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AN INTEGRATED MODEL OF FOOD LOSS AND WASTE DETERMINATION ALONGSIDE THE AGRIFOOD CHAIN

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Abstract

The Food Loss and Waste (FLW) phenomenon is an important issue in the current development of economy as a whole. This phenomenon is emerging in all economic contexts, starting from food production and processing, known as food loss (FL), to the consuming stages, known as food waste (FW). In this matter, identifying key causes and quantifying the impact of FLW is essential. The current paper is an integrated summative description of several research results related to FLW obtained by the authors and elaborated in previous papers. Thus, the paper includes a bird-eye view of the entire model alongside the agri-food chain, taking into account modalities of measuring the FL during its components and a specific measurement of FW on the consuming component. The approach takes into account methodologies and instruments from various domains, such as statistics, data processing, automated learning (e.g., machine learning), System Dynamics or networks. The expected results are the description of the model and the resulted data. Conclusions can be used further to study and challenge the FLW phenomenon causes effects for any interested stakeholders.

Key words: *agrifood chain, food loss and waste, modelling, statistics, automated learning*

INTRODUCTION

Food Loss and Waste (FLW) is one of the most pressing challenges of the contemporary agri-food chain ([9] Luo, N. et al. (2022)), with major economic, social and environmental causes ([12] Nijloveanu, D. et al. (2023)) and implications. From production and processing ([17, 18] Omolayo, Y. et al. (2021)), to distribution ([7] Derqui, B. et al. (2016); [1] Arunraj, N.S. et al. (2014)) and consumption ([13, 15] Nijloveanu, D. et al. (2023, 2024), [2] Bucatariu, C. (2014)), food is lost or wasted ([25] Santeramo, F.G. et al. (2021)) in significant quantities, affecting food security ([24] Santeramo, F.G. & Lamonaca, E. (2018)) and the sustainability ([21] Parfitt, J. et al. (2010)) of the agri-food system ([14] Nijloveanu, D. et al. (2023)). In this context, it is essential to identify the causes of FLW, measure its impact and develop effective prevention ([6] De Clercq, D. et al. (2017); [22] Peira, G. et al. (2018)) and intervention models ([10] Magalhães, V.S.M. et al. (2021); ([2] Chandadevi, G. et al. (2019); [8] Graham-Ro., E. et al. (2015)).

This research proposes an integrated approach to the FLW phenomenon ([16] Nijloveanu, D. et al. (2023)), with a focus on the consumption ([3] Chereji, A.I. et al. (2022)) component, using a combination of statistical methods, formal modeling (Petri nets, system dynamics) ([31] Trevisan, C. &Formentini, M. (2023); [20] Pan, S. et al. (2018)), behavioral analysis (questionnaire) and artificial intelligence tools (neural networks and decision trees) ([11] Malefors, C. et al. (2022); [19] Ozcil, I.E. (2024)). Through this approach, the study aims to identify the determinants of food waste behavior ([27] Schanes, K. et al. (2018)), classify consumption patterns ([23] Pocol, C.B. et al. (2020); [4, 5] Chereji, A.I. et al. (2022, 2023)), and build predictive models ([26] Sathiyaraj, R. et al. (2022); [28] Segarra, L. et al. (2019); [29] Shopnil, M. et al. (2023)) that can support the formulation of effective policies and actions at the consumer level ([30] Singh, B. et al. (2024)).

The research is organized into several steps, the first of which is a bibliographic analysis of the relevant literature, followed by a structural modeling of the food chain's constituents, and then the development of predictions that are intended to be applied to the real world, this results in a coherent and accurate description of how food waste is understood, anticipated, and reduced.

This research aims to comprehensively explore the phenomenon of Food Loss and Waste (FLW) across the agri-food chain, with a particular focus on the consumption component.

The main objective is to identify the determinants of FLW, to model them using formal tools and to develop predictive models based on consumer behavior, in order to substantiate effective policies and measures to reduce food waste.

MATERIALS AND METHODS

The research proposes an integrated and multidisciplinary approach to the FLW phenomenon, combining:

-quantitative methods (descriptive and inferential statistics);

-formal methods (Petri modeling and System Dynamics);

-modern artificial intelligence methods (Machine Learning and Neural Networks);

-applied behavioral analytics.

This combination allows not only a descriptive and explanatory understanding of the FLW phenomenon, but also the development of predictive and operational tools applicable to public policies and sustainable strategies.

