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Factors Affecting the Waste of Selected Agricultural Products with an Emphasis on the Marketing Mix

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Abstract: Unusual levels of agricultural product waste are becoming one of the issues and dangers that human societies face in their efforts to achieve food security. Therefore, reducing agricultural product waste is one of the main strategies for the optimal use of production resources and support food security. In this study, a multilevel Bayesian technique was used to examine the characteristics of customers and the effects of marketing mix on the waste of selected agricultural products—a subgroup of fruits and vegetables in Mashhad, Iran. Based on this, 368 consumers (at the first level), 53 fruit and vegetable markets (at the second level), and 3 main supply centers of fruit and vegetables in the city (at the third level) were evaluated using the Bayesian multilevel model. The results showed that approximately 56% of food waste variance was caused by differences between consumers, 29% is due to the differences between fruit and vegetable markets, and almost 14% is due to the differences between the main supply centers of Mashhad. Also, the effects of the marketing mix showed that the place of distribution of agricultural products always has an increasing effect on the waste of agricultural products. Moreover, increasing the price of agricultural products reduces waste by consumers and keeps the consumer away from unnecessary purchases. The product factor also has an increasing effect on the waste of agricultural products, and consumers are encouraged to consume more and create more waste. A good way to reduce agricultural product waste is to use solutions that slow down the spoilage process and extend the shelf life of fruit and vegetables. Using an appropriate marketing mix and considering the characteristics of consumers can also control the waste of agricultural products.

Keywords: agricultural products waste; marketing mix; consumer; retailers; multilevel Bayesian

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1. Introduction

According to the United Nations reports, the world's population will grow from 7.2 billion to 9.1 billion between 2016 and 2050, which is a 38% increase [1]. As a result of population growth, food consumption needs for malnutrition elimination and population growth needs will be 150–170 percent higher by 2050 [1–4].

Today, one of the problems and threats to achieving food security in human societies is the extraordinary amount of agricultural waste produced [1]. Although definitions and estimates of food waste vary from country to country [5–7], it is estimated that around a third of the total food produced—around 1.3 billion tons—is wasted by humans each year [8–10] with a monetary value of 936 billion dollars being lost or wasted [9,11].

To achieve the 2030 Sustainable Development Goals, the United Nations (UN) proposes to reduce (by up to 50%) the waste of global agricultural products at various levels of producers, retailers, consumers, and throughout the supply chain process [12,13]. Today, efforts are being made to reduce food waste throughout the supply chain, and households are now being targeted as one of the main sources of waste in the supply chain [14–16].

According to FAO, Iran's share in the world's agricultural products waste generation is 2.7% or 35 million tons (of the total 1.3 billion tons of waste generated worldwide) and includes mainly bread, fruit, vegetables, and rice [17–21]. Iran could meet the food needs of 15 million people with this amount of agricultural waste [20,22]. However, the presence of this amount of waste in Iran's agricultural products is an indication of a significant waste of resources and the way the country's resources (especially water) are managed in light of the country's climatic situation [23–28].

To achieve sustainable development, and sustainable agricultural development in particular, better management of resources is very important. However, the problem of agricultural waste, in addition to the loss of resources and inputs used, has a negative and direct impact on producers and consumers of agricultural products and causes them to suffer financially [29,30].

According to the latest published statistics for 2018–2019, around 23.5 million tones of horticultural products were produced in Iran in 2019 Khorasan Razavi Province has always been among the top 10 provinces in terms of horticultural production in the country [31], but approximately 10% of crops and 15% of horticultural products are wasted annually, and for over 5 years, almost half of all crops produced in a year were wasted [32].

On the other hand, agricultural waste causes significant losses in the activities of the agricultural value chain. Fruit and vegetable subgroups account for the largest share of household consumption, but there are no recent statistics on per capita household consumption by product in Iran. It is important to note that the amount of waste generated by consumers varies according to their behavioral characteristics [33], ranging from 1 kg per person per week [34] to 4.5 kg per person per week [35].

In this context, the current study tried to evaluate the effects of consumer characteristics and the marketing mix on the wastage of selected agricultural products in the subset of fruits and vegetables in Mashhad, Iran. Mashhad is the second most populous city in Iran (with a population of over 3 million and pilgrimage potential) and the capital of Khorasan Razavi Province. This study investigates the waste of selected agricultural products at the levels of consumers, the fruit and vegetable markets and the main supply center using a multilevel model.

The following section provides a literature review on agricultural product waste and highlights the contribution of this study. Then, the research method is introduced and the application of this method in solving the research problem is emphasized. Finally, the discussion, conclusions and policy implications of the research are presented.

2. Literature Review

This section considers the important factors in the generation of waste in agricultural products (in production, harvesting and storage, packaging and processing, distribution, retail and wholesale) as well as the role of the marketing mix on the generation of waste in agricultural products.

The effects of the marketing mix on agricultural product waste have been mentioned in various studies. In this regard, factors such as labeling and expiration date [23, 24], the packaging size [25], and excessive demand [26] have an important role in the formation of waste by consumers. Table 1 lists the main sources of agricultural waste at each stage of the supply chain as reported in the relevant literature.

Table 1. Agricultural product waste generated in supply chain and role of marketing mix.

