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## Modeling Viral Marketing to Strengthen the Online Purchasing Channel: A Mixed Approach with the SWARA Technique Based on Genetic Algorithms

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### ABSTRACT

The aim of the present research is to model and prioritize components to provide optimal viral marketing rules in online businesses. It is a mixed-methods applied research study. In the qualitative section of this research, 15 individuals were selected through purposeful sampling by the researcher to ensure their relevance and expertise regarding the research topic, and the quantitative part includes 460 customers of online businesses using a stratified random sampling method. The data collection tools in the qualitative section used the projection technique and in-depth interviews. Using the MAXQDA software, the interviews were analyzed and summarized, through which six components were identified. Then, in the quantitative section, 12 experts determined the Lavash index, and subsequently, exploratory factor analysis was conducted using the SPSS software. Using the SWARA technique, the identified indicators were ranked based on expert opinions according to their degree of importance, and to identify the most influential component, the genetic metaheuristic algorithm was used, with WEKA and RAPIDMINER software employed in this section. Finally, utilizing the decision tree method and MATLAB software, viral marketing optimization rules were identified. The findings in the qualitative section showed that online persuasion, online trust, online support, online services, and online attractiveness were the components of viral marketing, and in the quantitative section, online persuasion and online trust were determined as the best feature or component.

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## 1. Introduction

Viral marketing means spreading messages or content containing advertisements and information related to a company's brand through social media. In other words, viral marketing is a strategy that encourages individuals to send advertising messages to one another, so the advertising message spreads among people like a virus (Ephraim, 2012). Viral marketing is a marketing method that greatly helps online businesses. In this method, content or information is designed in such a way that it is quickly shared and spread among users. The goal is to use the network effect so that the company's or product's message reaches the target audience organically and without heavy advertising costs (Adha et al., 2023). Nowadays, viral marketing is considered one of the successful marketing methods in online businesses due to the increased use of social networks and the speed of content dissemination in the online space (Fitri et al., 2023). By designing attractive content and sharing it on social media platforms, one can quickly attract a large audience and ultimately convert them into loyal customers (Agesti et al., 2021). Some of the advantages of viral marketing can be stated as follows: reaching the target audience at low costs, building trust and stronger connections with the audience, increasing brand awareness and its retention in the audience's mind, and the possibility of reaching new audiences through content sharing (Annas, 2023). Viral marketing refers to a process in which a marketing message is designed in such a way that users freely and voluntarily share it with their friends and acquaintances. The main goal is to create engaging and valuable content that users will want to share (Anindya & Indriastuti, 2023). Millward Brown stated in a 2018 report, titled "Digital and Media Predictions," that online video advertising, due to its uniqueness and ability to actively engage viewers, is the most important form of content marketing. In addition, online viral branding campaigns (viral advertising) are considered an emerging trend, resulting in advertisers creating engaging and entertaining promotional messages and registering them on video platforms, allowing consumers to share the messages with their online social networks (Hsiang, 2019). Viral marketing is the foundation and cornerstone of the marketing world. One of the main reasons for considering its importance is to create a powerful force or opportunity to encourage product use through customer-to-customer interaction on social media (Zhang et al., 2017). E-commerce emerged in 1990 and, given its advantages and existing potential, attracted the attention of businesses, companies, and consumers (Haryanto et al., 2021). In Iran, considering the Takfa<sup>1</sup> program, approved in 2002 and aimed at the development of e-commerce, the Electronic Commerce Law was passed in 2005, creating the conditions for the operation and activity of electronic stores. In the continuation, e-commerce was approved in the Fifth Development Plan, and an institution, named the Center for E-Commerce Development, officially began its work. Based on recent research studies, people tend to trust information received from friends, relatives, and family more than information obtained through public advertising networks such as television and radio. Therefore, researchers and experts believe that viral marketing is one of the most influential marketing strategies in the present time (Long & wong, 2014). The goal of viral marketing is to use consumer-to-consumer or peer-to-peer communications to disseminate information about a product or service (Yeo et al., 2020), allowing the product or service in question to reach the consumer faster and cheaper than the market price (Bruyn & Lilien, 2008). Viral marketing is a technique that spreads and disseminates advertisements through social networks (Hendrayati & Pamungkas, 2021). Viral marketing spreads information quickly from one node to the entire network through word-of-mouth (Fan et al., 2018). Regarding the mechanism of viral marketing, it can be stated as follows: creating engaging and entertaining content, sharing content on social networks and messaging apps, encouraging users to share content by offering appropriate incentives, creating reward programs for active users in content sharing, and using promotional schemes such as contests and lotteries (Erwin et al., 2023). Compared to traditional media, viral marketing is highly cheap (Razali et al., 2023). The only cost is for creating the message and its initial distribution, and the recipients spread it (Ershadi et al., 2019). In recent years, the use of social networks, such as Instagram, Telegram, and WhatsApp, has significantly increased in Iran (Purwanto, 2023). This issue has led Iranians to widely share content and information on these platforms. Iranian