Research stages

The research was structured in several complementary stages, carried out chronologically and logically interconnected:

(i)Bibliographic analysis and identification of factors (exploratory stage): The research started with a comprehensive study of the literature that identified the primary causes of food loss and waste (FLW). Using academic sources from Dimensions.ai and the VOSviewer term analysis tool, the identified factors were grouped into five broad categories – behavioral, demographic, biological, economic, and political – each mapped to specific stages of the agri-food chain. Descriptive statistical study and correlational analysis: To quantify the influence of these factors, the next step consisted of a correlational statistical analysis, using data from official sources such as Eurostat [32], FAO [33] and INS Tempo Online [34]. The Pearson correlation coefficient was calculated between the independent variables and the food waste indicators, and the significance of the relationships was statistically tested using the t-test.

(ii)Systemic modeling of the agri-food chain – the Petri Nets approach: The formal modeling stage involved representing the dynamics of losses and food flows using Petri Nets. Using the CPN Tools application, a graphical and mathematical model was built that simulates the states of food (raw materials, processed products, waste) and the transitions between them, highlighting the critical points of the agri-food chain, including recycling processes.

(iii)Behavioral study – ReWaFA questionnaire: To analyze consumer behaviors related to food waste, a structured online questionnaire was developed, distributed at national level (NUTS-2 regions). The questionnaire included questions on food purchasing, storage and management habits, and 364 valid responses were collected.

(iv)Statistical analysis of responses – identification of behavioral patterns: The data obtained were analyzed both univariately (frequencies, means, distributions) and multivariately, by applying the Hierarchical Cluster Analysis (HCA) method. This analysis allowed the identification of distinct behavioral patterns depending on the attitudes, habits and perceptions of consumers regarding food waste.

(v)Predictive Modeling – Neural Networks and Decision Trees: Based on the collected data, an artificial neural network (ANN) model was built in Python using the tensorflow and sklearn libraries. The model was trained on 80% of the data and tested on the remaining 20%, aiming to predict the perceived food waste category (FWP), based on 34 input

variables. The model performance was evaluated by accuracy, precision, recall, F1 score and loss function. In parallel, a second predictive model was developed, based on the CART (Classification and Regression Tree) algorithm, implemented in the Orange software. This model offers superior interpretability and was evaluated by the same indicators as NNA, complemented by ROC–AUC and the MCC coefficient for evaluating binary classification and sensitivity to unbalanced data.

The summary of the stages is shown in Table 1.

Table 1. The summary of the stages

No.	Stage	Objective	Methods	Tools	Result (Data/Model)	Stage in Agrifood Chain
1	Identification of FLW factors (literature review)	To define the main factors influencing FLW	Bibliographic study, term mapping	Dimensions.ai, VOSviewer	Taxonomy of factors (behavioral, economic, etc.)	Entire agrifood chain
2	Statistical analysis of indicators	To determine the relationships between factors and food waste quantities	Pearson correlation, t-test	Eurostat, FAO, INS Tempo Online	Statistically significant relations between variables	Entire agrifood chain
3	Formal modeling	To model the dynamics of FLW processes and flows	Formal modeling, simulation	CPN Tools, CPN IDE	Petri Net model with food states and transitions	Entire agrifood chain
4	Behavioral study (ReWaFaQuestionnaire)	To collect data on consumer food waste behavior	Online questionnaire, convenience sampling	Google Forms	364 structured responses	Consumption component
5	Statistical analysis of survey responses	To identify behavioral patterns related to FLW	Univariate & multivariate analysis (HCA)	Orange 3.37.0 / Excel	Behavioral clusters (consumer profiles)	Consumption component
6	Predictive modeling – Neural Network (NNA)	To predict food waste behavior	Machine Learning – Neural Network	Python (Tensorflow, Sklearn)	Predictive model (numerical or categorical outputs)	Consumption component
7	Predictive modeling – decision tree (DTA)	To classify food waste behavior	Machine Learning – CART algorithm	Orange 3.37.0	Decision tree model with classification outputs	Consumption component

Source: Authors' conception.

The research was structured in several complementary methodological stages, carried out chronologically. It began with a bibliographic analysis to identify factors influencing food losses and waste (FLW), followed by a statistical analysis of relevant indicators. Then, a formal model of the agri-food chain was developed using Petri nets to capture the dynamics of losses by stage. Consumer behavior was investigated through an online questionnaire, and the responses were statistically analyzed and grouped into behavioral patterns. Based on this data, two predictive models — a neural network and a decision tree — were built to identify waste trends at the consumption level. All these stages were supported by rigorous data processing and integration processes.

