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CUSTOMER LIFETIME VALUE PREDICTION IN MOBILE GAMING INDUSTRY: FUZZY LOGIC APPROACH

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Abstract: The Customer Lifetime Value (CLV) is an essential metric in customer relationship management (CRM), allowing companies to identify valuable customers and refine their advertising strategies. Traditional customer lifetime value prediction methods, including regression and machine learning techniques, frequently depend on accurate and predictable input data, making them less effective at capturing the inherent uncertainty and unpredictability in customer behavior. This research presents a fuzzy logic-based Customer Lifetime Value prediction model that integrates Recency, Frequency, and Monetary Value (RFM) as essential input factors. The proposed approach utilizes fuzzy membership functions and fuzzy inference systems (FIS), enabling consumers to possess partial membership in different CLV categories, hence offering a more adaptable and comprehensible framework for CLV calculation. A rule-based IF-THEN fuzzy system is established to categorize clients into various CLV segments, and defuzzification methods are employed to derive a precise CLV score. Experimental results indicate that the fuzzy logic model adeptly manages uncertainty and imprecision, outperforming traditional hard-segmentation methods by providing a continuous and adaptable strategy for CLV prediction. This research underscores the benefits of fuzzy logic in customer analytics, offering enterprises an easy and flexible instrument for customer segmentation, retention strategies, and revenue optimization.

Keywords: Customer lifetime value (CLV), Fuzzy logic, Fuzzy inference system, Customer segmentation, Recency-frequency-monetary (RFM) model

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1. Introduction

Predicting Customer Lifetime Value is essential in contemporary marketing, allowing organizations to optimize resource distribution, tailor customer interactions, and ultimately improve profitability (Pollak, 2021). Conventional approaches to Customer Lifetime Value (CLV) prediction frequently depend on statistical and econometric models, which may falter in addressing the intrinsic uncertainties and ambiguities linked to customer behavior and preferences. These models commonly presume accurate data and well-defined relationships, assumptions that seldom reflect reality, where consumer data is usually inadequate, inconsistent, or open to subjective interpretations (Hızıroğlu et al., 2018). Furthermore, the fluidity of customer connections, shaped by numerous factors, including market trends, competitive pressures, and individual client situations, affects the accuracy of CLV prediction. Fuzzy logic techniques have emerged as a potent alternative to tackle these difficulties, providing a flexible and resilient framework for modeling the uncertainties and imprecision inherent in customer and data behavior (Marin Diaz, 2025). Fuzzy logic, capable of managing ambiguous and subjective data, offers a more realistic and flexible method for predicting Customer Lifetime Value (CLV), enabling organizations to make better-informed decisions amid uncertainty (Burelli, 2019).

Fuzzy logic is characterized by using fuzzy sets and membership functions to denote degrees of truth, in contrast to the binary logic of conventional sets (Zadeh, 1994). This functionality facilitates the depiction of language characteristics, such as 'high value' or 'low risk,' as exemplified by linguistic variables (Zadeh, 1975). Moreover, fuzzy logic enables the integration of expert knowledge and qualitative insights into the modeling process, enhancing the analysis with significant contextual information that may be challenging to quantify through conventional methods. Fuzzy inference systems facilitate the development of rule-based models that emulate human thinking, converting qualitative descriptions of customer behavior into quantitative customer lifetime value forecasts. The variance related to a customer's anticipated CLV is a crucial element to evaluate, as it signifies the level of uncertainty in the estimates (McCarthy et al., 2016). By elucidating the subtleties of customer behavior and integrating expert insights, fuzzy logic models can yield a more thorough and accurate evaluation of client value, resulting in enhanced marketing strategies and superior customer relationship management.

