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Towards the Investigation of Online Shopping Behaviours Using a Fuzzy Inference System

Anett Forgács[1], Judit Lukács[2], Ágnes Csiszárik-Kocsir[3*], Richárd Horváth[2]

[1] Doctoral School on Safety and Security Sciences, Óbuda University, Hungary
[2] Bánki Donát Faculty of Mechanical and Safety Engineering, Óbuda University, Hungary
[3] Keleti Károly Faculty of Business and Management, Óbuda University, Hungary

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ABSTRACT

Online shopping has experienced substantial growth over the past decade, and this trend is expected to persist. The convenience it offers consumers serves as a driving force behind this expansion. Online retailers stand to benefit from a comprehensive understanding of consumer behavior and online shopping habits, as it enables them to formulate more effective marketing strategies and tailor their communications to the preferences of online shoppers. This paper aimed to develop a bespoke questionnaire leveraging data from a EuroStat report in 2021. As novel methodology a Sugeno- type predictive fuzzy model was constructed using these data, empowering businesses to make more precise predictions regarding the requirements and behaviors of distinct consumer groups. The study examined the following areas of consumers: online shoppers belonging to the X, Y, and Z generations; living in small towns, towns, or in the capital; and studying, working, or both. In addition, the likelihood of spending money online was determined regarding the following product categories: Bills, utilities; (2) Food, shopping; (3) Entertainment; (4) Wellness, beauty; (5) Electronic items; (6) Fashion; (7) Home, decoration and (8) Other goods. The results of this survey, combined with the fuzzy model developed, serve as valuable resources for online retailers seeking to enhance their marketing strategies and gain a deeper understanding of customer preferences. The conclusions highlight patterns and preferences among different age groups and locations, providing valuable insights for online retailers to enhance their marketing strategies when identifying main target groups for specific products. Additionally, the research offers a more comprehensive understanding of demographic attributes associated with these age cohorts than EuroStat data.

1. Introduction

Online shopping has grown significantly over the past decade and will continue to grow with the increasing number of online shoppers and the availability of online commercial platforms worldwide. Online shopping habits can be diverse, depending on the products shoppers seek, how much they

* *Corresponding author:*
E-mail address: kocsir.agnes@uni.obuda.hu

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spend, or how they use online shopping tools [1]. Shoppers usually use the internet to search for products, compare prices and make purchases. Online shoppers generally find it convenient to shop online, as they do not have to leave their homes and can buy a wide range of products at their convenience. Online shoppers can also enjoy the benefits of shopping in online stores, such as online payment options, free delivery, and other benefits associated with online shopping [2].

A deeper understanding of consumer behavior and online shopping habits can offer many benefits to online retailers, who can better understand how consumers think and act. In addition, an overall comprehension of consumer behavior and online shopping habits will enable online retailers to implement more effective marketing strategies and communicate with online shoppers in a more targeted way [3].

As described in the previous section, the need to assess purchasing habits highlights that the same target group and size significantly influence the complexity of how companies operate. By their very nature, the decisions of the customers are difficult to predict using classical mathematical methods. They are mainly rooted in algorithmic difficulties, lack of information, uncertainty, and vagueness. Biologically inspired techniques have been introduced to resolve these contradictions. The most used solutions are fuzzy systems, artificial neural networks, and genetic algorithms. In the case of fuzzy inference, the main idea is to describe how humans think and make decisions by extending bivalent logic to multivalued logic using transients [4], Ponsard examined consumer behavior in 1979 and rejected the usual assumptions of the classical theory of consumer behavior that consumers can distinguish perfectly between different goods [5]. Several studies have investigated consumer behavior using soft computing methods; Lo and Zakaria [6] classified electricity consumers according to their energy consumption, while Meier *et al.,* [7] used fuzzy logic to map customer loyalty. Sun and Collins [8] used the traditional approach of the Means-End Chain (MEC) to examine the consumption values of consumers for a given product category. In a business context, Tettamanzi *et al.,* [9] described predictive modeling of customer behavior through a case study in which predictive models were represented, such as fuzzy rule-based systems. Marketing-oriented businesses are mainly concerned with modeling consumer behavior to refine their visual information and help their market decision-making processes [10]. Research in this area has shown that a significant factor is security and trust experienced during the purchase process [11],[12] ensuring customer satisfaction [13], in voluntary tipping as payment for services [14]. Basha and Ameen [15] investigated consumer behavior from an international perspective using the fuzzy method by collecting data on consumer risk assessment. Consumers are becoming more demanding, and retailers need to develop and implement new ways of getting to know their customers to maintain their position even when a new player enters the market [16]. Fuzzy logic offers a different approach to describing economic and marketing phenomena. Replacing exact, crisp values with fuzzy sets has proven an effective solution for analyzing customer behavior [17]. Perceptions of the emergence of e-commerce and their attitudes toward websites significantly impact their online shopping intentions. Nilashi and Ibrahim [18] presented a model using TOPSIS and Fuzzy logic to detect the level of purchase intention against the factors influencing purchase intention on business-to-consumer (B2C) websites. More and Gochhait [19] showed that fuzzy concepts could be used to influence consumer perceptions and promote good consumer behavior. The emergence of online commerce platforms facilitates the collection of information on purchases, allowing the development of commerce systems based on the profiling of customers, thus making it possible to identify purchasing habits and preferences of the customers [20],[21]. The information thus obtained will further help both to conduct marketing activities and to define the pricing strategy [22]-[24]. To investigate customer loyalty, Cengiz Toklu [25] applied a multi-criteria decision-making approach consisting of the Fuzzy Analytic Network Process and the Fuzzy Decision Testing and Evaluation Laboratory Methods.