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1. The Takfa plan is an abbreviation of the phrase "Iran's Information and Communication Technology Application Development Program." This plan was approved by the Cabinet in July 2002. Its credit sources were also provided for in Note 13 of the budget laws for the years 2002, 2003, and 2004.

users, like those in other parts of the world, are mostly looking for engaging, entertaining, and practical content. These conditions increase the likelihood of success for viral marketing in this market. Considering the existing restrictions on online advertising in Iran, viral marketing is proposed as a suitable alternative solution. Businesses can use this method to increase brand awareness and attract customers (Sarioğlu, 2023). Metaheuristic algorithms, such as genetic algorithms, bee colony algorithms, and particle swarm algorithms, can be effectively used to optimize viral marketing strategies (Fan et al., 2024). These algorithms are capable of providing optimal solutions for issues such as identifying key and influential individuals in social networks who can quickly and effectively spread marketing messages within the network, determining the optimal timing for viral marketing message dissemination to maximize impact and reach, identifying the most suitable content for viral marketing messages, optimally allocating resources and budgets for viral marketing under existing conditions and constraints, and designing and optimizing algorithms for disseminating viral marketing messages in social networks (Jose & Paul, 2024). These algorithms, using evolutionary processes and intelligent search in the solution space, can find optimal solutions for viral marketing problems. In fact, by using these algorithms, viral marketing strategies can be optimized intelligently and automatically (Khavandi et al., 2023). The genetic algorithm, inspired by the process of natural evolution, creates a population of solutions and gradually optimizes them. For viral marketing, genetic algorithms can be used to optimize parameters such as selecting key individuals, timing the message release, and the content of the message. By defining an appropriate objective function (for example, maximizing the range of message dissemination), the algorithm can gradually find optimal solutions (Liang et al., 2024). In Iranian society, word-of-mouth recommendations hold great importance. Viral marketing, by creating engaging content, is able to enhance this word-of-mouth effect online. Overall, the characteristics of Iranian society and the online business environment in the country have created a suitable ground for the success of viral marketing. Businesses can easily reach their target audiences and successfully attract customers using this method. In the field of viral marketing, very few studies have been conducted, and most of the research focuses on traditional and non-online viral marketing. However, the studies that can be briefly mentioned in this area are as follows:

Fazeli Veisari et al. (2021) concluded in an article titled "Developing a viral marketing model in online businesses using a hybrid approach" With the aim of identifying the components and developing the internal relationships of viral marketing components in online business, they reached this conclusion, The viral marketing model in online businesses is that online support is related to online attractiveness, online attractiveness is related to online persuasion, online attractiveness is related to online trust, and online trust is related to online risk. Online services are not related to online attractiveness, and online persuasion is not related to online risk.

