comp_par_ch5$house)
df_comp_par_ch5$Q7=as.ordered(df_comp_par_ch5$Q7)
df_comp_par_ch5$age_young=as.ordered(df_comp_par_ch5$age_young)
df_comp_par_ch5$age_old=as.ordered(df_comp_par_ch5$age_old)
df_comp_par_ch5$income=as.ordered(df_comp_par_ch5$income)
df_comp_par_ch5$Q131=as.ordered(df_comp_par_ch5$Q131)
df_comp_par_ch5$Q132=as.ordered(df_comp_par_ch5$Q132)
df_comp_par_ch5$Q133=as.ordered(df_comp_par_ch5$Q133)
df_comp_par_ch5$Q134=as.ordered(df_comp_par_ch5$Q134)

#--------------------------- CH5 Step 1.2: Some Boxplots -------------------------
#gender vs job type
ctable(
  y = as.character(df_comp_par_ch5$gender),
  x = as.character(df_comp_par_ch5$Q6) #job item non-grouped
)


#various boxplot
par(mfrow = c(2,2))
boxplot(df_comp2$Q121~df_comp2$gender,main = "Composting by gender",
        xlab = "Gender (0:male;1:female)", ylab = "Composting")
boxplot(df_comp2$Q121~df_comp2$Q2 ,main = "Composting by Household size",
        xlab = "Household Size", ylab = "Composting")
boxplot(df_comp2$Q121~df_comp2$children, main = "Composting by Children",
        xlab = "Children Dummy", ylab = "Composting")
boxplot(df_comp2$Q2~df_comp2$children,main = "Household Size by Children",
        xlab = "Children Dummy", ylab = "Household Size")

#second batch
par(mfrow = c(2,2))
boxplot(df_comp2$Q121~df_comp2$rural_area,main = "Composting by Rural Area",
        xlab = "Rural Area Dummy", ylab = "Composting")
boxplot(df_comp2$Q121~df_comp2$age_10,main = "Composting by Age Groups",
        xlab = "Age groups", ylab = "Composting")
boxplot(df_comp2$Q7~df_comp2$gender,main = "income by gender",
        xlab = "Gender", ylab = "Job")
boxplot(df_comp2$Q7~df_comp2$age_10,main = "Income by Age Groups",
        xlab = "Age groups", ylab = "Income")

#third batch
par(mfrow = c(2,2))
boxplot(df_comp2$Q121~df_comp2$Q6,main = "Composting by job detailed",
        xlab = "Job Detailed", ylab = "Composting")
boxplot(df_comp2$Q121~df_comp2$house,main = "Composting by House",
        xlab = "Live in a house Dummy", ylab = "Composting")
boxplot(df_comp2$Q121~df_comp2$Q7,main = "Composting by Inconme",
        xlab = "Income", ylab = "Composting")
boxplot(df_comp2$Q121~df_comp2$marriage,main = "Composting by Marriage",
        xlab = "Marriage", ylab = "Composting")

par(mfrow = c(2,2))
boxplot(df_comp2$garden_degree~df_comp2$Q6,main = "Garden by Job Detailed",
        xlab = "Job", ylab = "Garden")
boxplot(df_comp2$Q121~df_comp2$garden2_degree,main = "Composting by garden2",
        xlab = "garden2", ylab = "garde2")
boxplot(df_comp2$Q121~df_comp2$garden3_degree,main = "Composting by garden3",
        xlab = "garden", ylab = "comp")
boxplot(df_comp2$Q121~df_comp2$Q131,main = "Composting by farming",
        xlab = "farming", ylab = "comp")

par(mfrow = c(2,2))
boxplot(df_comp2$garden2_degree~df_comp2$rural_area,main = "gardening by rural",
        xlab = "rural", ylab = "gardening")

#I don't know, I vaguely know, I know whether or not it exists
boxplot(df_comp2$Q121 ~ df_comp2$Q261_epi,main="Incentives_AWR_1")
```

```
boxplot(df_comp2$Q121 ~ df_comp2$Q262_epi,main="Incentives_AWR_2")
boxplot(df_comp2$Q121 ~ df_comp2$Q263_epi,main="Incentives_AWR_3")

par(mfrow = c(1,2))
boxplot(df_comp2$Q121 ~ df_comp2$Q85,main="Vegetarian")
boxplot(df_comp2$Q121 ~ df_comp2$Q129,main="Organic")

par(mfrow = c(1,1))

#correlation plot
round(cor(df_comp2[,c(
  'Q205' , 'Q206' , 'Q207' , 'Q208' , 'Q2010', 'Q209'
  , 'Q121','compost_dummy'
  ,'Q261', 'Q262','Q263'
  , 'Q271', 'Q273' , 'Q275' , 'Q276', 'Q277'
  , 'Q141' , 'Q142'
)]
, method='spearman'), digits=4)

getmode <- function(v) {
  uniqv <- unique(v)
  uniqv[which.max(tabulate(match(v, uniqv)))]
}