Consumers play a vital role in the life cycle of products, as the manufacturing process and product [26],**Error! Reference source not found.** design are strongly consumer-centric [28]-[31]. Understanding consumers and consumer choices is of paramount importance today [32],[32], in order to understand supply and demand side decisions [33],[34]. Recently, several studies have focused on the predictive potential of using fuzzy logic to generate predictions using marketing tools [35]-[38]. Fuzzy Tech is a unique software product that supports fuzzy modeling. It was used by Shahzad Ashraf *et al.,* **Error! Reference source not found.** to define the specificities of cosmetology services, marketing, and communication elements. Mandal *et al.,* [39] investigated a recommendation technique to understand the preferences of the customers through the Fuzzy market research system approach. Furthermore, Bozanic *et al.,* [40] presented fuzzy logic system for ranking challenges, risks and threats. Li [40] analyzed the decision-making power of the customers based on a Back Propagation neural network and a fuzzy mathematical model. The presented model for behavior prediction emphasizes rationality and irrationality equally and describes the integration of artificial neural networks and fuzzy mathematics [42]-[44]. Several studies show that physiological, social, personal, and economic aspects significantly influence the consumer behavior of women, categorizing their perceptions of purchase intentions, acceptance, and need for recognition [45]-[48].

This article focuses on an important area, online shopping. Online shopping habits were analyzed in detail in the EU based on the EuroStat database. Based on the EU database, a questionnaire was created. The main goal was to identify links not included in the Eurostat report and compare the results of our database with those of the EU survey. In addition, a new methodology, a fuzzy inference system, was introduced based on earned detailed data. That resulted in an effective novel marketing tool to predict the selected consumer needs (age group, products, etc.).

2. Database and Methods

2.1. Analysis of EuroStat data

The current study examines the data from a EuroStat report of 2021 on online shopping in the European Union regarding the relationships between product categories. Data analysis helps provide a more comprehensive and accurate understanding of EU online shopping patterns. Furthermore, comparing and identifying the links can be essential for understanding and developing the e-commerce market.

The EuroStat 2021 report covers online commerce in the Member States of the European Union. The report considers several aspects, such as product categories of online shopping, the number of shopping occasions, the value of shopping baskets, and the origin of products. Consumers are divided into specific age groups: 16-24 years, 25-54 years, and 55-74 years to ensure comparability. The report shows the product categories most frequently purchased online, with the average purchase frequency and the average value of shopping baskets for each type. It also shows the origin of online purchases, distinguishing between national and foreign sellers.

Based on the evaluation of these events, clothing, footwear, and accessories were the product categories with the highest online purchase rate in the European Union, with 68% of individuals buying such products online. On the other hand, the lowest online purchase rate was for music (CDs, vinyl records, etc.) purchased online by only 6% of individuals (Figure 1). In terms of the number of online purchases, most individuals had made between 1 and 5 online purchases in the previous three months. The highest proportion was in the 3-5 times category for all age groups (32% and 34%). The ratio of online purchases more than ten times was highest in the 25-54 age group and lowest in the 55-74 age group.

Regarding financial expenditure, most individuals spent less than €100 online shopping in the previous three months. The proportion of individuals in the "less than €50" category was highest in the 16-24 and 55-74 age groups (18% and 13% respectively).

On the other hand, the proportion of individuals spending €1,000 or more was highest in the 25-54 age group and lowest in the 16-24 age group. Looking at the origin of online purchases, most individuals in all age groups bought from a domestic seller. A smaller percentage bought from sellers in other EU countries, while an even smaller percentage bought from sellers outside the EU.