Data Management

A key component of the research was the collection and processing of data across the agrifood chain, with emphasis on the consumer level. The data included: (1) historical statistics on food waste and economic trends, (2) results from a dedicated consumer behavior questionnaire, and (3) data generated through applied methods such as factor analysis, system dynamics diagrams, statistical correlations, Petri net modeling, and cluster analysis.

The questionnaire responses (highlighted in Table 2) served as the main dataset for building the prediction models. These were complemented by statistical and historical sources and analyzed using various modelingand analytical tools to uncover patterns and causal relationships in food waste behavior.

Table 2. The data configuration

Data Category	Data Source	Data Generation Method	Resultant Data	Resulted Data Form
Statistical data	Historical datasets	Direct observation and collection	Economic (e.g., GDP per capita), social and environmental indicators	Plots
Statistical data	*Questionnaire*	*Collection*	*FLW behavior indicators*	*Plots*
FLW factor determination	Literature review	Factorial analysis, correlation	Correlation data be-tween factors and FLW amount	Plot, factor diagram
Cause and effect	FLW factor determination	System Dynamic	Cause and effect influences	Cause and effect diagram
Structured data	Literature review, FLW factor determination	Petri nets, graph structures	Agrifood chain dynamic	Petri net
Clusters	Questionnaire	Hierarchical Cluster Analysis (HCA)	Consumer-related FW clusters	HCA dendrogram
Prediction data	Prediction models	NN and DT	Prediction and classification data	Plots, clusters

Source: Authors' conception.

The data used in the research were processed according to the source: historical statistical data were analyzed through correlations and interpolations; questionnaire responses were coded, normalized and divided into training/test sets for predictive models; and derived data (graphs, Petri nets, clusters) were structured and integrated into explanatory and predictive models. This processing allowed for both quantitative analysis and structural understanding of the FLW phenomenon.

RESULTS AND DISCUSSIONS

The following section presents the results obtained in the research on the phenomenon of food losses and waste (FLW), with a focus on consumer behavior. The results are structured according to the methodological steps followed, including bibliographic and statistical analysis, formal modeling of the agri-food chain, analysis of data obtained through the questionnaire, as well as the development and evaluation of predictive models. Each subsection provides a presentation of the data, models or patterns identified, accompanied by interpretations relevant to understanding and combating FLW, especially at the consumption stage.

Results of the bibliographic and statistical analysis

This section presents the conclusions drawn from the literature review and statistical correlations based on historical and economic data on food waste. The main relationships identified between socio-economic indicators and the amount of reported food waste are highlighted.

Following the identification and classification of factors influencing food losses and waste (FLW), five main categories of factors were outlined: behavioral, demographic, biological, public policy and economic. Behavioral factors include purchasing patterns, habits, attitudes,

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social norms and educational level, reflecting how individual choices influence waste. The factors are presented in Table 3.

Table 3. The factors that are identified as being influential in the FLW are combined with the food chain

No.	Category		Factor
1	Behavioural		Buying patterns
			Habits
			Attitudes
			Subject norms
			Educational background
2	Demographic		Age
			Number of members in household
			Region
3	Biological		Food perishability
			External biological agents (e.g., COVID-19 pandemic, food toxins, bacteria, viruses)
4	Policy		Social policies related to food waste
			Economic policies related to income
5	Economic	Producer	Productivity
			Management type
		Processing	Number of processing phases
			Quality standards
		Packaging	Package parameters
		Logistics	Logistic parameters
			Storage
		Distribution	Promotions
			Sales volume
			Low prices
		Consuming	GDP per capita
			Income

Source: Authors' conception.

To highlight the causal relationships between the identified factors and the phenomenon of food loss and waste, a cause-and-effect diagram was created using the System Dynamics methodology. This diagram allows for the visualization of interdependencies between variables such as consumer behaviors, public policies, economic conditions, and food product characteristics. The diagram can be seen in Figure 1.

The loop structure highlights both the amplifying loops (e.g. the effect of purchasing habits on the amount of waste) and the regulating ones (e.g. the impact of education or policies on FLW reduction), providing an integrated perspective on the dynamics of the phenomenon.

Fig, 1. The cause–effect diagram of the model built using system dynamics
Source: Authors' conception using Vensim PLE tool.

Formal model results

The formal model of the agri-food chain using Petri nets is presented, highlighting the system states, transitions and flows of food resources, including waste generation and recycling. Observations obtained from the model simulation and interpretation of the system dynamics are included. The resulted Petri net is shown in Figure 2.

