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Consumer Happiness in the Purchase of Electric Vehicles: a Fuzzy Logic Model

Felicidad del consumidor en la compra de vehículos eléctricos: un modelo de lógica difusa

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ABSTRACT

This study analyzes customer happiness in acquiring an electric vehicle, considering pleasure as an ambiguous language term that conventional models have inadequately incorporated. This research was conducted using a fuzzy Delphi method survey targeting a specific consumer group and two fuzzy inference systems: a multi-input single-output FIS model and an FIS Tree employing a hierarchical fuzzy inference structure, which leverages the survey's training data to optimize the models using different machine learning algorithms. The FIS tree model demonstrated superior efficacy in predicting the consumer satisfaction index, achieving an average forecast error of 0.65%. This approach could assist automobile agency marketers in creating accurate predictions to evaluate the purchasing decision-making process.

Keywords: Fuzzy Logic; Consumer happiness; Fuzzy logic models; Decision-making.

JEL code: C65, D81, M31.

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RESUMEN

Esta investigación analiza la felicidad del consumidor en la compra de un vehículo eléctrico, desde la perspectiva de la felicidad como una variable lingüística ambigua que los modelos tradicionales no han integrado eficazmente. Para ello, se aplicó el método Delphi difuso a un grupo específico de consumidores y se desarrollaron dos modelos difusos: uno de múltiples entradas y una salida y otro de árbol jerárquico optimizados con algoritmos de aprendizaje automático. Se concluye que el modelo de árbol es más efectivo para pronosticar la felicidad del consumidor con un error promedio del 0.65%. Este modelo ayudaría a los especialistas y gerentes de marketing para realizar predicciones confiables y analizar el proceso de toma de decisiones de compra de vehículos eléctricos.

Palabras clave: Lógica difusa; Felicidad del consumidor; Modelos de lógica difusa; Toma de decisión.

Código C65, D81, M31.

INTRODUCTION

Over the past ten years, happiness has expanded beyond traditional academic boundaries, enhancing comprehension of consumer behavior. Historically, happiness has been defined in various ways, evolving. Experts commonly associate it with well-being or subjective well-being, often describing satisfaction. In contemporary society, happiness is strongly related to pleasure and fulfillment (Dutta & Kumar, 2021).

In marketing literature, the term happiness is used interchangeably with subjective well-being, life satisfaction, and welfare (Easterlin, 2003), so happiness in this research refers to an emotional state of well-being and contentment, that impacts customer purchase intent and loyalty (Bettiga & Lamberti, 2020; Kim & Yoon, 2023; Razmus et al., 2022).

Consequently, marketers have initiated efforts to expand and deepen their research (Barbosa, 2017; Dunn et al., 2011; Mogilner, 2010). According to the tenets of neoclassical economic theory, there is also a direct and positive correlation between consumption and happiness (Wang et al., 2019).

Today, consumers seek to buy brands for what they represent and the emotional experiences they offer (Bhattacharjee & Mogilner, 2014; Dutta & Kumar, 2021). Consumers, while purchasing items, not only derive pleasure from them but also strive to attain experiences that enhance their happiness (Van Boven & Gilovich, 2003). Similarly, other consumers appreciate simple and extraordinary experiences, such as moments that bring them happiness (DeVoe & House, 2012), resulting from their direct and indirect interactions and encounters with brands (Bruhn & Schnebelen, 2017; Schmitt, 1999).

However, a subset of customers actively pursue the acquisition of experiential goods, which, in contrast to tangible objects, elicit a heightened state of happiness (Bhattacharjee & Mogilner, 2014; Nicolao et al., 2009).

Insufficient effectiveness in incorporating the drivers of consumer happiness into traditional models for analyzing decision-making processes and user behavior can be attributed to their ambiguous nature. Users express many of these factors through expressions and linguistic variables, which challenge their integration into computational models. Artificial intelligence (AI) methodologies and technologies, such as fuzzy logic (Chaturvedi, 2010) and Machine Learning algorithms, have significantly transformed the landscape of this field of study.

The current study uses fuzzy logic to construct two inference models in MATLAB, FIS unique and FIS tree. It proceeds by conducting a Fuzzy Delphi Method (FDM) survey on a specific sample and utilizes the survey's training data to tune the models using distinct machine-learning techniques. Subsequently, following the validation of the models, researchers proceeded to analyze the outcomes and the associations between happiness and its many determinants.

Section 1 of this paper presents a comprehensive theoretical framework that explores the topic of happiness in the literature and the various applications of fuzzy logic. Section 2 provides a thorough explanation of the proposed research methodology. Section 3 presents the results of the various stages of the method and the inference processes carried out using different algorithms. Section 4 presents the study's conclusions and limitations.

This study contributes to scientific advancement in understanding the various dimensions of the concept of happiness by examining the components and clusters of factors that impact happiness in the purchase of electric vehicles on the Mexican market. In addition, the suggested model assists automobile organizations in accurately forecasting consumer happiness based on their expressed preferences for economic, social, technological, and environmental aspects.

OVERVIEW OF THE ELECTRIC VEHICLE MARKET

Within the automotive industry sector, vehicle manufacturers, in addition to public officials in regulatory entities, are paying more attention to electric vehicles (EVs), including their different technologies: Hybrids (HEVs), Plug-in Hybrid PHEVs, Battery Electrics (BEVs), and Fuel Cell Electrics (FCEVs). Likewise, opportunities have been facilitated to contribute to both zero-emission transportation and energy transition of cities and countries (World Resource Institute, 2023).

Consequently, worldwide sales of electric vehicles have increased from 4% in 2020 to 14% in 2022. Overall sales in 2023 are projected to reach nearly 14 million units, marking a 35% increase compared to 2022 (International Energy Agency, 2023).

According to the Mexican Association of the Automotive Industry, the sales figures for Mexico from January to December 2022 amounted to 1,094,728 units (Asociación Mexicana de la Industria Automotríz, 2023). Among these units, 51,065 were electric vehicles, representing approximately 4.6% of the total automobile sales. Furthermore, there has been a significant increase of 82.82% in EV acquisitions from 2016 to 2022.