Recent studies have increasingly integrated fuzzy logic with machine learning to address challenges related to data uncertainty, interpretability, and decision flexibility. Fuzzy logic, with its ability to model partial truth using fuzzy sets and membership functions, complements the data-driven strengths of ML by introducing linguistic reasoning and approximate inference capabilities. For instance, Abo El-Hamd et al. (2012) employed a fuzzy Q-learning framework to predict customer lifetime value under uncertain environments, demonstrating improved decision robustness over traditional reinforcement learning. Similarly, Tekin et al. (2022) developed a fuzzy clustering-based ensemble for lifetime value prediction in the gaming industry, enhancing prediction accuracy by integrating fuzzy rules with machine-learned outcomes. In healthcare, fuzzy-neuro models, such as ANFIS (Adaptive Neuro-Fuzzy Inference System), have been optimized using particle swarm optimization to enhance the accuracy of medical diagnoses (Rajabi et al., 2019). These hybrid models utilize fuzzy logic to interpret human-centric attributes (e.g., "high risk" or "moderate loyalty") while employing machine learning for pattern discovery and model training, thereby offering a balance between accuracy and transparency in predictive modeling. Additionally, Dalar and Egrioglu noted that the hybridization of ML and FL provides a robust, flexible, and interpretable framework, which is particularly compelling when handling uncertain or fuzzy real-world data, surpassing traditional ML in both practical performance and explainability (Dalar and Egrioglu, 2025).

In recent years, there has been a growing interest in applying fuzzy logic to predict customer lifetime value (CLV), with researchers investigating various strategies and methodologies to enhance forecast accuracy and model interpretability (Aeron et al., 2010). Fuzzy clustering algorithms have been utilized to categorize customers according to their behavioral patterns and attributes, facilitating the recognition of distinct customer segments with differing CLV profiles. Fuzzy rule-based systems, utilizing fuzzy inference methods, have been created to simulate the correlations between customer qualities and customer lifetime value (CLV), enabling the production of tailored CLV predictions based on distinct customer profiles. Furthermore, hybrid methodologies that integrate fuzzy logic with other machine learning techniques, including neural networks and evolutionary algorithms, have demonstrated the potential to enhance prediction accuracy and robustness. These hybrid models leverage the advantages of fuzzy logic and machine learning, combining the interpretability of fuzzy rules with the learning capabilities of neural networks and the optimization efficiency of genetic algorithms. CRM necessitates cultivating enduring relationships with consumers and deploying resources to sustain these connections (Aeron et al., 2010).

The advantages of fuzzy logic in Customer Lifetime Value prediction include heightened accuracy, better interpretability, and greater resilience. The capacity of fuzzy logic to manage imprecise data and subjective information enhances the accuracy of Customer Lifetime Value forecasts, especially in contexts with poor data quality or significant variability in customer behavior. Furthermore, the rule-based framework of fuzzy inference systems enhances model interpretability, allowing marketers to understand the determinants of CLV projections and identify significant client categories with substantial potential value. Integrating expert knowledge and qualitative insights enhances the modeling process, resulting in more substantial and actionable outcomes. Customer Lifetime Value (CLV) is assessed at the individual customer or segment level, enabling the distinction between more and less profitable customers (Chen, 2018). Moreover, fuzzy logic models exhibit intrinsic robustness to outliers and noisy data, ensuring steady and reliable CLV predictions despite data defects.

Notwithstanding the numerous advantages, obstacles persist in implementing fuzzy logic for CLV prediction, including the need for meticulous selection of membership functions, the risk of rule explosion, and the computational complexity of specific fuzzy inference methods. Choosing suitable membership functions is crucial for accurately representing the uncertainty and ambiguity associated with customer qualities, requiring a meticulous evaluation of domain knowledge and data characteristics. The quantity of fuzzy rules may increase exponentially with the number of input variables, resulting in a rule explosion issue that can impede model interpretability and computational efficiency. Confronting these issues necessitates meticulous model design, feature selection, and optimization methodologies. The difficulty resides in forecasting future gains when the timing and advantages of forthcoming transactions remain uncertain (Chen, 2018).