Causes	Supply Chain Cycle *					Marketing Mix Mentioned in Each Cause **	Author(s)
	R	D	PP	PS	AP		
Surplus production and storage	✓		✓		✓	P1, P3	[13,36–40]
Incorrectly estimate demand	✓		✓		✓	P1, P2	[13,37,38,41–48]

Poor operational performance			✓	✓	✓	P1	[13,37,39,49–52]
Climate change and temperature changes					✓		[45,48,50,53]
Non-compliance with retail specifications	✓		✓	✓	✓	P2, P3	[13,41,45,46,48,54,55]
Production quality (diseases and product contamination)	✓		✓	✓	✓	P1	[45,46,48,56,57]
Lack of technical and managerial skills	✓				✓	P2, P4	[36,42,51,53]
Considering seasonal effects					✓	P1, P2, P3	[40,50]
Proximity to expiration shelf life in products	✓	✓	✓	✓	✓	P1, P3, P4	[38,39,41,45,55]
Inadequacy of transportation systems		✓	✓	✓	✓	P1, P3	[39,45,52,58]
Inefficiencies in supply chain (lack of coordination and information sharing)	✓	✓	✓	✓	✓	P2, P3	[41,45,46,55]
Overflow			✓	✓	✓	P1, P3	[39,52]
Lack of storage facility equipment	✓	✓	✓	✓		P3	[36,37,39,43,52,58]
Poor packaging	✓	✓	✓	✓		P1, P2, P3, P4	[37,41,43,45,46,52,54]
Storage in non-standard temperatures	✓		✓	✓		P3	[37–39,45,46,49,52]
Poor processing and storage			✓			P1, P3	[13,39,45]
Price and promotion management strategies (command price policy)	✓					P2, P4	[37,41–43,45,46,59]
Inappropriate handling by retailers and consumers	✓					P2, P3	[39,45,46]
Inefficient store management	✓					P2, P4	[39,45,46]

* AP = agricultural production; PS = post-harvest handling and storage; PP = processing and packaging; D = distribution; R = retail and wholesale); ** P1 = product, P2 = price, P3 = place, P4 = promotion; Source: research findings. Note: The ✓ symbol shows the most focus of any mentioned research on supply chain.

Table 1 only mentions the effect of the marketing mix on agricultural product waste, without considering the economic and social characteristics of consumers. However, Table 2 summarizes important studies about economic and social variables that affect the waste of agricultural products. Therefore, it is important to consider the role and behavior of consumers in reducing this waste.

Table 2. Important individual variables affecting agricultural products waste.

Variables	Author(s)
Age, gender	[44,45]
Income	[45,46]
Monthly income percentage for buying fruits and vegetables	[44]
Household size	[44,47]
Occupation, number of purchases	[44]
Having a child in the family, the importance of product cost	[46]
Education level	[45]
Head of the household education level	[48]
Feeling guilty for throwing away product	[44,46]
Quality of purchased product, quantity purchased of product, other use of product waste, expiration date	[47]

Habit of throwing away food waste, waste reduction awareness, using a shopping list	[44]
Just-in-time purchasing (JIT), purchase from shorter distances with more referrals	[49,50]
Time spent shopping for food products	[51]
Online purchasing, increasing frequency of visits by online purchasing	[52,53]

Source: research findings.

By examining the literature review, it was concluded that few studies have been conducted regarding the effect of the marketing mix on the waste of selected agricultural products at the level of consumers, retailers, and wholesalers. Therefore, the contribution of this research is that the waste of selected agricultural products has been investigated at three levels using a multi-level Bayesian model, which has not been performed in previous studies. Therefore, the current research can play a useful role in reducing the amount of agricultural product waste based on the effectiveness of the marketing mix and other behavioral variables.

3. Materials and Methods

The statistical population of the study are consumers in Mashhad, Iran, in 2022 at the first level. Using Cochran's formula, the optimal sample size for consumers was determined to be 384, and 400 questionnaires were collected through face-to-face interviews with consumers using two-stage cluster sampling according to the determined sample size.

The method involves two steps. Firstly, Mashhad municipality is divided into 13 regions based on the geographical proximity of households within a cluster and the size of the clusters. Secondly, a simple random sampling of the 13 regions, including consumers, is conducted according to the population ratio of each region.

After collecting information from consumers and evaluating the completed questionnaires, 32 incomplete questionnaires were removed from the sample, and finally, 368 correct questionnaires were evaluated. In addition, 53 questionnaires were filled in from fruit and vegetable markets of Mashhad (second level) and 3 questionnaires were filled in from wholesalers in the main supply centers of fruit and vegetables (third level) to assess the agricultural product waste at each level of the supply chain.

3.1. Multilevel Models

In this study we assume that there is heterogeneity among the fruit and vegetable markets and the main supply centers of fruits and vegetables and that each may have a different percentage of agricultural product waste in addition to Mashhad consumers. Therefore, a model should be chosen that can account for the heterogeneity of the studied society, as differences in urban areas can vary. So, the multilevel model was deemed a more appropriate tool and is discussed in the following section.

If the hierarchical structure, heterogeneity, and heteroskedasticity that exist in society are not taken into account in research, this will lead to biases in the estimation.

In multilevel models, the coefficients of the explanatory variables and the constant term are considered variable terms, and therefore the hierarchical and grouped structures of society are taken into account in the modeling. This leads to an improvement in efficiency, taking into account the correlations between levels and allowing them to change at higher levels (in random parameter format) [60–62].