The primary factor contributing to sustained growth in sales can be attributed to the implementation of economic incentives by the government of Mexico, as stated by the National Commission for the Efficient Use of Energy- Secretary of Energy in 2023

(Comisión Nacional para el Uso Eficiente de la Energía-Secretaría de Energía, 2023). It should be noted that most automotive agencies in Mexico provide a minimum of one EV model, constituting a market segment characterized by a unit price of USD 25,800 in the mid-range segment, exceeding USD 205,900 in the luxury segment.

THEORETICAL FRAMEWORK

Consumer happiness

Obtaining a physical product signifies a distinct transaction that provides a satisfying encounter for the consumer associated with holding it (Barbosa, 2017; Nicolao et al., 2009). Consequently, marketers have started incorporating this aspect into their purchasing procedures, aiming to deliver a contextual experience that enhances customer happiness (Dutta & Kumar, 2021).

In a competitive market, companies must go beyond consumer happiness and focus more on their happiness. Academic evidence indicates that good customer experiences positively impact brand loyalty (Barbosa, 2017; Khan & Hussain, 2013) and their commitment to the company (Dutta & Kumar, 2021).

Most marketing research has focused primarily on purchasing and consumption scenarios (Bruhn & Schnebelen, 2017). However, there is a relatively new area of study that involves the evaluation of consumer happiness, specifically in the purchasing process. This is primarily due to the subjective nature, uncertainty, and ambiguity associated with accurately measuring a concept as abstract and elusive as happiness (Martínez, 2012). In addition, there is a challenge in identifying and prioritizing the factors that influence the contextualization of joy, considering the significant importance of this index in marketing.

In line with this, marketers have successfully developed a connection between fuzzy logic methods and strategic decision-making processes. This connection allows them to express the linguistic levels of a variable, thereby bridging the gap between mathematical models and their interpretations (Bojanowska & Kulisz, 2023; Meier et al., 2017; Meier & Donzé, 2012). However, this aspect of consumer theory has not been extensively explored.

Customers increasingly exhibit heightened expectations in the competitive landscape of brands, and many elements influence their long-term happiness (Lin et al., 2020; Nicolao et al., 2009). Consumer happiness refers to an individual's subjective evaluation of their overall well-being and quality of life resulting from their interactions with a product or service (Gong & Yi, 2018). These interactions, occurring during and after the purchase, are crucial in shaping a positive experience (Rawson et al., 2013).

People desire to assess every factor they see as contributing to their overall well-being and regard any aspect of the consumer journey as integral to their pleasure. Consumers enjoy consuming products or services that align with their preferences, as they include desired traits (Reena & Dangi, 2023). Consequently, companies can capitalize on this by increasing their buying intention (Kim & Lee, 2019).

From different perspectives, happiness has been measured; from the economic perspective, global happiness is valued through six factors that play an important role: income, health, social support (having someone to consider), having a sense of freedom to make key decisions in life, generosity, and the perception of corruption (Helliwell et al., 2023). From the psychological and sociological perspectives, popular scales stand out to measure it through emotional elements (Bruhn & Schnebelen, 2017), such as the Affect Balance Scale (Bradburn, 1969), the Positive Negative Affect Schedule (PANAS) [Positive and Negative Affect Schedule] (Bradburn, 1969), the Memorial University of Newfoundland Happiness Scale (MUNSH) (Kozma & Stones, 1980), the Affect meter (Kammann & Flett, 1983), and the Happiness Questionnaire from Oxford (Oxford Happiness Questionnaire OHQ) (Hills & Argyle, 2002).

In both marketing and consumer research, there exists a range of happiness metrics that encompass multiple items. These metrics consider the frequency and intensity of positive emotions, the absence of negative feelings, and the overall level of happiness (Argyle & Crossland, 1987). Furthermore, these metrics are associated with spiritual reflection, care for others, and financial detachment (Cherrier & Lego, 2007). Moreover, happiness can be assessed by considering factors such as joy, vigor (Bruhn & Schnebelen, 2017), pride, and tranquility, which are influenced by technological, social, economic, environmental, and organizational forces (Kumar, 2021).

Other studies have established that happiness exhibits a temporal dimension that varies throughout an individual's lifespan. This variability is influenced by ordinary and extraordinary experiences, which are contingent upon the consumer's age or level of maturity (Bhattacharjee & Mogilner, 2014; Mogilner et al., 2012). In addition, happiness is found to be influenced by the socioeconomic status of the consumer. Specifically, people from lower socioeconomic backgrounds tend to derive greater enjoyment from material purchases rather than experiential ones (Thomas & Millar, 2013).

Consumer happiness can be predicted by various factors, such as the attitude of service employees (Söderlund et al., 2011; Söderlund & Rosengren, 2010), service quality (Gong & Yi, 2018), duration and quality of customer visits (Thomas & Millar, 2013), and personalized experiences (Kim & Lee, 2019). Companies must identify these factors and assess their significance based on customer needs (Liang et al., 2021).

Similarly, previous research has indicated that different forms of consumption, such as the acquisition and ownership of a car, contribute to feelings of happiness (Bettingen & Luedicke, 2009; Robertson, 2016). According to Srivastava and Kaul (2016) and Prentice et al. (2019), vehicle firms already provide a range of complimentary service perks to incentivize customers to routinely visit their workshops and avail themselves of preventative and/or corrective maintenance services (Srivastava and Kaul, 2016; Prentice et al., 2019).
Consumer happiness in the purchasing process: A fuzzy logic approach

The development of fuzzy sets aimed to mathematically capture the concepts of uncertainty and vagueness while offering formalized methodologies for addressing the inherent flaws in verbal explanations of diverse problems. Fuzzy logic is a highly effective method for organizing and representing cognitive systems (Emrouznejad & Ho, 2017). also, Fuzzy logic replicates the mental process by which individuals examine situations and make judgments based on ambiguous or inaccurate values rather than depending on absolute facts or falsehoods (Rosário et al., 2023).

Many methodologies in a fuzzy inference system aim to elucidate the significance of confusing factors in diverse circumstances. Some research utilizes a multi-input, single-output Mamdani Fuzzy Inference System (FIS) to address the conventional Failure Mode and Effect Analysis (FMEA). This novel methodology addressed significant challenges, including data uncertainty and the diverse array of unclear input values (Geramian & Abraham, 2021).