#mean, std, kurtosis, and skewness
sapply(df_comp2[,c(
  'Q15', 'Q121'
  ,'Q201' , 'Q203' , 'Q202', 'Q204'
  ,'Q207'  , 'Q2010' , 'Q208' ,'Q209','Q205','Q206', 'Q2011'
  ,'Q231_nr' , 'Q282', 'Q284', 'Q285'
  ,'Q141' , 'Q142'
  ,'Q276', 'Q275' , 'Q262_epi' , 'Q261_epi', 'Q263_epi'
  ,'garden3_degree'
  ,'Q281' , 'Q283' , 'Q291'
  ,  'Q273', 'Q277', 'Q278', 'Q279'
  ,  'Q255'  , 'Q256' , 'Q254' , 'Q21' , 'Q2013'
)], function(x) c("Mean"= mean(x),"Std."= sd(x), "Mode"=getmode(x), "Ske"=moments::skewness(x), "Kur"= moments::kurtosis(x))
)

#-------------------------- CH5 Step 2 TCV PLS-SEM-----------------------
start_time <- Sys.time()

tcv<- "
# Structural model
COMPOST ~  PROS + CONS  + GENDER + SIZE + HOUSE + EPI  + SOCIAL  + AVB + EMOTION  + CONV  + GARDEN + SKNG
# Composite model
#dependent 1) do you recycle food waste, 2) do you compost (no/not now/yes), 3) do you use a volume reducing machine
COMPOST=~ Q15 + Q121    #Q15


#fuctional values:  how usefull the behaviour is and how much it fits one's life
PROS =~  Q201 + Q203 + Q202  + Q204 #(its effectiveness on reducing waste)
CONS =~ Q207  + Q2010 + Q208 + Q209  + Q205 + Q206 + Q2011#+ Q2011 #+  + Q206+ Q209 #barriers to engagement + Q205 + Q2010 + Q206 +
CONV =~  Q231_nr + Q282 + Q284 + Q285

CONV ~ CONS
CONV ~ PROS


#EPISTEMIC VALUE
#SKNG ~ GKNG
SKNG =~ Q141 + Q142
EPI =~ Q276 + Q275 + Q262_epi + Q261_epi + Q263_epi #+Q141 + Q142
#GKNG =~ Q302 + Q303 + Q305 + Q306 + Q307

#CONDITIONAL VALUES (GARDENING)
GARDEN <~ garden3_degree
```

```
AVB =~ Q281 + Q283 + Q291  #+Q9_new + Q11 excluded from low loadings

#SOCIAL VALUE
SOCIAL =~  Q273 + Q277 + Q278 + Q279

#EMOTIONAL VALUE
EMOTION =~  Q255  + Q256 + Q254 + Q21 + Q2013

#Demographics
GENDER <~ gender
SIZE <~ Q2 #household size
HOUSE<~house #house(1)/appartment (0)
#INCOME<~income
"

# ---------------------------- CH5 FINAL VERSION TCV (Run) ----------------------
r_5<- csem(.data = df_comp_par_ch5,
           .model = tcv,
           .tolerance = 1e-06,
           .disattenuate = FALSE, #PLS-SEM and not PLS-SEMc
           .resample_method = "bootstrap",
           .R               = 5000,
           .seed            = 47,
)

sum_r5=cSEM::summarize(r_5)
as_r5=assess(r_5,.quality_criterion = c( "aic", "bic", "ave",
                                         "rho_C",
                                         "effects",
                                         "reliability",
                                         "srmr",
                                         "htmt", "htmt2","r2", "r2_adj",
                                         "rho_T", "vif",
                                         "vifmodeB"), .only_common_factors = TRUE)

pred_r5 <- cSEM::predict(
  .object = r_5,
  .benchmark = "lm",
  .approach_score_target = "mean",
  .treat_as_continuous = TRUE,
  .cv_folds = 5
)

end_time <- Sys.time()
time_r=end_time - start_time

write_xlsx(boot_scores_ch5, "C:/Users/xxxxx/Documents/xxxx/ch5_construct_scores.xlsx")

#---------------------------------------------- CH6 Dropouts -------------
"
This analysis goal is to identify within what are the main reasons to stop composting. And what good points they associate with compost.
-Compare their barriers with the non-practitioners' barriers
-Compare their view on the benefits of composting versus the practitioners beliefs
-See their distribution between the clusters of CH4

"

df_dropout_ch6=df_prof_ch4[df_prof_ch4$Q15==2,]

#number of dropouts: 102 - 6.9% of the sample
nrow(df_dropout_ch6)

#gender 51 obs and 51 obs;
df_dropout_ch6 %>% group_by(gender, .drop = FALSE) %>% count()

#average age
mean(df_dropout_ch6$age)
```

```
#mode household size
getmode <- function(v) {
  uniqv <- unique(v)
  uniqv[which.max(tabulate(match(v, uniqv)))]
}

getmode(df_dropout_ch6$Q2)
mean(df_dropout_ch6$Q2)


#boxplot on age
par(mfrow = c(1,3))
#doing it
g1<-ggplot(df_comp2[df_comp2$Q15==3,], aes(x = as.character(age_10))) + geom_bar(aes(y =
(..count..)/sum(..count..))) +
    ylab("Percentage") + scale_x_discrete(name= "Age (Composters)"
                , labels=c("3" = "30's", "4"="40's", "5"="50's", "6" = "60's", "7" ="70's")
                )
#dropout
g2<-ggplot(df_dropout_ch6, aes(x = as.character(age_10))) +  geom_bar(aes(y = (..count..)/sum(..count..))) +
  xlab("Age (Dropouts)") + ylab("Percentage") + scale_x_discrete( labels=c("3" = "30's", "4"="40's", "5"="50's", "6" =
"60's", "7" ="70's")
  )
#overall sample
g3<-ggplot(df_comp2, aes(x = as.character(age_10)))+ geom_bar(aes(y = (..count..)/sum(..count..))) +
  xlab("Age (Total Sample)") + ylab("Percentage") + scale_x_discrete( labels=c("3" = "30's", "4"="40's", "5"="50's",
"6" = "60's", "7" ="70's")
  )
grid.arrange(g1,g2,g3, nrow = 1, ncol=3)
par(mfrow = c(1,1))