Dafonte-Gómez et al. (2020) emphasized that when a viral video reaches millions of views, the determining feature of the viral video is that it has been widely shared. Serrano and Iglesias (2016) used agent-based simulation (ABSS) in their article titled "Validating viral marketing strategies in Twitter via agent-based social simulation." Adelsarbanlar and Khoshtinat (2016) highlighted that advantage factors and critical factors affect viral marketing. Fadil (2015) mentioned that viral marketing is a highly effective tool in relation to online marketing, and if companies understand their online customers and treat them with value, they will succeed in the future.

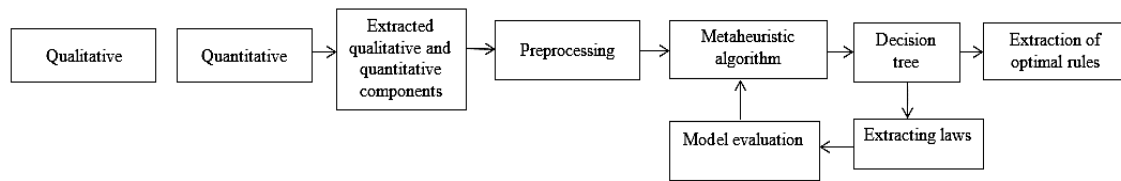
To optimize problems, traditional methods such as differentiation are used, but for complex problems where specific functions do not exist, due to the limitations of mathematical methods, metaheuristic methods are being recently employed.

The present research includes three main objectives:

- 1) Identifying and discovering new dimensions and components of viral marketing in online business.
- 2) Arranging the most important indicators based on their degree of importance.
- 3) Identifying the most influential component and optimizing viral marketing in online business using genetic algorithm and decision tree.

## **2. Research Methodology**

Considering the limited research conducted in the field of viral marketing modeling, this study is of a mixed type and aims to identify new components of viral marketing, prioritize them, and ultimately, model and extract the governing rules of viral marketing, as illustrated through a process in Figure 1.



**Fig. 1. Steps in Modeling Viral Marketing**

Based on Figure 1, the quantitative data are based on the components identified through the qualitative phase of the research. These components are then ranked according to their degree of importance using the SWARA technique based on expert opinions. Subsequently, data preprocessing is conducted to remove incomplete data and clean the dataset. In the next step, decision tree analysis is used to extract rules, and to optimize these rules according to decision-making criteria, different decision trees are constructed in each iteration using a genetic algorithm. The extracted rules are then evaluated. This process continues until the optimal decision tree is selected, and finally, the optimized decision tree rules are obtained as the final output of this overall process.

### 2-1. Qualitative Research Method

Considering the limitations of studies and scale in the field of viral marketing, the qualitative section of this research attempts to identify new components of viral marketing and employs the projective method. The main idea in this method is that people are more inclined to project their emotions onto others rather than attributing them to themselves. Projective methods vary depending on the amount of information they produce and are expressed as follows: word association, sentence completion, and dream exercises.

**Word association:** The idea is to present participants with a series of unrelated words to express the first thing that comes to their mind.

**Completing sentences:** The objective here is to elicit spontaneous and unreflective associations—that is, the first thoughts that come to mind—resulting in responses that are typically more elaborate than a single word.

**Dream exercises:** In dream exercises, the researcher takes advantage of the fact that dreams are a realm of imagination with various possibilities.

In this research, interviews were the primary data collection tool in the qualitative section of the study, designed based on the projection technique and conducted as individual interviews with participants. The statistical population of the qualitative section includes informed individuals in the field of online business, and the interviewees of different ages have been selected based on three generations: Generation X (from 1966 to 1976), Generation Y (from 1977 to 1994), and Generation Z (from 1995 onwards) These are, in order: Generation X (6 participants), Generation Y (5 participants), and finally Generation Z (4 participants). The number of interviews conducted was 15, with the specific participants being deliberately chosen by the researcher. The concept of “theoretical saturation” in qualitative research refers to the point at which no new information, themes, or insights are observed in the data—that is, additional interviews are unlikely to provide further meaningful contributions (Fazeli Veisari et al, 2021). The condition for conducting sampling has been reaching theoretical saturation. Therefore, based on continuous comparative analysis and ongoing coding, we demonstrated that conducting 15 interviews was sufficient to achieve theoretical saturation in this context. The software used in this section is MAXQDA.

