Millennials and Generation Z: A Study on Food Waste Reduction Behavior During the Covid-19 Pandemic using PLS-Structural Equation Modeling

Romadhani Ardi
Department of Industrial Engineering, Faculty of Engineering, Universitas Indonesia

Trias Puspita Angel
Department of Industrial Engineering, Faculty of Engineering, Universitas Indonesia

Early Lula Afif
Department of Industrial Engineering, Faculty of Engineering, Universitas Indonesia

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Romadhani Ardi*, Trias Puspita Angel, Early Lula Afif
Department of Industrial Engineering, Faculty of Engineering, Universitas Indonesia, Indonesia

*Author to whom correspondence should be addressed:
E-mail: romadhani.ardi@ui.ac.id

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Abstract: The problem of food waste is important for Indonesia because of its huge impact on the economy, environment, and society. Millennial and generation z as the population with the largest composition in Indonesia are the age group that throws away food the most, but on the other hand, youth are also increasingly concerned about their environment. This study aims to evaluate the factors that can influence the behavior of reducing food waste in the millennial generation and generation z. Respondents are millennial generation and generation z in DKI Jakarta who were born in 1981-2012. To explain behavior, the theory of planned behavior is used and modeled using PLS-SEM. The validity and reliability of the structural and measurement model are tested before drawing conclusions. Information from social media, knowledge of food waste, perception of environmental impacts, attitudes, subjective norms, perceived behavioral control and intentions have a significant positive relationship with behavior to reduce food waste, either directly or indirectly. Intentions perceived behavioral control, and shopping behavior during the Covid-19 Pandemic provide the largest total effect value.

Keywords: food waste; waste reduction behavior; COVID-19; PLS-SEM; Theory of Planned Behavior

1. Introduction

Food waste is a global concern that has led to environmental issues, deterioration of residential areas, and the need for more incinerators and landfills to handle the garbage[1]. Approximately 8-10% of worldwide greenhouse gas emissions correspond with this unconsumed food[2]. Food waste from consumption is increasing at a rapid rate, which is one of the major environmental issues that has to be solved[3]. A significant rise in food waste will result in an increase in greenhouse emissions, and this will significantly contribute to global warming[4].Food loss and waste have serious consequences not just for food security and the environment, but also for the global, regional, and national economies[5]. Everything that relates with the consumption of food, even with the food loss and waste, have become a big issue because it has huge impact on the economic losses, environmental damage, and social perspective[6].

One of the developing countries that has the food loss and waste issue is Indonesia. Data from the Indonesian Ministry of Environment and Forestry (MoEF) shows that food waste accounted for up to 40% of all waste generated in the country in 2022[7]. Based on that data, through The Indonesian Ministry of National Development Planning has issued 45 food loss and waste management strategies for 2020-2045, grouped into 5 policy directions, one of which is behavior change[8]. Consumer behavior is one of Indonesia's main causes and drivers of food loss and waste, the most dominant behavior carried out by Indonesian people in handling food waste is to just throw it away and dumping in landfills[8]. According to data from a Ministry of National Development Planning study on food loss and waste, almost 53% of participants said that they typically had food leftover from meals they had purchased or prepared for consumption at home[8]. Meanwhile, 51% of participants stated that after eating, there was typically leftover food on their plates[8]. As many as 44% of respondents revealed they typically give their pets the leftover food and put the leftover food waste straight into the garbage without any further processing[8]. This practice is one of the primary ways that many people dispose of discarded garbage, which has contributed to global climate change and put the conditions of daily life in danger[9].

Based on 2020, total population in Indonesia is 270.2 million, which the majority age group that covers more than half of the population is the millennial generation and generation z[10]. Many researchers who study food waste conclude that young people aged 18-34 years are the age group that wastes the most food compared to other age groups[11]. This behavior is caused by several things, such as limited knowledge about how to store food or how to prepare different types of food from the same material[12,13], little experience in cooking and tending to cook too large portions[14], as well as the habit of not checking food stocks, not making or not following grocery lists by buying things impulsively[12,15]. But on the other hand, young people are increasingly concerned about the impact of food waste on the environment[16]. As many as 99.5% of generation z students in DKI Jakarta support the government's waste reduction and handling program a form of support to participate in disseminating information about the program through social media by 53.2%. As a generation of technology, social media (IG, Twitter, FB, etc.) is the main and influential source of information for generation z students with a percentage of 97.3%. Intention and self-awareness are the second most important factors that make generation z students want to sort and dispose of waste in its place[17].

There has been a decrease in food waste composition from before and after the Covid-19 pandemic. In 2018, Indonesia's food waste accounted for 44% of the total waste; in 2020, it dropped to 40%[18]. The head of the Jakarta Environmental Agency claimed that the Work from Home policy made the average waste tonnage from the previous 9,346.16 tons per day to 8,726.44 tons per day. The pandemic supports reducing food waste by shopping less frequently, more rigorous meal plan, eating food that has been stored for a long time, using the freezer to store the food, and buying foods with a longer lifespan[19]. In contrast, significant reason for food wastage due to changes in behavior during the Covid-19 pandemic can increase food waste, such as overcooked food, exceedingly long-term fridge-storage, over buying, moldy food, and poor food storage[19].

