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Examining online purchasing patterns through the utilization of a fuzzy inference system.

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Abstract

The last decade has seen an explosion in online shopping, and this trend is set to continue. Understanding consumer behavior and shopping habits is vital for online retailers, so we conducted our survey based on the Eurostat 2021 report and then created a fuzzy predictive model to analyze the results. The results can help retailers develop more effective marketing strategies, focusing on differences between age groups and geographical areas. The research provides deeper insights into consumer preferences by covering a broad spectrum of demographic characteristics. Our case study details the application of fuzzy inference, highlighting the complexity of customer preferences and helping retailers position themselves more effectively in the online marketplace and provide personalized services.

Keywords: online shopping, EuroStat, Fuzzy inference system, marketing, target group selection

1. Introduction

Online shopping has surged in the last decade and continues to grow globally. Shopping habits vary based on product preferences and spending behaviors [1]. Consumers appreciate the convenience of browsing, comparing prices, and making purchases from the comfort of their homes. Online shoppers also enjoy perks like diverse product availability, online payment options, and free delivery [2]. Customer decisions, challenging to predict mathematically due to algorithmic complexities and uncertainty, are addressed through biologically inspired methods like fuzzy systems, neural networks, and genetic algorithms. Fuzzy inference extends bivalent logic to multivalued logic, resembling human decision-making [3]. Ponsard [4] refuted classical assumptions about consumers' perfect distinctions between goods. Studies like Lo and Zakaria's electricity consumer classification [5] and Meier et al.'s fuzzy logic for customer loyalty mapping employ soft computing methods to explore diverse aspects of consumer behavior [6].

Marketing-oriented businesses focus on modeling consumer behavior to improve their visual information and support market decision-making processes [7]. Consumers play a vital role in the life cycle of products, as product design and the manufacturing process are strongly consumer centric. Several studies have shown that consumer behavior is significantly influenced by physiological, social, personal, and economic factors. These factors influence purchase intention, acceptance, and perception of the need for recognition [8][9][10].

2. The database and method

2.1 Creating an individual questionnaire

Analyzing product categories in online shopping habits offers significant benefits for businesses and consumers, aiding in precise marketing, inventory management, and understanding preferences. The study's focus on consumers' purchasing preferences involved a thorough demographic analysis, extracting comprehensive insights into diverse consumer groups' shopping habits.

While the study utilized data from the EU Statistical Report on Online Shopping as a foundation, it acknowledges the need for a more detailed analysis to understand the intricate dynamics between consumers and their preferred product categories. The survey, targeting over 700 consumers in higher education institutions in Hungary, aimed to gather valuable insights into preferences and behaviors in this specific group.

The analysis focused on participants' circumstances, examining simple features like age, employment status, and residence. Respondents assessed these conditions and expressed preferences for online shopping in different categories. In this instance, we investigated the participants' situations by selecting straightforward criteria for analysis: Age, Employment status, and Residence. Respondents were provided with three options to evaluate these conditions (refer to Table 1). Additionally, they had the opportunity to express their preferences for online shopping across various product categories (refer to Table 2).

1. Table 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

2. Table outcomes variables

Bills, utilities	Food, shopping	Entertainment	Wellnes, beauty	Electronic items	Fashion	Home, decoration	Other

The study aims to address limitations in existing reports by providing a more detailed and focused analysis to gain deeper insights into the relationship between consumers and specific product categories.

2.2 Method

This paper analyzes data from the European Union's 2021 Online Shopping Report, focusing on the relationships between product categories. The data analysis contributes to a comprehensive and accurate understanding of online shopping habits in the EU. Furthermore, identifying the relationships can be essential for understanding and developing the e-commerce market.

Predictive models are essential for decision-making, as they allow for predicting future events and trends. These models use statistical and machine learning techniques to determine future events' probability or expected values. Data-driven predictive diagnostic systems help decision makers to plan and react effectively to upcoming events and risks. Predictive models have many applications, including economics, finance, marketing, social sciences, and health [11][12].

