Designing a Model for the Impact of Viral Marketing in Social Networks Using Adaptive Neuro-Fuzzy Inference Systems



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Abstract				

The aim of this study is to design a model for the impact of viral marketing in social networks using the Adaptive Neuro-Fuzzy Inference System (ANFIS). This research utilizes the Adaptive Neuro-Fuzzy Inference System due to its ability to implement human knowledge through concepts like timestamps and fuzzy rules, its nonlinear nature, adaptability, and superior accuracy compared to other methods in conditions with limited data. These features are among the most significant advantages of ANFIS systems. The MATLAB software was employed in the ANFIS framework to modify inputs and outputs. This research followed the steps of input fuzzification, fuzzy rule base development, fuzzy inference engine construction, aggregation phase, and defuzzification when employing the Adaptive Neuro-Fuzzy Inference System. Value-based marketing relies on the principle that individuals who have used a product or service and had a positive experience share this experience with others, encouraging them to use the product or service as well. Viral marketing is, in a way, a form of partnership where an individual shares their experience with another person who needs the product or service. Due to its broad reach, low cost, high speed, and simplicity, companies can implement controlled viral marketing campaigns through principled and regulatory-compliant marketing efforts, thereby contributing to the growth of the company. This is because, within a short period, many people become familiar with the company and its brand name.

Keywords: Viral marketing, Social networks, ANFIS, Word-of-mouth marketing, Viral.

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1. Introduction

Viral marketing, especially in digital media such as social networking sites, has become prominent [1]. If marketers effectively target social media influencers, they possess a significant asset. Influencers can promote products or services through free items or discounts, sharing their positive opinions with other consumers (e.g., word-ofmouth) [2].

Through virtual social networks, individuals can communicate with one another without time and location constraints [3, 4]. One emerging service within social networks is viral marketing. Viral marketing, a form of social network-based marketing, enables the rapid and costeffective dissemination of marketing information among a large audience in the online environment [5, 6].

Several factors influence the success and effectiveness of viral advertising, including those related to consumers exposed to the message, the message senders, or the characteristics of the message and the medium transmitting it. A lack of awareness regarding customers' behavior, attitudes, and tendencies can have negative consequences for companies. Negative impacts are rapidly disseminated communication through social systems and recommendation-based advertising, potentially causing substantial damage to companies' market shares. It is critical to identify the factors in this type of marketing that motivate customers to purchase a product, enabling companies to influence these factors and encourage customers to perceive their product as superior to alternatives, even recommending it to others [5, 6].

The advent of the internet has increasingly boosted viral marketing. Information sources like blogs, websites, and social networks where product advertisements and user opinions are shared underscore viral marketing's influence on customer purchase intent. Today, before making a purchase decision, customers often research products or services they are interested in online. Customers frequently review previous buyers' opinions, gaining insights about products during the purchase process [7].

One challenge marketers face is understanding the complexities of customer behavior, including product attributes, diverse brands, and various shopping environments, each containing different messages that may influence customers to share them with others. Customers' perception of these messages affects their purchasing decisions, and the source of the message significantly impacts customer perceptions [8].

In a competitive market, understanding customer needs and implementing effective advertising are critical for survival. The expansion of the internet and virtual networks has provided companies with significant opportunities for advertising. Consequently, studying electronic marketing methods and models has become increasingly important. One of the most recent methods, viral marketing, relies on word-of-mouth advertising and has significant potential. Viral marketing is based on the principle that within any social network, some users exert substantial influence over others. By identifying these users and creating compelling advertising messages, companies can engage in effective marketing [9].

Social media is filled with likes, tweets, shares, posts, and miscellaneous content [10]. It is not just young people who use these platforms; social media is global and ubiquitous. Astonishing statistics reveal that 72% of internet users are now active on social media [7, 9]. Among users, 89% of individuals aged 18 to 29 use social media, 82% of those aged 30 to 49 are active on these platforms, 65% of individuals aged 50 to 64 use social media, and 49% of individuals over 64 are active users (Pew, 2014). Clearly, regardless of age, people today spend significant time on social media, continuously sharing and reviewing information.

