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RESEARCH PAPER

Identifying types of behavior of food SMEs towards food waste management

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Abstract. Food waste is a significant sustainable challenge in Indonesia, particularly in commercial centers of Banyumas, which is ranks as the second largest source of food waste. Despite the availability of information on food waste management, a substantial amount of food waste continues to be generated by food Small and Medium-sized Enterprises (SMEs). This research aims to classify food SMEs in Banyumas based their food waste management behavior. The extended Norm Activation Model (NAM) framework was employed to assess the behavior of food SMEs in managing food waste. A questionnaire survey was conducted on 115 food SMEs in Banyumas, leading to the formation of two clusters through *K-Means* clustering: unmanageable and manageable. The unmanageable cluster exhibited the lowest levels of knowledge, awareness, and intention regarding food waste management and still requires substantial improvement in managing food waste. In contrast, the manageable cluster comprises food SMEs that have successfully implemented food waste management practices. These businesses demonstrate a heightened awareness of the food waste issue, take individual responsibility for addressing it, actively work to reduce waste. The finding of this research can serve as a basis for developing tailored mitigation strategies based on the behavior of SMEs in each cluster.

Keywords: Food waste management; clustering; K-Means; food service industry; extended norm activation model

1. Introduction

Food waste poses a multifaceted sustainability challenge in Indonesia, impacting various dimensions including social, economic, and environmental aspects. According to data from National Waste Management Information System (SIPSN, 2021), Indonesia generated a total of 21,653,011 tonnes of waste, with food waste accounting for 28.34 % of this total. From a social perspective, the amount of food produced in Indonesia has the potential to support a significant portion of the population – approximately 61 – 125 million individuals, representing 29 – 47% of those facing malnutrition. Therefore, a reduction in food waste could address the pervasive issue of malnutrition, which affects approximately 30% of Indonesia's total population. On the economic front, the financial losses attributable to food waste in Indonesia between 2000 – 2019 ranged an estimated 213 – 551 trillion Indonesian Rupiah annually. This corresponds to approximately 4%

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to 5% of Indonesia's Gross Domestic Product (GDP). Additionally, food waste in Indonesia has substantial environmental implication. Over the course of 20 years (2000 – 2019), the cummulative emissions associated with food waste amounted to approximately 1,702.9 Mt CO_2-eq, contributing an average annual share of approximately 7.29% to the country's total greenhouse gas emissions (Ministry of National Development Planning of the Republic of Indonesia, 2021).

The regions in Indonesia with the highest waste generation rates are notably Central Java, producing a substantial daily waste volume of 11,652.69 tons. Within Central Java, Banyumas ranks as the third largest contributor to waste, averaging approximately 535.23 tons of waste generated per day. Food waste in Banyumas originates from various sectors, with commercial centers standing as the second-largest contributors after households, as reported by SIPSN (2021). Among the entities in commercial sectors, food SMEs in Banyumas emerge as significant source of food waste. This occurrence is primarily due to the disposal of surplus food during food preparation or the inability to reuse food items, often arising during the serving stage (Betz et al., 2015).

Understanding behaviour is critical for devising policies that align with community's awareness and willingness to participate in food waste management initiatives (Ariyani & Ririh, 2020). This is paramount because one of the key drivers of food waste is the behaviour of both food traders and consumers (Ministry of National Development Planning of the Republic of Indonesia, 2021). Furthermore, the FAO's (2014) study emphasized that changing consumer behaviour is pivotal approach in reducing food waste. While numerous prior studies have investigated factors influencing waste management decision in food services from the customer perspective (Flanagan & Priyadarshini, 2021; Ho et al., 2018; Kim & Che, 2022; Pocol et al., 2020; Teng et al., 2022; Wang et al., 2022). Research on the behaviour of food service owners in this context has been relatively limited compared to consumer behaviour. Existing studies on food waste management from the viewpoint of food service owners have primarily focused on identifying factors contributing to food waste in the food industry (Betz et al., 2015; Stirnimann & Zizka, 2022; Tekler et al., 2019; Wu et al., 2021). SMEs in food sector sector, including food SMEs, significantly contribute to food waste. However, only a scant few have explored the behavioral aspects of food waste management by SME owners, particularly concerning efforts to reduce food waste stemming from their operations.

This research introduces a novel approach by categorizing food SMEs based on the behavior of SME owners' managing behaviour in managing food waste. The study applies the Norm Actovation Model (NAM) theory. Notably, the model incorporates an additional variable, 'technology', to account for the utilization of Salinmas and Jeknyong technologies aimed at food waste reduction in Banyumas. Furthermore, knowledge of food waste management is included as essential variable, given its influences on the intention to manage food waste effectively. Given this context, the primary objective of this study is categorize food SMEs based on their behaviors concerning food waste management. The outcome of of this research will serve as valuable resource for devising targeted strategies to reduce food waste, toiloring each strategy to specific characteristics of the the SME cluster it addresses. By segmenting SMEs into distinct clusters, the implemented strategies can be more precise and, therefore, more effective in addressing the unique needs of each cluster.

2. Literature review

2.1. Food waste and food management

There is no universally accepted definition of food waste, and discussion on this topic involve varying definitions and methodologies (Priestley, 2016). The Food and Agricultural Organization (FAO), a global authority responsible for overseeing the world's food and agriculture sector, offers a specific definition of food waste. According to FAO (2019), food waste refers to reduction in both the quantity and quality of food resulting from decisions and actions taken by food traders, restaurant owners, and consumers. In Indonesia, numerous factors contribute to food waste, including income levels, food vendors choices (Soma, 2020), limited awareness about food waste among both food vendors and consumers, consumer habits of ordering excessive food portions, technological limitations, food pricing, absence of food waste policies, market competition, and constrained consumer purchasing power (FAO, 2019).

Five widely employed food waste management methods in developing countries, including Indonesia, comprise giving food waste to animals, composting, Anaerobic Digestion (AD), incineration, and landfill (Bao et al., 2015). Various factors influence food waste management at the household level, such as government interventions, environmental awareness, shopping planning habits (Ariyani & Ririh, 2020). A study by Susilo et al., (2021) highlighted the need for enhanced efforts in food waste management among Indonesians due to the lack of public understanding about waste management and limited information on waste disposal available in the media. Figure 1 outlines priority actions for preventing and diverting food waste. This figure presents different management strategies for food waste, with the top level being the most effective in terms of its significant benefits for the environment, society, and the economy (US EPA, 2020).