For multilevel models, the patterning method can be expressed as Equation (1):

$$Y_{ijk}^{*} = X_{ijk}\beta + W_{jk}\delta + V_{k}\gamma + u_{jk} + v_{k} + e_{ijk} \quad (1)$$

in which

$$p_{ijk} = \Pr(Y_{ijk}^{*}) \quad (2)$$

$$e_{ijk} = \sum_{h=0}^{m1} e_{hijk} Z_{hijk}^{(1)} \tag{3}$$

$$u_{jk} = \sum_{h=0}^{m2} u_{hjk} Z_{hjk}^{(2)} \tag{4}$$

$$v_{k} = \sum_{h=0}^{m3} v_{hk} Z_{hk}^{(3)} \tag{5}$$

and $Z_0 = \{1\}$

$Z_0 = \{1\}$ has a vector with a unit entry matrix.

Also, X, W, and V are the explanatory variables matrices for the first level (consumers of Mashhad city), the second level (fruit and vegetable markets), and the third level (main supply centers), and β , δ and γ are the coefficients corresponding to each level.

In other words, $i = 1, 2, 3, \ldots, 368$ represents a sample of Mashhad city consumers, $j=1,2,3,\ldots,53$ is a sample of fruit and vegetable markets, and $k=1,2,3$ is the number of Mashhad's main supply centers, which are Sepad, Razavi, and Noghan, respectively.

On the other hand, $u_{jk} + v_k + e_{ijk}$ is the random part of the model in $Z^{(1)}$, $Z^{(2)}$, and $Z^{(3)}$ for each of the mentioned matrices of explanatory variables at the first, second, and third levels, which represent random coefficients [63]. Parts $Z^{(1)}$, $Z^{(2)}$ and $Z^{(3)}$ are subsets of X, W, and V, respectively, and e_{ijk} is the set of random effects of the first level (Mashhad city consumers) including random coefficients in each e_{0ijk} (i.e., $h = 0$) with error distribution being the same as the normal function with zero mean and constant variance. u_{jk} and v_k are the set of random coefficients of the second level (fruit and vegetable markets) and the third level (main supply centers), respectively. Moreover, $u_{jk} \sim (0, \sigma_2^2)$ are level 2 disturbances with zero mean and variance of σ_2^2 and $v_k \sim (0, \sigma_3^2)$ are level 3 disturbances with zero mean and σ_3^2 variance [61,63,64].

To confirm the multilevel model, it is necessary to first confirm the intra-level-unit correlation (ILC) between the responses of the consumers of Mashhad city (first level).

The ρ statistic or ICC calculates the ratio of variances for between-level differences [65–67]. Another indicator is the design effect index (Deff), which measures the inflation in the variability of the estimates in the clustering performed and is often used as a rule of thumb to indicate whether a multilevel model should be used [68]. The design effect index is expressed as Equation (6), where n indicates the average number of respondents in each cluster or the average cluster size.

$$Deff \quad Index = 1 + (n - 1)ICC \tag{6}$$

Usually, values more than 2 for this index indicate that multilevel modeling has been chosen correctly [68,69].

3.2. Multilevel Bayesian Framework

Considering the advantages of a Bayesian analysis and the study by [69] on the prediction of municipal waste generation rates using a multilevel Bayesian framework, the current research has used this method. The Bayesian approach is based on the Bayesian inference for modeling data, the main feature of which is that each model parameter is a random variable [70]. This feature allows the Bayesian models to explicitly model uncertainty in parameters. Based on this, the Bayesian theory for modeling the probability of parameter θ of a data set Y establishes the following Equation (7):

$$p(\theta \mid y) = \frac{p(y \mid \theta) p(\theta)}{p(y)} \tag{7}$$

Using this method, the probability distribution of a parameter can be estimated. Moreover, $p(\theta|y)$ shows different relative values for the parameter, depending on the data and the model [71]. The main result of a Bayesian analysis is that the probability distribution of a parameter, $p(\theta|y)$, can be estimated as the posterior distribution; this is proportional to the information in the data (probability), $p(y|\theta)$, and the information available before observing the data (prior), $p(\theta)$. In other words, in the Bayesian model, according to the observed data y, a statistical model for $p(y|\theta)$ can be chosen to describe the distribution of y conditional on θ [72].

Using this approach, Bayesian modeling requires the determination of a likelihood function for the data (i.e., $y_i \sim \mathrm{N}(\mu, \sigma)$) and a prior distribution for the model parameters (i.e., $\mu \sim \mathrm{N}(0,1)$), followed by an estimate of the posterior distribution, which is usually performed using numerical techniques [73].

Numerical techniques for fitting these models are usually based on Markov Chain Monte Carlo (MCMC) simulations. For many methods a Gibbs sampler or Hamiltonian sampler approach is used. In other words, in the simplest problems, the calculation of the posterior distribution requires the calculation of multiple integrals, but doing so for many multiple integrals is difficult (the old obstacle of the Bayesian approach).

MCMC methods have solved this problem to some extent and generally consist of several discrete steps, making it easy to extend the algorithm to more complex structures. MCMC are simulation-based methods that, instead of obtaining point estimates, run through many iterations and in each iteration, obtain an estimate for each unknown parameter. The estimates in each iteration will not be independent, and the estimates from the previous iteration will be used to obtain the next estimates.

This approach aims to obtain a sample of the values from the posterior distribution of the unknown parameters. This means that these methods are useful for obtaining accurate interval estimates. Direct sampling methods, such as Gibbs for known distributions, and indirect sampling methods, such as the Metropolis-Hastings algorithm for unknown distributions, are used to construct Markov chains for MCMC with a limited suitable distribution [74].