The change in community behavior during the Covid-19 Pandemic is supported by the behavior of millennial and generation z youth, who tend to waste food more often, so it is necessary to identify factors that can influence the millennial and generation z to reduce food waste. This study uses the Theory of Planned Behavior to understand the behavior of millennial and generation z that affects food waste reduction. The theory of Planned Behavior (TPB) has been successfully used to explain and predict behavior in many behavioral domains[20]. The theory offers a clearly defined structural model, which provides a conceptual framework for considering the determinants of behavior and which can be submitted for empirical testing through multiple regression or structural equation modeling. Structural Equation Modeling (SEM) has the ability to incorporate latent variables into analysis, allowing researchers to model complex relationships[21]. Attitudes toward behavior, subjective norms, perceived behavioral control, and intentions are assessed through reflective indicators. Researchers handpick reflective items, and are indicators of the underlying latent construct[20].

Mondejar-Jim Enez used TPB to conduct a study of 380 students of the University of Tuscia in Viterbo and the University of Castilla La Mancha[22]. This study elucidates youth behavior towards food waste with an important role played by perceived behavioral control. Zepeda and Balaine conducted a pilot study of 106 college students and showed that youth have knowledge, their attitudes reflect the perception that food waste is harmful to the environment and harmful, and their behavior, at least in theory, reflects their intentions[23]. PLS-SEM has been widely used to model consumer attitudes and behaviors towards various types of waste and environmentally friendly behavior, for example, research by Mondéjar-Jiménez , Burlea-Schiopoiu and Teoh[22,24,25].

Based on the literature review, changes in people's behavior towards food waste during the Covid-19 pandemic provide a significant picture of people's behavior to reduce food waste. On the one hand, the millennial generation and generation z are the generations that waste the most food. There has been no research that analyzes the factors that influence the behavior of generation millennial and generation z in reducing food waste. The aim of this research is to evaluate and analyze factors that can influence the behavior of the generation millennial and generation z in reducing food waste. The theory of Planned Behavior model is used to form an initial conceptual model to explain the behavior of the generation millennial and generation z towards reducing food waste during the Covid-19 pandemic. Aside from that, SEM analysis is also used to see the complex relationship of factors that influence each other.

2. Research Methodology

This study used SEM methodology to explore the relationship between the factor that matters to the behavior of food waste reduction during Covid-19 pandemic. The idea behind SEM as a second-generation multivariate analysis technique that enables researchers to look at how recursive and non-recursive variables relate to one another in order to get a situation's overall picture[26]. The initial stage of SEM methodology is making conceptual model and develop hypothesis based on the literature study. The next stage is spread the questionnaire and do the pilot testing to test the reliability and validity. This study using PLS-SEM to processing and analyze the data. PLS-SEM can also be used to test hypotheses from conceptual models by testing the reliability and validity of hypotheses[27]. The results will be analysis based on multi-generation analysis to testing the differences between generation, millennial and generation z.

2.1 Data Collection

This study evaluated the factors influencing food waste reduction behavior in millennial and generation z. The object of this study is multi-generational youth, especially millennial and generation z, who resides in Jakarta, the capitol of Indonesia. Jakarta was chosen as the research object because, according to Ministry of National Development Planning, the cities of Jakarta (east, west, south, north, and central Jakarta) generate more than 50% of total garbage[8)]. Aside from that, Kubíčková stated that big cities waste more food than small cities[28)] and Jakarta is one of the biggest cities in Indonesia.

This study used two types of questionnaires, namely elicitation questionnaires and validation questionnaires. Three hundred respondents born between 1981 – 2007 participated in this study. The data that has been collected will be processed using the SEM method, where the SEM method used is PLS-SEM which is based on the purpose and characteristics of the data used. Data processing is carried out using SmartPLS 3.0 software. Data from two groups of respondents were also assessed using multigroup analysis to test possible differences between groups. The theoretical basis used in this study is the Theory of Planned Behavior (TPB).

Applying TPB to behavioral categories can be done by creating a list of action types representing the category[20)]. Activities that are used as a reference as a form of participating in reducing food waste are: understanding date labels, reprocessing food waste, avoiding excess portions and making shopping lists[22,28)]. Categories are set to be indicators for assessing constructs. The value of each indicator to measure the construct is usually obtained using questionnaires distributed to respondents. Indicators are obtained from literature studies and elicitation processes which experts then validate. The indicator translated into questionnaire items with the rating scale used is the Likert Scale with 5 choices, namely: (1) strongly disagree, (2) disagree, (3) neutral, (4) agree, and (5) strongly agree. Based on the Cohen and Hair guidance to calculate the recommended sample size in PLS-SEM[29,30)], this research requires a minimum of 124 respondents for each generation. The questionnaire was distributed through online platform and social media.