On the other hand, machine learning algorithms, especially ensemble learning algorithms such as Extreme Gradient Boosting (Chen and Guestrin, 2016), Catboost (Prokhorenkova et al., 2018), and Random Forest (Breiman, 2001), have an essential place in the literature for predicting CLV. Numerous studies are in the literature for predicting CLV (Asadi et al., 2024; Kumari et al., 2024; Todupunuri, 2024; Tudoran et al., 2024; Haddadi and Hodjat, 2025). However, fuzzy logic has an advantage in terms of interpretability of results, computational time, and resources.

This study consists of five main sections. The first section highlights the significance of fuzzy logic in predicting CLV, offering a comprehensive review of the relevant literature. The second section shows the preliminaries of Fuzzy Logic. The third section details the dataset and methodology employed in this study, and the performance of fuzzy logic in the calculation stage is evaluated using actual values of CLV. Finally, the last section discusses the study's recommendations, limitations, and suggestions for future research.

2. Materials and Methods

In mobile gaming, predicting CLV is crucial for optimizing marketing strategies, player retention, and monetization (Tekin et al., 2022). However, player behavior is highly uncertain and nonlinear, making traditional CLV prediction models ineffective. Fuzzy logic offers a robust framework for handling uncertainty by incorporating degrees of membership rather than rigid classifications. This section introduces the fundamental concepts of fuzzy logic and its application to CLV prediction in mobile games.

Customer Lifetime Value (CLV) represents the total revenue a company expects to earn from a player throughout their engagement with the game (Tsai et al., 2013). Unlike traditional retail models, CLV in mobile gaming is influenced by:

- In-App Purchases (IAPs) – Direct revenue from item purchases.
- Ad Revenue – Revenue from watching rewarded ads.
- Session Length & Frequency – Indicators of long-term engagement.
- Retention Rate – Probability of a player staying active over time.

A general CLV model for mobile games is given in equation 1:

$$CLV = \sum_{t=0}^{T} \frac{(IAP_t + AdRev_t) x\, P_t}{(1+d)^t} \tag{1}$$

where:
IAP_t = In-app purchase revenue at time t,
$AdRev_t$= Ad revenue generated at time t,
P_t = Probability of the player being active at t,
d = Discount rate,
T= Predicted player lifespan.

Uncertain player behavior, sparse transactions, and nonlinear progression in mobile games cause challenges in predicting CLV in mobile games. Fuzzy logic provides a way to handle these uncertainties by categorizing players into fuzzy segments rather than rigid groups.

Fuzzy logic, introduced by Zadeh (1965), is a mathematical approach for handling imprecise data. Unlike classical binary logic (true/false), fuzzy logic assigns degrees of truth between 0 and 1.

A fuzzy set A in a universal set X is defined by a membership function. It is given in equation 2:

$$\mu_A : X \rightarrow [0,1 \tag{2}$$

where:
$\mu_A(x)$ represents the degree of membership of x in set A. Values closer to 1 indicate strong membership; values near 0 indicate weak membership.

Membership functions define how crisp values (e.g., session length, spending) are mapped into fuzzy values. Common types include:

The Triangular Membership Function is given in equation 3:

$$\mu_A(x) = \begin{cases} 0, & x \le a \; or \; x \ \ge c \\ \dfrac{x-a}{b-a}, & a < x \ \le b \\ \dfrac{c-x}{c-b}, & b < x < c \end{cases} \tag{3}$$

The Triangular membership function is shown in Figure 1.

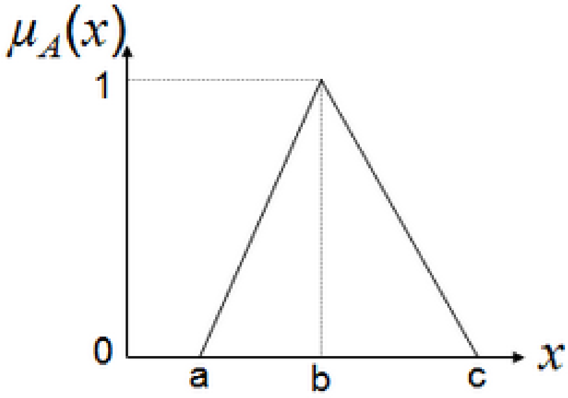

Figure 1. Triangular membership function.