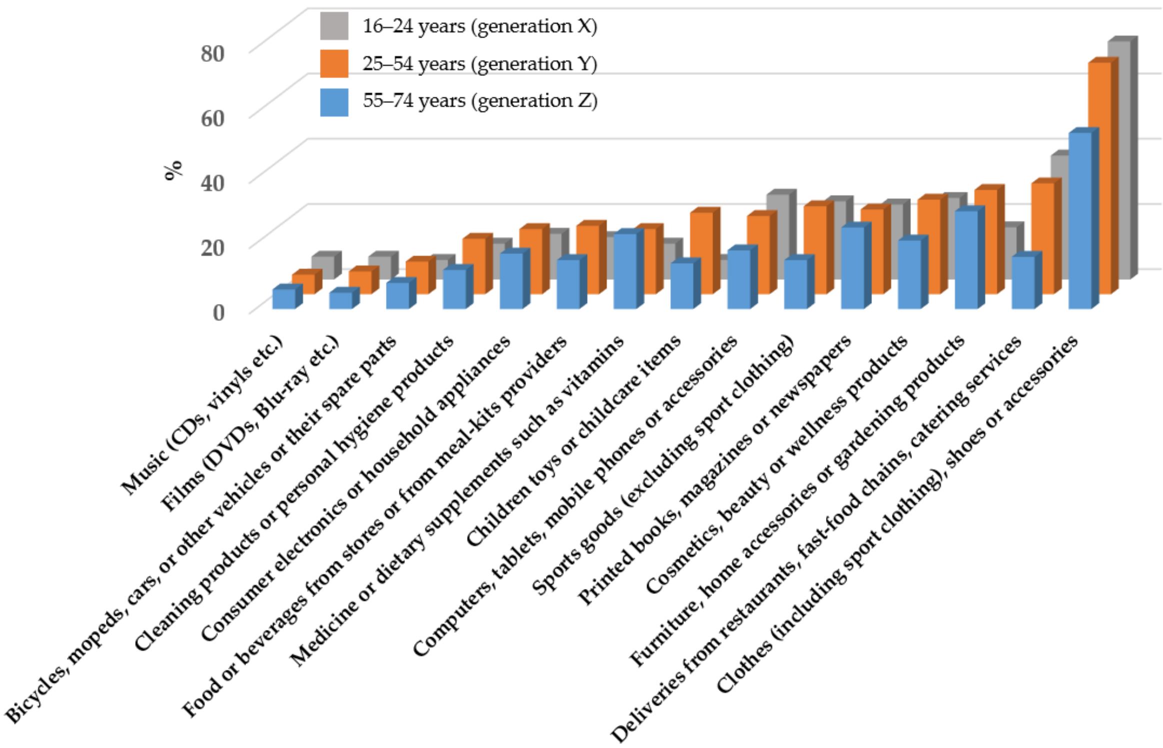


Fig 1. Distribution of online purchases of goods in percent (individuals, EU [49])

In total, it can be said that the EuroStat database introduced above provides a comprehensive overview including some further aspects. However, the results lack several connections which can be informative when investigating consumer needs.

2.2. Creating an individual questionnaire

To overcome the aforementioned shortcomings a comprehensive examination of product categories in the context of online shopping habits can yield substantial benefits for both consumers and businesses. Such analysis enables businesses to formulate precise marketing strategies, streamline inventory management and stocking procedures, enhance their understanding of consumer preferences, monitor competitive activities, and identify novel opportunities for product development. The primary objective of the current study was to conduct a thorough investigation into consumers' purchasing preferences. To achieve this, we conducted an in-depth analysis of consumers' demographic characteristics, such as age, place of residence, and employment status. Through our survey, comprehensive data were gathered on these demographic factors to acquire profound insights into the shopping habits and preferences of diverse consumer groups.

The data utilized in this study were based on the European Union Statistical Report on Online Shopping, providing foundational information. However, it is essential to note that the report needs to comprehensively analyze the intricate dynamics between consumers and their preferred product categories, thus limiting its ability to identify precise consumer groups. In order to address this limitation, our study aims to conduct a more detailed and focused analysis to gain deeper insights into the relationship between consumers and their preferences within specific product categories. The survey was administered to consumers currently enrolled in higher education institutions in Hungary, and the number of recorded responses exceeded 700. By targeting this specific group of consumers, the study aimed to gather valuable insights into the preferences and behaviors of individuals pursuing higher education. In this case, the circumstances of the participants were examined. Some simple features were chosen for the analysis; Age, the status of Employment, and the place of Residence. Respondents were given three options to assess these conditions (Table 1). Participants in the study were able to express their preferences for online shopping across different categories of goods: Bills, utilities; Food, shopping; Entertainment; Wellness, beauty; Electronic items; Fashion; Home, decoration; and Other goods.

Table 1
Levels of the independent input variables

Levels	Age	Employment	Residence
1	X generation (1965-1979)	Student	Small town
2	Y generation (1980-1994)	Both	Town
3	Z generation (1995-2007)	Employee	Capital

Preferences were indicated by marking preferred types with "1" and non-preferred with "0" during the evaluation process. The collected data were aggregated for evaluation, and the average of the provided responses was calculated. These values were used to measure the inclination of the participants. Table 2. illustrates the various combinations of circumstances alongside the corresponding degrees of preference for specific product categories.

Table 2
Results of the questionnaire

No.	Age	Employment	Residence	Bills, utilities	Food, shopping	Entertainment	Wellness, beauty	Electronic items	Fashion	Home, decoration	Other
1.	1	1	2	0.000	0.000	0.000	1.000	0.000	0.000	0.000	0.000
2.	1	1	3	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
3.	1	2	1	0.500	0.000	0.000	0.500	0.000	0.000	0.000	0.500
4.	1	2	2	0.500	0.000	0.500	0.000	0.500	0.500	0.000	0.500
5.	1	2	3	0.800	0.400	0.800	0.600	0.400	0.600	0.400	0.400
6.	1	3	1	0.688	0.625	0.688	0.313	0.625	0.500	0.438	0.625
7.	1	3	2	0.735	0.353	0.559	0.471	0.500	0.441	0.412	0.412
8.	1	3	3	0.778	0.528	0.639	0.500	0.556	0.500	0.278	0.528
9.	2	1	1	1.000	0.000	0.000	0.000	0.500	0.500	0.000	0.000
10.	2	1	2	0.667	0.667	0.667	1.000	0.333	0.667	1.000	1.000
11.	2	1	3	1.000	1.000	1.000	1.000	0.667	0.667	0.667	0.667
12.	2	2	1	0.600	0.600	0.400	0.200	0.600	0.600	0.200	0.400
13.	2	2	2	0.714	0.714	0.429	0.714	0.714	0.714	0.429	0.714
14.	2	2	3	0.846	1.000	1.000	0.846	0.846	0.769	0.692	0.769
15.	2	3	1	0.842	0.474	0.632	0.474	0.526	0.474	0.316	0.579