The questionnaire was filled by total of 300 respondents in DKI Jakarta, with demographic data shown in Table 1 and the distribution of respondents based on birth year shown in Fig. 1. In this study, 150 millennials with birth years ranging from 1981 to 1997 completed a questionnaire, with 1988 and 1991 having the highest number of respondents (13 each). Aside from that, up to 150 Generation z members completed a questionnaire with birth years ranging from 1998 to 2007, with 71 persons filling out the questionnaire in the year 2000. Based on the respondent, this research meets the required sample size criteria, which is 150 respondents from each generation.

Table 1. Respondent Demographic Data.

Characteristic	Number of Respondents	Percentage
Gender		
Woman	236	79%
Man	60	20%
Choose not to answer	4	1%
City of Domicile		
North Jakarta	77	26%
Central Jakarta	28	9%
West Jakarta	48	16%
East Jakarta	69	23%
South Jakarta	78	26%
Education		
Master’s Degree	10	3%
Bachelor’s Degree	141	47%
Vocational Degree	21	7%
High School	121	40%
Vocational High School	1	0,30%
Junior High School	5	2%
Elementary School	1	0,30%

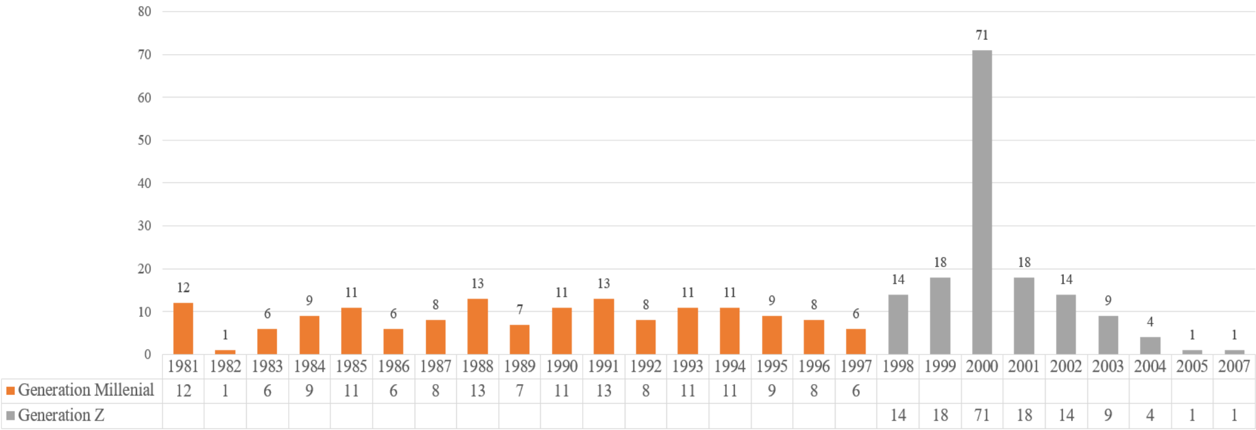


Fig. 1: Distribution of Respondents by Year of Birth and Generation.

2.2 Conceptual Model and Research Hypothesis

A construct is a factor that cannot be observed, or latent while an indicator or what is generally called a measured/observed variable is used to measure a latent construct that cannot be measured directly. The first step in the application of PLS-SEM is to establish structural models and measurements. The conceptual model used in the study is shown in Fig. 2. The model is designed based on the conceptual framework provided by the Theory of Planned Behavior[31)]. Because the purpose of this study is exploratory, several variables are also added to better explain the model that suits the characteristics of the intended respondents. The addition of these variables is also intended to enrich the theory of planned behavior that continues to develop. The variables added include Shopping Behavior during the Covid-19 Pandemic, Information from Social Media, Perception of Environmental Impact and Knowledge of Food Waste. The research hypothesis and theoretical basis underlying the variables used are described in Table 2. There are nine constructs to be measured, namely Shopping Behavior during the Covid-19 Pandemic, Information from Social Media, Knowledge about Food Waste, Perception of Environmental Impact, Attitudes, Subjective Norms, Perceived Behavior Control, Intentions, and Behavior to Reduce Food Waste.