The Trapezoidal Membership Function is given in equation 4:

$$\mu_A(x) = \begin{cases} 0, & x \le a \; or \; x \ \ge d \\ \dfrac{x-a}{b-a}, & a < x \ \le b \\ 1, & b < x \le c \\ \dfrac{d-x}{d-c}, & c < x < d \end{cases} \tag{4}$$

The Trapezoidal membership function is shown in Figure 2.

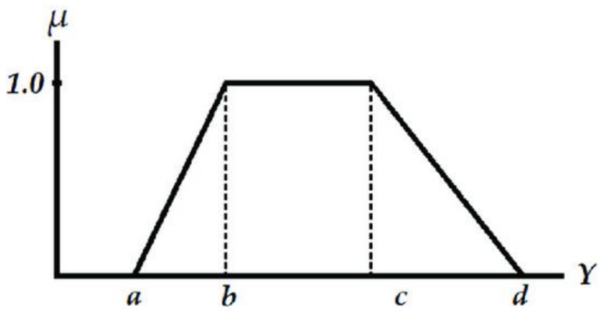

Figure 2. Trapezoidal membership function.

Gaussian Membership Function is given in equation 5:

$$\mu_A(x) = \exp\left(-\frac{(x-c)^2}{2\sigma^2}\right) \tag{5}$$

The Gaussian membership function is shown in Figure 3.

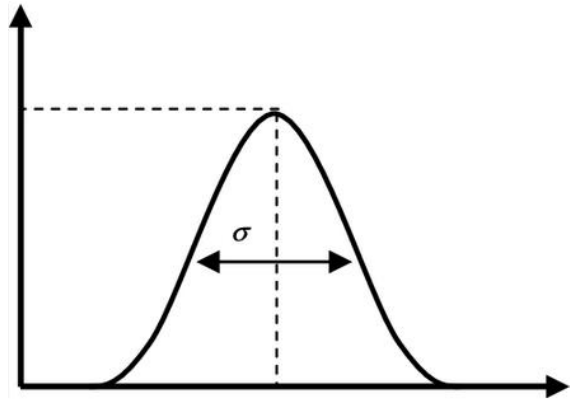

Figure 3. Gaussian membership function.

A Fuzzy Inference System (FIS) maps input variables (Recency, Frequency, Monetary) to an output variable (CLV) using IF-THEN rules. Input variables and their fuzzy categories are shown in Table 1.

Table 1. Input variables and fuzzy categories

Input Variables	Fuzzy Categories
Recency (R) days	Recent, Medium, Inactive
Frequency (F) (sessions/week)	Low, Medium, High
Monetary Value (M) ($spent)	Low, Medium, High

The output variables and their corresponding fuzzy categories are presented in Table 2.

Table 2. Output variables and fuzzy categories

Output Variable	Fuzzy Categories
Customer Lifetime Value (CLV)	Low, Medium, High

Fuzzy Rule Base:
Rules define relationships between inputs and CLV.
Example IF-THEN Rules

- IF Frequency is High AND Monetary is High, THEN CLV is High.
- IF Frequency is Medium AND Recency is Recent, THEN CLV is Medium.
- IF Frequency is Low AND Monetary is Low, THEN CLV is Low.

Each rule is evaluated using fuzzy logic operators:

- AND = Minimum (min) function.
- OR = Maximum (max) function.
- Implication (firing strength) = Apply rule strength to CLV membership.