No.	Age	Employment	Residence	Bills, utilities	Food, shopping	Entertainment	Wellness, beauty	Electronic items	Fashion	Home, decoration	Other
16.	2	3	2	0.707	0.537	0.610	0.634	0.561	0.659	0.439	0.512
17.	2	3	3	0.778	0.556	0.667	0.481	0.685	0.537	0.389	0.537
18.	3	1	1	0.224	0.408	0.461	0.566	0.605	0.645	0.250	0.566
19.	3	1	2	0.364	0.591	0.614	0.500	0.614	0.614	0.386	0.545
20.	3	1	3	0.411	0.664	0.738	0.682	0.766	0.748	0.336	0.701
21.	3	2	1	0.391	0.609	0.696	0.457	0.478	0.630	0.370	0.587
22.	3	2	2	0.553	0.426	0.745	0.617	0.745	0.362	0.191	0.617
23.	3	2	3	0.613	0.713	0.775	0.700	0.688	0.700	0.413	0.538
24.	3	3	1	0.556	0.722	0.722	0.444	0.500	0.500	0.444	0.611
25.	3	3	2	0.739	0.696	0.609	0.565	0.652	0.696	0.522	0.783
26.	3	3	3	0.600	0.660	0.680	0.700	0.700	0.620	0.440	0.680

2.3. Database and methods

In order to increase competitiveness in many areas of business processes, such as production management, strategic decision-making, or targeting, it is proposed to use methods beyond classical and conservative forecasting systems. Predictive models are an essential tool for decision-making, allowing predictions to be made about future events and trends. These models use statistical and machine learning techniques to predict the probability of future events or expected values. Predictive diagnostic systems built from data allow decision-makers to plan and react effectively to upcoming incidents and risks. Predictive models can be applied in various fields, including economics, finance, marketing, social sciences, and health [50],[51]. One of the most commonly used empirical models is linear regression, which uses a linear relationship between data to make predictions. However, machine learning-based phenomenological models, such as decision trees, clustering, and neural networks, can also be very effective in predictive modeling [52]. Cluster analysis is a statistical method that allows the grouping of data points with similar characteristics. This method is a valuable tool to gain a deeper understanding of consumer groups and identify patterns. For example, cluster analysis can identify similar consumer groups in their purchasing habits, motivations, and preferences. That technique makes it possible to segment a given market and develop strategies tailored to different groups [53]. Using the aggregation function to perform the proactive assessment, PRISM is ideal for complex risk analysis and forecasting [54].

However, building predictive models is only sometimes straightforward, and there are many factors to consider, such as the data quality, the validity of the model, and the evaluation of its performance. Therefore, when using predictive models, it is essential to interpret the results correctly and ensure that the model works well in the application domain [55]. The fuzzy set theory was introduced by Zadeh [56]. The main goal was to provide new methods for describing and solving problems that could not be defined or solved efficiently within the framework of classical set theory. The fuzzy set theory applies fuzzy boundaries to sets and partially defines membership degree and truth content to reflect how people think. Since then, the concept of fuzzy set theory has been further developed, and the fuzzy rule-based systems created have been widely applied in many fields of science [57]-[59]. These systems enable efficient and flexible decision-making, uncertainty management, and modeling of nonlinear behavior. Fuzzy set theory contributes to understanding and solving complex problems and significantly impacts scientific research and applications. The basic structure of a fuzzy inference system (FIS) consists of four initial parts (Figure 2). The fuzzifier is used to determine membership functions for each variable – input and output parameters – uniquely focusing on the described intervals. Since people are likely to use words and qualitative expressions when describing situations connected to complex systems [60], in this part, special linguistic variables can also be used, not only numerical values. In this part, data are transformed into membership functions.

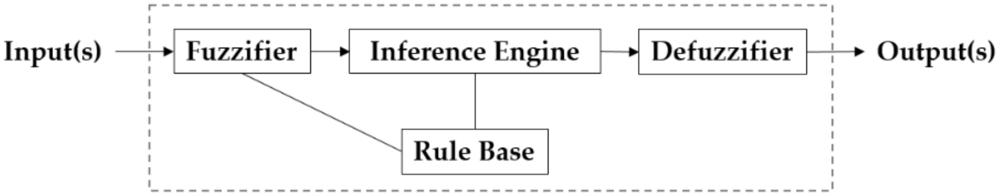


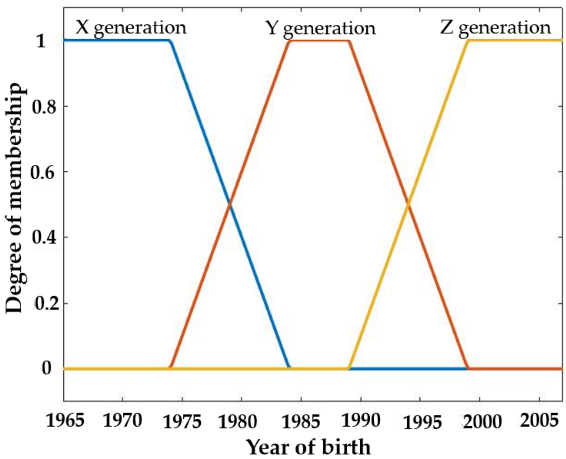
Fig. 2. General structure of a FIS (based on [5])

The rule base contains the connection among input and output variables in the following form: IF … THEN … (ELSE …). The first part contains the conditions from the input side, and the second is the consequence(s) (output). The inference engine is the central part of the system. In this section, the rules are activated, and the strength of the antecedents is determined and forwarded to the output sets. The most commonly used inferences are the Mamdani [61],[62] and the Sugeno-types [63]. In general, defuzzification is the final step of the inference, which is a technique to convert fuzzy output into crisp values. Different methods can be used for that purpose. However, Sugeno-type inference does not need an exact defuzzification [64],[65].