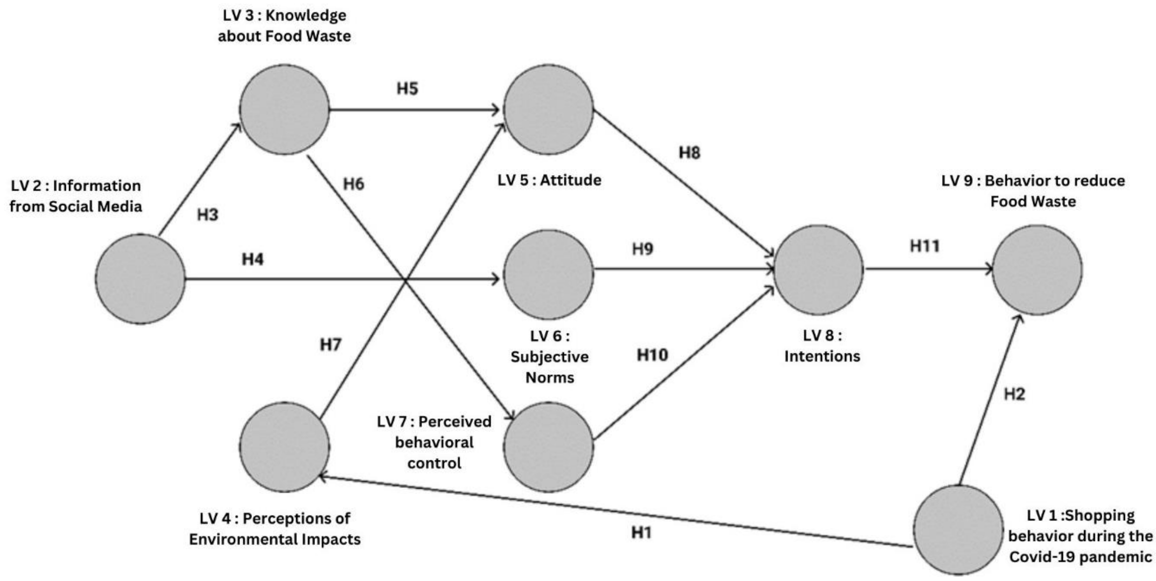


Fig. 2: Conceptual Model.

Table 2. Research Hypothesis.

Hypothesis	Theory
H1: Shopping behavior during the Covid-19 pandemic significantly directly affects youth perceptions of environmental impacts on food waste.	The COVID-19 pandemic has affected young people's responsible behavior towards food waste, both directly and indirectly, mediated by food waste ethics and perceptions of the impact of food waste on the environment[24].
H2: Shopping behavior during the Covid-19 pandemic significantly directly affects youth behavior to reduce food waste.	The COVID-19 pandemic has affected young people's responsible behavior towards food waste[24].
H3: Information from social media significantly directly affects youth knowledge of food waste.	Social media is an important platform to spread awareness about the importance of practicing food waste prevention behaviorss[25].
H4: **Information from social media** significantly affects the subjective norms of youth towards food waste.	Information shared by friends or acquaintances on social media is considered valuable and trustworthy advice that can influence behavior[32].
H5: **Knowledge about food waste** significantly directly affects youth attitudes towards food waste.	Knowledge of the causes, forms, and consequences of food waste is the basis of any young person's responsible attitude and behavior towards food waste[24].
H6: **Knowledge about food waste** significantly directly affects the perception of youth behavioral control over food waste.	The accuracy of information might affect the behavior, norms, or control individuals believe. What must be considered is the knowledge that can guide behavior, not just general knowledge of behavior[20].
H7: **Perceptions of environmental impacts** have a significant direct effect on youth attitudes toward food waste.	Attitudes toward behavior are assumed to be a function of easily accessible beliefs regarding possible consequences of behavior, called behavioral beliefs. Behavioral beliefs are a person's subjective likelihood that performing a certain behavior will lead to a certain outcome or provide a certain experience[20].
H8: **Attitude** has a significant direct effect on the Intention of youth to reduce food waste.	According to the TPB, attitudes toward behavior determine behavioral intentions, subjective norms regarding behavior, and perceived behavioral control[20].
H9: **Subjective norms** significantly directly affect youth's Intention to reduce food waste.	According to the TPB, attitudes toward behavior determine behavioral intentions, subjective norms regarding behavior, and perceived behavioral control[20].
H10: **Perceived behavioral control** significantly directly affects youth's Intention to reduce food waste.	Perceived behavioral control significantly influences the Intention to reduce food waste[22].
H11: **Intention** significantly directly affects youth behavior to reduce food waste.	The direct antecedent of behavior in the TPB is the Intention to perform the behavior in question[20].

2.3 PLS-SEM Processing and Research Results

There are five stage of the PLS-SEM processes, which are model specification, evaluation of the measurement model (outer model), and evaluation of the structural model (inner model), evaluation of measurement invariance of composite models (MICOM), and evaluation of differences in generational classification using multigroup analysis. Latent variables are represented by the circular symbols on the model, whilst indicators are shown by the rectangle symbols. Arrows are used in the model to depict the relationships between the latent variables and the indicators, as well as between each individual latent variable.

This study conducted elicitation regarding the preparation of indicators based on the constructs that were identified through a review of the literature. Elicitation was done in order to gather data and viewpoints that were suitable for Indonesian social circumstances. The elicitation results of all variables are also adjusted based on indicators in literature studies. The constructs and indicators that have been prepared are validated by lecturer in social psychology and lecture in environmental engineering. The elicitation process, literature reviews, and expert conversations throughout the validation phase were the sources of the indicators used in the assessment. To apply the TPB to a behavior category, you can create a list of types of actions that represent the category as a whole[20]. It is decided that these categories would serve as indicators while evaluating the construct. Three types of activities can lead to "positive" behavior about food waste: reading food labels, repurposing food waste for new items, and creating shopping lists[22]. The model employed in this study is depicted in Fig. 3, and the codes used and indicators for each latent variable are described in Table 3.

Table 3. Codes used for each latent variable.