### 2-2. Quantitative Method

The quantitative section of this research consists of three parts. In the first part, the researcher recruited 12 experts who had published research articles in this field, had doctoral theses related to the subject, or had practical expertise, and 105 items were provided to the experts. After collecting the completed questionnaires from the experts, the researcher calculated the CVR for each item and used the Loush index as the experts' credibility for item refinement. The appropriate percentage of the item for 12 experts is 56 percent.

In the second part, to identify and discover the main dimensions or constructs of the research data, the exploratory factor analysis method using SPSS software was employed to identify the influencing factors, their contribution to variance explanation, and their prioritization.

In the third section, since questionnaires were used as the data collection tool in this study, the overall structure of the research questionnaires was validated for content validity using confirmatory factor analysis with the Amos software. EFA was used to discover the underlying factor structure, while CFA was subsequently used to formally test, confirm, and validate that structure. This two-step process increased the rigor, reliability, and generalizability of the results. In the following, the Cronbach's alpha method was employed with SPSS software to measure reliability.

The statistical sample in this section includes buyers from the online business, for whom 460 questionnaires were distributed. In the quantitative section of this research, the statistical population consisted of customers of online businesses. To ensure a representative sample from this diverse population, a stratified random sampling method was employed. The population was divided into relevant strata based on key demographic variables, such as age, gender, and purchase frequency. Then, random samples were drawn from each stratum in proportion to their size in the population, resulting in a total of 460 participants. This approach was chosen to increase the accuracy and generalizability of the findings by ensuring that all significant subgroups were adequately represented in the final sample. Among all respondents, there were 267 women (58%) and 193 men (42%). In terms of marital status, 272 participants were single (59.1%), while 40.4% were married. Two respondents did not provide this information. Regarding age, 257 participants (55.9%) were under 25 years old (55.9%), and 50 were between 25 and 35 years old. Additionally, 140 had a high school diploma (30.4%), 60 held a doctoral degree (13%), and the rest had bachelor's and master's degrees. Concerning social network usage for purchasing decisions, Instagram was the most frequently used platform (93 respondents), followed by Telegram (56 respondents), WhatsApp (45 respondents), and Google Plus (37 respondents). A total of 242 respondents used the Digikala website the most frequently for purchases, followed by Zambil website (35 respondents), and Shahr-e Ketab Online website (34 respondents).

### 2-2-1. SWARA Multi-Criteria Decision-Making Method

In the SWARA method, the identified qualitative indicators are primarily ranked based on their importance according to experts' opinions using the projection technique. Therefore, the most important index has been placed in the first row. To calculate the weight of the criteria in the SWARA technique, equations 1, 2, and 3 are used.

$$KJ = SJ+1$$

$$Qj = (qj-1)/kj$$

$$Wj = \frac{qj}{\sum qj}$$

### 2-2-2. Metaheuristic Algorithm

In the metaheuristic algorithm section, the genetic algorithm was used to find the most effective dimensions of viral marketing identified in the qualitative section to model them optimally. The genetic algorithm is one of the best and most effective optimization algorithms for finding the best subset from a set of strings or graphs (Theodoridis et al., 2020). The representation of a chromosome in a genetic algorithm is in the form of a consecutive string of symbols. First, a series of strings of symbols are randomly generated and evaluated based on the fitness function of each string. In the next step, a new generation of courses is selected based on combination and mutation operators and elitism with the help of the roulette wheel. In the next step, the competency function for new fields is calculated, and if the competency function is not satisfied, these steps continue sequentially (Sia & Alfred, 2020). The dataset obtained from the qualitative and quantitative sections of the research is uploaded as raw data, and then, preprocessing is carried out to remove faulty information and prepare the data for use in the metaheuristic algorithm. In the next stage, important dimensions of viral marketing are extracted using a hyper-heuristic method based on the genetic algorithm. The software used in this section is WEKA and RAPIDMINER (Khare & Viswanathan, 2020).