#percentage wise
par(mfrow = c(1,3))
#doing it
g1<-ggplot(df_comp2[df_comp2$Q15==3,], aes(x = age_10)) + geom_bar(aes(y = (..count..)/sum(..count..))) +
  xlab("Age (Composters)") + ylab("Percentage")
#dropout
g2<-ggplot(df_dropout_ch6, aes(x = age_10)) + geom_bar(aes(y = (..count..)/sum(..count..))) +
  xlab("Age (Dropouts)") + ylab("Percentage")
#overall sample
g3<-ggplot(df_comp2, aes(x = age_10)) + geom_bar(aes(y = (..count..)/sum(..count..))) +
  xlab("Age (Total Sample)") + ylab("Percentage")
grid.arrange(g1,g2,g3, nrow = 1, ncol=3)
par(mfrow = c(1,1))


#household size - the most common was the 2 and 3 household size
par(mfrow = c(1,3))
#doing it
g1<-ggplot(df_comp2[df_comp2$Q15==3,], aes(x = Q2)) + geom_bar() +
  xlab("Household Size doing it") + ylab("Nº of Obs")
#dropout
g2<-ggplot(df_dropout_ch6, aes(x = Q2)) + geom_bar() +
  xlab("Household Size dropouts") + ylab("Nº of Obs")
#overall sample
g3<-ggplot(df_comp2, aes(x = Q2)) + geom_bar() +
  xlab("Household Size total") + ylab("Nº of Obs")
grid.arrange(g1,g2,g3, nrow = 1, ncol=3)
par(mfrow = c(1,1))

df_dropout_ch6 %>% group_by(Q2, .drop = FALSE) %>% count()

#housetype (apartment/house) -> live in more houses
df_dropout_ch6 %>% group_by(house, .drop = FALSE) %>% count()


par(mfrow = c(1,3))
#doing it
g1<-ggplot(df_comp2[df_comp2$Q15==3,], aes(x = income)) + geom_bar(aes(y = (..count..)/sum(..count..))) +
  xlab("Income doing it") + ylab("Percentage")
```

```
#dropout
g2<-ggplot(df_dropout_ch6, aes(x = income)) + geom_bar(aes(y = (..count..)/sum(..count..))) +
  xlab("Income dropouts") + ylab("Percentage")
#overall sample
g3<-ggplot(df_comp2, aes(x = income)) + geom_bar(aes(y = (..count..)/sum(..count..))) +
  xlab("Income total") + ylab("Percentage")
grid.arrange(g1,g2,g3, nrow = 1, ncol=3)
par(mfrow = c(1,1))


#prefecture (%)
pre<-df_dropout_ch6 %>% group_by(loacation, .drop = FALSE) %>% count()
pre$n<-pre$n/nrow(df_dropout_ch6)

#total sample prefecture distribution
pre_tot_ch6<-df_comp2 %>% group_by(loacation, .drop = FALSE) %>% count()
pre_tot_ch6$n<-pre_tot_ch6$n/nrow(df_comp2)

#garden interest: they have less than the practitioners, but more than the whole sample
df_dropout_ch6 %>% group_by(garden3_degree, .drop = FALSE) %>% count()
par(mfrow = c(1,3))
#doing it
g1<-ggplot(df_comp2[df_comp2$Q15==3,], aes(x = as.character(garden3_degree))) + geom_bar(aes(y =
(..count..)/sum(..count..))) +
  xlab("Garden Interest (Composters)") + ylab("Percentage") +
  scale_x_discrete( labels = function(x) stringr::str_wrap(c("1" = "No interest", "2"="Herb/Balcony Garden",
"3"="Community/Backyard Gardening"
                                                            , "4"="Farming"), width = 10)
  )
#dropout
g2<-ggplot(df_dropout_ch6, aes(x = as.character(garden3_degree))) + geom_bar(aes(y = (..count..)/sum(..count..))) +
  xlab("Garden Interest (Dropouts)") + ylab("Percentage") +
  scale_x_discrete( labels = function(x) stringr::str_wrap(c("1" = "No interest", "2"="Herb/Balcony Garden",
"3"="Community/Backyard Gardening"
                                                            , "4"="Farming"), width = 10) )
#overall sample
g3<-ggplot(df_comp2, aes(x = as.character(garden3_degree))) + geom_bar(aes(y = (..count..)/sum(..count..))) +
  xlab("Garden Interest (Total Sample)") + ylab("Percentage") +
  scale_x_discrete( labels = function(x) stringr::str_wrap(c("1" = "No interest", "2"="Herb/Balcony Garden",
"3"="Community/Backyard Gardening"
                                                            , "4"="Farming"), width = 10) )
grid.arrange(g1,g2,g3, nrow = 1, ncol=3)
par(mfrow = c(1,1))