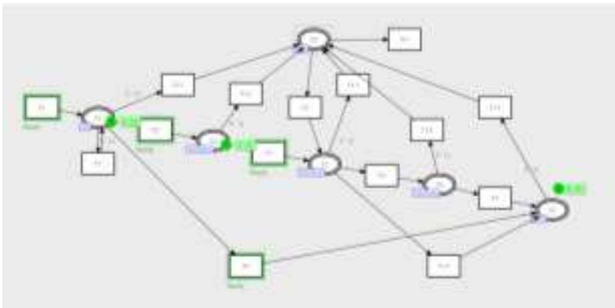

Fig. 2. The model built using Petri nets and graphs
Source: Authors' conception using CPN IDE tool.

The primary goal of the research using Petri nets was to explore the waste cycle within the agri-food chain, with a particular focus on food losses and food waste, in order to identify the most effective strategies for managing waste in the agri-food industry. In the model, the components of the agri-food chain – such as farmers – are represented as states, while the transitions between these states are modeled as processes. Arcs illustrate the links between states and the transformations that occur. For example, transition T1 is connected to state S1, representing the generation of raw materials through agricultural processes. In this case, the food's status within the system is labeled as "Farm Raw Material."

Behavioral study results

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This subsection summarizes the data obtained from the consumer questionnaire, focusing on the socio-demographic characteristics of the respondents and their food purchasing, storage and waste behaviors. The data collected through the questionnaire are structured into three main sections: demographic information (age, gender, education, income), food purchasing habits (percentage of income, places of purchase) and perceptions of food waste (quantity, types of products wasted). Figure 3 presents the demographical data.