The most basic Bayesian multilevel model is the varying intercept model, which allows the members of each level to vary. In other words, $j - 1 \ldots N$ can be different (β_{0j}) but have the same slope (β_1). The multilevel Bayesian model can be expressed [69] as follows in Equations (8) and (9).

$$y_{ij} \sim Exponential(\lambda_{ij}) \tag{8}$$

$$\log(\lambda_{ij}) = \beta_{0j} + \beta_1 X_{ij} \tag{9}$$

$$\beta_{0j} \sim N(\mu_0, \sigma_0) \tag{10}$$

$$\beta_1 \sim N(\mu_1, \sigma_1) \tag{11}$$

$$\mu_0 \sim N(3, 0.5) \tag{12}$$

$$\sigma_0 \sim Exponential\,(3) \tag{13}$$

where β_{0j} follows a normal distribution with μ_0 and σ_0 parameters. μ_0 is the average of intercepts along the levels and σ_0 is the changes in the intercepts. It is possible to expand the varying intercept model as a varying slope model so that the slope is different for each level. This condition is obtained by inserting it into Equation (10) as shown in Equation (14).

$$\beta_{1j} \sim N\,(\mu_1, \sigma_1) \tag{14}$$

By adding the distribution of model parameters, they are shown as Equations (15) and (16).

$$\mu_1 \sim N\,(3, 0.5) \tag{15}$$

$$\sigma_1 \sim Exponential\,(3) \tag{16}$$

The varying slope model can be useful in cases where, for example, an increase in income leads to a corresponding increase or decrease in the percentage of waste generated by consumers. Other research parameters will also benefit from this statement.

4. Results

This section presents and analyses the results and findings of the research. Table 3 shows the descriptive statistics of quantitative and qualitative variables related to consumers. For example, a 4-person household with 27.45 percent of the sample (101 consumers) was the largest size of a household. The maximum number of hours spent per week on buying agricultural products is 34.51 percent of consumers who spend 1–2 h for purchasing.

Table 3. Descriptive statistics of variables related to the first level or consumers.

Investigated Variables	Variables Unit	Mean or Percentage (Frequency or Standard Deviation)
Education level	Less than diploma	34.78 (128)
	diploma to bachelor	36.41 (134)
	Master's degree and higher	28.80 (106)
Household size	1-person	7.34 (27)
	2-person	18.48 (68)
	3-person	21.74 (80)
	4-person	27.45 (101)
	5-person	19.02 (70)
	6-person and up	5.98 (22)
Number of employed persons in family	1-person	62.23 (229)
	2-person	29.35 (108)
	3-person	2.72 (10)
	4-person	0.82 (3)
	5-person and up	4.89 (18)
Time spent on buying agricultural products (hours per week = h/w)	Hours/Week	[0–0.5] = 1.09
		[0.5–1] = 30.98
		[1–2] = 34.51
		[2–5] = 31.25
		[5 and up] = 2.17
Distance (to first agricultural products shopping center)	Distance (meters)	[0–100] = 6.25
		[100–200] = 13.59
		[200–500] = 31.52

		[500–1000] = 16.57
		[1000–2000] = 17.12
		[2000 and up] = 14.95
Number of visits per week to agricultural products shopping centers	Number	[1] = 44.57 (164 person)
		[2] = 36.14 (133)
		[3] = 15.22 (56)
		[4] = 2.45 (9)
		[5] = 0.82 (3)
		[6] = 0.27 (1)
		[7 and up] = 0.54 (2)
	Other investigated variables	
investigated variables	Variables type	percentage or amount available (number)
Age	Year	39.7 (min = 22; max = 69)
Gender	Male = 1; Female = 0	41.58 (215) %male
		58.42 (153) % female
Occupation (Job) Type	1 = Self-employment	1 = 30.72 (113) %
	2 = employee;	2 = 44.29 (136) %
	3 = Other (student/retired/housewife/worker etc.)	3 = 25.00 (92) %
Household income (Rial (The Rial is the official *currency* of *Iran*. At the time of this research, 1 IRR was equal to 0.000024 USD.))	1 = less than 40 million	1 = 25.82 (95) %
	2 = Between 40 and 88 million	2 = 26.09 (96) %
	3 = Between 80 and 120 million	3 = 29.35 (108) %
	4 = Between 120 and 200 million	4 = 10.33 (38) %
	5 = More than 200 million	5 = 8.42 (31) %
Vehicle type	1 = Private car	1 = 37.23 (137) %
	2 = Bus	2 = 17.93 (66) %
	3 = Taxi	3 = 16.03 (59) %
	4 = Motorcycles and bicycles	4 = 8.97 (33) %
	5 = Walk	5 = 19.84 (73) %
Place of purchase (or distribution place of agricultural products)	1 = Retail market	1 = 39.95 (147) %
	2 = Fruit and vegetable market	2 = 31.79 (117) %
	3 = main supply centers	3 = 16.03 (59) %
	4 = Internet order	4 = 0.82 (3) %
	5 = Combination of the above	5 = 11.41 (42) %
Price of agricultural products	1 = Very low	1 = 4.35 (16) %
	2 = Below average	2 = 10.60 (39) %
	3 = average	3 = 16.85 (62) %
	4 = Above average	4 = 45.11 (166) %
	5 = Very high	5 = 23.10 (85) %
Product (Agricultural production process)	1 = Very low	1 = 8.42 (31) %
	2 = Below average	2 = 23.10 (85) %
	3 = Average	3 = 22.01 (81) %
	4 = Above average	4 = 34.51 (127) %
	5 = Very high	5 = 11.96 (44) %
Promotion (Promotion of agricultural products)	1 = Very low	1 = 12.23 (45) %
	2 = Below average	2 = 22.83 (84) %
	3 = Average	3 = 34.78 (128) %
	4 = Above average	4 = 20.38 (75) %
	5 = Very high	5 = 9.78 (36) %
Dependent variable (waste generated by consumers in a subgroup of raw fruits and vegetables)	Percentage	[0–1) = 12.81 %
		[1–5) =57.22 %
		[5–10) =22.61 %
		[10 and up] = 7.36 %