#intention
df_dropout_ch6 %>% group_by(intention, .drop = FALSE) %>% count()
par(mfrow = c(1,3))
#doing it
g1<-ggplot(df_comp2[df_comp2$Q15==3,], aes(x = as.character(intention))) + geom_bar(aes(y =
(..count..)/sum(..count..))) +
  xlab("Intention (Composters)") + ylab("Percentage") +
  scale_x_discrete( labels = function(x) stringr::str_wrap(c("1" = "Definitely not"
                                                            , "2"="Most likely not"
                                                            , "3"="Probably not"
                                                            , "4"="Probably yes"
                                                          ), width = 10) )
#dropout
g2<-ggplot(df_dropout_ch6, aes(x = as.character(intention))) + geom_bar(aes(y = (..count..)/sum(..count..))) +
  xlab("Intention (Dropouts)") + ylab("Percentage") +
  scale_x_discrete( labels = function(x) stringr::str_wrap(c("1" = "Definitely not"
                                                            , "2"="Most likely not"
                                                            , "3"="Probably not"
                                                            , "4"="Probably yes"
                                                            ,"5" = "Most likely yes"
                                                            ,"6"= "Definitely yes"), width = 10) )
#overall sample
g3<-ggplot(df_comp2, aes(x = as.character(intention))) + geom_bar(aes(y = (..count..)/sum(..count..))) +
  xlab("Intention (Total Sample)") + ylab("Percentage") +
  scale_x_discrete( labels = function(x) stringr::str_wrap(c("1" = "Definitely not"
                                                            , "2"="Most likely not"
                                                            , "3"="Probably not"
```

```
                                                , "4"="Probably yes"
                                                ,"5" = "Most likely yes"
                                                ,"6"= "Definitely yes"), width = 10) )
grid.arrange(g1,g2,g3, nrow = 1, ncol=3)
par(mfrow = c(1,1))

#clusters
# a lot of the dropouts belong to the responsible consumers
# and after to the average practitioners

df_dropout_ch6 %>% group_by(cluster_name, .drop = FALSE) %>% count()
#49 Responsible Consumers; 29 Average Practitioners; 5 Sporadic Adopters; 19 Environmentally Involved

ctable(
  y = as.character(df_prof_ch4$Q15),
  x = df_prof_ch4$cluster_name
)

#women come mostly from the responsible consumers
#men came from the average practitioners
ctable(
  y = as.character(df_dropout_ch6$gender),
  x = df_dropout_ch6$cluster_name
)


#relation between the two items about composting/food waste recycling
ggplot(df_dropout_ch6, aes(x = Q121)) + geom_bar(aes(y = (..count..)/sum(..count..))) +
      xlab("Food Waste Recycling") + ylab("Percentage")

df_dropout_ch6$Q121_cat<-cut(df_dropout_ch6[,c("Q121")], 6, labels=c("Never","Hardly Ever" ,"Sometimes"
                                    , "Often" , "Usually"
                                    , "Always"))

par(mfrow = c(1,2))
g1<-ggplot(df_dropout_ch6, aes(x = Q121_cat)) + geom_bar(aes(y = (..count..)/sum(..count..))) +
  xlab("Food Waste Recycling") + ylab("Percentage") +  ggtitle("Dropout's Food Waste Recycling Rate") +
  theme_update(plot.title = element_text(hjust = 0.5))
g2<-ggplot(df_dropout_ch6, aes(x = cluster_name, y = Q121)) +
  geom_boxplot(show.legend = FALSE) + ggtitle("Food Waste Recycling per Cluster") +
  xlab("Cluster") + ylab("Food Recycling Rate") +
  scale_x_discrete(labels = function(x) stringr::str_wrap(x, width = 10)) +
  theme_update(plot.title = element_text(hjust = 0.5))

grid.arrange(g1,g2, nrow = 1, ncol=2)
par(mfrow = c(1,1))

boxplot(df_dropout_ch6$Q121 ~ df_dropout_ch6$garden3_degree,main="food recycling per garden interest")


ctable(
  x = as.character(df_dropout_ch6$loacation),
  y = as.character(df_dropout_ch6$Q121)
)

#---------------------------------- CH6 Reasons' Graphs ----------
#reasons to stop it

#Likert-scale Graph for the excluded behaviours cooking/food consumption habits
df_stop_drop_ch6 <- data.frame("Time Consuming" = cut(df_dropout_ch6[,c("Q171")], 6, labels=c("Strongly
Disagree","Disagree" ,"Slighly Disagree"
                                                , "Slightly Agree" , "Agree"
                                                , "Strongly Agree"))
                    ,"Bad Smell" = cut(df_dropout_ch6[,c("Q172")], 6, labels=c("Strongly Disagree","Disagree" ,"Slighly
Disagree"
                                                , "Slightly Agree" , "Agree"
                                                , "Strongly Agree"))
                    ,"Vermin" = cut(df_dropout_ch6[,c("Q173")], 6, labels=c("Strongly Disagree","Disagree" ,"Slighly
Disagree"
                                                , "Slightly Agree" , "Agree"
                                                , "Strongly Agree"))
```