2.4. Adaptation

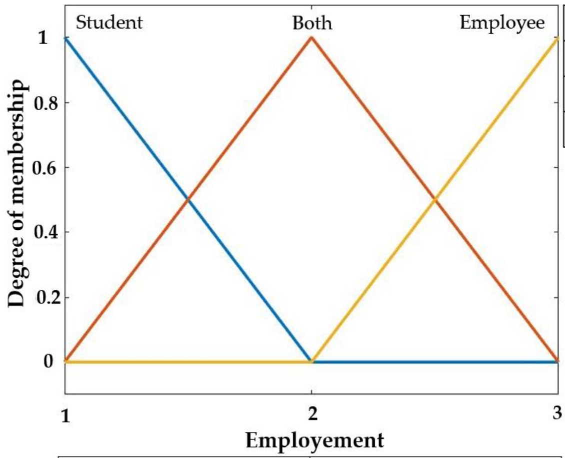
In this paper, a Sugeno FIS is created to estimate the likelihood of buying several items based on simple parameters. A Sugeno-type multi-input system was introduced based on the results of the questionnaire. As independent variables, qualitative (QL) and quantitative parameters (QN) were chosen: Age (QN), state of Employment (QL), and place of Residence (QL). These variables were varied in three levels (Table 1). The partition of the input variables is shown in Figure 3. In this FIS, trapezoid and triangular-shaped membership functions were used.

(**a**)



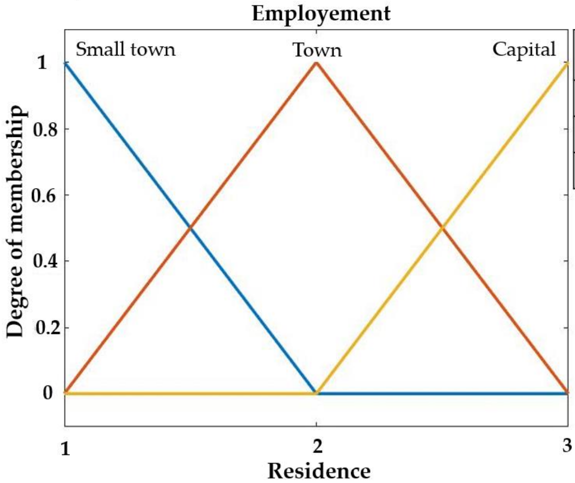
Level	Parameters
X generation	[1950, 1963, 1975, 1985]
Y generation	[1975, 1985, 1990, 2000]
Z generation	[1990, 2000, 2015, 2023]

(**b**)



Level	Parameters
Student	[1, 1, 2]
Both	[1, 2, 3]
Employee	[2, 3, 3]

(**c**)



Level	Parameters
Small town	[1, 1, 2]
Town	[1, 2, 3]
Capital	[2, 3, 3]

Fig. 3. Membership functions for the independent input variables: (a) Age, (b) Employment, (c) Residence

The output of the system was the likelihood of shopping the different categories of goods and services: (1) Bills, utilities; (2) Food, shopping; (3) Entertainment; (4) Wellness, beauty; (5) Electronic items; (6) Fashion; (7) Home, decoration and (8) Other goods. The range of the output values was 0…1 with an equivalent spacing of 0.05. For training the algorithm, average data were used from Table 2. In addition, the output levels were determined by using the Table 2 which describe the likelihood of the choice of the consumers. In this case, average data were turned into tuning parameters.

In total, 26 rules were used to combine independent input and output variables. Table 2. contains the levels of the input and the output variables as well that belong together in the rule base.

3. Results

The generated Sugeno-type fuzzy inference system was evaluated for each output category in a graphical way. It can be said that the effect of three different independent variables can not be represented in a 3D plot. Therefore, Employment, as a quantitative parameter, was fixed. As a result, each level was analyzed separately. To have a better chance of finding patterns, 3D plots were turned into top-view diagrams. In these cases, the color was connected to the likelihood: yellow meant higher, and blue meant lower value. The most exciting patterns found are detailed below.

Regarding Bills and utilities, it can be said that the highest likelihood and the output range increase with higher levels of Employment. In addition, the mean value is also being. Figure 4 shows that students born in 1980-1990 and living in small towns or in the capital are more likely to pay for their bills online (Figure 4 (a)). However, employees produce a lower probability. In addition, those who study and work as well tend to spend money online for bills when living in the capital. Nevertheless, the working population, mainly middle-aged living in small towns, can be considered a target group.