Customers are vital assets for a company, but acquiring them can be costly. This study focuses on customer acquisition, a critical issue for any organization. Ensuring that the inflow of customers exceeds the outflow is no simple task. Consequently, marketers are constantly competing to capture the attention and consideration of potential customers. Many have shifted their marketing efforts from directly engaging with potential customers to leveraging existing customers. This shift stems from the growing acknowledgment that information received from others profoundly influences people and that word-of-mouth advertising (WOM) is the most effective information source for a customer. Empirical research has confirmed that when customers make purchase decisions, they heavily rely on advice from others in their personal networks, and positive WOM significantly affects business outcomes such as sales [11].

Social media marketing offers several advantages for companies. Beyond facilitating the free exchange of ideas and information among consumers, social media platforms enable two-way communication between consumers and brands. This interaction helps reduce consumer bias against brands, thereby enhancing brand value. By actively participating in online discussions, companies can guide conversations and create more meaningful content. In doing so, companies can familiarize consumers with their brands by engaging them in marketing activities and other initiatives [8].

The primary research question in this study is: What is the model for the impact of viral marketing in social networks using the Adaptive Neuro-Fuzzy Inference System (ANFIS)?

2. Methodology

To collect data, this study employed library research and a questionnaire (focused on viral marketing and its influencing factors) based on a five-point Likert scale.

Content validity and face validity were used to assess the validity of the questionnaire items. After designing the questionnaire, it was reviewed by 15 experts, who were asked to rate each item using a three-point scale: "essential," "useful but not essential," and "not essential." According to Lawshe's table, the minimum acceptable CVR index value for each item with this number of experts is 0.76. Initially, the questionnaire contained 117 items, which were reduced to 98 after content validation. The CVI index, calculated as the aggregation of agreement scores for each item, was above 0.79, confirming validity.

To test reliability, 50 questionnaires were completed and analyzed using Cronbach's alpha in SPSS software. The calculated Cronbach's alpha coefficient for each index (viral marketing and its influencing factors) exceeded 0.8, indicating internal consistency among items and the reliability of the instrument.

3. Findings

In this research, the Adaptive Neuro-Fuzzy Inference System (ANFIS) was employed due to its ability to implement human knowledge using concepts such as timestamps and fuzzy rules, its nonlinearity, adaptability, and superior accuracy compared to other methods in conditions with limited data. A critical feature of fuzzy systems is their ability to establish connections between input and output spaces, facilitated through a set of fuzzy rules. Additionally, neural networks can establish appropriate relationships between input and output variables due to their training capabilities using various training patterns. Therefore, combining fuzzy inference systems and artificial neural networks creates a powerful tool, known as ANFIS, capable of predicting outcomes using available numerical data. This system uses neural network algorithms and fuzzy logic to design a nonlinear mapping between input and output spaces.

The construction of concepts originates from an abstract perspective, identifying commonalities in social phenomena through empirical findings based on observations and their generalization (Ghasemi, 2018). Fuzzy logic is well-suited for this purpose. It facilitates the gradation of concepts, enabling the incorporation of categorical concepts into subsequent dimensions. A fuzzy logic-based approach allows for the creation of "quasi-interval" scales, thereby enhancing precision. Fuzzy decision-making helps model through "if-then" ambiguous conditions rules. Consequently, ANFIS can effectively interpret values, norms, and relationships within a model.

- 1. **Input Fuzzification**: Converting numerical variable values into a fuzzy set.
- Fuzzy Rule Base: A set of "if-then" rules applying logical operators that allow combinations of low, medium, and high input conditions to simultaneously influence the output.
- 3. **Fuzzy Inference Engine**: Converting inputs into outputs.
- 4. **Aggregation**: Combining all defined rules in the ANFIS system.
- 5. **Defuzzification**: Converting the fuzzy output from the aggregation stage into a precise numerical value.

The components of the ANFIS used in this research are further elaborated. The general structure of the ANFIS model, including inputs, fuzzy rules, and outputs, is illustrated below.