Furthermore, MahmoumGonbadi et al. (2019) implemented a fuzzy system using a two-step approach. In the first stage, clients were ranked based on four factors, including customer loyalty, using a FIS (Fuzzy Inference System). The ultimate priorities of the clients were determined in the second stage using another FIS based on the results of this stage and the waiting time. In two scenarios and across five system statuses, they also showcased the superior performance of their methodology compared to the FIFO (First in, First out) and TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) methodologies.

Current buyer decision-making models need to be better suited for real-life circumstances that are unpredictable and imprecise. Therefore, it is necessary to create a new conceptual and quantitative model (Sadikoglu & Saner, 2019). Consequently, fuzzy logic has emerged as a significant component within the scientific domain of marketing, highlighting the benefits of using membership functions rather than precise values (0,1).

Fuzzy logic and fuzzy reasoning are employed most effectively in the social sciences, particularly in the context of marketing models (Enache, 2015), aligning with this assertion.

In their recent publication, Shaopei and Guohua (2023) have presented a collection of recommendations on utilizing management-oriented fuzzy approaches, as proposed by Meier and Donzé (2012), within the domains of marketing and customer relationship management.

The literature also presents various applications of fuzzy logic in consumer studies. For example, it examines using FIS to forecast customer purchasing behavior (Nayak et al., 2013). Sadikoglu and Saner (2019) provide guidance on applying fuzzy logic in consumer decision-making and purchasing. Ulyanov (2020) develops a model to analyze purchasing behavior and the resulting hedonic happiness. Lastly, Bojanowska and Kulisz (2023) focus on applying fuzzy logic in customer relationship management.

Other researchers have also used FIS to quantify consumer loyalty within the context of a customer relationship. Fuzzy logic has recently started to be developed and employed in the context of happiness, comparable to its early application in marketing. The study conducted by Tadi et al. (2016) suggests assessing individual happiness by considering psychological factors and life happiness. Similarly, Bahreini et al. (2019) employ a facial emotion recognition model to identify various indicators of an individual's happiness. Kumar (2021) examines the determinants of customer happiness in authorized automotive service workshops to improve customer retention. The fuzzy Delphi method and the fuzzy analytic hierarchy process (FAHP) were used to determine the weighting index of each factor. These analysis approaches are commonly used in diffuse-type research.

Fan, Gou, and Weng (2024) have recently proposed a novel fuzzy feature generation technique to predict happiness based on behavioral and emotional data. They employed IF-THEN fuzzy rules to enhance feature selection and improve model accuracy. Their conclusions indicate that the fuzzy approach shows improved prediction accuracy compared to traditional methods, highlighting the adaptability of fuzzy models in emotion prediction tasks.

However, some research provides information on how fuzzy logic models can be applied to understand and improve consumer happiness and decision-making in the electric vehicle market. Gupta and Gupta (2024) used the fuzzy analytic hierarchy process (FAHP) and concluded that consumer trust and environmental benefits were the most influential factors in consumer intentions to purchase green vehicles.

Eti, Dinçer, Yüksel, and Gökalp (2024) proposed a fuzzy decision-making model to address customer satisfaction issues in the charging infrastructure of electric cars, highlighting the importance of technological improvements and increased charging stations. Aungkulanon, Atthirawong, and Luangpaiboon (2023) applied the FAHP to evaluate decision criteria influencing EV adoption. They used fuzzy numbers to capture imprecision in stakeholder input and determined that cost-effectiveness and environmental benefits were the critical drivers in the adoption.

For its part, Kang and Zhu (2022) explored the use of fuzzy logic in the design of hybrid electric vehicles that improve consumer emotional satisfaction and purchase intent through fuzzy linguitic variables (energy efficiency, affordability, and aesthetics) and concluded that enhancing emotional satisfaction through design and functionality increases purchase intentions. Hussain et al. (2020) used fuzzy inference systems to increase user satisfaction and operational efficiency in charging power among multiple EVs. Jena (2020) analyzed consumer sentiment toward EVs, identifying price, maintenance, and safety as key concerns, and Yogi (2016) employed fuzzy logic to evaluate consumer satisfaction with product quality. Both directly impact the purchase intention of electric vehicles.

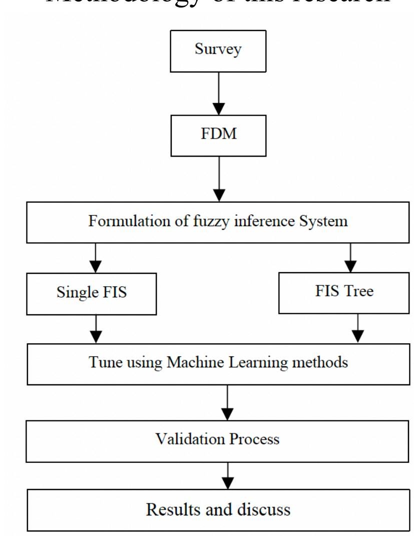
RESEARCH METHOD

First Stage: happiness metrics

This quantitative research was developed in five stages described in the following (figure 1). The first stage is happiness metrics and survey application to a targeted sample.

Figure 1

Methodology of this research



Source: own elaboration.

The survey was initially produced using the Delphi method within a fuzzy universe (Aliev & Ahmedov, 2004) to represent the linguistic variables and factors. These variables and factors were derived from the Saaty scale (Saaty, 1987), which was adjusted to have a beginning value of one and a final value of ten. At first, the factors considered were those suggested by Kumar (2021). After a review by five experts, only characteristics relevant to the electric car purchasing process were selected (Table 1). Only factors with a mode statistic Mo≥ 3 were chosen.

This study resulted in selecting 27 elements, consisting of 5 questions focused on sociodemographic data, 21 elements related to the elements that drive happiness, and an additional element representing the happiness index, which is the model's output. This study examines the correlation between the 21 characteristics and the happiness score.

The research sample consisted of 52 current consumers who have expressed interest in owning an electric car in any of its variants and technologies. These participants were voluntary users of electric or hybrid cars in Mexico. From November 13 to December 23, 2023, the survey was conducted using Google Forms.