Latent Variable	Code	Indicators
Food Shopping Behavior during the Covid-19 Pandemic	PC	PC 1, PC 2, PC 3, PC 4, PC 5, PC 6, PC 7
Information from Social Media	SM	SM 1, SM 2, SM 3, SM 4, SM 5, SM 6
Knowledge about Food Waste	PF	PF 1, PF 2, PF 3, PF 4, PF 5, PF 6
Perception of Enviromental Impact	DL	DL 1, DL 2, DL 3, DL 4, DL 5, DL 6, DL 7
Attitude	SI	SI 1, SI 2, SI 3, SI 4, SI 5, SI 6, SI 7
Subjective Norms	NS	NS 1, NS 2, NS 3, NS 4, NS 5
Perceived behavior control	KP	KP 1, KP 2, KP 3, KP 4, KP 5, KP 6, KP 7
Intention	NI	NI 1, NI 2, NI 3, NI 4, NI 5
Behavior to reduce food waste	PS	PS 1, PS 2, PS 3, PS 4, PS 5
Total Indicators		55

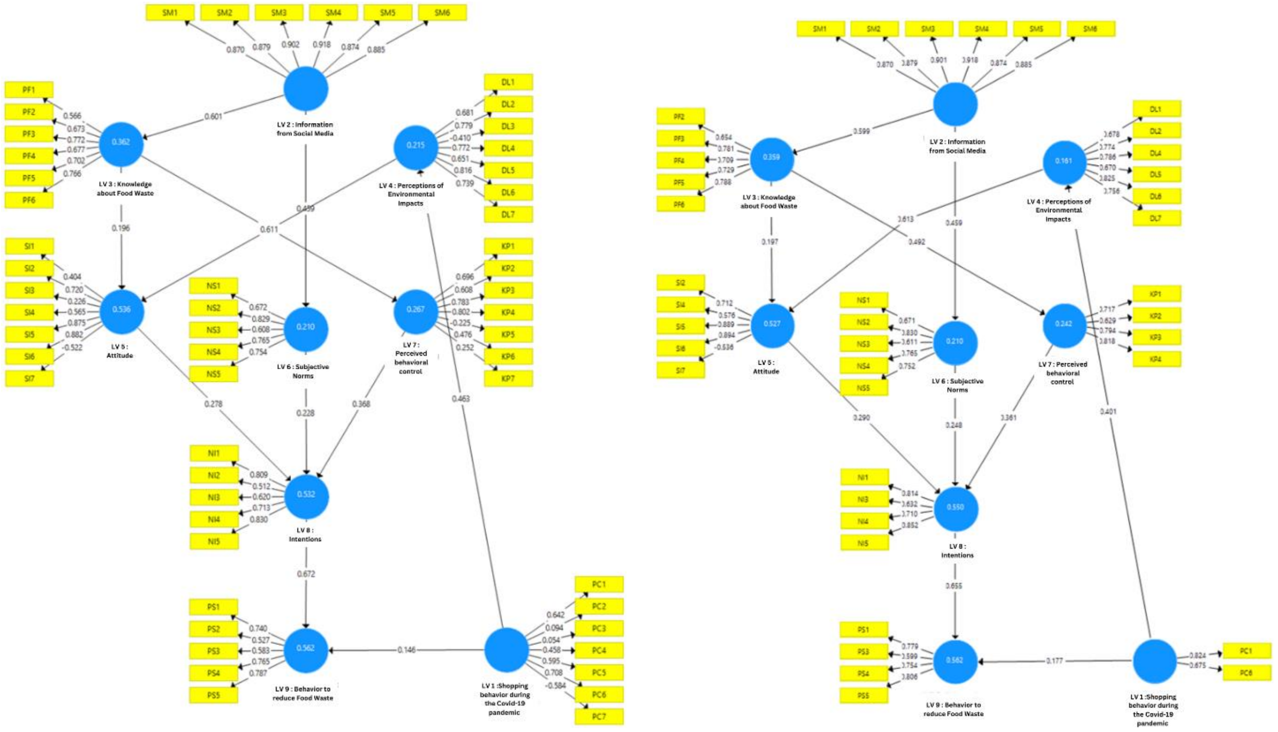
Fig. 3: SEM Model Specifications.

Reliability testing of external models is carried out by testing Internal Consistency Reliability and Reliability Indicators. Internal Consistency Reliability is seen using the Composite Reliability assessment, and it is said to be reliable if the Composite Reliability value > 0.7. The reliability indicator is seen using the loading factor assessment, and it is said to be reliable if the loading factor is > 0.7. To see the validity of outside models based on Convergent Validity and Discriminant Validity. Convergent validity testing uses Average Variance Extracted (AVE) assessment, which is said to be valid if the AVE value > 0.5. Discriminant Validity uses Cross Loadings assessment. In Cross Loadings assessment, the outer loadings value of the indicator should have the highest value with its latent construct, not with other latent constructs[30].