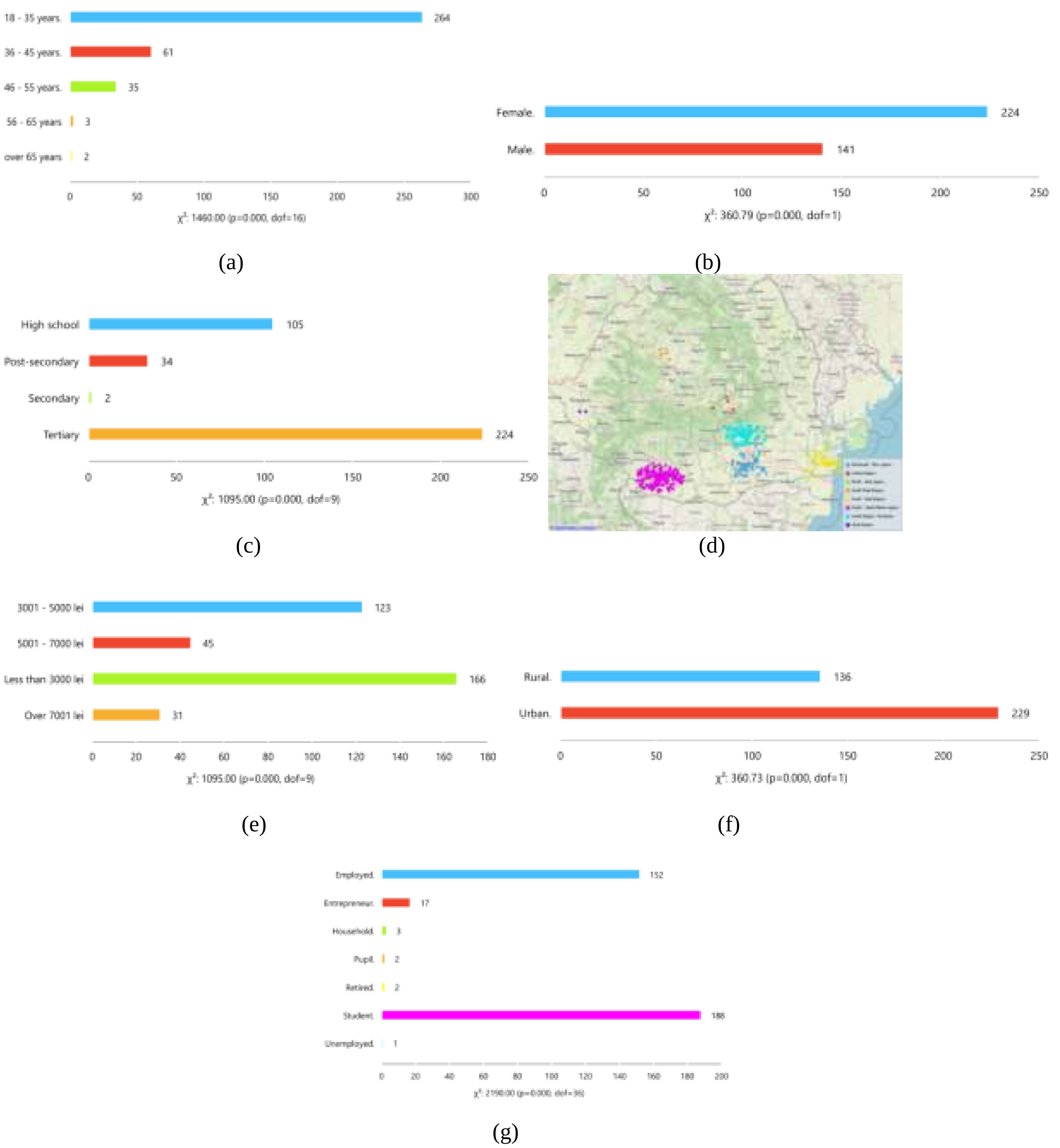
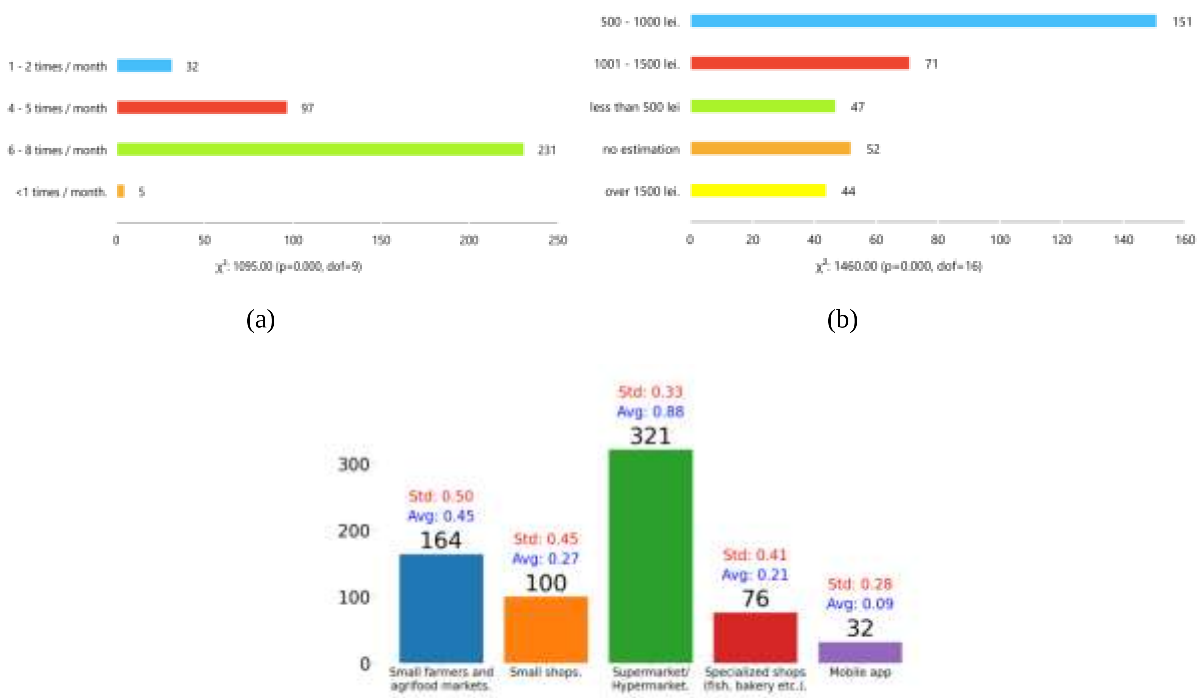


Fig. 3. The presentation of the demographic characteristics of the sample group: (a) age; (b) gender; (c) formal education level; (d) NUTS-2 geographical distribution; (e) monthly income; (f) residence; (g) socio-economic category
Source: Authors' conception from the consumer questionnaire

Demographic data reveals that the majority of respondents fall within the 18–35 age range (approximately 73%), indicating strong interest in the topic among younger individuals. Additionally, over 60% of participants are women, and the overall education level is high, with a significant proportion holding higher education degrees (ISCED levels 5–8). This suggests a well-informed audience with a solid understanding of food waste issues. Geographically, the majority of respondents come from the South-West region of Romania, which reflects a relatively unbalanced regional distribution. Approximately half of the respondents declare monthly incomes below 3,000 lei, which could influence a more cautious attitude towards waste. The majority of respondents come from urban areas and belong to the blue-collar socio-economic category.