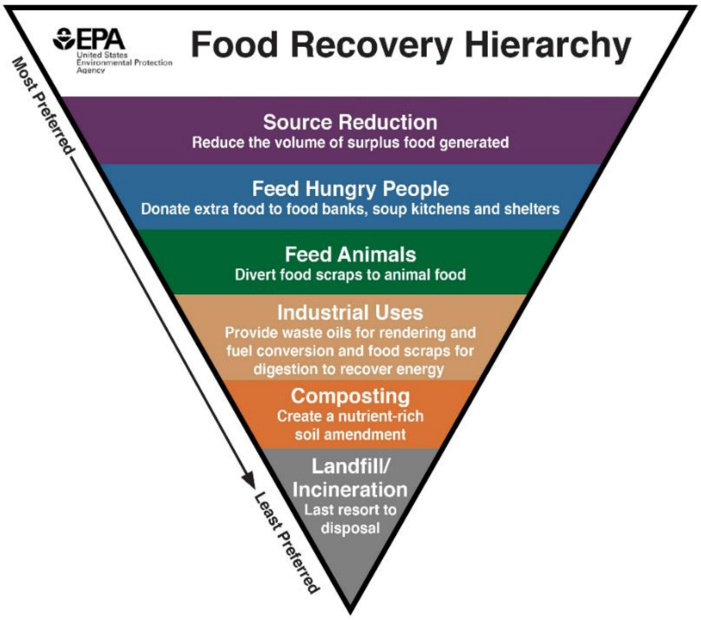

Figure 1. Food recovery hierarchy (US EPA, 2020)

2.2. Norm Activation Model (NAM)

The NAM theory is widely employed to explain pro-social and pro-environmental behavior (Steg & de Groot, 2010). Pro-social behavior encompasses individual actions aimed at assisting or benefiting others or broader community (Groot & Steg, 2009). Examples of pro-social behavior include resource sharing, providing assistance, collaboration, and donation (Kopaei et al., 2021). Pro-environmental behavior in inherently pro-social because it impacts others, even though the individuals implementing such behavior may not directly benefit (Groot & Steg, 2009). This behavior is primarily driven by moral considerations rather than economic incentives, with individuals acting based on their moral rightness for the environment (Setiawan et al., 2020).

The NAM theory has been successfully applied for explain various forms of pro-environmental intention and behavior, including composting (Kopaei et al., 2021), waste separation (Wang et al., 2019), waste management (Tekler et al., 2019), and energy consumption including food waste reduction (Jiang et al., 2020; Kim & Che, 2022; Wang et al., 2022; Wang et al., 2021). At the core of the NAM theory lies the personal norm variable (Schwartz, 1977), representing moral inclination to undertake specific pro-environmental action. Hence, the NAM theory is particularly suitable for explaining food waste reduction behavior (Kim & Che, 2022).

The NAM model consists of three pivotal variables that exert an influence on the inclination to engage in pro-social behavior. These variables encompass awareness of the consequences (AC), ascription of responsibility (AR), dan personal norm (PN). Awareness of the consequences entails knowledge about the impacts of one's behavior. Ascription of responsibility denotes the feeling of being accountable for consequences of one's actions that affect society. Personal norm represents an ethical obligation either to perform or refrain from specific behaviors. Behavioral intention refers to an individual's intention to act in a particular manner (Groot & Steg, 2009). When someone harbors an intention to undertake a behavior, they are more likely to take active steps towards its realization (Tweneboah-Koduah et al., 2020). Figure 2 provides an illustrative representation of the relationships among these variables.

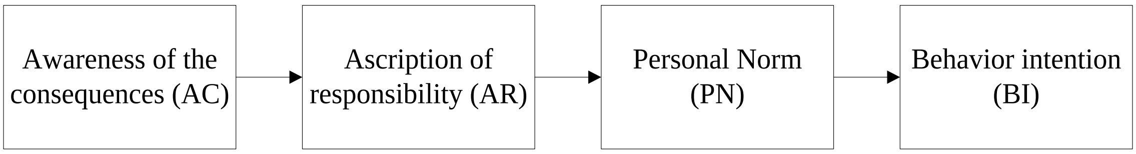

Figure 2. Norm Activation Model (NAM) (Groot & Steg, 2009)

The original NAM model lacks precision when applied to all domains of study, necessitating adjustments to explain pro-environmental behavior in specific contexts (Wang et al., 2022). In research concerning food waste reduction, several variables have been introduced as extension to the original NAM framework. This addition include self-efficacy (Kim & Che, 2022; Wang et al., 2022), good provider norms (Wang et al., 2021), as well as pride and guilt (Onwezen et al., 2013). In this particular research, two novel variables, technological innovation and knowledge of food waste management, were introduced into the original NAM model, constituting innovative modifications previously unexplored.

Technology plays a pivotal role, serving primary tools employed by governments, states, businesses, NGOs, and other stakeholders to combat food waste (UNEP DTU Partnership and United Nations Environment & Programme, 2021). Technology-based innovation has consistently emerged as a viable strategy for curbing waste generation and enhancing waste management practice (Martin-Rios et al., 2018). The perceived usefulness and ease of use of technology significantly influence the intent to utilize it. When individuals recognize technology as beneficial, adding value (perceived usefulness), and easy to operate (ease of use) (Davis, 1989), they become more inclined to engage in food waste management activities facilitated by such technology.

Achieving an understanding of food waste management substantially increases the intention to undertake waste reduction efforts. Mitigation efforts are closely related with the manager's grasp of food waste management principles and their willingness to actively minimize waste. A lack of knowledge serves as a barrier, impeding individuals from effectively addressing food waste (Filimonau et al., 2019). Ultimately, without knowledge of proper food waste management, waste is often discarded without prior consideration. By fostering awareness and knowledge about food waste management, individuals are more likely to be motivated and equipped implement effective management practices.

3. Methodology

3.1. Selecting objective

In this research, clustering is as tool for data simplification. The data pertaining to SMEs' will be grouped based on their food waste management characteristics, enabling the analysis of tailored mitigation strategies for each distinct group. The selection of variables was conducted through a comprehensive literature review, resulting in the identification of seven variables encompassing 37 item indicators (see Appendix).