```
2395.                   ,"Costly" = cut(df_dropout_ch6[,c("Q174")], 6, labels=c("Strongly Disagree","Disagree" ,"Slighly
Disagree"
2396.                                                   , "Slightly Agree" , "Agree"
2397.                                                   , "Strongly Agree"))
2398.                   ,"No Use to The Compost" = cut(df_dropout_ch6[,c("Q175")], 6, labels=c("Strongly
Disagree","Disagree" ,"Slighly Disagree"
2399.                                                   , "Slightly Agree" , "Agree"
2400.                                                   , "Strongly Agree"))
2401.                   ,"Family Objection" = cut(df_dropout_ch6[,c("Q176")], 6, labels=c("Strongly
Disagree","Disagree" ,"Slighly Disagree"
2402.                                                     , "Slightly Agree" , "Agree"
2403.                                                     , "Strongly Agree"))
2404.                   ,"No Space" = cut(df_dropout_ch6[,c("Q177")], 6, labels=c("Strongly Disagree","Disagree" ,"Slighly
Disagree"
2405.                                                   , "Slightly Agree" , "Agree"
2406.                                                   , "Strongly Agree"))
2407.                   ,"Failure" = cut(df_dropout_ch6[,c("Q178")], 6, labels=c("Strongly Disagree","Disagree" ,"Slighly
Disagree"
2408.                                                   , "Slightly Agree" , "Agree"
2409.                                                   , "Strongly Agree"))
2410.                   ,"Did not know about compost" = cut(df_dropout_ch6[,c("Q179")], 6, labels=c("Strongly
Disagree","Disagree" ,"Slighly Disagree"
2411.                                                   , "Slightly Agree" , "Agree"
2412.                                                   , "Strongly Agree"))
2413.                   ,"Bothersome" = cut(df_dropout_ch6[,c("Q1710")], 6, labels=c("Strongly
Disagree","Disagree" ,"Slighly Disagree"
2414.                                                   , "Slightly Agree" , "Agree"
2415.                                                   , "Strongly Agree"))
2416.
2417.                   ,"Not Enough Waste to Compost" = cut(df_dropout_ch6[,c("Q1711")], 6, labels=c("Strongly
Disagree","Disagree" ,"Slighly Disagree"
2418.                                                   , "Slightly Agree" , "Agree"
2419.                                                   , "Strongly Agree"))
2420.                   ,"Use Food Waste to Animals" = cut(df_dropout_ch6[,c("Q1712")], 6, labels=c("Strongly
Disagree","Disagree" ,"Slighly Disagree"
2421.                                                   , "Slightly Agree" , "Agree"
2422.                                                   , "Strongly Agree"))
2423.                   ,"Neighbourhood Nuisance" = cut(df_dropout_ch6[,c("Q1713")], 6, labels=c("Strongly
Disagree","Disagree" ,"Slighly Disagree"
2424.                                                   , "Slightly Agree" , "Agree"
2425.                                                   , "Strongly Agree"))
2426.
2427.
2428.
2429.                   ,"cluster" = df_dropout_ch6$cluster_name
2430. )
2431. # grouping = df_extrad$cluster
2432. likt_minus_ch6 <- likert(df_stop_drop_ch6[1:13])
2433. plot(likt_minus_ch6,
2434.      centered=FALSE,
2435.      legend.position="right",
2436.      plot.percent.neutral=FALSE,
2437.      plot.percent.low=FALSE,
2438.      plot.percent.high=FALSE,
2439.      reverse=FALSE)
2440.
2441.
2442. df_stop_gen_ch6 <- data.frame("Time Consuming" = cut(df_prof_ch4[,c("Q171")], 6, labels=c("Strongly
Disagree","Disagree" ,"Slighly Disagree"
2443.                                                     , "Slightly Agree" , "Agree"
2444.                                                     , "Strongly Agree"))
2445.                         ,"Bad Smell" = cut(df_prof_ch4[,c("Q172")], 6, labels=c("Strongly Disagree","Disagree" ,"Slighly
Disagree"
2446.                                                   , "Slightly Agree" , "Agree"
2447.                                                   , "Strongly Agree"))
2448.                         ,"Vermin" = cut(df_prof_ch4[,c("Q173")], 6, labels=c("Strongly Disagree","Disagree" ,"Slighly
Disagree"
2449.                                                   , "Slightly Agree" , "Agree"
2450.                                                   , "Strongly Agree"))
2451.                         ,"Costly" = cut(df_prof_ch4[,c("Q174")], 6, labels=c("Strongly Disagree","Disagree" ,"Slighly
Disagree"
```

```
                                                    , "Slightly Agree" , "Agree"
                                                    , "Strongly Agree"))
                        ,"No Use to The Compost" = cut(df_prof_ch4[,c("Q175")], 6, labels=c("Strongly
Disagree","Disagree" ,"Slighly Disagree"
                                                                , "Slightly Agree" , "Agree"
                                                                , "Strongly Agree"))
                        ,"Family Objection" = cut(df_prof_ch4[,c("Q176")], 6, labels=c("Strongly
Disagree","Disagree" ,"Slighly Disagree"
                                                            , "Slightly Agree" , "Agree"
                                                            , "Strongly Agree"))
                        ,"No Space" = cut(df_prof_ch4[,c("Q177")], 6, labels=c("Strongly Disagree","Disagree" ,"Slighly
Disagree"
                                                             , "Slightly Agree" , "Agree"
                                                             , "Strongly Agree"))
                        ,"Failure" = cut(df_prof_ch4[,c("Q178")], 6, labels=c("Strongly Disagree","Disagree" ,"Slighly
Disagree"
                                                            , "Slightly Agree" , "Agree"
                                                            , "Strongly Agree"))
                        ,"Did not know about compost" = cut(df_prof_ch4[,c("Q179")], 6, labels=c("Strongly
Disagree","Disagree" ,"Slighly Disagree"
                                                                , "Slightly Agree" , "Agree"
                                                                , "Strongly Agree"))
                        ,"Bothersome" = cut(df_prof_ch4[,c("Q1710")], 6, labels=c("Strongly
Disagree","Disagree" ,"Slighly Disagree"
                                                              , "Slightly Agree" , "Agree"
                                                              , "Strongly Agree"))