Figure 1. ANFIS Model Structure

The model inputs comprise four independent variables influencing viral marketing: brand equity (CBE), brand reputation and credibility (BRC), individual characteristics (ICH), and message attributes (MFE). For each input and output variable, it is essential to define a membership function. Accordingly, membership functions for each fuzzy set parameter are defined as triangular membership functions.



Figure 2. Membership Function and Input Variable Attributes

The three triangular curves represent the low, medium, and high levels of independent variables (inputs). Based on fuzzy set rules, the values of each input are categorized into three levels (low, medium, high), which can be illustrated using triangular graphs. The horizontal axis represents field data on a five-point scale (1 to 5), while the vertical axis indicates fuzzy membership degree, ranging from 0 to 1.

The viral marketing variable (VM) is defined as an output in three levels (low, medium, high) using triangular membership functions. The membership functions of the output are depicted below.

high	
med	
low	
output variable "VM"	

Figure 3. Membership Function and Output Variable Attributes (VM)

During the aggregation stage, input combinations are processed using the "and" operator based on the product function, inference using the minimum function, and aggregation using the maximum function. In the defuzzification stage, the fuzzy set output from aggregation is converted into a single, precise value. This value lies within the defined range for the output variable (scale 1 to 5), indicating the expected output value based on the defined fuzzy inference system and the given input vector. The "wtaver" method indicates that output determination is calculated as a weighted average. The parameters are defined in the table below:

Parameter	Operator/Method
"And" Operator	prod
Inference Method	min
Aggregation Method	max
Defuzzification Method	wtaver

The inference system is based on fuzzy "if-then" rules with learning capabilities to approximate nonlinear functions. For a given process, constructing fuzzy inference systems involves defining the governing fuzzy rules. Fuzzy rules are formulated as "if-then" statements, with the "if" part referred to as the antecedent and the "then" part as the consequent. In this research, each defined rule combines two or three variables. The total number of theoretically possible rules, based on KKK variables each having LLL levels, is LKL^KLK. Some combinations, however, may be unrealistic or impossible. For each fuzzy rule, combinations of input levels lead to output values for the dependent variables, as shown above.

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12. If (CBE is Med) and (BRC is low) and (ICH is med) and (MEF is med) then (VM is med) (·
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14. If (CBE is Med) and (BRC is med) and (ICH is med) and (MEF is med) then (VM is high) (1)
15. If (CBE is high) and (BRC is med) and (ICH is med) and (MEF is med) then (VM is high) (1)
16. If (CBE is high) and (BRC is high) and (ICH is med) and (MEF is med) then (VM is high) (1)
17. If (CBE is high) and (BRC is low) and (ICH is med) and (MEF is med) then (VM is med) (1)
18. If (CBE is high) and (BRC is med) and (ICH is low) and (MEF is med) then (VM is med) (1)
19. If (CBE is high) and (BRC is med) and (ICH is med) and (MEF is low) then (VM is med) (1)
20. If (CBE is high) and (BRC is med) and (ICH is high) and (MEF is med) then (VM is high) (1)
21. If (CBE is high) and (BRC is med) and (ICH is med) and (MEF is high) then (VM is high) (1)

Figure 4. Defined Rules in ANFIS

The rule linking inputs in this study employs the "and" rule, displayed in the "Connection" section. Based on each defined rule, a specific combination of input conditions results in a particular output. The weight assigned to fuzzy rules plays a critical role in this stage, as weights directly influence the consequent. In this study, all rules have equal weights of "1," as indicated in the "Weight" section and shown in parentheses next to each fuzzy rule.

After these definitions, all rules in the ANFIS system are combined and aggregated. In this research, all rules were combined and aggregated. Aggregation adheres to the principle of commutativity, ensuring that different rule sequences lead to identical outputs.

The ANFIS is a six-layer network consisting of nodes and connecting edges. The appropriate structure of the ANFIS depends on input data, membership degree, rules, and output membership functions. The architecture of the neuro-fuzzy network in this research is depicted below.