Source: research findings.

According to consumer's opinions, 45.11% (166 consumers) stated that the effect of the price of agricultural products has an above average effect on the reduction of waste of fruit and vegetable products, while 4.35% (16 consumers) noted that the relative price of agricultural products has a very low effect on reducing waste.

Considering the fact that in this study, the effect of the marketing mix, such as the price or quality of selected agricultural products (fruits and vegetables), on the waste of these products has been investigated, consumer's opinions regarding the impact of each of these factors on the level of waste has been asked about. It should be noted that since a specific product of the agricultural sector was not examined in this research, the price level or the specific quality of that product cannot be questioned. Since the question was about fruit and vegetable waste in general (not a specific product), the question is in general and consumer's opinions are asked about the effect of price or product or promotion on the waste level of these products in general. Product variable in this study means the level or amount of product (fruit and vegetables) processing, which can be very low (unprocessed) or high (processed), and this level of processing can have an effect on the waste. Promotion variable also means advertising and promoting of fruits and vegetables, which can increase their consumption and, as a result, increase waste.

Table 4 shows the characteristics of all three levels of study in the multilevel model. In the first level of consumers, 368 questionnaires were completed and the percentage of waste is presented in a spectrum.

The highest percentage of waste by consumers was between 1% and 5%, with 57.22% frequency. Also, 93% of consumers of fruit and vegetable products waste up to 10 percent of waste from these products. On average, consumers waste 3.63 % of agricultural products (min 0% - max 25%).

Table 4. Specifications related to multilevel model (3 levels).

Variable	Observation	Number of Stores	Percentage of Agricultural Product Waste	Mean	Std. Dev	Min	Max
Level 1 (Consumers)	368	-	[0–1) = 12.81% [1–5) = 57.22% [5–10) = 22.61% [10 and up] = 7.36%	3.6348	3.5126	0%	25%
Level 2 (Fruit and vegetable markets)	53	-	[2.8–4) = 25.00% [4–5) = 44.84% [5 and up] = 30.16%	4.4529	0.7207	2.80%	6%
Level 3 (main supply centers)	3	1 = 38 2 = 157 3 = 173	-	-	-	38	173

Source: research findings.

The second level is fruit and vegetable markets in Mashhad, from which 53 retailers were considered and the percentage of waste generated by them was investigated. At the second level, the minimum amount of waste generated was 2.8%, and the maximum amount of waste generated by fruit and vegetable markets was 6%. The majority of fruit and vegetable markets (44.8%) reported that waste was between 4% and 5%.

Also, the average percentage of waste generated by these markets was 4.45%, which shows that, on average, fruit and vegetable markets generate a higher percentage of waste than consumers.

The third level of research is the main fruit and vegetable centers in Mashhad, of which the three main centers of Sepad (with 173 booths), Razavi (with 157 booths), and Noghan (with 38 booths) were considered. In the third level, only the intercept is considered in the evaluation of effects, and no variables are included. The researchers are looking at whether the main centers of fruit and vegetables themselves affect the percentage of waste or not.

Based on theoretical foundations and previous studies, parameters, such as distance, price, and time spent purchasing agricultural products have an impact on consumer behavior, including consumption, purchasing, and waste. Accordingly, consumers pay attention to the positions and characteristics of third-level main supply centers.

The dependent variable is the percentage of waste in fruit and vegetable products. Independent variables include gender, level of education, household size, number of family members with employment, occupation type, household income, time spent on agricultural product purchase (hours per week = h/w), approximate distance to first agricultural product shopping center (meters), vehicle type, and marketing mix (including four factors of place of purchase, prices, production process, and promotion of agricultural products).

Table 5 presents the results of the multicollinearity test among the explanatory variables before presenting the results.

Table 5. Variance inflation factor (VIF) test results for multicollinearity.

Variables	VIF	1/VIF
Distance (to first agricultural products shopping center)	1.31	0.7613
Household income	1.28	0.7823
Place of purchase	1.28	0.7837
Household size	1.24	0.8068
Buying agricultural products (hours per week = h/w)	1.19	0.8386
Occupation (Job) Type	1.19	0.8431
Education level	1.18	0.8489
Vehicles type	1.13	0.8849
Price	1.11	0.9022
Product	1.1	0.9056
Promotion	1.08	0.9259
Gender	1.07	0.9344
Number of employed persons in the family	1.07	0.9346
Mean VIF	1.17	

Source: research findings.

As the results of the multicollinearity test in Table 5 show, there is no multicollinearity among the explanatory variables.