### 2-2-3. Decision Tree

The decision tree is one of the most common data mining algorithms and part of supervised classification techniques. The decision tree is used in decision analysis to identify the strategy that is most likely to achieve the goal. This technique is used for discovering and extracting knowledge from a database as well as for creating predictive models. To identify the optimal chromosome with the best features at each stage, a decision tree is constructed using the C5 algorithm. Decision diagrams have advantages such as simplicity of understanding, handling large and complex data, and easy reusability. If a decision tree is constructed for a problem, different instances of that problem can be calculated and predicted using that decision tree (Behnampour, 2013).

To construct a decision tree, a top-down approach is primarily used. In the next step, using a pruning algorithm, the extra branches of the tree are removed. The purpose of pruning is to reduce the height of the tree to prevent overfitting and to remove noise data (Khodaei et al., 2019). The decision tree construction includes three phases as follows (Mabarti, 2020):

**Determining the type of branching:** At each node, depending on the type of data, the branching can be binary or multiple. For continuous feature values, the type of split is usually binary, and if the feature values are discrete, the split may be either multiple or binary.

**Selecting the best feature:** To select the best feature in the production of each node, attention must be paid to the purity level and the distribution of records based on classes. The split that increases the purity of the data by the highest amount is the best split. In this article, for selecting the appropriate feature for the node, the Gini index, entropy, and classification error, according to equations 1 to 3, have been used, where  $P_j$  is the fraction of records with class label  $j$  in node  $t$ , and  $m$  represents the number of classes.

a) Gini coefficient

$$(1) \text{Gini}(t) = 1 - \sum_{j=1}^m P_j^2$$

b) Entropy

$$(2) \text{Entropy} = \sum_{j=1}^m P(j|t) \log P(j|t)$$

c) Classification error

$$(3) \text{Error}(t) = 1 - \max(P|t)$$

**Determining the stopping time:** Determining the stopping condition is one of the most important issues in recursive algorithms. To determine when to stop expanding the tree, the following criteria are applied:

- a) all training records in the current node belong to a single class;
- b) the maximum permitted tree depth has been reached;
- c) the number of records in the current node is below a predefined threshold;
- d) the value of the selection criterion falls below the specified threshold;
- e) the input data for the tree consist of preprocessed qualitative and quantitative variables; and
- f) the output produced by the genetic algorithm.

The implementation is conducted using the RAPIDMINER software environment.

**Model Evaluation:** Obtaining the fitness function is the most important part of the genetic algorithm for solving the problem. Considering that the objective of this research is model building and classification, the accuracy, recall, and precision of the model can be effective in selecting a suitable chromosome. As a result, the use of all three criteria has been proposed for constructing the competency function. To evaluate the performance of the classifier, the confusion matrix for the decision tree test data must first be formed according to Table 1, and the following values must be calculated:

**Table 1. Chaos Matrix**

	Unfavorable	Favorable
Unfavorable	TP	FN
Favorable	FP	TN

TN: The number of records whose actual category was positive, and the classification algorithm correctly identified them as positive.

TP: The number of records whose actual category is unfavorable, and the classification algorithm has correctly identified their category as unfavorable.

FN: The number of records whose actual category is unfavorable; however, the classification algorithm incorrectly identified their category as favorable.