The first variable pertains to awareness of the impact of food waste, denoting consumer's cognizance of the detrimental consequences stemming from food wastage (Wang et al., 2022). The variable emphasizes the importance of individuals understanding the adverse effects of failing to preserve food, with knowledge and environmental awareness being pivotal factors that positively affect the intention to manage household food waste (Ariyani & Ririh, 2020), motivating individuals to actively reduce food waste. The second variable focuses on the ascription of responsibility, which plays a significant role in shaping personal norms and driving individuals to adopt behavior that mitigate food waste. Personal norms, the third variable, reflect an the individual intrinsic commitment to reducing food waste, driven by a feeling of a moral obligation to act accordingly (Setiawan et al., 2021). Notably, personal norm exhibit a positive effect on reducing food waste (Wang et al., 2022). The fourth variable is technological innovation. It is underscores the role of technology-based innovations as effective strategies for waste reduction and enhanced waste management (Martin-Rios et al., 2018). The presence of user-friendly and beneficial technologies that facilitate food waste management is expected to boost individual intentions management to engage in such practices. The fifth variable, knowledge of food waste management, emphasizes the importance of being informed about methods to reduce, reuse, and recycle food waste, which can significantly enhance an individual's likelihood of actively participating in food waste reduction activities (Ariyani & Ririh, 2020). Lastly, intention to manage food waste, stands as a variable that directly influences individuals to engage in food waste management behaviors. The stronger individual's intention to perform such behavior, the higher the likelihood that will implement them (Ajzen, 2015). Additionally, the variable food waste management behavior has been incorporated to observe the specific food waste management behaviors exhibited by each cluster.

This research employed a questionnaire as the primary data collection tool. Variables which were determined through an extensive literature review, were then structured into questionnaire format. The questionnaire employed a Likert scale from 1 to 5, ranging from strongly disagree to strongly agree, to measure the responses to each question. In the context of behavior measurement, two pivotal considerations are validity and reliability. Validity concerns the meaningfulness of the research components and ensuring that measure variables align with the research objectives. While, reliability focuses on the extent of consistency in measurement results when the same instrument is used for repeated measurement (Ellen, 2016). To assess validity, the Pearson Bivariate Correlation method was employed, while reliability was determined through the calculation of Cronbach Alpha value.

The pilot study was conducted using the first thirty questionnaire responses to evaluate the questionnaire's validity and reliability. Employing a significant level (alpha) of 5%, the validity and reliability results indicated that a Cronbach's Alpha value exceeding 0.7 is considered acceptable. Moreover, if the Cronbach Alpha value exceeding 0.5, it remains acceptable, particularly when the variable comprises two or three indicators (Richter, 2017).

3.2. Designing the research

The data collected for this research utilized a questionnaire employing a Likert Scale ranging from 1-5 to assess the behavior of food waste management among food SMEs in Banyumas. The population of this research comprising food SMEs, including restaurants, snack manufacturers, catering services, and food vendors located in Banyumas. Data collection involved conducting offline survey among randomly selected food SMEs owners within the Banyumas regency. For this research, a sample of 115 respondents were utilized. Data collection took place during August-September 2022 across 13 districts in the Banyumas Regency.

3.3. Data analysis Clustering

3.3.1. Outlier detection, similarity and standardizing data

Outlier detection was performed using the Z-Score method. This method is instrumental in identifying unusual behavior or anomalies by comparing data values to their respective means and standard deviations. Outlier detection through data standardization essentially transform the original data value into Z-scores, where the equation for this conversion process follow Anusha et al. (2019). Data is considered an outlier if the Z-Score exceeds three or falls below -3 (α = 0.05). From the outlier detection using the Z-Score method, six data points were identified as outliers, with values exceeding three or dropping below -3. These outliers were subsequently removed, resulting in a final dataset of 99 data points.

The similarity measure essential for assessing the similarity between objects to be clustered, primarily relies on distance measure in cluster analysis. The Euclidean distance is the most commonly employed distance measure and widely recognized. The calculation of the Euclidean Distance follows Hair (2010).

Standardizing data plays a crucial role in data mining applications, facilitating more meaningful model comparisons (Guleryuz, 2020). This process significantly simplifies the comparison of variable as they are brought onto a common scale. Positive values are positioned above the mean, while negative values fall below it (Hair, 2010).

3.3.2. Clustering

Clustering, a process of classifying observational data without the need for supervision, plays a significant role in various multidisciplinary across daily life. The approach of clustering to identify distinct types of consumer behavior has been carried out in numerous countries with the of facilitating targeted interventions for each behavioral category. In Turkey, for instance, Coskun (2021) identifies characteristic types of household waste producers, resulting in four distinct categories: converser, considerate, reluctant, and prodigal. Meanwhile, in Ireland, Flanagan and Priyadarshini (2021) divided consumer behavior regarding food waste into two clusters: conscientious and unconcerned customers. Another investigation, conducted by Guleryuz (2020) to classify consumers based on their perceptions of food waste, employed K-Means algorithm, yielding three clusters: careless, precautious, and ignorant. The selection of the K-Means algorithm was influenced by its widespread usage and proven effectiveness (Guleryuz, 2020).

The clustering process comprises six stages (Hair, 2010). First, it entails defining the objectives of cluster analysis, which involves addressing research questions and specifying relevant variables. Secondly, the research design phase poses four key questions concerning sample size, outlier management, similarity metrics, and standardized. The third stage revolves around examining assumptions pertinent to cluster analysis, with a focus on sample representation and the presence of multicollinearity among variables in the cluster variate. Fourthly, cluster are derived, and overall fit evaluated, necessitating the selection of partitioning method for clusters formation and determining the optimal number of clusters. The fifth stage involves interpreting the clusters, examining each cluster's characteristics to assign appropriate names or labels that accurately reflect their inherent nature. Finally, the last stage entails the validation and profiling the resulting clusters.

Assumption in Clustering

Cluster analysis predicted two critical assumptions: the representativeness of the sample and the absence of multicollinearity (Hair, 2010). The sampling adequacy test concerns the ability to identify managerially relevant segment rather than statistical issues (Hair, 2010). Adequate statistical power is typically achieved with relatively large effect sizes, indicating clear subgroup differentiation. Ideally, each subgroup contain a sample size ranging from 20-30 (Dalmaijer et al., 2022).

Multicollinearity, on the other hand, is assessed by examining the correlation values between variables. Multicollinearity is deemed to exist when the correlation coefficient exceeds 0.80. The results of correlation analysis between variables are less than 0.80, indicating the absence of multicollinearity.

Deriving clusters

This study uses the K-Means algorithm because its widespread usage and consistently favorable outcomes (Guleryuz, 2020). Initially, the number of clusters (k) is determined using both Elbow method and Silhouette method. The calculation of these methods was conducted using Python. Notably, the Elbow method is considered the most reliable technique for identifying the optimal number of clusters (Guleryuz, 2020). It calculates the sum of squared (SS) distances at each k value to the nearest center, where higher k values correspond to lower the SS distances occurs, signifying the most substantial deviation from previous SS distances value (Bhavani et al., 2021; Cui, 2020). Beginning with k = 2 in Elbow method, there is no noteworthy change in the SS distances value. Meanwhile, the highest value of Silhouette method is 0.241 at k = 2. Based on both these results, the most suitable number of clusters for this analysis is 2.