Table 6 shows the results of the multilevel Bayesian model estimation. This approach treats the distribution of variables as unknown and uses indirect sampling methods, including the Metropolis-Hastings algorithm. Also, to obtain a sample of the values of the posterior distribution of the unknown parameters (with many and independent replicates), the MCMC simulation method is used with 10,000 replicates and 2500 degrees of rotation.

Table 6. Bayesian multilevel regression via Metropolis-Hastings and Gibbs sampling.

MCMC iterations	12,500

Burn-in						2500
MCMC sample size						10,000
Acceptance rate						0.7575
					minimum	0.0018
					average	0.5630
					maximum	0.7827
Variables	**Mean**	**Std. Dev.**	**MCSE**	**Median**	**[95% Cred.**	**Interval]**
Gender	0.3189	0.3577	0.0043	0.3201	−0.2792	1.0187
Education level	−1.2341	0.4110	0.0049	−1.2336	−2.0430	−0.4086
	0.1363	0.4731	0.0056	0.1398	−0.8170	1.0610
Households size	0.3792	0.1417	0.0017	0.3796	0.1046	0.6558
Number of employed persons in the family	0.2863	0.1813	0.0020	0.2857	−0.0654	0.6422
Occupation (Job) type	−0.0604	0.2513	0.0030	−0.0637	−0.5468	0.4361
Household income	−0.0828	0.7970	0.0049	−0.0648	−1.6522	1.4551
	−0.0855	0.7389	0.0096	−0.0867	−1.5339	1.3751
	0.3856	0.7360	0.0092	0.3815	−1.0496	1.8180
	0.1251	0.7808	0.0105	0.1260	−1.4252	1.6485
Time spent on buying agricultural products (hours per week = h/w)	−0.3328	1.0367	0.0133	−0.3454	−2.3608	1.7109
	−0.4815	1.0446	0.1315	−0.4923	−2.5498	1.5902
	−1.5637	1.2526	0.1480	−1.5534	−4.0578	0.9112
Distance (to first agricultural products shopping center)	0.00008	0.0003	3.3×10^{-6}	0.00008	−0.0004	0.0006
Vehicles type	−0.5489	0.3933	0.0050	−0.5508	−1.3150	0.2243
Place of purchase	0.0302	2.1058	0.0264	0.0505	−4.1130	4.1746
	1.6119	0.6169	0.0076	1.6112	0.4161	2.8285
	1.4810	0.6381	0.0085	1.4838	0.2523	2.7404
	2.7567	0.7141	0.0089	2.7710	1.3500	4.1259
Price	−0.0470	0.1428	0.0017	−0.0493	−0.3293	0.2370
Product	0.1105	0.1373	0.0017	0.1103	−0.1556	0.3872
Promotion	0.1041	0.1424	0.0017	0.1041	−0.1702	0.3858
Constant	−0.1676	2.0895	0.1432	−0.1449	−4.3284	3.8515

Source: research findings.

The acceptance rate of the MCMC simulation model to achieve the desired results was 75%. This shows that the estimated model has a reasonable acceptance rate (generally the acceptance rate should be more than 60%). Note that in the Bayesian method, instead of estimating the coefficients, the distribution of the coefficients is calculated. Therefore, the placement of the mean of the variables in the confidence interval is used to interpret the independent variables [75,76].

5. Discussion

According to the results of Table 6, when the buyer of fruit and vegetables is female, the waste of these products decreases. This result seems reasonable given the characteristics of women in terms of buying according to their needs and is in line with previous studies [77–81].

Regarding the level of education of consumers, it can be concluded that fruit and vegetable waste increases as the level of education increases from a bachelor's degree onwards. This result can be influenced by the occupational position of consumers according to their level of education, so when people with a better occupational position earn more income, their consumption increases and they generate more waste as a result. The results of this part is similar to that of [77,79,80].

Household size has a positive effect on the amount of fruit and vegetable waste, and an increase in household size increased the wastage of these products. This result can be attributed to increased consumption and higher purchase volumes by consumers. Other studies such as [14,77,78,82] have reached similar results.

The number of employed persons in the family causes an increase in the waste of fruit and vegetable products. This result indicates that with the increase in the number of employed persons in the families; the amount of monthly income of the household increased and consequently, the amount of consumption and waste increased.

The occupation type variable also has a significant impact on the reduction of fruit and vegetable waste and with the improvement of the occupation position, the amount of waste decreases in comparison to the self-employed group. Studies by [14,78,80,81] have pointed to the role of household size and occupation type, on their consumption.

Household income increases lead to an increase in fruit and vegetable wastage for households with incomes of more than 120 million Rials per month. This result confirms the results of the studies [44,47], which stated that due to the higher income of consumers, the volume of products purchased, the non-use of product waste, and also the habit of throwing away product waste increases.

The time spent buying agricultural products (hours per week = h/w) also had a negative effect on the percentage of waste declared by consumers, which means that as the time spent buying of fruit and vegetables increases, the amount of waste generated by them decreases. Increasing the amount of time spent shopping for agricultural products reduces the tendency to buy in bulk and unnecessarily. This reduces waste at home. This result is consistent with the studies by [14,78,80,82].

The distance from the first shopping center for agricultural products was also effective in reducing fruit and vegetable waste and the amount of waste increased with increasing distance.

The type of vehicle has been examined in two categories: with a private vehicle (code 1) and without a private vehicle (code 0). As shown in Table 6, consumers reduce the wastage of agricultural products by having a private vehicle.