After applying fuzzy rules, we get a fuzzy CLV value. To convert it into a crisp CLV estimate, we use defuzzification. Common defuzzification methods are shown below.
The Centroid function is given in equation 6:

$$CLV = \frac{\sum(\mu(x).x)}{\sum \mu(x)} \tag{6}$$

The Mean of the Maximum function is given in equation 7:

$$CLV = \frac{x_{max1} + x_{max2}}{2} \tag{7}$$

3. Results

Customer Lifetime Value (CLV) is one of the key metrics used in customer relationship management to estimate the total revenue a company can expect from a customer in their lifetime. CLV consists of two major components in a mobile game. These are in-app Revenue Streams triggered in the Google Play Store and Apple App Store, as well as in-ad revenue streams triggered by an ad the user sees within the game. Accurate CLV estimation helps companies optimize their marketing strategies, resource allocation, and customer churn prevention efforts. However, predicting CLV is complex due to the uncertainty and variability in customer behavior, as well as demographic differences.

Traditional approaches to CLV prediction, such as machine learning algorithms (Sun et al., 2023; Bauer and Jannach, 2021), regression models, and Markov chains (Cheng et al., 2012; Mzoughia and Limam, 2015; Ekinci et al., 2014), often work with customer behavior following deterministic or probabilistic patterns. These models can predict well in structured and predictable data, but they struggle to deal with imprecise real-world customer interactions.

Fuzzy logic provides a more realistic and flexible approach to CLV prediction by handling uncertainty and modeling imprecise customer behaviors. Fuzzy logic provides partial membership in multiple categories instead of hard classes like low-value or high-value customers. Challenges in traditional CLV prediction models are explained below.

3.1. Challenges in Traditional CLV Prediction

3.1.1. Uncertainty and variability in customer behavior

Customers can interact with businesses in different ways. Two customers can have similar histories but behave differently in the future. It makes it challenging to predict customers' future behavior. Because statistical models rely on fixed rules and assumptions, some customers make small monetary values while others make them infrequently, but they can create high monetary values. Additionally, some customers may suddenly churn, despite having a history of consistent transactions in the system. Therefore, it enables their CLV to be predicted using traditional methods. For example, Customer A plays the game daily, but they can only create one dollar in a month. Customer B plays the game weekly but can make five dollars in one month.

A traditional regression-based CLV model might classify Customer A as a low-value user and Customer B as a high-value user. However, Customer B's behavior introduces high uncertainty and makes inaccurate classifications.

3.1.2. Hard segmentation in traditional models

Many traditional models rely on hard segmentation, assigning customers to distinct strict groups. For example, if the user creates five dollars, he can be assigned to high-value users, and the other users will be assigned to a low-value user group. This approach ignores gradual transitions between customer categories. For example, if a customer creates \$4.9, he may behave like a high-value customer but be assigned to a low-value user group. Fuzzy logic will eliminate this issue by allowing customers to have partial membership in multiple categories. For example, if a customer spends 4.5 dollars, he could be 70% in the Medium CLV category and 30% in the High CLV category instead of being assigned to one group.

3.1.3. Difficulty in handling multi-dimensional factors

Traditional CLV models often rely on a few key variables such as Recency, Frequency, and Monetary value. However, these models struggle to integrate additional qualitative factors such as Customer Engagement, Customer Satisfaction, and Churn probability. Fuzzy logic can handle multiple dimensions by incorporating additional input variables without increasing model complexity.

Given these challenges, fuzzy logic provides an alternative approach that more effectively captures real-world customer behavior. It allows customers to have partial membership in multiple CLV categories instead of hard classes. So, it handles uncertainty in CLV calculation. Also, fuzzy logic uses IF-THEN rules to capture human-like decision-making, so it incorporates expert knowledge. On the other hand, fuzzy logic can integrate multiple qualitative and quantitative factors into the prediction model, so it adapts to complex patterns.

3.2. Proposed Methodology

3.2.1. Membership Functions Overview

The Python programming language and the skfuzzy library were used in the application phase, and Microsoft SQL Server was used in the data preparation phase in the study.