After the testing, the constructs in the model are still invalid and reliable. Of the nine constructs, eight have a value of > 0.7, indicating internal consistency. One other construct, Shopping Behavior during the Covid-19 Pandemic, has a value below 0.7, so it does not meet internal consistency. With a critical value of AVE > 0.5, seven variables are declared invalid. Of the 55 indicators, 27 indicators are declared unreliable with a critical value used of > 0.7. Twenty-one have loadings factor values > 0.4 and < 0.7 (Fig. 4(a)). Researchers decided to remove unreliable indicators based on the consideration of reliability tests and validity tests. The first indicator removal method is looking at constructs with low AVE values. The indicator with the lowest loadings factor in each construct is removed until it reaches AVE above 0.5 and composite reliability above 0.7. The loading factor value > 0.7 is the expected value, but the loadings factor values > 0.4 and < 0.7 can be reconsidered for removal or retention. Meanwhile, indicators with a loadings factor value of < 0.4 should be omitted from the measurement model[30].

The respecified conceptual model is shown in Fig. 4(b). Of the 55 indicators in the initial model, 14 were omitted. PC6, PF2, DL1, DL5, SI4, SI7, NS1, NS3, KP2, NI3 and

PS3 are unreliable indicators based on a critical value 0.7. However, the value of the factor loading indicator is above 0.4, even without eliminating the indicator. Composite Reliability and AVE, as shown in Table 4 and Table 5, have been achieved, so the researchers decided to include them in the model anyway. The respecified model can be used for the next stage, i.e., deep model testing.



(a) (b)

Fig. 4: (a) Factor Loading Value of Each Indicator and Path Coefficient between Constructs. (b) Factor Loading Value of Each Indicator and Path Coefficient between Second Iteration Constructs.

Table 4. Second Iteration of Internal Consistency Reliability Testing Result.

Measurement	Result		Critical Value	Evaluation
	Construct	Value		
Internal Consistency Reliability	Shopping Behavior during the Covid-19 Pandemic	0,722	>0,7	Reliable
	Information from Social Media	0,957		Reliable
	Knowledge of *Food Waste*	0,853		Reliable
	Perception of Environmental Impact	0,885		Reliable
	Attitude	0,738		Reliable
	Subjective Norms	0,849		Reliable
	Control of Perceived Behavior	0,83		Reliable
	Intention	0,841		Reliable
	Behavior to Reduce *Food Waste*	0,826		Reliable

Table 5. Second Iteration of Convergent Validity Testing Result.

Measurement	Result		Critical Value	Evaluation
	Construct	Value		
Convergent Validity	Shopping Behavior during the Covid-19 Pandemic	0,567	>0,5	Valid
	Information from Social Media	0,789		Valid
	Knowledge of *Food Waste*	0,538		Valid
	Perception of Environmental Impact	0,563		Valid

	Attitude	0,543		Valid
	Subjective Norms	0,532		Valid
	Control of Perceived Behavior	0,552		Valid
	Intention	0,573		Valid
	Behavior to Reduce *Food Waste*	0,546		Valid

Evaluation of the structural model is carried out to evaluate the predictive capabilities of the model as well as the relationships between constructs. Since PLS-SEM does not assume a normal distribution, researchers must apply Bootstrap to determine the significance level of each indicator weight. The significance of the construct relationship can be determined through t-values and p-values that will give the same result. The significance level that has been set previously is 5%. To establish whether the relationship between constructs is significant, the p-value required must be < 0.05 to be significant. From the direct effect bootstrapping test values and total effects in Table 6 and Table 7, the relationship in the model proved significant.

Table 6. Bootstrapping Direct Effect Testing Result.

	Original Sample (O)	**Sample Mean (M)**	**Standard Deviation (STDEV)**	**T Statistics (|O/STDEV|)**	**P Values**	**Evaluation**
LV1 -> LV4	0,401	0,406	0,05	8,023	p < 0,0001	Significant
LV1 -> LV9	0,177	0,179	0,046	3,815	p < 0,0001	Significant
LV2 -> LV3	0,599	0,602	0,039	15,319	p < 0,0001	Significant
LV2 -> LV6	0,459	0,462	0,048	9,565	p < 0,0001	Significant
LV3 -> LV5	0,197	0,198	0,049	4,033	p < 0,0001	Significant
LV3 -> LV7	0,492	0,496	0,046	10,631	p < 0,0001	Significant
LV4 -> LV5	0,613	0,617	0,05	12,247	p < 0,0001	Significant
LV5 -> LV8	0,29	0,291	0,051	5,648	p < 0,0001	Significant
LV6 -> LV8	0,248	0,249	0,055	4,499	p < 0,0001	Significant
LV7 -> LV8	0,361	0,363	0,058	6,248	p < 0,0001	Significant
LV8 -> LV9	0,655	0,657	0,043	15,173	p < 0,0001	Significant

Table 7. Bootstrapping Total Effect Testing Result.