Having a personal vehicle can prevent bulk purchases and consequently reduce the amount of waste generated at home. Owning a personal vehicle also reinforces the concept of just-in-time (JIT) purchasing, which is based on the needs of the consumer, and makes it easier for the consumer to access agricultural shopping centers. This reduces the amount of waste generated by consumers. On the other hand, consumers who don't have a private vehicle, usually to avoid transport costs or to avoid buying at the right time, have to buy more with each purchase (bulk purchases), and when the amount purchased is more than needed, there is more wastage.

The effect of the four marketing mix factors (4P) is presented at the end of Table 6. The place of purchase of agricultural products is one of the influencing parameters; it has a significant impact on the amount of waste generated by consumers.

According to the results of Table 6; consumers buying from fruit and vegetable markets (parameter distribution mean = 0.0302), main supply centers (parameter distribution mean = 1.6119), internet ordering (parameter distribution mean = 1.4810), and a combination of the above (parameter distribution mean = 2.7567) increase the percentage of waste formed compared to when products are bought from retail market.

The lowest intensity of the influence of the place of purchase on agricultural products is also in the category of fruit and vegetable markets (with an average parameter distribution = 0.0302). Based on these findings, the more the consumer moves away from retail markets (which are naturally the closest to the majority of consumers), the more the amount of waste generated will increase. In simpler terms, appropriate locations for product distribution can give consumers greater access and choice. As a result, consumers can avoid buying in bulk or worrying about running out of products at nearby markets; they can then avoid and reduce the amount of waste they generate. This result is consistent with studies such as [14,47,78,82–85], which mentioned the topics of time spent on shopping by consumers, in-the-moment purchases, fewer purchases with more visits to the shopping center, and on-time and low-volume purchases.

The product factor in Table 6, with an average distribution of the parameter equal to a positive value of 0.1105, causes an increase in waste generation in agricultural products. Product variety, packaging methods, labeling and dates, branding, shape, color, size, quality, and product names are some aspects of product factors that can increase agricultural waste because each of these aspects can increase consumer purchases and subsequent waste [86–89].

Therefore, according to the results, the above factors lead to consumers' desire and confidence to consume more products. If the product factor works properly, consumers' willingness to buy and consume increases. As a result, with the increase in the number of purchases (unnecessary purchases and sometimes the feeling that comes from the way products are packaged and shaped), the possibility of formed waste increases.

The factor of promoting agricultural products (mean of the distribution of the parameters = 0.1041), due to its positive sign, increases the waste generated. Specifically, motivation and willingness to buy would increases with better product introduction, effective advertising mix, and connecting the production process to its consumption, creating favorable environments for consumers and supplying agricultural products in specific markets or social media.

Therefore, it can be said that advertising helps shape consumers’ attitudes towards product features and change their priorities. Advertisements can also provide consumers with general information about product features. They can also show enough product features to arouse consumer curiosity [90,91].

Table 7 shows the statistics related to the specifications of the multilevel model. At the second level, according to the correctly completed questionnaires, 53 fruit and vegetable markets in all 13 districts of Mashhad were considered. The highest and lowest number of questionnaires in the fruit and vegetable market in different regions of Mashhad were 13 and 4 questionnaires, respectively, and an average of 6.94 questionnaires were completed by agricultural product retailers in each region.

The third level was the main fruit and vegetable supply centers in Mashhad. As Table 7 shows, the amount of variance of error terms that includes the first level (i.e., consumers) is equal to 9.8139. The variance values of the intercept and the percentage of waste formed in the second level (fruit and vegetable markets) are equal to 7.0117 and 0.3054, respectively.

The intercept variance is also 4.9614 at the third level. This means that the random intercepts of the second and third levels explain the 7.0117 and 4.9614 percent of the total variance, respectively. Therefore, the first step of using the multilevel model is confirmed, considering that the total variance of the multilevel Bayesian model is influenced by the variances generated at the second and third levels. If the values of the second and third-level variances are close to zero, it can be decided that the use of a multilevel model makes no difference to a simple linear model. In the next step of using the multilevel model, it is necessary to calculate the ICC statistic [66].

By calculating the intra-unit correlation, it is determined that the value of the intra- and intra-unit correlation for the first, second, and third levels is 0.5659, 0.2894, and 0.1446, respectively. These results show that around 56% of the variance in waste is due to differences among consumers. In other words, the differences in individual characteristics of consumers contain 56% of the variance of the formed waste, and the rest of the differences and variance are caused by the differences in higher levels (i.e. second and third level).

Table 7 shows that differences among fruit and vegetable markets accounting for 29% of the variation in waste. Also, the intra-unit correlation value for the third level shows that approximately 14% of the variance in waste is caused by the differences among the main supply centers of Mashhad.

Table 7. ICC statistic and Deff index in multilevel model.

Group Variable	**Number of Groups**		**Observations per Group**		
			Minimum	**Average**	**Maximum**
Level 2	53		4	6.94	13
Level 3	3		38	122.66	173
		Variance	Var^2	First Value	ICC (in constant)
LEVEL 2	var(Level 2)	0.3054	0.0932	0.0005	0.2894
	var(_cons)	7.0117	49.164	0.2888	
LEVEL 3	var(_cons)	4.9614	24.6155	0.1446	0.1446
	var(Residual)	9.8139	96.3139	0.5659	0.5659
			Average cluster size (group)		Deff Index
Design effect Index	1 + (n − 1)ICC		6.9433		2.7202
			122.6667		18.5976

Source: research findings.