Figure 5. ANFIS Architecture

The flow of relationships in the network occurs from the input layer to the output layer in a recursive manner. The input layer consists of predictors; in this study, as shown in Figure 5, there are four inputs. This layer includes nodes or hidden units, and the value of each hidden unit is a function of the predictors. The output layer represents reactions. In

this research, the dependent variable, or target, is viral marketing, which is estimated by the predictor variables. While the foundation of ANFIS lies in fuzzy sets, numbers, and rules, both the inputs and outputs are precise numerical values. In the first layer, input values are entered as exact and definitive numbers. In the second layer, the membership level of each input within different fuzzy ranges (low, medium, and high) is determined. The third layer, the rules layer, defines how inputs are combined. The fourth layer produces various fuzzy outputs based on applying the rules to the input values. The fifth layer aggregates and combines these fuzzy outputs into a single fuzzy output. The final layer provides the definitive network output as an exact, non-fuzzy number within the defined range (1 to 5 in this study).

Modeling the fuzzy inference system occurs in two stages: "training" and "testing" the system. To modify the mapping between inputs and outputs, a structure similar to neural networks can be used. Neural networks can be employed to map inputs to membership functions and their parameters, and subsequently, map output membership functions to outputs. Errors are typically calculated using the sum of squared errors (SSE). ANFIS estimates membership function parameters using the backpropagation method or a combination with least squares estimation. The goal of training the network is to minimize the error between the network's output and the actual output. During the training phase, input values are adjusted to better approximate real values by modifying membership parameters based on acceptable error levels. The primary training method in this system is backpropagation. This technique uses a gradient descent algorithm to propagate the error toward the inputs and adjust the parameters. In this study, a piecewise network discretization approach was used, where the type of membership function is determined by the user. Before implementing the ANFIS model, normalization was performed to enhance the network's accuracy and response speed to input messages. For system modeling with actual data, the data were divided into three categories: training

data (70%, equivalent to 280 data points), testing data (20%, equivalent to 80 data points), and validation data (10%, equivalent to 40 data points). The selection of training, testing, and validation data was done randomly.

After testing various functions, the gussmf function with 18 epochs produced the best result, achieving an RMSE (Root Mean Square Error) of 0.0002, which is less than 0.05, indicating the model's suitability.

Test data enable evaluating the generalizability of the fuzzy inference system. The validation dataset's primary purpose is to identify overfitting in the model. When training is improperly conducted, the model perfectly fits the training data but performs poorly on non-training data. Validation data help detect overfitting because, during the training process, the model error on the validation set initially decreases. However, once overfitting begins, the validation error sharply increases. Parameters of the membership functions are determined such that the model's error is minimized on both the validation and training datasets.

Two similar datasets were used for training and validation, with slight perturbations added to the validation data for distinction. This study demonstrates how the ANFIS editor's graphical interface can be utilized to mitigate model overfitting effects. The training data provided to ANFIS were entirely different from the validation data.

All inputs were kept fixed at the midpoint of the scale. Under these conditions, as in the hypothesis testing section, the values for innovation management can be altered from the minimum to the maximum, and the corresponding changes in output can be calculated. MATLAB also allows observing input and output changes through the ANFIS file, which is demonstrated in this section.



Figure 6. ANFIS for Visualizing Input Impact on Output

Figure 6 shows that when brand equity is 0.326 (the standardized average value based on field data), brand reputation and credibility is 0.267, individual characteristics

are 0.211, and message attributes are 0.205, the viral marketing score is 0.252.



Figure 7. Model Outputs

4. Discussion and Conclusion

Viral marketing, a type of word-of-mouth marketing, is a form of marketing disseminated as digital content on the internet. This marketing approach is highly cost-effective and impactful. Each viral marketing method has its unique characteristics, discussed below:

Value-based marketing relies on individuals sharing their positive experiences with a product or service with others, encouraging them to try it. For businesses producing highquality products, this method is highly effective in increasing customers within a short time.

Vital marketing operates as a partnership where individuals share their product or service experiences with others who may need them. However, this approach only works if the individual is entirely confident about the product's or service's quality. Once satisfied, they recommend it to others.