The k-means algorithm proceeds through the following steps to assign members in each cluster. First, it calculates the centroid coordinates, which represent the center point of the data within each group. Second, it computes the distance between each data point and the centroids. Third, it assigns objects to clusters based on their minimum distance to the centroid. These steps are iterated until stability is reached, meaning that no further reassigning of objects occurs.

Validating, Interpreting, and profiling clusters

Cluster validation involves comparing the differences between each cluster, typically using ANOVA. The F value assess variations both between cluster averages and within cluster averages. A higher F value indicates greater dissimilarity among these variables within the formed clusters. Cluster interpreting entails assigning names or labels based on the distinctive features of each cluster. This interpretation process begins by analyzing the mean values and patterns, which are typically displayed in a bar chart, with a focus on the extreme values within each category. Differences between clusters across various variables are examined by comparing the mean values of each indicator across clusters. Cluster profiling aims to explain the unique characteristics of each cluster, helping to explain the disparities in each dimension. This profiling involves describing the demographic data within each cluster, as outlined in Hair (2010).

4. Results and Discussions

4.1. Descriptive Analysis

All items featured in the questionnaire were validated and demonstrated reliability, thus affirming their suitability for this research. Subsequent to validation and reliability assessment, the questionnaire was disseminated to respondents for the collection of research data.

Table 1 presents the socio-demographic characteristics of the 99 food SMEs samples. Among the respondents, 61% are male, while 39% are female. SME owners are exhibit a fairly balanced distribution across the 20-40 age range, with a notable dominance of the 20-25 age group, comprising 30% of the sample. Additionally, 54% of respondents report a daily income of less than IDR 500,000. Street food business are the most prevalent type of SME, and the majority of these enterprises employ between 1-3 workers. Considering the income per day, SME type, and number of workers, it is evident that small-scale SMEs remain the predominant category among the respondents. Furthermore, a significant portion of the respondent hails from North Purwokerto.

Table 1. Socio-demographic characteristics by cluster membership

Socio-demographic	Categories	Percentage
Gender	Male	59%
	Female	41%
Age	20 - 25	23%
	26 - 30	20%
	31 - 35	20%
	36 - 40	13%
	41 - 45	11%
	46 - 50	5%
	50 years and over	7%
Income per day	under IDR 500,000	53%
	IDR 500,000 - 1,500,000	41%
	IDR 1,600,000 - 2,600,000	4%
	Over IDR 2,700,000	1%
Type of SME	Restaurant	37%
	Catering	2%
	Street food	49%
	Snack manufactures	13%
Number of workers	0 person	5%
	1 - 3 persons	81%
	4 - 6 persons	9%
	7 - 9 persons	3%
	Over 10 persons	2%
Sub-district	South Purwokerto	13%
	Sokaraja	8%
	North Purwokerto	20%
	Sumbang	1%
	East Purwokerto	13%
	Banyumas	10%
	West Purwokerto	1%
	Kembaran	3%
	Kemranjen	13%
	Kebasen	10%
	Somagede	2%
	Ajibarang	4%
	Baturaden	1%

4.2. Result of K-Means clustering

The K-Means clustering analysis was conducted with a predetermined number of clusters, determined using both the Elbow and Silhouette methods, resulting the selection of two clusters. The K-Means clustering model achieved stability after five iterations with two clusters as depicted in Table 2.

Differences in means between clusters were assessed using ANOVA, with the null hypothesis stating that all population means are equal. A significance level of 5% was applied. If any p-value exceeded 5%, the respective item was removed, signifying no significant difference in means between the two clusters.

In the initial clustering experiment, three items exhibited calculated F values lower than the F table value (3.94) or a p-values exceeding 0.05, indicating no distinction between clusters. Consequently, these three items within variable x_1 were excluded. The F-values between the formed clusters are presented in Table 3. Subsequently, a subsequent clustering experiment was conducted using 33 indicators across six variables, as illustrated in Table 4, with no calculated F values falling below the F table value.

Table 2. Iteration history

Iteration	Change in cluster centers	
	1	2
1	5.776	3.984
2	.157	.441
3	.143	.434
4	.110	.367
5	0.000	0.000

Table 3. F values between clusters of the first experiment

	Cluster		Error		F	Sig.
	Mean Square	df	Mean Square	df		
X11	**.018**	**1**	**.949**	**97**	**.019**	**.890**
X12	**1.070**	**1**	**.955**	**97**	**1.120**	**.293**
X13	**1.807**	**1**	**1.021**	**97**	**1.771**	**.186**
X14	10.264	1	.466	97	22.002	.000
X15	13.230	1	.538	97	24.585	.000
X16	22.614	1	.434	97	52.153	.000
X21	11.582	1	.563	97	20.556	.000
X22	8.446	1	.668	97	12.641	.001
X23	5.806	1	.646	97	8.986	.003
X31	12.934	1	.647	97	19.976	.000
X32	9.958	1	.792	97	12.575	.001
X33	11.814	1	.894	97	13.213	.000
X34	17.286	1	.570	97	30.340	.000
X35	10.506	1	.504	97	20.865	.000
X41	7.639	1	.531	97	14.388	.000
X42	5.369	1	.591	97	9.078	.003
X43	6.730	1	.546	97	12.316	.001
X44	14.695	1	.453	97	32.468	.000
X51	44.867	1	.358	97	125.207	.000
X52	19.293	1	.385	97	50.147	.000
X53	22.988	1	.642	97	35.802	.000
X54	19.965	1	.341	97	58.539	.000
X55	23.729	1	.354	97	67.038	.000
X56	37.381	1	.347	97	107.703	.000
X57	30.498	1	.388	97	78.513	.000
X58	22.563	1	.450	97	50.188	.000
X59	22.765	1	.417	97	54.566	.000
X510	30.722	1	.699	97	43.920	.000
X511	44.187	1	.583	97	75.792	.000
X512	37.407	1	.448	97	83.421	.000
X61	11.733	1	.538	97	21.821	.000
X62	20.857	1	.413	97	50,482	.000
X63	19.794	1	.745	97	26.571	.000
X64	25.641	1	.639	97	40.123	.000
X65	19.855	1	.726	97	27.359	.000
X66	13.678	1	.665	97	20.577	.000
X71	27.785	1	.578	97	48.047	.000