FP: The number of records whose actual category is positive; however, the classification algorithm incorrectly identified them as negative.

$$4. \text{ Recall}^{\text{favorable}} = \frac{\text{TN}}{\text{FP} + \text{TN}}$$

$$5. \text{ Recall}^{\text{unfavorable}} = \frac{\text{TP}}{\text{FN} + \text{TP}}$$

$$6. \text{ Precision}^{\text{favorable}} = \frac{\text{TN}}{\text{TN} + \text{FN}}$$

$$7. \text{ Precision}^{\text{unfavorable}} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

$$8. \text{ Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{TN} + \text{FN}}$$

The Recall<sup>x</sup> metric indicates the precision of the classification of category X with respect to all records labeled X. The Precision<sup>x</sup> metric indicates the accuracy of classifying category X based on the total instances for which the label X has been proposed by the classifier for the records. The Recall<sup>x</sup> metric indicates the classifier's performance based on the number of occurrences of class X, whereas the Precision<sup>x</sup> metric is fundamentally based on the classifier's prediction accuracy and shows how much we can trust the classifier's output. After obtaining these three criteria, a weight should be assigned to each criterion based on its value. Considering that the value of the Accuracy criterion is higher than the other two criteria, it is given a weight of 4, and the other two criteria are given a weight of 1.

$$9. f(\text{Subset of Features}) = \frac{1}{\text{Precision}^{\text{favorable}} + 4 * \text{Accuracy} + \text{Recall}^{\text{favorable}}}$$

### 3. Research Findings

As shown in Figure 1, the present research method consists of 10 steps, the findings of which are presented below.

#### 3-1. Analysis of the Qualitative Section

In order to identify and extract new components of viral marketing in online businesses, qualitative content analysis was used. In general, the following steps were implemented in the application of the content analysis method:

**Implementation of interviews:** The recorded interviews were transcribed using Word software.

**Data summary:** The findings from each interview were formulated and coded in the form of tables using the MAXQDA software.

**Data categorization:** The findings from each interview were placed in a separate table. Such a general table was completed for the codes assigned to the concepts. The information extracted from the interviews from the perspective of viral marketing components in online businesses consisted of 512 sentences, 76 open codes, and 21 axial codes.

Higher-level concepts were categorized as main categories, and lower-level concepts were defined as subcategories, based on the descriptive method used for the subcategories. From the interviews, 76 components were identified as open codes. Considering their semantic proximity and relationships, these were further grouped into 21 axial codes. These axial codes were then consolidated into 6 selective codes: online trust, online encouragement, online support, online services, online attractiveness, and online risk-taking. These codes are summarized in Table 2.

**Table 2. Characteristics of Concepts and Axial and Open Codes Extracted from Interview Analysis**

Abundance of open-source codes	Number of components	Subcategory of conceptualization in the form of axial coding	Component
5	2	Reluctance and harassment	Online risk-taking
	2	Saving	
	1	Risk-taking aversion	
15	3	Encouragement and motivation	Online Persuasion
	3	Public fame and word-of-mouth advertising	
	2	24-hour shopping	
	3	Social capital and standardization	
7	4	Exaggerating	Online trust
	5	Trust and quality	
13	2	Authenticity and warranty	Online Support
	4	Support and comparison capability	
21	9	Technology-centric and abundance of information	Online services
	2	Market leadership	
	1	Mellifluous	
	6	Customer satisfaction and loyalty	
	6	Customer bargaining power	
15	6	Complimentary gifts and free services	Online Attractiveness
	1	Reputation	
	8	Website appeal and ease of access	
	3	Abundance and diversity of goods and brands	
76	3	Attention to detail in purchasing	The sum of axial and open codes
	21		

### 3-2. Quantitative Section Analysis

One of the most important parts of scientific research in the humanities is the analysis of information. In this section, the researcher's hypotheses are put to the test, and the validity and reliability of the research questions are examined. In the present section, the data is collected and analyzed using appropriate statistical techniques.