	Original Sample (O)	**Sample Mean (M)**	**Standard Deviation (STDEV)**	**T Statistics (|O/STDEV|)**	**P Values**	**Evaluation**
LV1 -> LV4	0,401	0,406	0,05	8,023	p < 0,0001	Significant
LV1 -> LV5	0,246	0,251	0,042	5,887	p < 0,0001	Significant
LV1 -> LV8	0,071	0,073	0,019	3,739	p < 0,0001	Significant
LV1 -> LV9	0,224	0,227	0,046	4,904	p < 0,0001	Significant
LV2 -> LV3	0,599	0,602	0,039	15,319	p < 0,0001	Significant
LV2 -> LV5	0,118	0,119	0,03	3,94	p < 0,0001	Significant
LV2 -> LV6	0,459	0,462	0,048	9,565	p < 0,0001	Significant
LV2 -> LV7	0,295	0,299	0,035	8,476	p < 0,0001	Significant
LV2 -> LV8	0,254	0,259	0,032	7,881	p < 0,0001	Significant
LV2 -> LV9	0,167	0,17	0,024	6,805	p < 0,0001	Significant
LV3 -> LV5	0,197	0,198	0,049	4,033	p < 0,0001	Significant
LV3 -> LV7	0,492	0,496	0,046	10,631	p < 0,0001	Significant
LV3 -> LV8	0,235	0,238	0,035	6,714	p < 0,0001	Significant
LV3 -> LV9	0,154	0,156	0,026	6,01	p < 0,0001	Significant
LV4 -> LV5	0,613	0,617	0,05	12,247	p < 0,0001	Significant
LV4 -> LV8	0,178	0,18	0,037	4,845	p < 0,0001	Significant
LV4 -> LV9	0,116	0,118	0,026	4,539	p < 0,0001	Significant
LV5 -> LV8	0,29	0,291	0,051	5,648	p < 0,0001	Significant

LV5 -> LV9	0,19	0,191	0,037	5,184	p < 0,0001	Significant
LV6 -> LV8	0,248	0,249	0,055	4,499	p < 0,0001	Significant
LV6 -> LV9	0,162	0,164	0,038	4,274	p < 0,0001	Significant
LV7 -> LV8	0,361	0,363	0,058	6,248	p < 0,0001	Significant
LV7 -> LV9	0,237	0,238	0,041	5,717	p < 0,0001	Significant
LV8 -> LV9	0,655	0,657	0,043	15,173	p < 0,0001	Significant

Acceptance and rejection of the research hypothesis is determined through the results of structural model testing where the relationship of each variable in the structural model is obtained through a bootstrapping procedure. The calculation results in Table 6 have shown all the direct relationships of each variable based on the p-value. Table 8 shows the 11 accepted research hypotheses by showing the value of total effect Total effect is the total influence of one variable on other variables. The total effect value is not only obtained through direct effect, but also indirect effect. The total effect value in Table 8 shows that all constructs have a significant direct and indirect influence on behavior to reduce food waste. Overall, Intentions have the greatest effect, followed by Perceived Behavioral Control, Shopping Behavior during the Covid-19 Pandemic, Attitudes, Information from Social Media, Subjective Norms, and the one with the lowest effect is Perception of Environmental Impact.

Table 8. Results of the Evaluation of the Research Hypothesis.

Description	Original Sample (O)	P Values	Evaluation
H1: Shopping behavior during the Covid-19 pandemic has a significant direct effect on youth perceptions of environmental impacts on food waste.	0,401	p < 0.0001	Accepted
H2: Shopping behavior during the Covid-19 pandemic has a significant direct effect on youth behavior to reduce food waste.	0,177	0,036	Accepted
H3: Information from social media has a significant direct effect on youth knowledge of food waste.	0,599	p < 0.0001	Accepted
H4: Information from social media has a significant effect on the subjective norms of youth towards food waste.	0,459	p < 0.0001	Accepted
H5: Knowledge of food waste has a significant direct effect on youth attitudes towards food waste.	0,197	p < 0.0001	Accepted
H6: Knowledge of food waste has a significant direct effect on the perception of youth behavioral control over food waste.	0,492	p < 0.0001	Accepted
H7: Perceptions of environmental impacts have a significant direct effect on youth attitudes towards food waste.	0,613	p < 0.0001	Accepted
H8: Attitude has a significant direct effect on the intention of youth to reduce food waste.	0,29	p < 0.0001	Accepted
H9: Subjective norms have a significant direct effect on youth's intention to reduce food waste.	0,248	p < 0.0001	Accepted
H10: Perceived behavioral control has a significant direct effect on youth's intention to reduce food waste.	0,361	p < 0.0001	Accepted
H11: Intention has a significant effect on youth behavior to reduce food waste.	0,655	p < 0.0001	Accepted

3. Discussion and Analysis

Shopping Behavior during the Covid-19 Pandemic has a positive relationship with two other constructs: Perception of Environmental Impact (H1) and Behavior to Reduce Food Waste (H2). Covid-19 is a wake-up call highlighting the urgency of fighting the global food waste crisis. The Covid-19 pandemic brought growing concerns over environmental issues[33)]. The younger generation has understood that their actions will impact the environment. This relationship shows that millennial and generation z youth carefully consider food waste's impact on the environment when shopping during the Covid-19 Pandemic. Shopping Behavior during the Pandemic also has a positive relationship with youth behavior to reduce food waste. Young people are more careful about allocating budgets when spending and spending becomes more planned[34)]. This leads to behaviors that can support the reduction of food waste. Supported by research by Burlea[24)], where the influence of the COVID-19 crisis on young people's food shopping has a direct and positive influence on young people's responsible behavior towards food waste and young people's perceptions of the impact of food waste on the environment.