Table 4. *F* values between clusters of the second experiment

	Cluster		Error		F	Sig.
	Mean Square	df	Mean Square	df		
X14	10.264	1	.466	97	22.002	.000
X15	13.230	1	.538	97	24.585	.000
X16	22.614	1	.434	97	52.153	.000
X21	11.582	1	.563	97	20.556	.000
X22	8.446	1	.668	97	12.641	.001
X23	5.806	1	.646	97	8.986	.003
X31	12.934	1	.647	97	19.976	.000
X32	9.958	1	.792	97	12.575	.001
X33	11.814	1	.894	97	13.213	.000
X34	17.286	1	.570	97	30.340	.000
X35	10.506	1	.504	97	20.865	.000
X41	7.639	1	.531	97	14.388	.000
X42	5.369	1	.591	97	9,078	.003
X43	6.730	1	.546	97	12.316	.001
X44	14.695	1	.453	97	32.468	.000
X51	44.867	1	.358	97	125.207	.000
X52	19.293	1	.385	97	50.147	.000
X53	22.988	1	.642	97	35.802	.000
X54	19.965	1	.341	97	58.539	.000
X55	23.729	1	.354	97	67.038	.000
X56	37.381	1	.347	97	107.703	.000
X57	30.498	1	.388	97	78.513	.000
X58	22.563	1	.450	97	50.188	.000
X59	22.765	1	.417	97	54.566	.000
X510	30.722	1	.699	97	43.920	.000
X511	44.187	1	.583	97	75.792	.000
X512	37.407	1	.448	97	83.421	.000
X61	11.733	1	.538	97	21.821	.000
X62	20.857	1	.413	97	50.482	.000
X63	19.794	1	.745	97	26.571	.000
X64	25.641	1	.639	97	40.123	.000
X65	19.855	1	.726	97	27.359	.000
X66	13.678	1	.665	97	20.577	.000
X71	27.785	1	.578	97	48.047	.000

The results of the second clustering experiment obtained the final cluster number and number of cases in each cluster. Table 5 shows the means and number of cases in each cluster. From Table 5, the mean values of cluster 1 are all below the average, and the mean values of cluster 2 are all above the average. The cluster below the average is SMEs who do not carry out food waste management, and the cluster above the average is SMEs who carry out food waste management. From these means, cluster 1 is people who do not do food waste management, and cluster 2 is those who do food waste management. Cluster 1 is identified as "Unmanageable", and Cluster 2 is identified as "Manageable". The cluster with the most members is Cluster 1 (75 members), and the cluster with the lowest number is Cluster 2 (24 members). This condition means many food SMEs still do not carry out food waste management compared to SMEs who do food waste management.

Table 6 provides an overview of the socio-demographic characteristics of each cluster. Notable similarities exist between cluster 1 and cluster 2 in terms of gender, age, type of SME, and number of workers. The majority of respondents in both clusters are males, both have a substantial representation of SMEs within the productive age range.

Table 5. Means and number of cases in each cluster

	Cluster	
	1	**2**
X14	.07	.68
X15	.14	.71
X16	.15	.97
X21	.14	.66
X22	.06	.62
X23	.02	.54
X31	.09	.75
X32	.14	.60
X33	.19	.62
X34	.23	.74
X35	.07	.69
X41	.02	.63
X42	.03	.52
X43	.03	.58
X44	.12	.78
X51	.33	1.24
X52	.11	.92
X53	.16	.97
X54	.17	.88
X55	.09	1.06
X56	.25	1.18
X57	.22	1.08
X58	.13	.98
X59	.14	.98
X510	.27	1.03
X511	.41	1.15
X512	.28	1.16
X61	.03	.78
X62	.13	.94
X63	.21	.83
X64	.27	.92
X65	.26	.79
X66	.16	.71
Number of cases	75.00	24.00

Regarding the type of SME, both clusters are predominantly composed of street food establishments, and both exhibit similar workforce compositions with 1-3 employees on average. However, disparities arise in terms of daily income and sub-district distribution. Cluster 1 encompasses SMEs with lower daily incomes, primarily below IDR 500,000, while Cluster 2 comprises SMEs with incomes below IDR 1,500,000. This distinction suggests that SMEs with lower levels are more likely to fall into the unmanageable cluster.

Furthermore, Cluster 1 demonstrates a broader distribution across sub-districts, encompassing 12 sub-districts, including South Purwokerto, Sokaraja, North Purwokerto, Sumbang, East Purwokerto, Banyumas, Kembaran, Kemranjen, Kebasen, Somagede, Ajibarang, and Baturaden. In contrast, Cluster 2 operates within eight sub-districts: South Purwokerto, Sokaraja, North Purwokerto, East Purwokerto, West Purwokerto, Kemranjen, Kebasen, and Ajibarang. North is predominant sub-district for both clusters, with Kemranjen also featuring prominently within Cluster 2.

Table 6. Socio-demographic cluster

Socio-Demographic	Categories	Cluster 1 (n=74)	Cluster 2 (n=25)
		Percent in Cluster	Percent in Cluster
Gender	Male	55%	71%
	Female	45%	29%
Age	20 - 25	21%	29%
	26 - 30	20%	21%
	31 - 35	21%	17%
	36 - 40	16%	4%
	41 - 45	9%	17%
	46 - 50	4%	8%
	50 years and over	8%	4%
Income per day	under IDR 500,000	56%	46%
	IDR 500,000 - 1,500,000	39%	50%
	IDR 1,600,000 - 2,600,000	4%	4%
	Over IDR 2,700,000	1%	0%
Type of SME	Restaurant	37%	38%
	Catering	1%	0%
	Street Food	52%	50%
	Snack manufactures	9%	13%
Number of workers	0 person	4%	8%
	1 - 3 persons	80%	83%
	4 - 6 persons	11%	4%
	7 - 9 persons	4%	0%
	over 10 persons	1%	4%
Sub-district	South purwokerto	12%	17%
	Sokaraja	5%	17%
	North purwokerto	20%	21%
	Sumbang	1%	0%
	East purwokerto	15%	8%
	Banyumas	13%	0%
	West purwokerto	0%	4%
	Kembaran	4%	0%
	Kemranjen	11%	21%
	Kebasen	11%	8%
	Somagede	3%	0%
	Ajibarang	4%	4%
	Baturaden	1%	0%

Figure 3 to 8 offer visual representations of the inter-cluster comparisons for each variable. The discern the distinctions in cluster characteristics, an analysis of mean and mean-centered value patterns, as shown in the bar chart, was conducted. Cluster 1 comprises SMEs that do not actively engage in food waste management, earning it the name “Unmanageable” due to its absence of food waste management practices. In contrast, Cluster 2 exhibits an average food waste management value surpassing the mean value, signifying proactive food waste management efforts. Consequently, Cluster 2 is named the “Manageable” cluster.