Three input and one CLV output variable are defined with their respective fuzzy sets. Three different fuzzy rules were created for each input variable and output variable. These rules were obtained based on the mobile game's specific geographical distribution of actual users' Recency, Frequency, and Monetary values. Additionally, the actual customer lifetime of these users was calculated based on their one-year generated revenue. As Jang (2013) stated, the Sugeno fuzzy inference system supports numerical output generation by combining fuzzy rules with learning capability; therefore, the Sugeno fuzzy inference system was applied in the methodology. The input variables and output variables, along with their Corresponding Fuzzy Sets, are defined in Table 3 and Table 4.

Table 3. Input variables and fuzzy sets

Variable	Fuzzy Sets (Categories)	Range
Recency (R) days	Recent, Medium, Inactive	0-60
Frequency (F) (sessions/week)	Low, Medium, High	0-20
Monetary Value (M) (\$spent)	Low, Medium, High	0-5

Table 4. Output variables and fuzzy sets

Variable	Fuzzy Sets (Categories)	Range
Customer Lifetime Value (CLV)(\$)	Low, Medium, High	0-50

3.2.2. Membership functions for input variables

3.2.2.1. Recency (days since last play)

- Recent (0-30 days)
- Medium (20-50 days)
- Inactive (40-60 days)

Mathematical Definitions

Recent (Triangular Membership Function):

$$\mu_{Recent}(x) = \begin{cases} 1, x = 0 \\ \dfrac{30 - x}{30}, 0 < x \leq 30 \\ 0, x > 30 \end{cases}$$

Medium (Triangular Membership Function):

$$\mu_{Medium}(x) = \begin{cases} \dfrac{x - 20}{50 - 20}, 20 \leq x \leq 50 \\ 0, \quad otherwise \end{cases}$$

Inactive (Triangular Membership Function):

$$\mu_{Inactive}(x) = \begin{cases} 0, x < 40 \\ \dfrac{x - 40}{60 - 40}, 40 \leq x \leq 60 \\ 1, x > 60 \end{cases}$$

3.2.2.2. Frequency (sessions per week)

- Low (0-5 sessions)
- Medium (5-15 sessions)
- High (10-20 sessions)

Mathematical Definitions

Low (Triangular Membership Function):

$$\mu_{Low}(x) = \begin{cases} 1, x = 0 \\ \dfrac{5 - x}{5}, 0 < x \leq 5 \\ 0, x > 5 \end{cases}$$

Medium (Trapezoidal Membership Function):

$$\mu_{Medium}(x) = \begin{cases} \dfrac{x - 5}{10 - 5}, \quad 5 \leq x \leq 10 \\ 1, \quad 10 < x < 15 \\ \dfrac{20 - x}{20 - 15}, 15 \leq x \leq 20 \\ 0, x > 20 \end{cases}$$

High (Triangular Membership Function):

$$\mu_{High}(x) = \begin{cases} 0, x < 10 \\ \dfrac{x - 10}{20 - 10}, 10 \leq x \leq 20 \\ 1, x > 20 \end{cases}$$

Fuzzy Membership Functions for Session Frequency are shown in Figure 4.

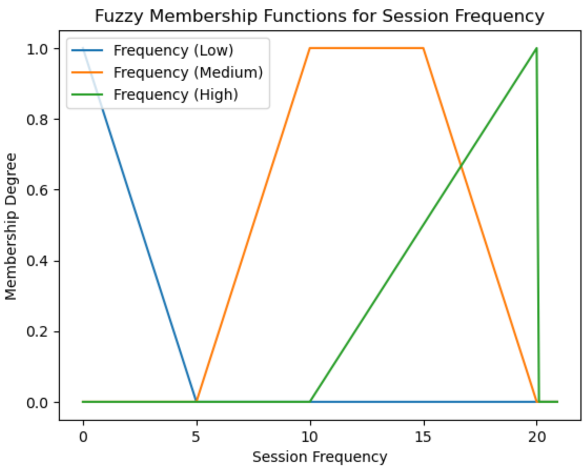

Figure 4. Fuzzy membership functions for session frequency.