                        ,"Not Enough Waste to Compost" = cut(df_prof_ch4[,c("Q1711")], 6, labels=c("Strongly
Disagree","Disagree" ,"Slighly Disagree"
                                                                 , "Slightly Agree" , "Agree"
                                                                 , "Strongly Agree"))
                        ,"Use Food Waste to Animals" = cut(df_prof_ch4[,c("Q1712")], 6, labels=c("Strongly
Disagree","Disagree" ,"Slighly Disagree"
                                                                 , "Slightly Agree" , "Agree"
                                                                 , "Strongly Agree"))
                        ,"Neighbourhood Nuisance" = cut(df_prof_ch4[,c("Q1713")], 6, labels=c("Strongly
Disagree","Disagree" ,"Slighly Disagree"
                                                               , "Slightly Agree" , "Agree"
                                                               , "Strongly Agree"))




                        ,"cluster" = df_prof_ch4$cluster_name
                       ,"adoption" = as.character(df_prof_ch4$Q15)
                       ,"Adp" = cut(df_prof_ch4[,c("Q15")], 3, labels=c("Non Composter","Dropout" ,"Composter"
                                                             ))
)
# grouping = df_extrad$cluster
likt_minus_gen_ch6 <- likert(df_stop_gen_ch6[(df_stop_gen_ch6$adoption!="3"),1:13], grouping =
df_stop_gen_ch6[(df_stop_gen_ch6$adoption!="3"),"Adp"])
plot(likt_minus_gen_ch6,
     centered=FALSE,
     legend.position="right",
     plot.percent.neutral=FALSE,
     plot.percent.low=FALSE,
     plot.percent.high=FALSE,
     reverse=FALSE)


#ranking of Reasons to and against
#'Q161','Q162','Q163','Q164','Q165','Q166','Q167','Q168','Q169','Q1610'

peb_not<-c("Time Consuming" ,"Bad Smell" ,"Vermin" ,"Costly" ,"No Use to The Compost"
           ,"Family Objection" ,"No Space" ,"Failure" ,"Did not know about compost"
           ,"Bothersome" ,"Not Enough Waste to Compost" ,"Use Food Waste to Animals" ,"Neighbourhood Nuisance" )
means_not <-
colMeans(df_dropout_ch6[,c('Q171','Q172','Q173','Q174','Q175','Q176','Q177','Q178','Q179','Q1710','Q1711','Q1712','Q171
3')])
df_not_ch6<- data.frame(peb_not,means_not)
```

```
df_not_ch6 <- df_not_ch6[order(df_not_ch6[, 'means_not'], decreasing=TRUE), ]

do_by_cluster <- df_dropout_ch6 %>% group_by(cluster_name) %>%
  summarise(across(c(Q161, Q162, Q163, Q164, Q165, Q166, Q167, Q168, Q169, Q1610), mean))
do_by_cluster_t<-transpose(do_by_cluster[,2:ncol(do_by_cluster)])
colnames(do_by_cluster_t)<-t(do_by_cluster[,1])


not_by_cluster <- df_dropout_ch6 %>% group_by(cluster_name) %>%
  summarise(across(c(Q171, Q172, Q173, Q174, Q175, Q176, Q177, Q178, Q179, Q1710, Q1711, Q1712, Q1713),
mean))
not_by_cluster_t<-transpose(not_by_cluster[,2:ncol(not_by_cluster)])
colnames(not_by_cluster_t)<-t(not_by_cluster[,1])

#significancy test
kruskal.test(Q161 ~ cluster_name, data = df_dropout_ch6)
kruskal.test(Q162 ~ cluster_name, data = df_dropout_ch6)
kruskal.test(Q163 ~ cluster_name, data = df_dropout_ch6)
kruskal.test(Q164 ~ cluster_name, data = df_dropout_ch6)
kruskal.test(Q165 ~ cluster_name, data = df_dropout_ch6)
kruskal.test(Q166 ~ cluster_name, data = df_dropout_ch6)
kruskal.test(Q167 ~ cluster_name, data = df_dropout_ch6)
kruskal.test(Q168 ~ cluster_name, data = df_dropout_ch6)
kruskal.test(Q169 ~ cluster_name, data = df_dropout_ch6)
kruskal.test(Q1610 ~ cluster_name, data = df_dropout_ch6)
kruskal.test(Q171 ~ cluster_name, data = df_dropout_ch6)
kruskal.test(Q172 ~ cluster_name, data = df_dropout_ch6)
kruskal.test(Q173 ~ cluster_name, data = df_dropout_ch6)
kruskal.test(Q174 ~ cluster_name, data = df_dropout_ch6)
kruskal.test(Q175 ~ cluster_name, data = df_dropout_ch6)
kruskal.test(Q176 ~ cluster_name, data = df_dropout_ch6)
kruskal.test(Q177 ~ cluster_name, data = df_dropout_ch6)
kruskal.test(Q178 ~ cluster_name, data = df_dropout_ch6)
kruskal.test(Q179 ~ cluster_name, data = df_dropout_ch6)
kruskal.test(Q1710 ~ cluster_name, data = df_dropout_ch6)
kruskal.test(Q1711 ~ cluster_name, data = df_dropout_ch6)
kruskal.test(Q1712 ~ cluster_name, data = df_dropout_ch6)
kruskal.test(Q1713 ~ cluster_name, data = df_dropout_ch6)