Unmanageable cluster comprises SMEs in need of food waste management. Their awareness regarding the consequences of food waste remains relatively low and requires enhancement, particularly in comprehending the genuine and substantial environmental implications of food waste. Delley and Brunner (2017) classified individuals in this cluster as part of an Indifferent group, reflecting their limited awareness of food waste issues. The aligns with Quested et al., (2013) assertion that individuals in this cluster may require assistance in grasping the connection between food waste and environmental harm. Essentially, the “Unmanageable” cluster represents SMEs in need of education regarding the tangible environmental impact of food waste.

On the other hand, the “Manageable” cluster consist of SMEs that have already implemented food waste management practices. Figure 3 illustrates that these SMEs possess a heightened awareness of food waste’s environmental impact, recognizing the genuine and substantial consequences it poses. Their awareness level regarding the potential repercussions of food waste aligns proportionally with their commitment processing food waste efficiently.

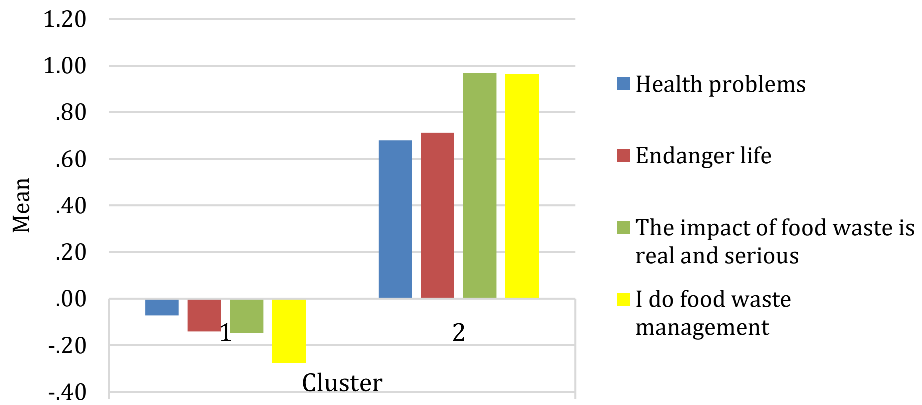

Figure 3. Awareness about the impact of food waste

Figure 4 shows the SME owner’s sense of responsibility regarding food waste management. In the “unmanageable” group, SMEs owners exhibit disinterest in food waste management, as evidenced their negative scores, indicating a lack of concern for responsibility concerning food waste. Their failure to engage in food waste management may stem from a sense of irresponsibility regarding this issue.

Figure 4. Ascription of responsibility

Conversely, the “manageable” group demonstrates a high level of responsibility for food waste management. They believe that everyone shares responsibility for food waste and acknowledge their own accountability for the generation of food waste and its subsequent impacts. A notable relationship exists between awareness of adverse consequences of food waste and the ascription of responsibility. Figure 5 and 6 depicts that clusters characterized by heightened awareness of the negative impact of food waste also exhibit a strong responsibility toward its generation. This relationship inversely applies to the “Unmanageable” cluster, underscoring that lower awareness regarding food waste. This finding align with the research conducted by Govaerts and Ottar (2022) and Kim and Che (2022) both which suggests that when heightened awareness of the adverse effects of food waste tend to foster a greater sense responsibility among individuals for the consequences of the food waste they generated.

Figure 7 provides insights into the personal norms and obligations of SME owners it comes to reducing food waste. In the "Unmanageable" groups, there exist a notable absence of obligation to reduce food waste. Morally, exhibit limited commitment to environmental preservation. Furthermore, they do not experience guilt when discarding food, even when many individuals remain food-insecure.

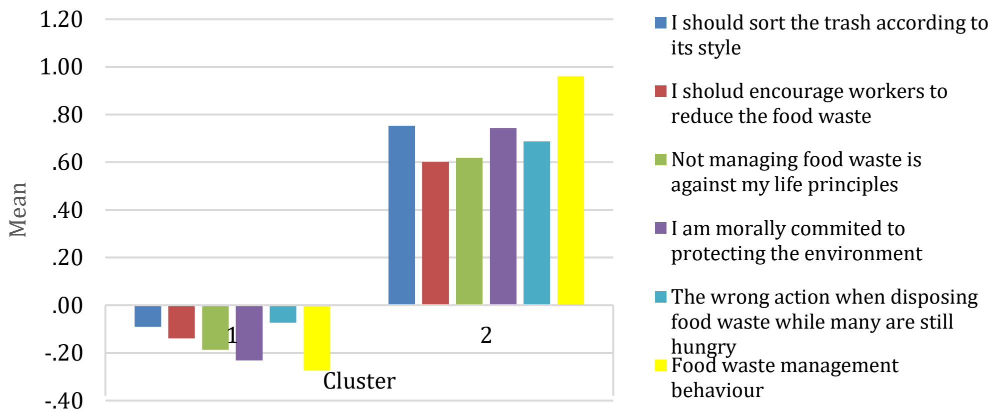

Figure 5. Personal norm

This aligns with the findings of Zhang et al., (2017), which suggest that individuals who do not acknowledge the negative repercussions of failing to separate waste and who evade responsibility are less likely to develop personal norms in this regard. Notably, the cluster with a limited understanding of adverse impacts of food waste maintains lower personal norms compared to the other cluster.

In contrast, the "manageable" cluster operates on the principle that they must protect the environment. They experience guilt when disposing of food waste, especially when there are other in need. This sentiment resonates with the research conducted by Flanagan and Priyadarshini (2021), which posits that individuals in the "caring" cluster feel guilt when wasting food, considering the plight of those who lack access to sufficient nourishment. This guilt is closely linked to their heightened knowledge about the consequences of food waste (Richter, 2017). Additionally, they perceive and obligation to segregate food waste by type and motivate their employees to reduce food waste.

Figure 6 shows insights into the perspectives of SME owners on technological innovation for waste management. Within the "unmanageable" cluster, there exists a prevailing negative sentiment toward technological innovation. These SME owners tend to perceive innovative technology as minimally helpful in addressing food waste concerns. In contrast, the "Manageable" cluster displays a more favorable stance toward technological innovation, concurring that it has a potential to transform food waste into high-value products. Moreover, they believe that technological innovation in waste management should serve the dual purpose of offering information and streamlining the waste management process. Additionally, they express the need for cost-effective technological innovations to effectively manage food waste.