However, it can be challenging to create predictive models because many factors must be considered, such as data quality, model validity, and performance evaluation. Therefore, when using predictive models, it is paramount to interpret the results correctly and ensure that the model works correctly in the application domain [13].

Fuzzy set theory was introduced by Zadeh in 1965. Its main aim was to solve problems that could not be precisely defined or efficiently solved within the framework of classical set theory. Fuzzy set theory adopts a methodological approach that defines sets in a fuzzy way, is flexible in treating partial definitions of membership and truth content, and thus mimics human reasoning [14].

A fuzzy inference system (FIS), also known as a fuzzy inference system, comprises four primary components. The fuzzification unit's first component defines membership functions for each input and output variable, considering the specified ranges. Since human language often uses words and qualitative expressions to describe complex systems, this section can be used for numerical values and specific linguistic variables. The purpose of this step is to convert the data into membership functions.

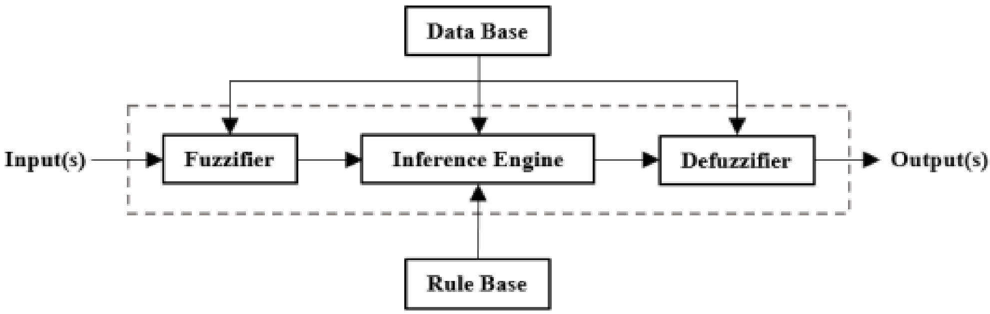

Figure 1: General structure of a FIS

The rule base establishes connections between input and output variables using IF... THEN... (ELSE...) statements. The first part outlines input conditions, while the second part specifies the consequences (output). The inference engine, crucial to the system, activates rules, assesses the strength of antecedents, and transmits this information to output sets. Commonly used inference types include Mamdani [15] and Sugeno [16]. Defuzzification, the final step, converts fuzzy output to precise values using various methods. Notably, Sugeno-type inference doesn't require exact defuzzification [17].

3. Conclusion

This manuscript conducts a thorough examination and assessment of a survey aimed at understanding the consumption behaviors of online shoppers. Utilizing a phenomenological model developed for this purpose, the study employs a Sugeno-type fuzzy inference system to predict the likelihood of online purchases across diverse product categories. The prediction process is facilitated by three easily measurable input parameters: demographic data (age, employment status, and residence). Moreover, eight output parameters representing distinct product categories, including bills and utilities, food and shopping, entertainment, wellness and beauty, electronics, fashion, home and decoration, and others, were established. The paper extensively delves into the practical application of the Fuzzy Inference System as a valuable tool for market forecasting within the scope of the case study. The conclusions drawn from the results are:

- The case study data, obtained through our research team's questionnaire survey, showcases the application of soft calculation methods.
- The developed inference system identifies patterns, aiding online retailers in refining marketing strategies and understanding customer preferences.
- Students born between 1980 and 1990, residing in small towns or the capital city, prefer paying bills online.
- Capital city students, especially mid to lower Generation Y, show a higher inclination for online food ordering.
- Entertainment spending is notably high among capital city students, particularly Generation Y.
- Students born after 1980 in urban areas, balancing work and study, exhibit the most favorable results for electronics sales.
- Generation Y participants in cities and Generation X participants in metropolitan areas are most likely to purchase home and decorative items.

Upon comparing our findings with Eurostat results, it becomes evident that the consumption habits of different age groups closely parallel those of European Union consumers. However, our analysis provides a more in-depth comprehension of the demographic attributes linked to these age cohorts.

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