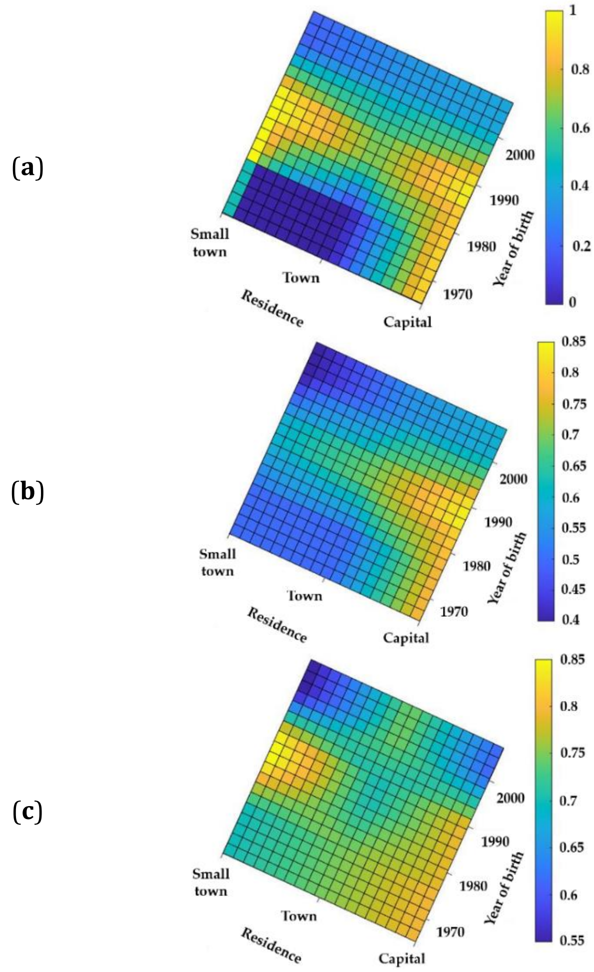


Fig. 4. Likelihood for Bills, utilities: (a) Students, (b) Students and employees, (c) Employees

In the case of the Food, students living in the capital are more likely to order online. The most promising age is the middle of Generation Y or under (Figure 5 (a)). Turning to people who study while working, it is proposed to focus on those who were born in the late 1980s and early 1990s. In addition, the tendency is slightly extended to towns as well (Figure 5 (b)). In contrast, Figure 5 (c) shows that employees prefer ordering food online only in the case of the younger generation, regardless of the place of residence. Furthermore, Generation X, living in small towns or towns, can reach the weakest chance for students and student-workers. For workers, this area is significantly smaller and unambiguously shifted to towns.

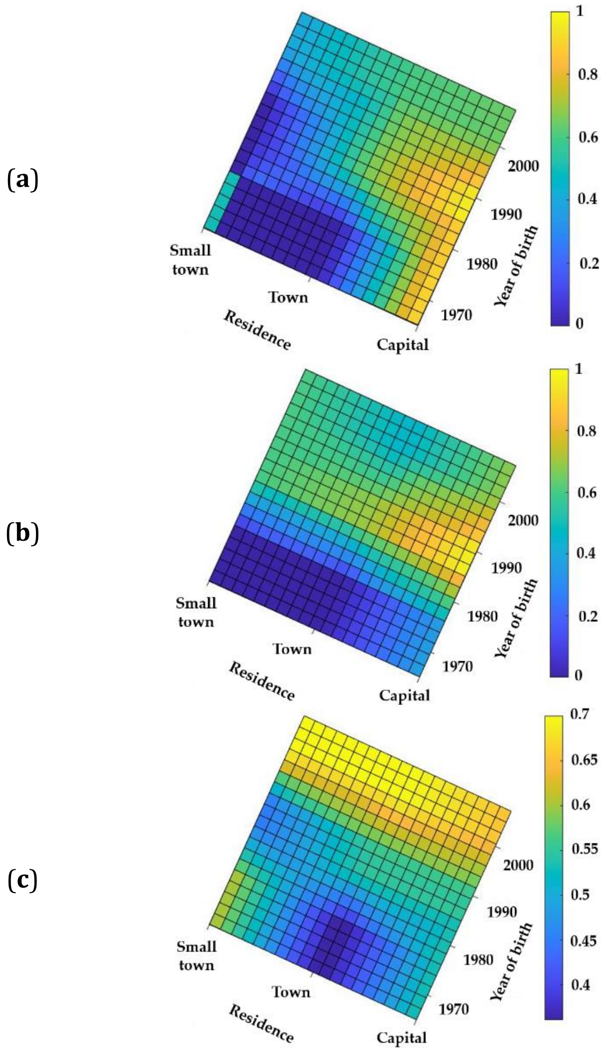


Fig. 5. Likelihood for Food, shopping: (a) Students, (b) Students and employees, (c) Employees

In terms of entertainment, it was found that the highest willingness to invest among students is found in the capital city population, specifically in Generation Y (Figure 6 (a)). Students and workers are shown in Figure 6 (b). A similar pattern can be observed, complemented by a significant upward trend in the likelihood of online shopping for Generation Z at all locations. Finally, for the working population, the maximum value of the purchase probability decreases (≈0.7) and shifts towards the edges of the range under study: small town Generation X, small town and capital Generation Z (Figure 6 (c)). For the minimum area, a similar shift in the areas as for Food can be identified, as well as an increase in the minimum value.