Knowledge about food waste management plays significant role in determining the pace of adopting sustainable restaurant practices (Martin-Rios et al., 2018). Figure 7 illustrates a conspicuous gap in knowledge within the "Unmanageable" cluster, particularly regarding food waste management. This cluster demonstrates limited awareness that food waste management contributes to environmental protection, which aligns with their overall low awareness of the impact of food waste. Furthermore, they remain unaware of various food waste management methods that could help reduce waste, such as composting, forecasting meal quantities accurately, proper cooking techniques, and donating unsold surplus. The primary method of reducing waste centers on reusing leftover food and accurately predicting order quantities.

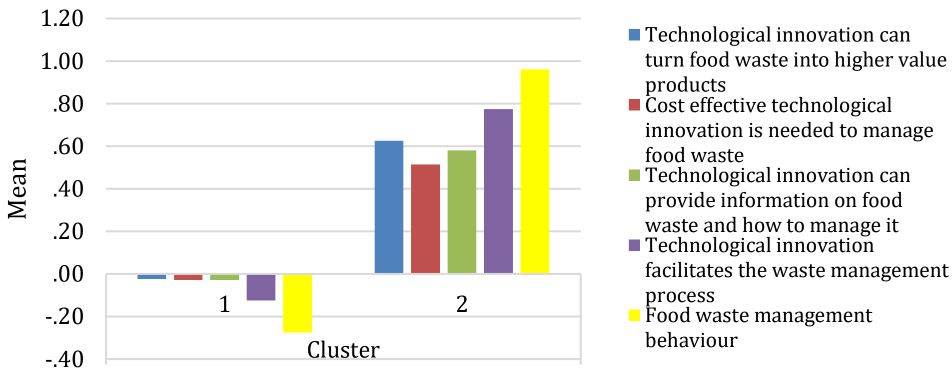

Figure 6. Technological innovation

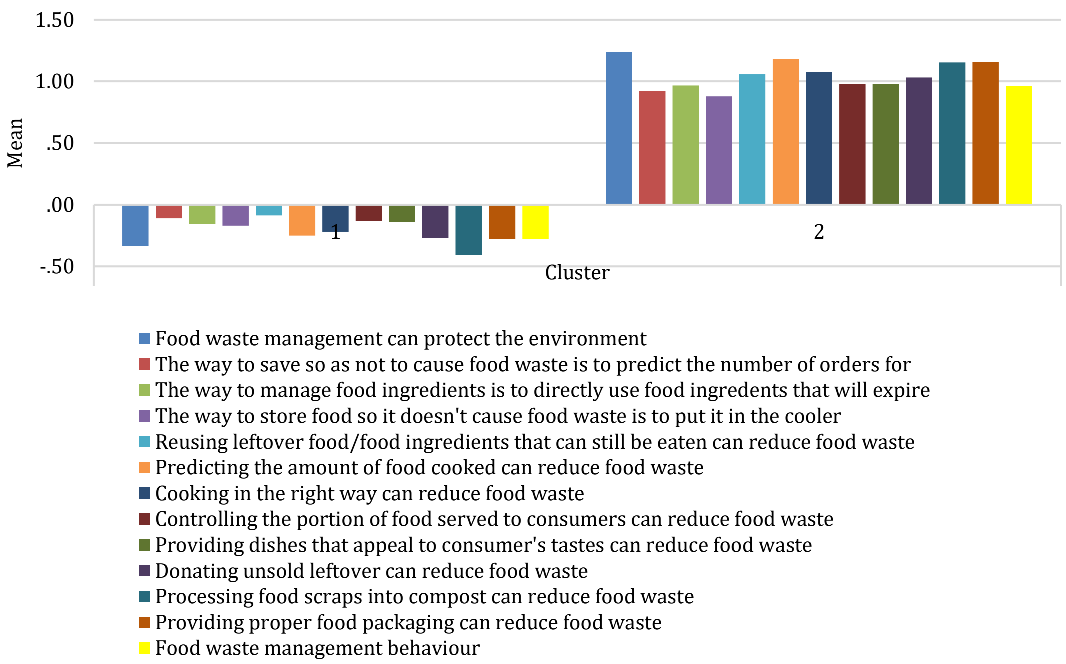

Figure 7. Knowledge of food waste management

Figure 8 provides comprehensive depiction of the intention levels concerning food waste management. Within the "Unmanageable" cluster, there exist a pronounced absence of desires to manage food waste. These individuals are disinclined to engage in actions like food waste donation, composting, strategic planning, or efficient meal provision. It is important to note that poor demand forecasting, reflection of managerial and staff incompetency, can contribute significantly to food wastage (Pirani & Arafat, 2015). Interestingly, when compared to Figure 9, their intention to abstain from food waste management is notably lower than their ignorance regarding food waste management. Consequently, it implies that their intention can be increased through the provision of knowledge regarding food waste management.

In contrast, the "Manageable" cluster exhibits a robust intention to manage food waste. Their intention closely aligns with their actual food waste management behaviors, reflecting a translation of intention into action. They actively seek ways to estimate food quantities accurately and employ efficient cooking practices to curtail food waste. Moreover, they express a willingness to partake in food waste reduction measures such as donating surplus items, engaging in composting initiatives, and embracing low-cost technological solutions.