#perform Dunn's Test with Bonferroni correction for p-values
dunnTest(Q161 ~ cluster_name, data=df_dropout_ch6, method="bonferroni")
dunnTest(Q162 ~ cluster_name, data=df_dropout_ch6, method="bonferroni")
dunnTest(Q163 ~ cluster_name, data=df_dropout_ch6, method="bonferroni")
dunnTest(Q164 ~ cluster_name, data=df_dropout_ch6, method="bonferroni")
dunnTest(Q165 ~ cluster_name, data=df_dropout_ch6, method="bonferroni")
dunnTest(Q166 ~ cluster_name, data=df_dropout_ch6, method="bonferroni")
dunnTest(Q167 ~ cluster_name, data=df_dropout_ch6, method="bonferroni")
dunnTest(Q168 ~ cluster_name, data=df_dropout_ch6, method="bonferroni")
dunnTest(Q169 ~ cluster_name, data=df_dropout_ch6, method="bonferroni")
dunnTest(Q1610 ~ cluster_name, data=df_dropout_ch6, method="bonferroni")
dunnTest(Q171 ~ cluster_name, data=df_dropout_ch6, method="bonferroni")
dunnTest(Q172 ~ cluster_name, data=df_dropout_ch6, method="bonferroni")
dunnTest(Q173 ~ cluster_name, data=df_dropout_ch6, method="bonferroni")
dunnTest(Q174 ~ cluster_name, data=df_dropout_ch6, method="bonferroni")
dunnTest(Q175 ~ cluster_name, data=df_dropout_ch6, method="bonferroni")
dunnTest(Q176 ~ cluster_name, data=df_dropout_ch6, method="bonferroni")
dunnTest(Q177 ~ cluster_name, data=df_dropout_ch6, method="bonferroni")
dunnTest(Q178 ~ cluster_name, data=df_dropout_ch6, method="bonferroni")
dunnTest(Q179 ~ cluster_name, data=df_dropout_ch6, method="bonferroni")
dunnTest(Q1710 ~ cluster_name, data=df_dropout_ch6, method="bonferroni")
dunnTest(Q1711 ~ cluster_name, data=df_dropout_ch6, method="bonferroni")
dunnTest(Q1712 ~ cluster_name, data=df_dropout_ch6, method="bonferroni")
dunnTest(Q1713 ~ cluster_name, data=df_dropout_ch6, method="bonferroni")


#among dropouts and the others
#significancy test
krusk_to<-
df_prof_ch4[(df_prof_ch4$Q15!=1),c('Q15','Q161','Q162','Q163','Q164','Q165','Q166','Q167','Q168','Q169','Q1610')]
krusk_to$Q15<-as.character(krusk_to$Q15)

```

```
wilcox.test(Q161 ~ Q15, data = krusk_to)
wilcox.test(Q162 ~ Q15, data = krusk_to)
wilcox.test(Q163 ~ Q15, data = krusk_to)
wilcox.test(Q164 ~ Q15, data = krusk_to)
wilcox.test(Q165 ~ Q15, data = krusk_to)
wilcox.test(Q166 ~ Q15, data = krusk_to)
wilcox.test(Q167 ~ Q15, data = krusk_to)
wilcox.test(Q168 ~ Q15, data = krusk_to)
wilcox.test(Q169 ~ Q15, data = krusk_to)
wilcox.test(Q1610 ~ Q15, data = krusk_to)


krusk_no<-
df_prof_ch4[(df_prof_ch4$Q15!=3),c('Q15','Q171','Q172','Q173','Q174','Q175','Q176','Q177','Q178','Q179','Q1710','Q1711',
'Q1712','Q1713')]
krusk_no$Q15<-as.character(krusk_no$Q15)
wilcox.test(Q171 ~ Q15, data = krusk_no)
wilcox.test(Q172 ~ Q15, data = krusk_no)
wilcox.test(Q173 ~ Q15, data = krusk_no)
wilcox.test(Q174 ~ Q15, data = krusk_no)
wilcox.test(Q175 ~ Q15, data = krusk_no)
wilcox.test(Q176 ~ Q15, data = krusk_no)
wilcox.test(Q177 ~ Q15, data = krusk_no)
wilcox.test(Q178 ~ Q15, data = krusk_no)
wilcox.test(Q179 ~ Q15, data = krusk_no)
wilcox.test(Q1710 ~ Q15, data = krusk_no)
wilcox.test(Q1711 ~ Q15, data = krusk_no)
wilcox.test(Q1712 ~ Q15, data = krusk_no)
wilcox.test(Q1713 ~ Q15, data = krusk_no)