Table 1
Drivers of happiness in the EV purchasing process

	Drivers of happiness *	**Validated Happiness Boosters ****	**Source**
Technological	Delivery quality	Vehicle delivery time	(Gong & Yi, 2018)
	Adherence to the process	NA	NA
	Guarantee Benefits	Vehicle Guarantee Benefits	(Tu & Hsee, 2016)
	Profitable development	NA	NA
	Workshop installations	Agency facilities	(Gong & Yi, 2018; Srivastava & Kaul, 2016)
	Washing Quality	NA	NA
	Service Reliability	Vehicle Reliability	(Tu & Hsee, 2016)
	Proximity to service center	Proximity to service center	(Gong & Yi, 2018)
Social	Personalized attention	Personalized attention	(Goldsmith, 2016; Söderlund & Rosengren, 2010)
	Staff behavior	NA	NA
	Time required for service	NA	NA
	Service reminder process	Service reminder process	(Gong & Yi, 2018; Kumar et al., 2017)
	Reservation process	NA	NA
	pick-up and delivery service	NA	NA
	Workshop schedule	NA	NA
	Post-service follow-up	NA	NA
	Delivery time for complaint resolution	Complaint response time	(Söderlund & Rosengren, 2010)
	CRM program	NA	NA
	Brand image	Brand prestige	(Tu & Hsee, 2016)
Environmental	Access path to the workshop	NA	NA
	Parking installation	Ease of parking at the agency	(Goldsmith, 2016; Gong & Yi, 2018)
	Client room	Attention room	(Gong & Yi, 2018; Srivastava & Kaul, 2016)
	Parts Availability	NA	NA

	Pollution level	Free of vehicle CO2 emission pollution	(Tu & Hsee, 2016)
	Waste disposal process	NA	NA
	Empathy	NA	NA
	Communication	NA	NA
	Market focus	NA	NA
	Internal cleaning	NA	NA
Economic	Number of free services	NA	NA
	Discounts on services and spare parts	Maintenance service cost	(Srivastava & Kaul, 2016)
	High repair cost	Repair cost in case of breakdown	(Srivastava & Kaul, 2016)
	Service frequency	Temporal interval between maintenance services	(Söderlund & Rosengren, 2010)
	Transparent Billing	Cost of spare parts	(Srivastava & Kaul, 2016)
	Cashless claims service	EV's price	(Srivastava & Kaul, 2016; Tu & Hsee, 2016)
	Parts life	Lifespan of vehicle components	(Kumar et al., 2017)
	Service promotion	Maintenance service promotions	(Söderlund & Rosengren, 2010)
Organization governance	Supervisor's competence	Supervisor Attention	(Söderlund et al., 2011; Srivastava & Kaul, 2016)
	Trained staff	Staff training	(Söderlund et al., 2011; Srivastava & Kaul, 2016)
	Culture	NA	NA
	Teamwork	NA	NA
	Customer Focus	NA	NA
	Employee empowerment	NA	NA
	Leadership	NA	NA
	Participation of the workers	NA	NA

Source: own elaboration * Happiness drivers proposed by Kumar, (2021) ** Happiness drivers from the cited authors and validated by 5 experts. NA: Not applicable.

Second stage: application of the fuzzy Delphi method

The Delphi method is utilized in a fuzzy universe (FDM) to determine the factors that influence consumer happiness. This is achieved by using fuzzy sets of three linguistic variables: "low," "medium," and "high" importance, as indicated by the findings of the initial stage. The FDM was used in this study in the following form: Initially, the interviewers assessed the elements using a modified Saaty linguistic scale ranging from 1 to 10 (Table 2). The outcomes are then provided based on each linguistic variable's fuzzy triangular number (FTN) (Chaturvedi, 2010).

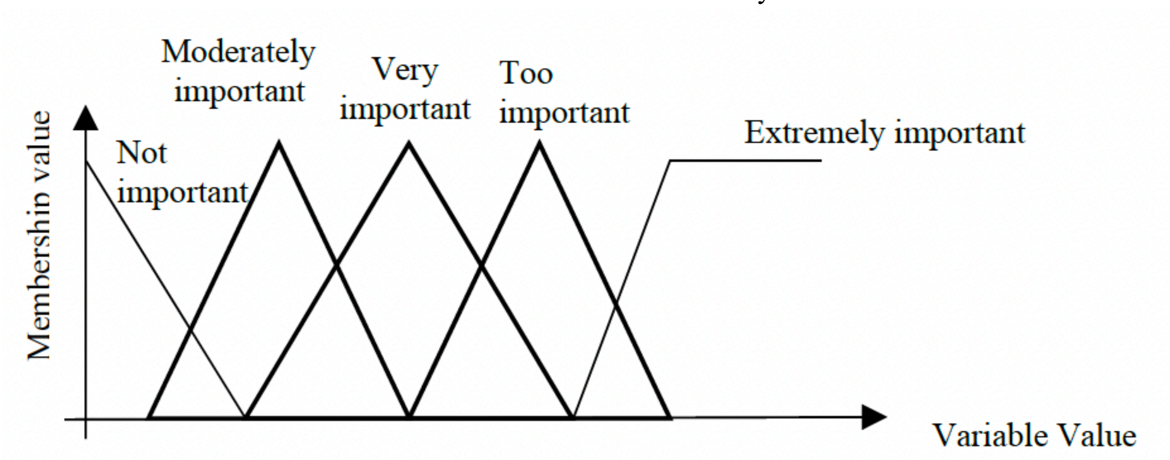
Table 2
Measurement scale for the FDM survey

Comparison index	Score	FTN
Extremely important	10	(0.7, 0.9, 0.9)
Too important	8	(0.5, 0.7, 0.9)
Very important	6	(0.3, 0.5, 0.7)
Moderately important	4	(0.1, 0.3, 0.5)
Not important	2	(0.1, 0.1, 0.3)

Source: own elaboration.

At this stage, the FTN triangular numbers are generated by splitting the range [0,1] between the five values of the comparison index according to the triangular format (a, b, c). Each of these numbers corresponds to one of the points in the triangle (Figure 2). It is important to note that the initial values will undergo modifications later in the machine learning process, wherein their bounds will be adjusted based on the consumers' expressed experiences, as indicated in the survey.

Figure 2
The FTNs for the FDM survey



Source: own elaboration.