3.2.2.3. Monetary value ($ spent)

- Low (0-2 dollars)
- Medium (1-3 dollars)
- High (2.5-5 dollars)

Mathematical Definitions

Low (Triangular Membership Function):

$$\mu_{Low}(x) = \begin{cases} 1, x = 0 \\ \frac{2-x}{2}, 0 < x \leq 2 \\ 0, x > 2 \end{cases}$$

Medium (Triangular Membership Function):

$$\mu_{Medium}(x) = \begin{cases} \frac{x-1}{3-1}, 1 \leq x \leq 3 \\ 0, \quad otherwise \end{cases}$$

High (Gaussian Membership Function):

$$\mu_{High}(x) = \exp\left(-\frac{(x-4)^2}{2\,x\,1^2}\right)$$

3.2.3. Membership functions for output variable (CLV)

- Low (0-20 dollars)
- Medium (15-35 dollars)
- High (30-50 dollars)

Mathematical Definitions

Low (Triangular Membership Function):

$$\mu_{Low}(x) = \begin{cases} 1, x = 0 \\ \frac{20-x}{20}, 0 < x \leq 20 \\ 0, x > 20 \end{cases}$$

Medium (Triangular Membership Function):

$$\mu_{Medium}(x) = \begin{cases} \frac{x-15}{35-15}, 15 \leq x \leq 35 \\ 0, \quad otherwise \end{cases}$$

High (Triangular Membership Function):

$$\mu_{High}(x) = \begin{cases} 0, x < 30 \\ \frac{x-30}{50-30}, 30 \leq x \leq 50 \\ 1, x > 50 \end{cases}$$

3.2.4. Calculating customer lifetime value (CLV) using fuzzy membership functions

This section provides a step-by-step calculation of Customer Lifetime Value using fuzzy membership functions, fuzzy rules, and defuzzification.

Let's assume we have a mobile game player with the following attributes. His recency is 10 days, his frequency is eight sessions per week, and his monetary value is $ 1.20.

3.2.4.1. Fuzzification (convert crisp values into fuzzy sets)

Each crisp input value is mapped into fuzzy sets using the membership functions we defined.

Recency (10 days) – Membership Calculation:

Fuzzy Sets for Recency:

- Recent (0-30 days) -> Triangular MF
- Medium (20-50 days) -> Triangular MF
- Inactive (40-60 days) -> Triangular MF

Calculate Membership Values:

Recent (0-30 days):

$$\mu_{Recent}(10) = \frac{30-10}{30} = 0.67$$

Medium (20-50 days):

$$\mu_{Medium}(10) = 0 \ (since\ 10 < 20)$$

Inactive (40-60 days):

$$\mu_{Inactive}(10) = 0$$

The recency fuzzification results are 0.67 Recent, 0 Medium, and 0 Inactive.

Frequency (8 sessions per week) – Membership Calculation:

Fuzzy Sets for Frequency:

- Low (0-5 sessions) -> Triangular MF
- Medium (5-15 sessions) -> Trapezoidal MF
- High (10-20 sessions) -> Triangular MF

Calculate Membership Values:

Low (0-5 sessions):

$$\mu_{Low}(8) = 0 \ (since\ 8 > 5)$$

Medium (5-15 sessions):

$$\mu_{Medium}(8) = \frac{8-5}{10-5} = 0.6$$

High (10-20 sessions):

$$\mu_{High}(8) = 0 \ (since\ 8 < 10)$$

The frequency fuzzification results are 0.6 Medium, 0 High, and 0 Low.

Fuzzy Sets for Monetary Value:

- Low (0-2 dollars) -> Triangular MF
- Medium (1-3 dollars) -> Triangular MF
- High (2.5-5 dollars) -> Gaussian MF

Calculate Membership Values:

Low (0-2 dollars):

$$\mu_{Low}(1.2) = \frac{2-1.2}{2} = 0.4$$

Medium (1-3 dollars):

$$\mu_{Medium}(1.2) = \frac{1.2-1}{3-1} = 0.1$$

High (2.5-5 dollars):

$$\mu_{High}(1.2) = 0$$

The monetary values fuzzification results are 0.4 Low, 0.1 Medium, and 0 High.