peb_to<-c("Acquaintance Recommendation", “Family Recommendation" ,"Eco-Friendly"
          ,"Fun"  ,"Health"  ,"Garden Use" ,"Reduce Waste"
          ,"Subsidy" ,"Many people in the area do it"  ,"Children's Education")
means_to <- colMeans(df_dropout_ch6[,c('Q161','Q162','Q163','Q164','Q165','Q166','Q167','Q168','Q169','Q1610')])
df_to_ch6<- data.frame(peb_to,means_to)
df_to_ch6 <- df_to_ch6[order(df_to_ch6[, 'means_to'], decreasing=TRUE), ]


g1<-df_not_ch6 %>%
  arrange(means_not) %>%    # First sort by val. This sort the data frame but NOT the factor levels
  mutate(peb=factor(peb_not, levels=peb_not)) %>%   # This trick update the factor levels
  ggplot( aes(x=peb_not, y=means_not)) +
  geom_segment( aes(xend=peb_not, yend=0)) +
  geom_point( size=4, color="darkred") +
  coord_flip() +
  theme_bw() +
  xlab("")+
  ylab("")+
  ggtitle("Reasons For Dropping Out")+
  scale_x_discrete(labels = function(x) stringr::str_wrap(x, width = 20)) +
  theme_update(plot.title = element_text(hjust = 0.5))

g2<-df_to_ch6 %>%
  arrange(means_to) %>%    # First sort by val.
  mutate(peb=factor(peb_to, levels=peb_to)) %>%   # updatethe factor levels
  ggplot( aes(x=peb_to, y=means_to)) +
  geom_segment( aes(xend=peb_to, yend=0)) +
  geom_point( size=4, color="darkgreen") +
  coord_flip() +
  theme_bw() +
  xlab("") +
  ylab("") +
  ggtitle("Reasons For Having Had Engaged") +
  scale_x_discrete(labels = function(x) stringr::str_wrap(x, width = 20)) +
  theme_update(plot.title = element_text(hjust = 0.5))

grid.arrange(g1,g2, nrow = 1, ncol=2)

#reasons to do it
df_plus_gen_ch6 <- data.frame("Acquaintance Recommendation" = cut(df_prof_ch4[,c("Q161")], 6,
labels=c("Strongly Disagree","Disagree" ,"Slighly Disagree"
```

```
                                                                , "Slightly Agree" , "Agree"
                                                                , "Strongly Agree"))
                        ,"Family Recommendation" = cut(df_prof_ch4[,c("Q162")], 6, labels=c("Strongly
Disagree","Disagree" ,"Slighly Disagree"
                                                              , "Slightly Agree" , "Agree"
                                                              , "Strongly Agree"))
                        ,"Eco-Friendly" = cut(df_prof_ch4[,c("Q163")], 6, labels=c("Strongly
Disagree","Disagree" ,"Slighly Disagree"
                                                              , "Slightly Agree" , "Agree"
                                                              , "Strongly Agree"))
                        ,"Fun" = cut(df_prof_ch4[,c("Q164")], 6, labels=c("Strongly Disagree","Disagree" ,"Slighly
Disagree"
                                                            , "Slightly Agree" , "Agree"
                                                            , "Strongly Agree"))
                        ,"Healthy" = cut(df_prof_ch4[,c("Q165")], 6, labels=c("Strongly Disagree","Disagree" ,"Slighly
Disagree"
                                                                , "Slightly Agree" , "Agree"
                                                                , "Strongly Agree"))
    ,"Garden Use" = cut(df_prof_ch4[,c("Q166")], 6, labels=c("Strongly Disagree","Disagree" ,"Slighly Disagree"
                                                              , "Slightly Agree" , "Agree"
                                                              , "Strongly Agree"))
                        ,"Reduce Waste" = cut(df_prof_ch4[,c("Q167")], 6, labels=c("Strongly
Disagree","Disagree" ,"Slighly Disagree"
                                                              , "Slightly Agree" , "Agree"
                                                              , "Strongly Agree"))
                        ,"Subsidy" = cut(df_prof_ch4[,c("Q168")], 6, labels=c("Strongly Disagree","Disagree" ,"Slighly
Disagree"
                                                            , "Slightly Agree" , "Agree"
                                                            , "Strongly Agree"))
                        ,"Many people in the area do it" = cut(df_prof_ch4[,c("Q169")], 6, labels=c("Strongly
Disagree","Disagree" ,"Slighly Disagree"
                                                                , "Slightly Agree" , "Agree"
                                                                , "Strongly Agree"))
                        ,"Children's Education" = cut(df_prof_ch4[,c("Q1610")], 6, labels=c("Strongly
Disagree","Disagree" ,"Slighly Disagree"
                                                              , "Slightly Agree" , "Agree"
                                                              , "Strongly Agree"))


,"cluster" = df_prof_ch4$cluster_name
,"adoption" = as.character(df_prof_ch4$Q15)
,"Adp" = cut(df_prof_ch4[,c("Q15")], 3, labels=c("Non Composter", "Dropout" ,"Composter"
                        ))
)
# grouping = df_extrad$cluster
likt_plus_gen_ch6 <- likert(df_plus_gen_ch6[(df_plus_gen_ch6$adoption!="1"),1:10], grouping =
df_plus_gen_ch6[(df_plus_gen_ch6$adoption!="1"),"Adp"])
plot(likt_plus_gen_ch6,
     centered=FALSE,
     legend.position="right",
     plot.percent.neutral=FALSE,
     plot.percent.low=FALSE,
     plot.percent.high=FALSE,
     reverse=FALSE)
```