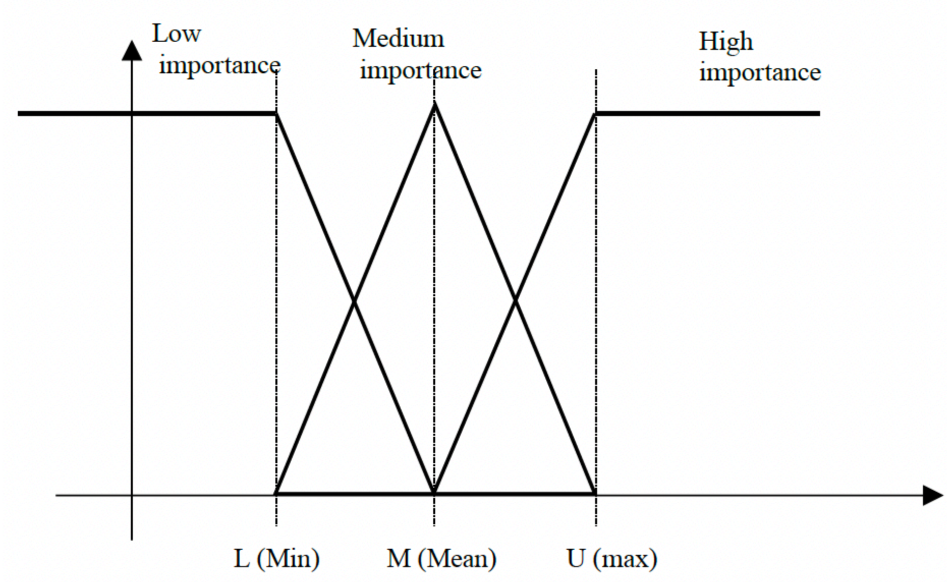
Afterwards and based on the results of the first survey, a single fuzzy set ($\tilde{a}_{ij}$) was generated for each factor, using equation 1:

$$\tilde{a}_{ij} = (l_{ij}, m_{ij}, u_{ij}) \qquad \text{Equation (1)}$$

Where: $\tilde{a}$ is the fuzzy number for factor j according to interviewer i, considering that$=1,2,\ldots,n$ and $j = 1,2,\ldots.m$.

From the fuzzy numbers of the factors and using equations (2) to (5), the main indices of the fuzzy set were obtained for each factor (l_j, m_j, u_j), as well as the fuzzy average (S_j), where figure 3 displays the fuzzy number of a factor with its three linguistic levels.

Figure 3
Formation of the fuzzy set of each variable based on the survey data



Source: own elaboration.

$$l_j = min_i(l_{ij}) \qquad \text{Equation (2)}$$

$$m_j = \frac{1}{n\sum_{i=1}^{n} m_{ji}} \qquad \text{Equation (3)}$$

$$u_j = max_i(u_{ij}) \qquad \text{Equation (4)}$$

$$S_j = \frac{(l_j + m_j + u_j)}{3} \qquad \text{Equation (5)}$$

Where: $j=1, 2....n$ are the number of factors studied.

In this stage, the comparison process is applied as part the methodology used by Naghadehi et al., (2009) to analyze the importance of the factors. Accordingly, the factor $B_1 = (l_1, m_1, u_1)$, expressed as a fuzzy set, is compared with $B_2 = (l_2, m_2, u_2)$, applying equations (6) and (7) and so on with the rest of the factors.

$$V(B_1 \geq B_2) = sup_{y \geq x}[\min(\mu_{B1}(x), \mu_{B2}(x))] \qquad \text{Equation (6)}$$

$$V(B_i \geq B_j) = \begin{pmatrix} 1 & if\ m_j \geq m_i \\ 0 & if\ l_i \geq u_j \\ \dfrac{l_i - u_j}{(m_j - u_j) - (m_i - l_i)} & for\ other\ cases \end{pmatrix} \qquad \text{Equation (7)}$$

Once this comparison of B_1 with all the other factors is made, the weight of factor B_1 is calculated by applying equation (8).

$$d'(B_i) = \min V(B \geq B_i) \qquad \text{Equation (8)}$$

Where $d'(B_i)$ is the importance value of B_i.

Third stage: formulation of fuzzy correlation models
Based on the findings from the previous stages, the fuzzy expressions of the factors are employed to construct two distinct models to establish a correlation between the driving forces and customer happiness.

The initial model was constructed using Mamdani multi-input single-output FIS (MISO), including the 21 inputs and the only output variable (happiness). This type of FIS is useful for input-to-output relationship mapping where there is data uncertainty (Geramian & Abraham, 2021)

The second model is a hierarchical fuzzy system (named FIS Tree), wherein the components are organized into distinct FIS to minimize the number of inference rules and enhance the model's tuning process. Categorization is performed based on the data shown in Table 1.

A hierarchical fuzzy system is a decentralized and structured depiction of a unified FIS comprising numerous FISs, each characterized by a reduced rule base. Therefore, utilizing an FIS tree facilitates comprehension of the inference procedure and enables expedited performance enhancement with a reduced number of adjustable parameters in contrast to a monolithic FIS.

As the amount of input to a fuzzy system escalates, there is an exponential growth in the number of rules. The extensive rule base reduces the computing efficiency of the fuzzy system. Additionally, it complicates the comprehension of the fuzzy system's functioning and adds complexity to the adjustment of rule and membership function parameters. A large rule base diminishes the generalizability of tuned fuzzy systems due to the restricted availability of training data in many applications.

The high-level fuzzy systems utilize the outputs of the low-level fuzzy systems as inputs within a tree structure. An FIS tree's computational efficiency and comprehensibility surpass those of a MISO FIS with an equivalent number of inputs.

In both models, the research has information about the input and output variables; however, there is no information about the inference rules. That is why, in both models, the formation of the rules is left to the next stage, which involves different types of machine learning algorithms.

Fourth stage: optimization and validation of the model
Developing an effective fuzzy inference system to comprehend the correlation between various membership functions poses a significant challenge, mainly when dealing with many

membership functions (MF) and other characteristics. Therefore, at this stage, multiple machine learning algorithms were utilized to optimize both FIS in this study.

This research uses the Fuzzy Logic Toolbox of MATLAB to adjust both models. Various optimization algorithms are used during the tuning process to develop potential sets of FIS parameters (Table 3). To include possible parameters in the FIS, a cost function is employed with the input/output training data obtained from the survey.