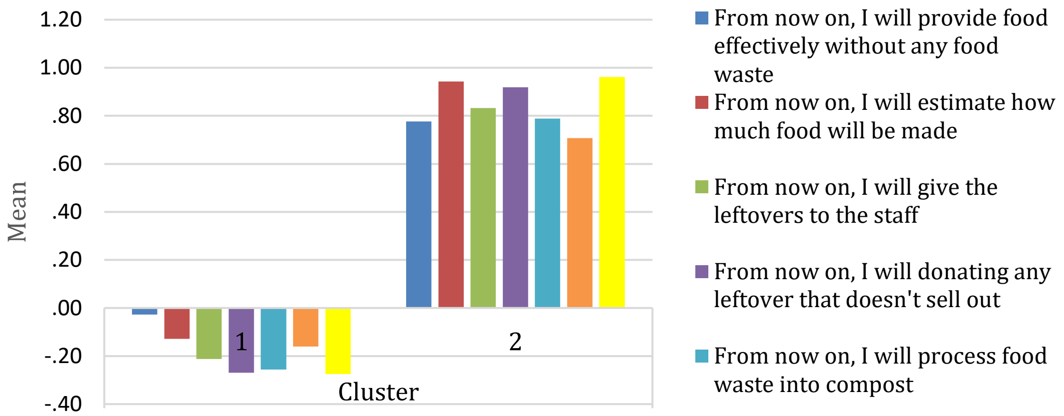

Figure 8. Intention to manage food waste

4.3. Mitigation

The "unmanageable" group emerges as the cluster with the least knowledge, awareness, and intention regarding food waste management. A closer examination of cluster membership reveals that the "Unmanageable" cluster outnumbers the "Manageable" cluster and is predominantly comprised of SMEs with daily incomes below 500,000 IDR. This distribution underscores the prevalence of low-income SMEs within the "Unmanageable" cluster. These SMEs are geographically dispersed across 12 sub-districts in Banyumas, with North Purwokerto being their most common location. Their awareness of the adverse impacts of food waste remains in need of substantial improvement. Therefore, as an initial mitigation, raising awareness about the negative consequences of food waste should take precedence. It is worth noting that increasing SME's awareness of these consequences represents the crucial first step in any comprehensive food waste reduction strategy (Kim & Che, 2022). Enhanced awareness is expected to the result in heightened senses of responsibility for food waste management and the moral obligation to reduce it, as demonstrated in various studies (Govaerts & Ottar, 2022; Kim & Che, 2022; Richter, 2017).

The "Manageable" cluster primarily comprises street food who possess knowledge, awareness, and an intention toward using technological innovation to facilitate food waste management. Notably, this cluster features a higher daily income range, typically falling between IDR 500,000 to IDR 1,500,000, as compared to the "Unmanageable" cluster. Geographically, the "Manageable" cluster is concentrated in North Purwokerto and Kemranjen. The characteristics of this cluster closely resemble those of the "Eco-Responsible" cluster identified in Delley and Brunner (2017) research. Members of this cluster exhibit the highest level of awareness regarding food waste issue and demonstrate a profound individual commitment to addressing the problem by actively seeking to reduce waste. They engage in thorough planning of food production processes and judiciously reuse leftovers. Furthermore, they are skilled at utilizing technology to streamline food waste management practices. Their intention to manage food waste is also notably high. It is worth highlighting that their awareness of significant of food waste management surpasses their actual food waste management behavior. Consequently, they may still benefit from guidance on implementing food waste management strategies effectively. Referring to Figure 8 and 9, it becomes evident that members of this cluster possess substantial knowledge of food waste management. However, their understanding of technological innovation knowledge in this context is comparatively less developed (Martin-Rios et al., 2018).

Mitigation measures suitable for the "Manageable" cluster includes introducing technological innovations that facilitate food waste management, such as promoting the adoption of Salinmas and Jeknyong applications (waste management information systems in Banyumas) or composting technologies. Additionally, with reference to Figure 1 on the Food Recovery Hierarchy, several strategies can be implemented, including source reduction (optimization storage management, adopting proper cooking techniques, using food items close to their expiry date, and providing suitable food packaging), donating unsold leftovers, reusing food remnants, and utilizing leftovers as animal feed.

5. Conclusions

The primary objectives of the research were to categorize food SMEs in Banyumas based on their approaches to food waste management, a classification achieved through K-Means Clustering. The outcome produced two distinct clusters: Unmanageable and Manageable. Despite similarities in socio-demographics characteristics, there exist notable differences between these two clusters, particularly in terms of daily incomes and a geographical distribution. The "Manageable" cluster, characterized by lower daily incomes and broader distribution across sub-district, stands in contrast to the "Manageable" cluster.

The "Unmanageable" cluster exhibits a conspicuous lack knowledge, awareness, and intention regarding food waste management, including a notably low level of awareness regarding the negative repercussions of food waste. Consequently, the foremost mitigation measure for this cluster is to elevate awareness regarding the detrimental impact of food waste. Conversely, the Manageable cluster is highly conscious of the food waste issue and assumes significant individual responsibility for addressing this problem. They diligently, endeavor to reduce food waste. In this cluster, mitigation strategies may include introducing technological innovations related to food waste management, reducing waste at the source, donating unsold leftovers, reusing remnants, and repurposing waste as animal feed.

It is imperative to acknowledge that this research's is confined to the Banyumas region. Nevertheless, this type of study has the potential to be expanded to a national scale, encompassing a more extensive and diverse range of SMEs. Future research avenues may include conducting separate investigations for each distinct type of food SME, recognizing the distinct processes and practices that characterize various subsectors within industry. Such an approach promises to provide more in-depth and precise insights. Additionally, exploring the adoption food waste management technology innovation among food SMEs could constitute a valuable area of inquiry in future research efforts.

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Appendix 1. Items used in the questionnaire

Symbol	Variable
X1	**Awareness about the impact of food waste**
X11	Food waste will result in the loss of resources such as water and oil
X12	Food waste will lead to resource depletion
X13	Food waste will accelerate global warming
X14	Food waste can cause health problems if not handled properly
X15	If people do not care about the environment, it can endanger the safety of living things
X16	I believe that the risks associated with the food waste problem are real and serious
X2	**Ascription of responsibility**
X21	Managing food waste is everyone's responsibility
X22	I feel responsible for the pollution and environmental damage caused by the food I produced
X23	The responsibility to manage the food waste lies with the people who produce it
X3	**Personal norm**
X31	I should sort the trash according to its type
X32	I have an obligation to encourage workers to reduce the food waste
X33	Not managing the food waste is against my life principles
X34	I am morally committed to protecting the environment
X35	The wrong action when disposing the food waste while many are still hungry
X4	**Technological innovation**
X41	Technological innovation can turn food waste into higher-value products
X42	Cost-effective technological innovation is needed to manage food waste
X43	Technological innovations can provide information about food waste and how to manage it
X44	Technological innovation facilitates the waste management process
X5	**Knowledge of food waste management**
X51	Food waste management can protect the environment
X52	The way to store the food ingredients so that they do not cause food waste is to predict the number of food orders
X53	The way to manage food ingredients is to use food ingredients that will expire directly
X54	The way to store the food ingredients is to put it in cooler
X55	Reusing food/food scraps that are still edible (not harmful to health) can reduce food waste

Symbol	Variable
X56	Predicting the amount of food cooked can reduce the food waste
X57	Cooking in the right way can reduce the food waste
X58	Controlling the portion of food served to consumers can reduce the food waste
X59	Providing food that appeals to consumer tastes can reduce the food waste
X510	Donating unsold leftovers can reduce the food waste
X511	Processing food scraps into compost can reduce the food waste
X512	Providing proper food packaging can reduce the food waste
X6	**Intention to manage food waste**
X61	From now on, I will prepare the food effectively without any food waste
X62	From now on, I will predict the amount of food
X63	From now on, I will give the leftovers to the staff
X64	From now on, I will donate any leftover food that does not sell out
X65	From now on, I will process food waste into compost
X66	From now on, I will manage food waste if there is a low-cost technology