Figure 4 presents the indicators related to food behavior.



(a) (b)

(c)

Fig. 4. The presentation of the food behavior indicators of the sample group: (a) frequency of food purchasing; (b) amount of money spent on food; (c) places chosen for food purchasing.
Source: Authors' conception from the consumer questionnaire.

Purchasing behavior was analyzed by frequency of purchases, monthly spending amount and preferred places for shopping. Most respondents buy food 1–2 times a week (6–8 times a month), spending between 500–1,000 lei per month (approx. 100–200 euro). In terms of purchasing sources, the most common are supermarkets/hypermarkets, followed by direct purchases from small agricultural producers.

Regarding food waste, respondents generally exhibit a responsible attitude, though they acknowledge certain limitations, particularly in managing their time effectively. Most estimate that they waste up to 10% of the total food they purchase. The most commonly discarded items include cooked meals, meat, and dairy products. The main perceived causes of waste are the large quantities of food purchased or cooked and their perishable nature. Food waste is rarely thrown away – it is more often reused, offered as animal feed or preserved. Most respondents also report checking expiration dates regularly; however, selective recycling is rarely practiced.

Common measures taken to reduce food waste include using a shopping list and prioritizing the purchase of local products.

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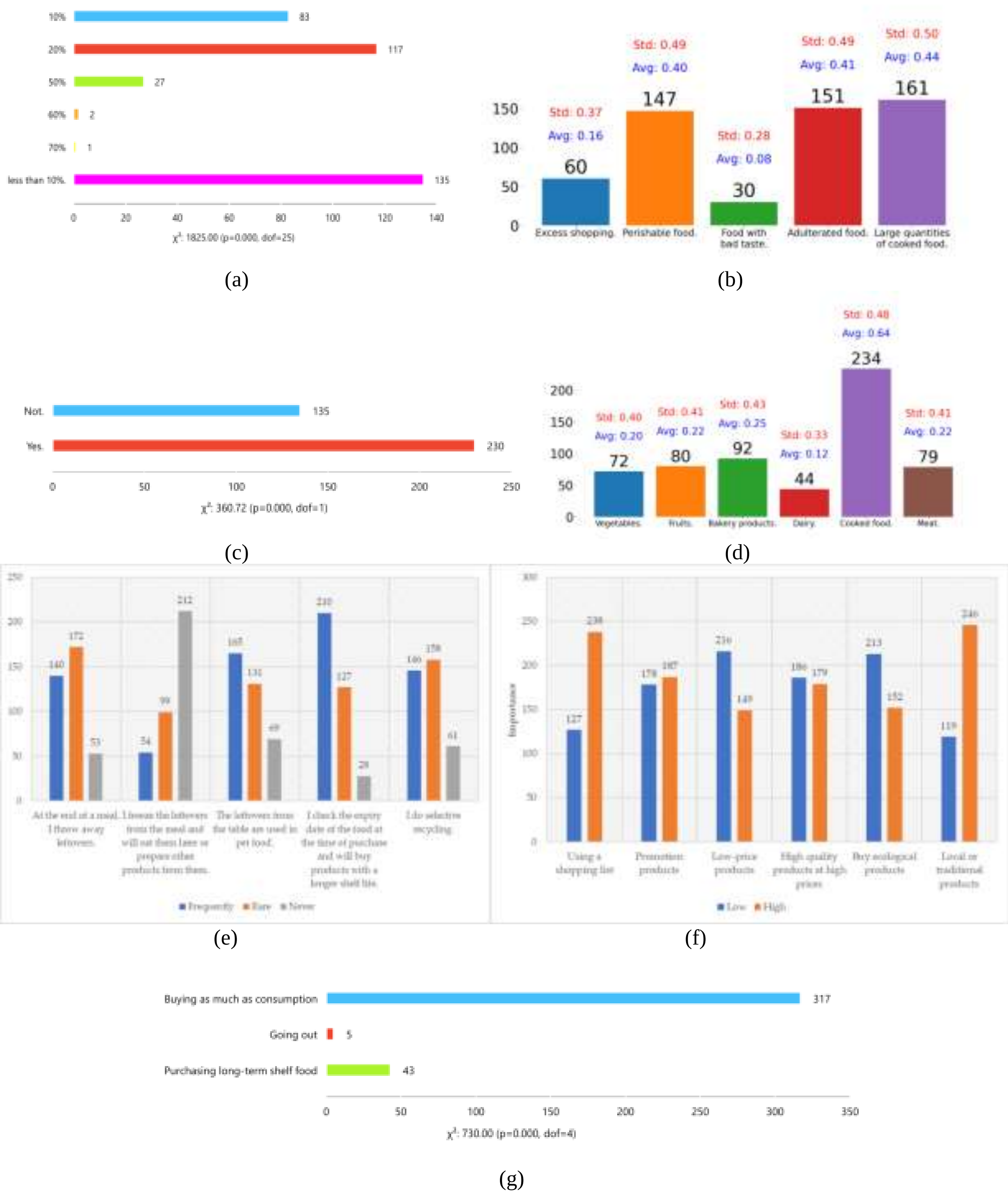