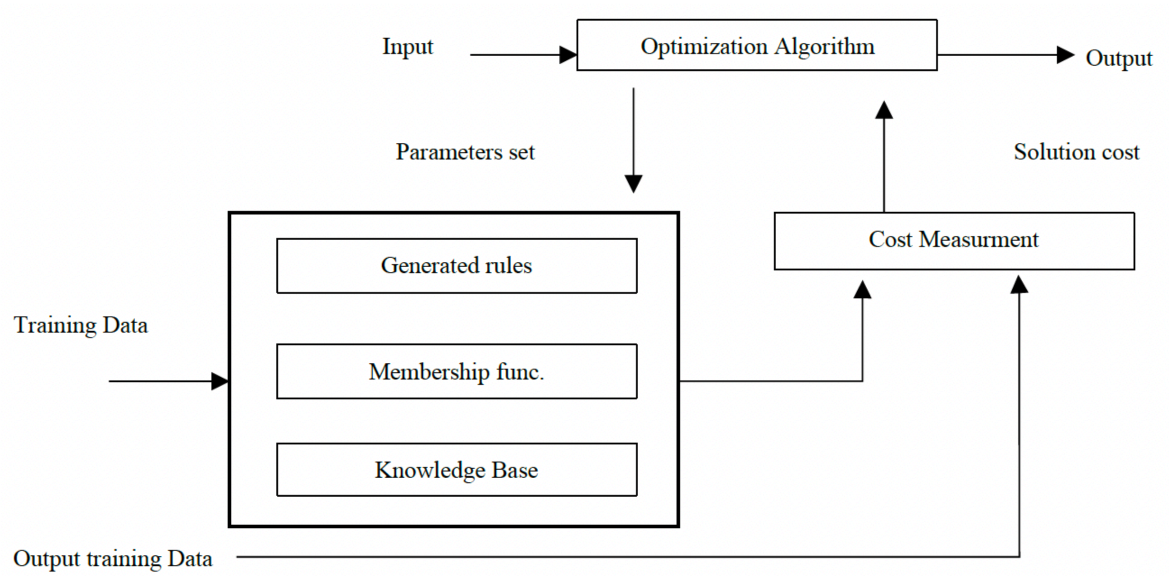
Table 3
Algorithms used

Algorithm	Description	References
Genetic Algorithm (GA)	This tool is well-suited for investigating a wide variety of parameter combinations in the FIS MISO model. It aids in avoiding local optima and identifying resilient solutions.	(Hooke & Jeeves, 1961)
Particle Swarm Optimization	The FIS Tree's parameters can be effectively adjusted by utilizing particle movements to converge towards favorable configurations.	(Hooke & Jeeves, 1961; Kennedy, 2011)
Pattern Search	This method is valuable for improving local solutions within the parameter space of the FIS Tree model without the need for derivative information.	(Hooke & Jeeves, 1961; Kennedy, 2011)
Simulated Annealing	This method is beneficial for improving local solutions within the parameter space of the FIS Tree model without the need for derivative information.	(Li et al., 2022)

Source: own elaboration.

A two-stage tuning method was implemented to enhance the learning efficiency of FIS models (Hooke & Jeeves, 1961), as depicted in Figure 4.

Figure 4
The tuning process applied in this research



Source: own elaboration.

The first step involved learning the rule base while maintaining the constant input and output MF parameters. The second step involved modifying the parameters of the input/output MFs and rules. The initial stage is more cost-effective regarding computer resources, as it involves a limited number of rule parameters. Additionally, it rapidly achieves convergence towards a fuzzy rule base during the training process. Using the rule base obtained in the first phase as an initial condition in the second step facilitates rapid convergence of the parameter tuning process. Given that the FIS tree has already acquired knowledge from the training data, employing a local optimization technique will rapidly converge the parameter values. Optimizing the FIS tree parameters requires a more significant number of iterations compared to the previous rule-learning process.

During optimization, the maximum number of rules for each Fuzzy Inference System (FIS) is limited to 20 in the initial step. The number of optimized rules in each FIS may be lower than the limit due to eliminating duplicate rules during the tuning process. To prevent becoming stuck in a local minimum when navigating through the parameters of a hierarchical fuzzy inference tree (HFIT), two optimization techniques that do not rely on derivatives, namely particle swarm optimization (PSO) and pattern search (PS), have been examined in this two-step tuning procedure.

It is important to note that, throughout the inference procedures, the Sugeno fuzzy inference approach was chosen over Mamdani to achieve more accurate outcomes. This decision was made based on the scenario that produced the most favorable findings, as Nayak et al. (2013) and Widjaja et al. (2002) specified. The model's dependability was assessed using the Cronbach alpha coefficient and the correlations between the survey findings and those derived from the fuzzy model.

A hierarchical tuning process is employed for each tree FIS. Subsequently, the complete FIS Tree set is tuned up by excluding the outputs of each factor group and concentrating exclusively on the production of happiness.

Fifth stage: comparison and discussion of the results

During the final stage, a comparative analysis is performed between the projected outcomes of the models and the training output data to assess the prediction error margins of both models. In addition, several sides of the relationship between the determinants of happiness are examined to gain a deeper understanding of electric vehicle users in Mexico.

RESULTS

According to the survey results on a targeted sample of consumers of electric or hybrid cars, Table 4 shows the diffuse parameters of each factor according to the equations of stage 1.

Table 4

Matrix of numerical results of the evaluation of factors expressed in fuzzy sets

Factor $\boldsymbol{B_j}$	Min $\boldsymbol{l_j}$	mean $\boldsymbol{m_j}$	Max $\boldsymbol{u_j}$
B1	5	8.91	10
B2	2	8.09	10
B3	5	8.18	10
B4	5	8.36	10
B5	5	7.73	10
B6	5	8.55	10
B7	3	7.09	10
B8	7	9.68	10
B9	4	7.91	10
B10	5	8.09	10
B11	7	9.23	10
B12	2	7.86	10
B13	3	8.27	10
B14	1	6.50	10
B15	1	8.41	10
B16	1	7.27	10
B17	3	8.14	10
B18	1	7.73	10
B19	1	6.68	10
B20	1	8.86	10
B21	2	8.23	10

Source: own elaboration according to the applied survey.