In addition to intra-unit correlation statistics, the use of a multilevel model can be confirmed or rejected by calculating the design effect index (Deff) as a more powerful tool. As Table 7 shows, the Deff index for the second and third levels is equal to 4.61 and 42.45, respectively. The high value of 2 for the Deff index indicates the correctness of multilevel modeling [69] and based on the results listed in Table 7, it can be said that the multilevel model was chosen correctly.

In order to select a more appropriate model using the DIC statistic, the multilevel Bayesian model, the linear multilevel model, and the OLS regression were also estimated. Bayesian information statistics (BIC), Akaike information statistics (AIC), and deviance information statistics (DIC) are commonly used to compare different estimated models [92], of which DIC is used in the present research. The formulation of the DIC equation is as follows in Equation (17):

$$Deviance(\theta) = -2\,Log(p(y\,|\theta)) + C \tag{17}$$

where y is equal to the data, and θ is an unknown parameter of the model. Also, $p(y|\theta)$ is the likelihood function, and C is the intercept [93]. Regarding the DIC statistic, the lower value of the statistic is superior to choosing a more suitable model [69].

Table 8 shows that model 2, i.e. multilevel Bayesian model estimation, is preferred to linear multilevel and OLS regression due to the lower value of the DIC statistic.

Table 8. Deviance information criterion statistics (DIC).

	Method 1	**Model 1**	**Model 2**
Deviance Information Criterion Statistics	Ordinary Least Squares Regression (OLS)	Linear Multilevel Model	Bayesian Multilevel Model
DIC	1652.258	1594.898	1592.482

Source: research findings.

Based on the statistics in Table 8, the interpretations of the results of Table 7 according to the estimation of the multilevel Bayesian approach are used as the final results of the research.

6. Conclusions

A significant amount of agricultural products in developing countries is wasted after harvesting. The world's population is growing, and urbanization is increasing in many developing countries. Therefore, more efforts should be made to reduce waste in the agricultural product supply chain.

Fruit and vegetables play an important role in human nutrition and health and are among the most important agricultural products. These products are perishable due to their high moisture content, and most of them become waste in the post-harvest phase. Reducing and minimizing the wastage of these products can be seen as one of the effective ways of effective usage of scarce resources and movement toward food security The present study attempted to investigate the effects of consumer characteristics and the marketing mix on the waste of selected agricultural products (the subgroup of fruits and vegetables) in Mashhad, Iran.

Therefore, the multilevel model was used, and due to the lack of a proper distribution of the parameters, the Bayesian approach was used. The final results of the research for the multilevel model, according to the ICC statistic and the design effect index (Deff), showed that approximately 56% of the variance in waste is caused by differences among consumers, 29% is caused by the differences among fruit and vegetable markets, and almost 14% is caused by the differences among the main supply centers.

Based on the results, it is suggested that in addition to trying to reduce the amount of waste from consumers, other links in the supply chain should also be considered, including distributors, wholesalers, and retailers. In other words, if all links in the supply chain are connected, efforts to reduce and minimize agricultural product waste will be fruitful.

Therefore, more precise feasibility and location of distribution points based on population distribution and income deciles are needed to strengthen the relationship between the variance related to waste generated and other levels (fruit and vegetable markets and main supply centers).

Regarding the final results of the multilevel Bayesian model, as shown in Table 7, some factors related to consumers had an increasing effect, while some had a decreasing effect on the waste generated by consumers. Females leave less waste from purchased products (compared to males), and based on this result, it is suggested that, where possible, purchases related to agricultural products as well as household supplies for cooking and the use of these products should be made by women so that less waste is generated.

The results for the factor of the place of distribution of agricultural products show that the places of distribution always have a positive effect on the generation of waste of agricultural products. However, the intensity of their effects is not the same. The lowest percentage of waste is generated when consumers buy from fruit and vegetable markets. However, the highest percentage of agricultural product wastage occurred when consumers used a combination of purchase methods (all places include retail markets, fruit and vegetable markets, main supply centers, and internet orders). Therefore, it is suggested that consumers buy from fruit and vegetable markets that are closer to them. This will save time and economic costs, and there will be less product waste.

In retail markets and other purchasing centers for agricultural products, it is suggested that appropriate packaging, labeling, grading, and variety of products adjusts the impact of price increases in the minds of consumers by the differences created.

Based on the results of Table 7, the effect of the product factor increases the waste of agricultural products. Depending on the variety of products, the way of packaging, labeling and date, brand, shape, color, size, quality, and name of the product, consumers are encouraged to consume more products.

In this regard, it is suggested that more research be carried out into the processing of agricultural products and the design of product packaging to increase the shelf life of raw products.

However, today's consumers are looking more for characteristics such as product freshness, naturalness, and simplicity. One of the most important problems in the field of increasing the shelf life of fruits and vegetables is that these products continue to live after harvesting and due to the process of respiration in the plant tissue and the reaction of oxygen with the internal tissues of the fruit, sugars and solids are consumed. As a result, fruit and vegetables lose their natural color and smell shortly after harvest.

Therefore, a good way to reduce product waste is to use solutions that slow down the spoilage process and extend the shelf life of fruits and vegetables. The use of post-harvest refrigeration (rapid reduction of product respiration and therefore waste), appropriate packaging, passive packaging or modified atmospheres (gas mixture to increase product life before packaging), use of desiccants, etc. are some of the methods that can be proposed to prevent further waste.

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