Applied fuzzy rules to determine which CLV categories get activated are shown in Table 5.

Table 5. Fuzzy rules and category activation

Rule	IF Conditions	THEN CLV	Firing Strength
R1	Recency is Recent (0.67) & Frequency is Medium (0.6) & Monetary is Low (0.4)	Medium CLV	min(0.67, 0.6, 0.4) = 0.4
R2	Recency is Recent (0.67) & Frequency is Medium (0.6) & Monetary is Medium (0.1)	Medium CLV	min(0.67, 0.6, 0.1) = 0.1

Thus, the CLV fuzzy output is Medium CLV at a strength of 0.4 and Medium CLV at a strength of 0.1. The firing strengths were determined according to the and operator. In the next step, defuzzification was applied to the dataset, and fuzzy outputs were converted into Crisp CLV Values. This conversion was applied with Sugeno's weighted average output method.

CLV Fuzzy Sets and their representative values are shown in Table 6.

Table 6. Fuzzy sets and representative values

CLV Set	Range	Representative Value
Low	0-20	10
Medium	15-35	25
High	30-50	40

The centroid function shown in Equation 6 is used to predict CLV.

$$CLV = \frac{(0.4\ X\ 25) + (0.1\ X\ 25)}{0.4 + 0.1} = 25$$

Thus, the predicted CLV for the player is 25 dollars.

The proposed methodology was applied to a dataset consisting of 10,000 unique users who downloaded the game within a specific period. These users have different demographic characteristics. After applying the proposed methodology, the predicted CLV was compared to the actual CLV. The obtained results have an R-squared value of 0.91 and a Root Mean Squared Error (RMSE) of 0.08. The applied method shows promising results, and instead of applying more complex methods for a machine learning-based prediction model, this model can be applied in the prediction stage. Because fuzzy logic handles ambiguity and models imprecise customer behaviors, the forecasts offer a more flexible and realistic approach to CLV prediction.

4. Discussion and Conclusion

In this study, CLV was estimated using fuzzy logic to optimize user acquisition strategies for lower cost and apply custom strategies to increase the mobile game industry's income. Fuzzy Logic was applied to the dataset acquired by a mobile game published in the Google Play Store and Apple App Store. Before applying the model, each user's recency, frequency, and monetary values were determined and grouped according to the selected boundaries. Due to the fuzzy logic nature, the results can be interpreted easily, and the calculation time and resource usage were optimized when we compared applying machine learning models. The estimations of the applied model were evaluated by calculating MAE and R-squared values according to the users' actual CLV values. The results indicate that fuzzy logic can be effectively utilized in estimating CLV values and enhancing marketing strategies.

This study has two primary limitations. First, the demographic information of the users not used in the study effect the CLV of the users. Second, before applying the model, a broader range of periods for the data can improve the group boundary selection stage.

Future research can expand on the findings of this study in several ways. First, the model can be applied according to users' demographic information in different clusters. Therefore, the boundaries can be adjusted, and more accurate results can be obtained in the estimation process. Second, hybrid fuzzy models with machine learning can enhance accuracy and adaptability in dynamic business environments. Third, the applied model can be tested in different mobile games, generating different values according to the game's retention values.

Author Contributions

The percentages of the author' contributions are presented below. The author reviewed and approved the final version of the manuscript.

	A.T.T.
C	100
D	100
S	100
DCP	100
DAI	100
L	100
W	100
CR	100
SR	100
PM	100
FA	100

C=Concept, D= design, S= supervision, DCP= data collection and/or processing, DAI= data analysis and/or interpretation, L= literature search, W= writing, CR= critical review, SR= submission and revision, PM= project management, FA= funding acquisition.

Conflict of Interest

The author declared that there is no conflict of interest.

Ethical Consideration

Ethics committee approval was not required for this study because of there was no study on animals or humans.

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