Both models were developed using the Fuzzy Logic Toolbox in MATLAB, employing the Sugeno approach, as previously stated (Nayak et al., 2013; Widjaja et al., 2002). The initial FIS model (with a MISO FIS) was derived from 21 inputs and one output. This model allows for the visualization of fuzzy sets representing the inputs and the output. The fuzzy number values for each entry are derived from the preceding stage (Table 3). However, the behavior of each factor is depicted in the three levels of importance (low, medium, and high). It is observed that certain factors exhibit a wider range of values for medium importance compared to other factors.

Based on the methodology proposed and according to stage 2, the weight of each of the 21 factors influences customer happiness. It has been discovered that, when considering aspects in isolation, the reliability component is most important in enhancing the enjoyment of electric car consumers in Mexico. The guarantee factor is closely followed, while the pricing factor ranks third in importance. In contrast to prevailing assumptions, pricing does not hold paramount significance. This is likely because electric vehicle prices are predominantly regarded within the upper economic range. As a result, the user prioritizes other variables, such as reliability, as more significant in determining their level of enjoyment (Table 5).

Table 5
Numerical results of factor evaluation

Factor	Description	$d'(B_i)$	Factor	Description	$d'(B_i)$
B4	Reliability	1.0000	**B8**	Agency facilities	0.6535
B7	Guarantee	0.8684	**B13**	Maintenance service cost	0.6535
B10	EV's price	0.7952	**B16**	Proximity to service center	0.6286
B5	Pollution	0.7857	**B1**	Personalized attention	0.6226
B21	Lifespan of vehicle components	0.7253	**B2**	Supervisor Attention	0.6055
B14	Brand prestige	0.7021	**B9**	Temporal interval between maintenance services	0.6055
B12	Repair cost	0.6947	**B6**	Ease of parking at the agency	0.5546
B20	Vehicle delivery time	0.6804	**B15**	Maintenance service promotions	0.5366
B3	Staff training	0.6735	**B19**	Attention room	0.5000
B11	Cost of spare parts	0.6667	**B17**	Service reminder process	0.4853
B18	Complaint response time	0.6600			

Source: own elaboration.

The development of the second model using the FIS Tree model is motivated by simplifying the tuning process since the categorization of factors aids in the classification of inference rules. The FIS Tree model (Figure 5) comprises five distinct fuzzy inference systems: FIS economic, FIS social, FIS technological, FIS environmental, and finally FIS happiness. Both models undergo a tuning process in the following steps:

The Genetic Algorithm is utilized in the MISO FIS model, employing a validation tolerance of 0.05, a maximum rule number of 100, and a learning optimization type. Given the multitude of input variables and the intricate nature of their associations with the happiness index, the model will need to produce 100 rules to achieve results with a minimal margin of error. It should be noted that the efficacy of the MISO FIS model progressively improves with the amplification of training data.

The tuning process for the second model, FIS Tree, was conducted by the subsequent steps:

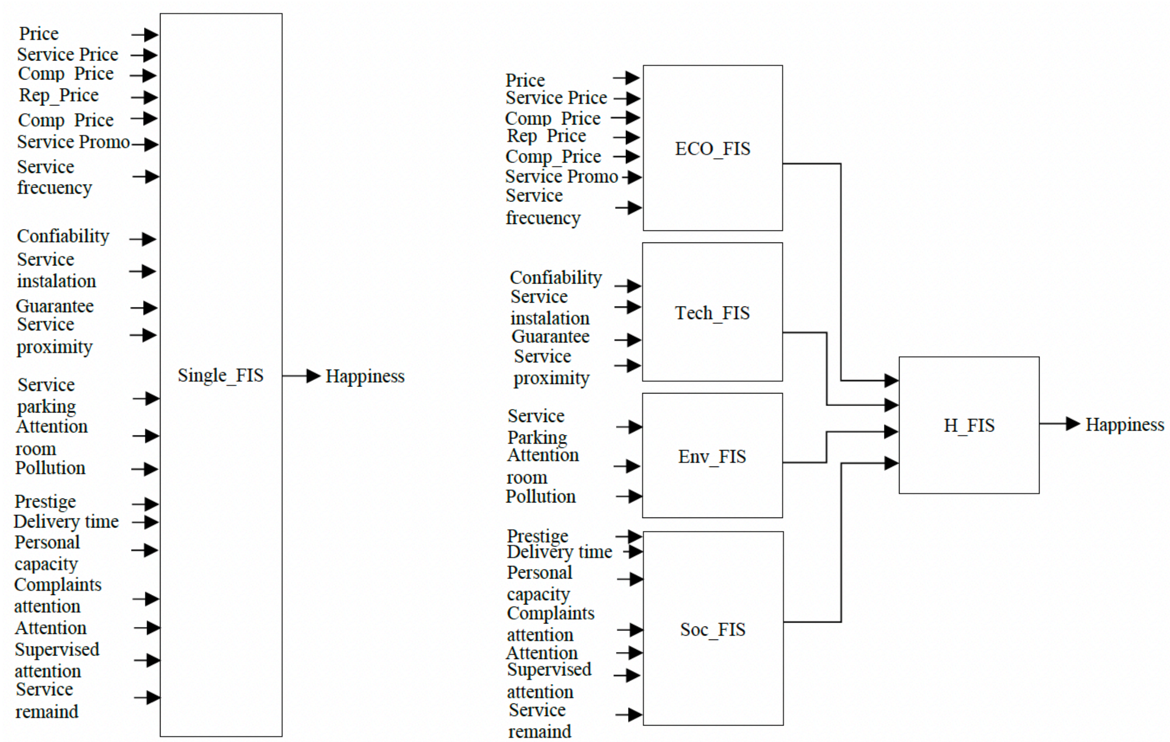
- The tuning method involved the application of numerous stages. Specifically, a minor tuning process was implemented on the sub-FIS, which consisted of FIS_Eco, FIS_Env, FIS_Soc, and FIS_Tech, to learn the rules.
- The data training process involved tuning each FIS in the global Tree FIS with all the previously generated rules.
- The Tress FIS underwent two tuning processes. The first phase involved learning new rules using Particle Swarm Optimization (PSO), while the second step involved modifying the parameters of the FIS Tree using the Pattern Search Method.

After completing the optimization processes for both models, the input variable data is utilized to compare the model's output data and assess the accuracy of the forecast provided by each model about the survey's output data. The comparison demonstrates the superior forecast effectiveness of the FIS tree model compared to the MISO FIS model (Table 6).