In spiral marketing, individuals who have used a product or service share moments of joy and positive experiences related to the product with others. This motivates others to purchase the product to experience similar positive feelings.

Due to its wide reach, low cost, high speed, and simplicity, companies can implement well-structured viral marketing campaigns aligned with regulations to support business growth. In a short period, many people will become familiar with the brand and company.

Authors' Contributions

Authors equally contributed to this article.

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Declaration of Interest

The authors report no conflict of interest.

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Ethical Considerations

All procedures performed in this study were under the ethical standards.

References

- [1] K. Motoki, S. Suzuki, R. Kawashima, and M. Sugiura, "A Combination of Self-Reported Data and Social-Related Neural Measures Forecasts Viral Marketing Success on Social Media," *Journal of Interactive Marketing*, vol. 52, pp. 99-117, 2020, doi: 10.1016/j.intmar.2020.06.003.
- [2] J. Robles, M. Chica, and O. Cordon, "Evolutionary multiobjective optimization to target social network influentials in viral marketing," *Expert Systems with Applications*, vol. 147, 2020, doi: 10.1016/j.eswa.2020.113183.
- [3] M. H. Al-Khasawneh, S. Al-Haddad, R. Mbaideen, R. Ghazi, T. Irshaid, and H. Alnaimi, "Investigating the impact of social media marketing on research online and purchase offline for fashion luxury brands," *International Journal of Business Excellence*, vol. 32, no. 1, pp. 25-49, 2024, doi: 10.1504/ijbex.2024.135933.
- [4] L. Jiang, "The Extent Social Media Marketing Is Contributable to Customer Based Brand Equity of Luxury Brands," pp. 485-497, 2024, doi: 10.2991/978-94-6463-408-2_55.
- [5] S. Mukherjee, M. K. Das, and T. K. Chakraborty, "Viral Marketing in Increasing Brand Awareness and Predicting Purchase Intention: Exploring Mediating Role of Brand Loyalty in FMCG Sector," *Sch J Econ Bus Manag*, vol. 4, pp. 61-77, 2023, doi: 10.36347/sjebm.2023.v10i04.001.
- [6] H. Ramadhani and N. Anggrainie, "Pengaruh Persepsi Harga, Brand Equity, Viral Marketing, Brand Ambassador, Review Produk, dan Customer Relationship, Terhadap Keputusan Pembelian Produk Skincare Skintific di Tiktok Shop," *Mufakat: Jurnal Ekonomi, Manajemen dan Akuntansi*, vol. 2, no. 4, pp. 703-717, 2023. [Online]. Available: https://jurnal.anfa.co.id/index.php/mufakat/article/view/983.
- [7] N. Barzegar Marvasti, "The Impact of Viral Marketing on Customer Purchase Intentions in Social Networks (Case Study: Tehran-based Users of Social Networks)," Master's Thesis, Shahid Beheshti University, 2015.
- [8] M. Ali Pour, F. Jafari, and A. Shafaqi Darvish Gournamaz, "Viral Marketing and Its Impact on the Success of Political Parties and Candidates in Electoral Competitions," *Political Science Journal*, no. 17, pp. 111-137, 2011.
- [9] F. Ohadi, M. Mohammadi, and M. Tarekh, "Evaluation of the Effectiveness of a Combined Viral Marketing Method with Network Clustering Method and Comparison of Results," *Technology Growth Journal*, vol. 15, no. 58, pp. 65-72, 2019.
- [10] I. Roelens, P. Baecke, and D. F. Benoit, "Identifying influencers in a social network: The value of real referral data," *Decision Support Systems*, vol. 91, pp. 25-36, 2016, doi: 10.1016/j.dss.2016.07.005.
- [11] K. Y. S. Putri, "Social Media or Word of Mouth: Maintaining a Healthy Lifestyle During the COVID-19 Pandemic in Indonesia," *International Journal of Innovative Research and Scientific Studies*, vol. 7, no. 4, pp. 1345-1353, 2024, doi: 10.53894/ijirss.v7i4.3296.