Fig. 5. The presentation of the food waste behavior indicators within the sample group: (a) main perceived causes of food waste; (b) perceived proportion of food wasted relative to total food purchased; (c) proportion of respondents who report discarding unconsumed food; (d) categories of food most frequently wasted; (e) responses to statements related to food waste attitudes and behaviors; (f) factors considered by respondents during the food purchasing process; (g) measures identified by respondents to reduce food waste.
Source: Authors' conception from the consumer questionnaire.

Results of multivariate analysis

Based on the collected data, multivariate classification methods were applied to identify behavioral patterns regarding food waste. The obtained clusters, associated behavioral profiles and relevant interpretations are presented. A dendrogram was resulted, but the image is too wide to be presented here. Thus, the clusters are shown in Table 4.

Table 4. The main clusters resulted in the multivariate analysis

Cluster	No. of respondents	Purchase frequency	Perceived food waste	Leftover management	Recycling	Main cause of waste
C1	22	Frequent	Low	Reused (mainly for pets)	Selective	Spoilage after cooking
C2	77	Frequent	10–20%	Partially preserved	Unpredictable	Perishability, excess food
C3	129	Frequent	~20%	Rarely preserved	Moderate	Excess cooked food
C4	51	4–8 times/month	<10%	Rarely preserved	Unpredictable	Spoilage of cooked food
C5	85	Frequent	10–20%	Occasionally reused (pets)	Slightly positive	Perishability

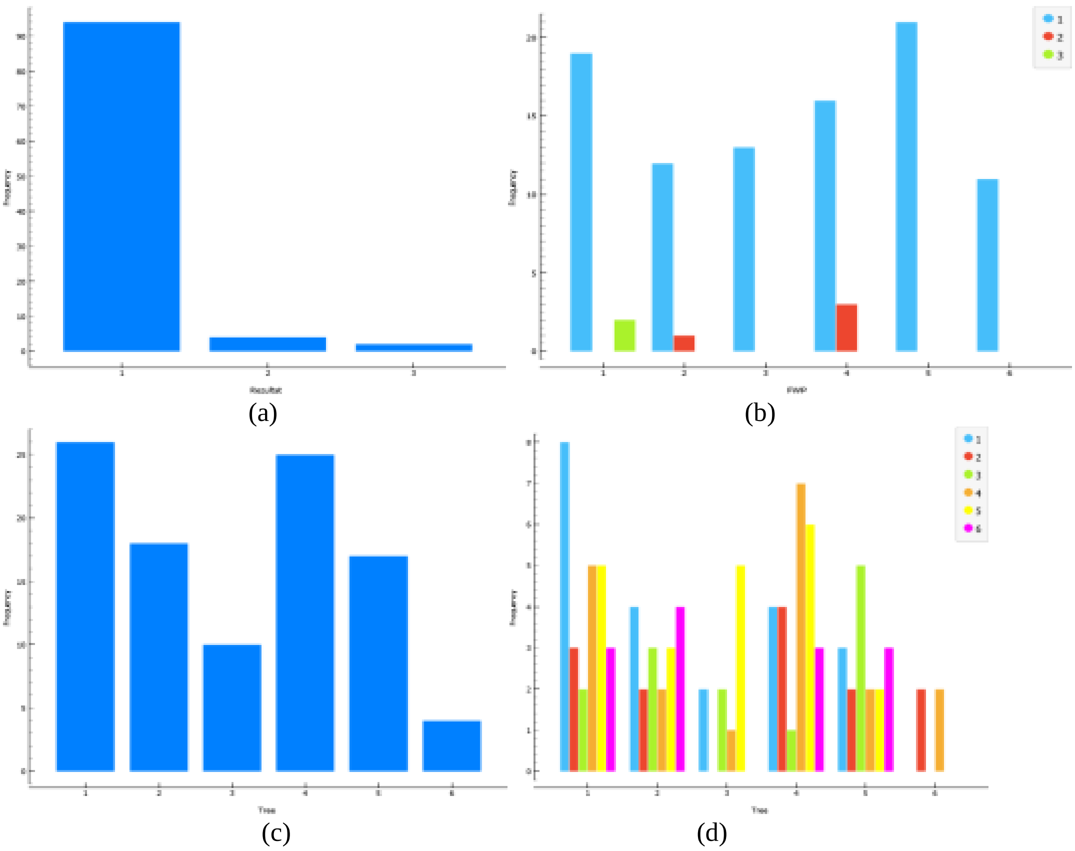
Source: Authors' conception from the consumer questionnaire data using Orange Data Mining tool