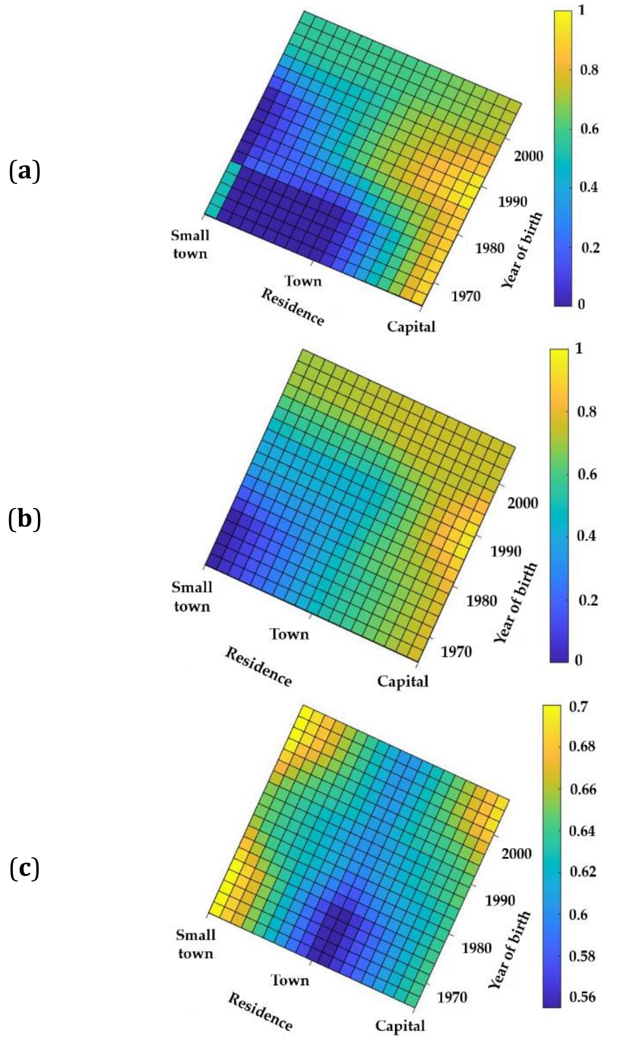


Fig. 6. Likelihood for Entertainment: (a) Students, (b) Students and employees, (c) Employees

For a relatively narrow range of students, it can be considered the intention to purchase Electronic items to be clearly positive for Generation X in the capital. However, there is also a significant transitional band (marked with green in Figure 7 (a)) for those born after 1990, where the probability of purchasing is around 0.6 or above. For participants studying and working simultaneously, the most favorable outcome for selling electronics is for those born after 1980 in the towns and cities. The core of this is for those born in the capital between 1985 and 1990. Finally, the maximum achievable probability for workers drops to near 0.7, but the minimum value remains at least 0.5. Generation Z metropolitan residents provide the best probability.

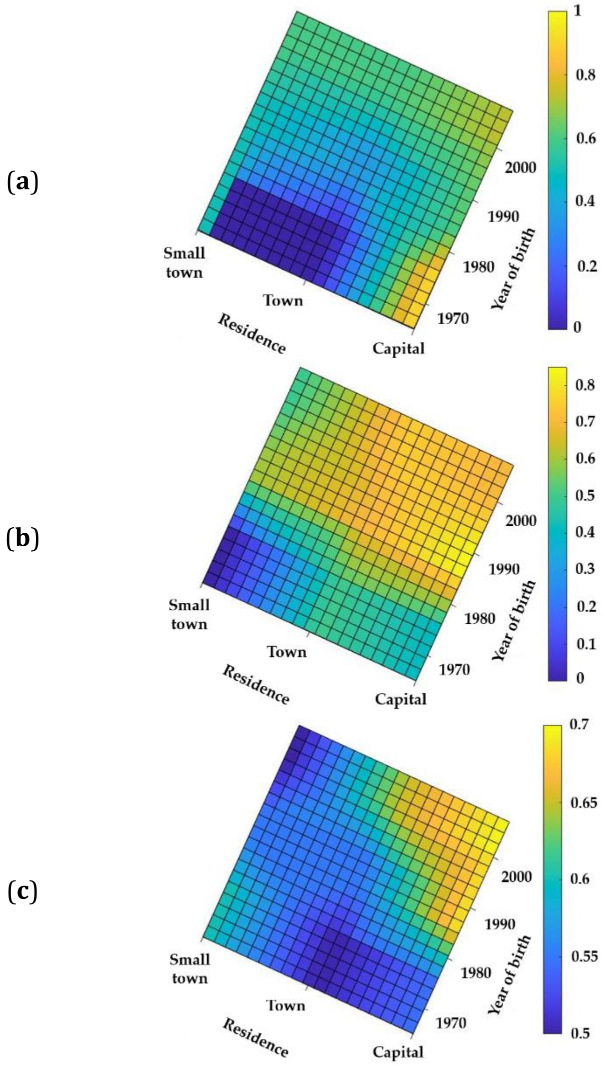


Fig. 7. Likelihood for Electronic items: (a) Students, (b) Students and employees, (c) Employees

The highest likelihood of purchasing Home and decoration items among students is for town-habitant Generation Y and capital-living Generation X participants (Figure 8 (a)). The core is observed in the first group. For student-workers, a shift of the core to the capital is noted, and a decrease in the maximum probability of shopping this product category (Figure 8 (b)). Figure 8 (c) shows that working people are not targeted sufficiently effectively by selling these products online. Although it is possible to define the highest likelihood of Generation Z as a maximum, it is limited to a value of around 0.5.

(**a**)

(**b**)

(**c**)