In contrast, the use of Fuzzy Logic modeling helps facilitate comprehension of the interplay between multiple driver factors and the happiness index, e.g.: when analyzing the fuzzy set generated by the first model for the "price" factor, it is observed that the triangle representing the "average" fuzzy value exhibits a wide range of values from 5 to 10. This range reflects consumers' perceptions and aligns with the actual conditions of the electric vehicle market. Prospective purchasers of these automobiles are cognizant of the substantial financial commitment involved. Hence, the criterion for deeming a price as "low" is elevated compared to other factors. This is due to the high initial cost of electric vehicles.

Figure 5

Single FIS model and FIS Tree model



Source: own elaboration based on MATLAB software.

Table 6

Degree of inaccuracy in the prediction of each model

Output training Data	Output MISO FIS	Output FIS Tree	$\Delta E_{single}\%$	$\Delta E_{\mathbf{Tree}}\%$
10	9.88	9.98	1.2	0.2
10	9.76	9.79	2.4	2.1
10	9.81	9.88	1.9	1.2
9	9.4	9.03	-4.44	-0.33
7	5.4	6.88	22.86	1.71
10	9.98	9.98	0.2	0.2
10	9.55	9.97	4.5	0.3
10	9.94	9.89	0.6	1.1
10	9.81	9.89	1.9	1.1
10	9.82	9.79	1.8	2.1
9	8.2	8.91	8.89	1
10	9.42	9.88	5.8	1.2
10	9.83	9.87	1.7	1.3
10	9.99	9.99	0.1	0.1
8	8.34	8.05	-4.25	-0.625
9	8.86	9.11	1.56	-1.22
7	7.43	7.19	-6.14	-2.71
10	9.65	9.89	3.5	1.1
7	5.99	7.22	14.43	-3.14
1	2.34	1.32	-134	-32
10	9.89	9.99	1.1	0.1
5	5.43	4.98	-8.6	0.4
10	9.85	9.97	1.5	0.3
8	8.31	7.98	-3.875	0.25
10	9.04	9.85	9.6	1.5
8	8.03	8.02	-0.375	-0.25
3	4.45	2.97	-48.33	1
10	9.88	9.99	1.2	0.1
10	9.59	9.87	4.1	1.3
10	9.32	9.88	6.8	1.2
		Average	**-3.74%**	**-0.65%**

Source: own elaboration.

Similarly, it is noted that the model considered a significant margin in terms of dependability, with a relatively high threshold for low reliability. In other words, people are expressing their desire to convey their level of happiness with the car's dependability. The classification of an electric vehicle as "highly" reliable is contingent on its ability to satisfy many fundamental criteria for its consumers.

When comparing the reliability and price factors with the guarantee factor, it is evident that the "low" importance curve exhibits a similar decline as observed in the case of reliability. However, the diffuse relationship of "high" in the case of the guarantee factor demonstrates greater tolerance, breadth, and inclusivity. It starts to increase from approximately 10, indicating a higher level of demand. This phenomenon can be attributed to the narrower width of the "high" curve compared to the other factors.

In another example, the second Tree FIS model is utilized to comprehend confusing linkages, such as the impact of service frequency on the economic aspects that influence happiness. In this case, customers have a higher degree of joy due to economic factors when the frequency of service is moderate. In contrast, customer happiness notably decreases as the interval between car service visits increases. This illustration is provided to underscore the importance of the suggested model in understanding the equivocal facets of the correlation between the determinants of pleasure among electric vehicle users within the Mexican setting.

CONCLUSIONS

Customer happiness is a complex and challenging concept to measure, yet it is essential to marketers since it significantly impacts customer behavior and purchasing decisions. Due to the inherent ambiguity and significant uncertainty surrounding this topic, fuzzy logic is proposed as an emerging yet auspicious instrument for its examination.

This research develops two fuzzy inference models, the MISO FIS and Tree FIS, which examine the determinants of electric car consumers' happiness in Mexico from distinct viewpoints. Upon conducting a thorough study and deliberation of both models using the implemented machine learning methods, the following results are put forth:

- The MISO FIS model encounters challenges when confronted with many input values, as it necessitates formulating numerous inference rules. However, this model helps to understand the importance of each element, regardless of the happiness index.
- The efficacy of the FIS Tree model in forecasting happiness levels is superior when considering input values associated with the driving forces; the average forecast error for the FIS tree is -0.65%, while it is -3.74% for the MISO FIS model.
- The FIS Tree model facilitates comprehension of the indeterminate connections between user happiness and the clusters of factors that impact it. In addition, it can provide a comprehensive understanding of the degree of happiness based on economic, social, technological, or environmental aspects.
- The study found that reliability, guarantee, and EV price have the most individual influence on consumers' happiness index when purchasing electric vehicles.
- The proposed happiness index is a new and useful technique for predicting the preferences of potential customers of electric car automobile companies, given the specified characteristics.

This methodology enables marketers to conduct a more precise analysis of consumers' buying choices and their subsequent bond with a particular brand. However, it is vital to understand the limitations of the research. There is a potential limitation in the number of surveys conducted, as it may not adequately cover the diverse range of customer ideas and preferences. In addition, obtaining expert perspectives on the consumption of a particular product within a certain market poses challenges.

This research's conclusions possess considerable theoretical and practical implications. The application of fuzzy logic models to investigate customer happiness in the acquisition of electric vehicles constitutes an innovative advancement in marketing and consumer behavior research. This method facilitates the systematic and measurable modeling of intricate and subjective notions, such as happiness, hence broadening the scope of consumer behavior study through the incorporation of artificial intelligence techniques inside social and economic frameworks.

This study's results offer significant resources for marketers and automotive agency managers. The FIS Tree model identifies reliability, guarantee, and pricing as primary determinants of consumer satisfaction, informing the development of more effective commercial tactics. Companies can emphasize enhancing the perceived reliability of electric vehicles and modify their warranty policies to improve customer satisfaction and loyalty. The suggested model enables more precise predictions of client preferences, optimizing decisions about service customization and communication strategies.

This research enhances the comprehension of customer happiness in Mexico's growing electric vehicle market and offers a methodological framework applicable to other markets and industries.

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