The cluster analysis revealed five behavioral patterns regarding food waste.

All clusters share the increased frequency of purchases and the preference for products with a long shelf life, but differ in the perceived level of waste (below 10% to 20%), the way in which waste is managed (from frequent reuse to neglect), recycling (selective or unpredictable), and the main causes of waste (perishability or excess cooked food). These results helped identify key variables for the predictive models and confirmed two of the initial hypotheses of the study.

Results of predictive models

The performance of the two built predictive models: neural network (NNA) and decision tree (DTA) is presented. Details on accuracy, classification scores, confusion matrix and other performance indicators are included. The differences between the two approaches are also discussed.



(a) (b) (c) (d)

Fig. 6. The composition of the classes associated with the new dataset for the Neural Network (NN) approach: (a) the distribution of the predicted classes; (b) the comparison between the predicted classes and the actual (randomly generated) classes.

The composition of the classes associated with the new dataset for the Decision Tree (DT) approach: (c) the distribution of the predicted classes; (d) the comparison between the predicted classes and the actual (randomly generated) classes.

The six classes correspond to the six possible responses to the question, “The perceived percent of food thrown away monthly”, which was treated as the dependent variable and encoded on a scale from 1 to 6. The visualized data illustrate the distribution of these classes as predicted by the model.

The first graphic shows the general distribution of the predicted classes, while the second graphic shows a grouped distribution of predicted classes as compared to the initial classes included in the dataset. The classes as determined from the questionnaire responses compared to the classification obtained after the appliance of the classification models for NN and DT are shown in Figure 6.

The neural network demonstrated superior performance, achieving an accuracy of 78% and a Matthews Correlation Coefficient (MCC) of 0.70, indicating a strong correlation between the predicted and actual values.

Confusion matrix analysis showed that the neural model correctly classified the majority of instances, demonstrating robustness and generalization capacity even in the presence of noise or outliers.

In contrast, the decision tree had an accuracy of only 31.5%, with a negative MCC (−0.028) and a ROC–AUC of 0.465, reflecting a performance close to random classification. The model faced overfitting problems and had difficulties in separating classes efficiently.

In addition to the technical aspects, the analysis of the models also highlighted a significant influence of socio-economic variables, especially demographic and economic ones, on the final results.

The 34 variables used contribute in combination to the accuracy of the predictions, and future research will aim to quantify the individual (univariate) influence of each variable to more clearly understand the role of each factor in generating food waste.

CONCLUSIONS

This research offered an integrated approach to the phenomenon of food loss and waste (FLW), combining quantitative methods, formal modeling tools, and predictive techniques to investigate its causes, behavioral patterns, and potential interventions, with a particular emphasis on the consumption stage.

In the first stage, the main factors influencing FLW were identified and classified, structured into behavioral, demographic, biological, political and economic categories, throughout the agri-food chain. Statistical analyses and formal modeling using Petri Nets highlighted the critical points of waste generation and allowed the simulation of food flows, providing a structural understanding of the phenomenon.

The data obtained through the questionnaire highlighted distinct patterns of food behavior, grouped into five clusters, reflecting purchasing habits, perception of waste, reuse of leftovers and recycling behaviors. These patterns were the basis for the development of two predictive models.

Comparing the performances of the neural network model with that of the decision tree showed a clear superiority of the former, with high accuracy (78%), robustness to noisy data and good correlation between predictions and actual values (MCC = 0.70). The decision tree, although easier to interpret, presented a poor performance, affected by overfitting and an inefficient separation of classes (accuracy 31.5%).

In conclusion, the integration of behavioral, socio-economic and structural data in a complex predictive approach represents a valuable tool for understanding and preventing food waste. In future research, it is necessary to deepen the individual influence of variables and extend the applicability of the models in different contexts for the formulation of efficient and personalized public policies.

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