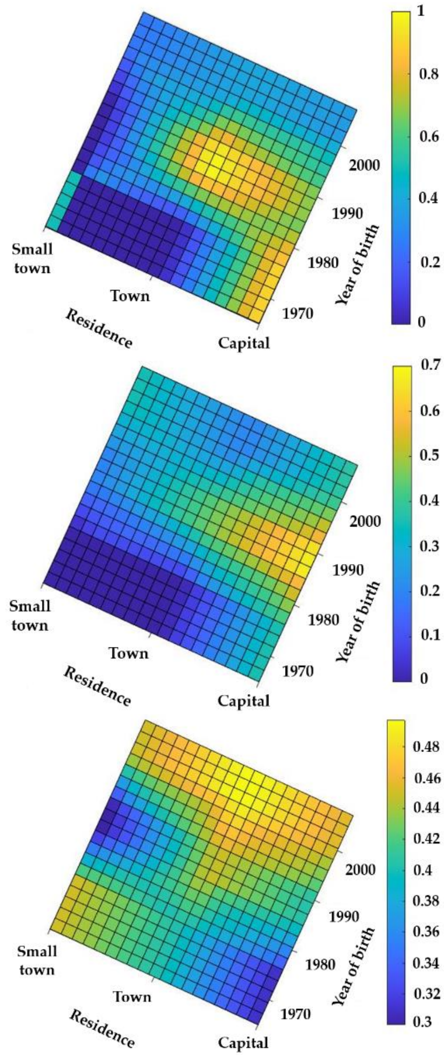
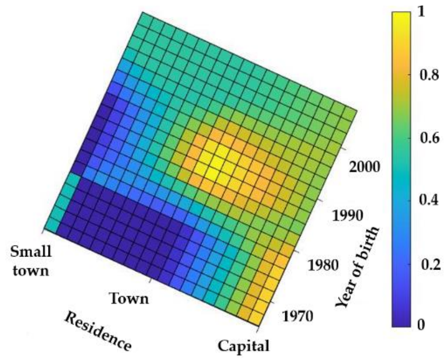


Fig. 8. Likelihood for Home decoration: (a) Students, (b) Students and employees, (c) Employees

The Other category provided very similar results to Home. Also, the town core of Generation Y students is apparent, with a shift towards the capital (Figure 9 (a) and 9 (b)). Based on Figure 9 (c), it is also noticeable for workers that the dominance of Generation Z is still present. However, unlike the previous category, products are sold effectively to young urban and metropolitan residents. In addition, the minimum likelihood of purchasing is significantly higher.

(**a**)



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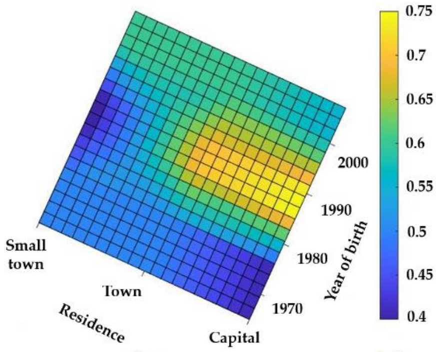

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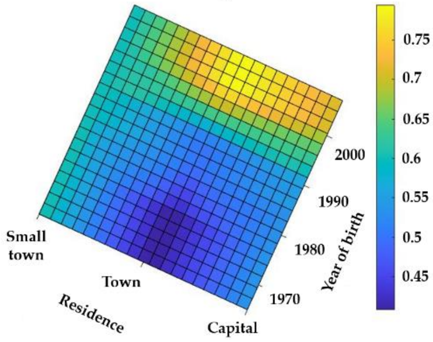

Fig 9. Likelihood for Other: (a) Students, (b) Students and employees, (c) Employees

4. Conclusion

This paper provides an in-depth analysis and evaluation of a survey conducted to investigate the consumption patterns of online shoppers. With the help of the collected data, a phenomenological model was developed to estimate these patterns. A Sugeno-type multi-input fuzzy inference system was created to predict the probability of online purchases across various product categories. Three distinct and simply determinable input parameters were chosen to accomplish the prediction process: demographic data (Age, status of Employment, and place of Residence). Additionally, eight output parameters were established representing different product categories, including Bills, utilities; Food, shopping; Entertainment; Wellness, beauty; Electronics; Fashion; Home, decoration; and Others.

The study delves extensively into the practical application of the fuzzy inference system as a valuable tool for market forecasting within the case study context. The data utilized for this case study was obtained through a questionnaire survey conducted by our research team, serving as a means to demonstrate and elucidate the application of the soft calculation method. The inference system introduced can be used to identify patterns, aiding online retailers in finding more precise target groups to enhance their marketing strategy and gain a deeper understanding of customer preferences. It was revealed that students born between 1980 and 1990, residing in either small towns or the capital, are more inclined to pay their bills online. In terms of Food and shopping, students residing in the capital city are more prone to online ordering, with the most promising age group being mid to lower Generation Y. Regarding Entertainment, it was observed that students in the capital city, particularly Generation Y, display the highest propensity to invest. Among participants simultaneously studying and working, those born after 1980 in urban areas demonstrate the most favorable results for electronic sales. The likelihood of purchasing a home and decorative items among students is highest for Generation Y participants living in cities and Generation X participants residing in metropolitan areas.

When comparing our findings with the results obtained from EuroStat, it can be said that the consumption habits of various age groups align with those of consumers in the European Union. Nevertheless, our analysis offers a more comprehensive understanding of the demographic attributes associated with these age cohorts. The following phase of the research involves studying, modelling and evaluating the behavior of businesses. This will enable a more comprehensive overview of business decisions from each side.

Author Contributions

Conceptualization, A.F., J.L. and R.H.; methodology, A.F., J.L. and R.H.; software, J.L.; validation, Á.Cs-K.; formal analysis, A.F., J.L. and R.H.; investigation, Á.Cs-K.; resources, A.F. and Á.Cs-K.; data curation, A.F. and Á.Cs-K.; writing—original draft preparation, A.F., J.L. and R.H.; writing—review and editing, A.F., J.L., R.H. and Á.Cs-K.; visualization, J.L, R.H.; supervision, Á.Cs-K.; All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement

In this section, please provide details regarding where data supporting reported results can be found, including links to publicly archived datasets analyzed or generated during the study. You might choose to exclude this statement if the study did not report any data.

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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