Information from Social Media directly and significantly has a positive relationship with two other constructs: Knowledge of Food Waste (H3) and subjective norms (H4). Social media is a massive place for disseminating information and is the platform most often used by millennial and generation z youth as a technology generation[35]. This relationship shows that the various forms of information that youth get lead to an increase in their knowledge of food waste. Various types of audio and visual media are powerful ways to disseminate information on social media to increase knowledge about food waste[36]. In addition to credible and practical information, exposure from people who participate in food waste reduction behavior can create normative beliefs for millennial and generation z youth in DKI Jakarta to reduce food waste. Supported by research conducted by Teoh proves that social media use is positively related to subjective norms[25].

Knowledge of Food Waste directly and significantly has a positive relationship with Attitude (H5) and Perceived Behavior Control (H6). The knowledge possessed by youth about food waste shapes the belief in the behavior of millennial and generation z youth in DKI Jakarta that the behavior of reducing food waste can produce profitable outcomes if done. Such knowledge can also be an input for youth in forming the belief that they have full control to reduce food waste. Knowledge of the causes, forms, and effects of food waste is the basis of every young person's responsible attitude and behavior toward food waste[24,37].

Perception of Environmental Impact has a significant positive relationship with Attitude (H7). This relationship shows that youth's perception of environmental impacts influences their attitudes towards reducing food waste behavior. Millennial and generation z understand the seriousness of the impact of food waste on the environment and the importance of protecting the earth[38]. Therefore, the belief is formed that the more positive the impact of food waste reduction behavior on the environment, the more positive attitudes are formed. Environmental concerns in the research of Tsai impact attitudes toward behavior, which shows that when consumers pay greater attention to environmental issues will help them reduce their food waste[39].

Attitude (H8), Subjective Norms (H15), and Perceived Behavior Control (H16) were significantly positively associated directly with Intention. All three relationships align with the theory used in research, namely the Theory of Planned Behavior. Based on the influence of attitude on Intention, millennial and generation z youth with a good attitude/outlook on food waste reduction behavior tend to have the Intention to carry out the behavior. The influence of subjective norms on Intention suggests that youth with family, friends, partners or work environments who carry out food waste-reducing behaviors also tend to have the Intention of performing behaviors. Millennial and Generation z youth with positive behavioral control also tend to have high intentions to implement food waste reduction behaviors[40]. This means that the more they believe that the barriers preventing them from reducing food waste can be overcome, the more intent to engage in the behavior is formed. Visscher and Werf recommend that food waste reduction interventions focus on TPB construction, such as Intention, perceived behavioral control, and attitudes[41,42]. Overall, our findings align with that.

Direct and significant intentions also positively influence Behavior to Reduce Food Waste (H11). This relationship states that the higher the Intention or plan of the youth to take actions to reduce food waste, such as reprocessing food waste, preventing excessive meals, and creating and following shopping lists within the next month, the more likely the actual behavior will be carried out. One study showed a significant effect characterizing Intention directly influences positive behavior to reduce food waste with a positive relationship[22].

4. Conclusion

This study aims to evaluate factors influencing food waste reduction behavior in millennial and generation z. The study was conducted on youth born from 1981-2012 in the Jakarta area. The main theory used as the basis for factor selection in research, namely the Theory of Planned Behavior. Based on this theory, nine constructs with 41 indicators are used in the study. The results showed that all variables influence behavior to reduce food waste of millennial and generation z. Shopping Behavior during the Covid-19 Pandemic, Information from social media, Knowledge of Food Waste, Perspectives on Environmental Impacts, Attitudes, Subjective Norms, and Intentions have a positive relationship directly and indirectly on Behavior to Reduce Food Waste. This relationship suggests that increasing these factors will increase behavior to reduce food waste. The most significant influence is exerted by Intention, Perceived Behavior Control, Attitudes, Shopping Behavior during the Covid-19 Pandemic and Information from social media, which makes these factors essential to prioritize. Based on the relationship between known factors, both the government and the media can make the Covid-19 Pandemic a momentum to improve the behavior of reducing food waste of the millennial and generation z by paying attention to the information disseminated to the public. Additionally, the food industry can make an insight about how to properly define “best before date" and "expiration date." This will assist consumer in making long-term food storage decisions by allowing them to limit their buying habit by considering best before and expiration dates. Knowledge of the right food waste, its impact on the environment and ways to reduce food waste can influence millennial and z to reduce food waste. Based on the research conducted, millennials and generation z behaviors, along with influencing factors, will help significantly reduce food waste. As a result of less food waste being produced, there will be less chance of global warming, which will benefit the environment by lowering gas emissions from food waste.

Based on the results of the research conducted, future research may consider taking research objects with age periods that are further apart and have significantly different characteristics. The results of the relationship of factors from the study can be used as a reference for designing strategies in improving food waste reduction behavior with targets millennial and generation z youth.

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