A total of the 105 items collected in the qualitative section of the research were presented to 12 experts. To validate the experts (CVR) for refining the items, the Lawshe index was used, which had a percentage of 56% for the 12 experts. According to the CVR results, 59 items remained, and the rest were discarded. To identify and discover the main dimensions or constructs of the research data for identifying effective factors and their contribution to variance explanation by these factors as well as their prioritization, the exploratory factor analysis method was used. From an initial set of 59 relevant questions, 9 were removed, resulting in a final selection of 50 items. These 50 items represent the valid and reliable questionnaire components that emerged after content validity ratio (CVR) assessment and exploratory factor analysis (EFA), forming the basis for the study's quantitative analysis.

To ensure the suitability of the sample size for factor analysis, Bartlett's test of sphericity was conducted. Furthermore, the Kaiser-Meyer-Olkin (KMO) index, a measure of sampling adequacy, indicated that the partial correlations between variables were small. With an average sampling adequacy of 74%, which exceeds the threshold of 50%, the questionnaire demonstrates an acceptable level of factorability. Additionally, according to the Bartlett's test of sphericity, since its value (Sig = 0.001) is less than 5%, as represented in Table 3, both indicators suggest that factor analysis is appropriate for the research data.

**Table 3. Results of the KMO and Bartlett's Test**

Sample mean adequacy size	0/736
K Square	48692/860
Degree of freedom	1225
Significance level	0/0001

The results obtained from conducting exploratory factor analysis on the data are summarized in Table 3. After determining the number of factors, we need to see which variables belong mainly to each factor. To make the factors more interpretable, we enter a third stage called factor rotation. Ideally, the result of rotation is to reach factors where only some variables load on them. The matrix,

resulting from the rotation of the factors, is presented in Table 4. This matrix plays a fundamental role in interpreting the results of factor analysis. Variables are assigned to a factor if they exhibit a higher loading on that factor compared to others. Regarding a specific variable, a loading of 30% suggests that this factor explains approximately 9% of that variable’s variance. The passage explains that after factor rotation in EFA, each variable is assigned to the factor where it has the highest loading. A loading of 0.30 is considered meaningful, as it shows that the factor explains approximately 9% of the variance for that variable. The rotated factor loading matrix is essential for interpreting the results, as it clearly delineates which variables load most significantly onto each factor, thereby defining their conceptual meaning. This amount of explained variance is sufficient to consider the factor loading significant. Loads of 3.0 and higher are considered significant. On the other hand, if a variable loads onto more than two factors, we should place that variable in the factor where it has the highest loading.

**Table 4. Rotated Factor Structure Matrix of the Scale Through the PC Method**

Indicators	Statements					
	1	2	3	4	5	6
S1	0/825					
S2	0/956					
S3	0/818					
S4	0/761					
S5	0/961					
S6	0/971					
S7	0/785					
S8	0/950					
S9	0/854					
S10	0/943					
S11	0/946					
S12	0/779					
S14	0/841					
S15	0/928					
S16	0/952					
S19			0/940			
S20			0/937			
S21			0/953			
S22			0/950			
S23			0/930			
S24			0/928			
S25			0/917			
S26			0/923			
S27						0/960
S28						0/951
S29						0/937
S30						0/898
S31						0/890
S34		0/945				
S35		0/936				
S36		0/931				
S37		0/920				
S38		0/903				
S39		0/895				
S40		0/865				
S41		0/874				
S43		0/876				
S44		0/881				
S45					0/930	
S46					0/923	
S47					0/913	
S48					0/893	
S50					0/879	
S51					0/679	
S52				0/916		
S53				0/910		
S54				0/922		
S56				0/901		
S58				0/868		
S59				0/870		

In this research, Confirmatory Factor Analysis (CFA) was conducted using Amos software to assess the validity and measurement scale of the questionnaire. The standardized factor loadings obtained from the CFA, representing the strength of the relationship between each latent factor and its observed variables, were all greater than 0.30 for every item. Therefore, the factorial structure of the questionnaire is confirmed, as illustrated in Figure 2.

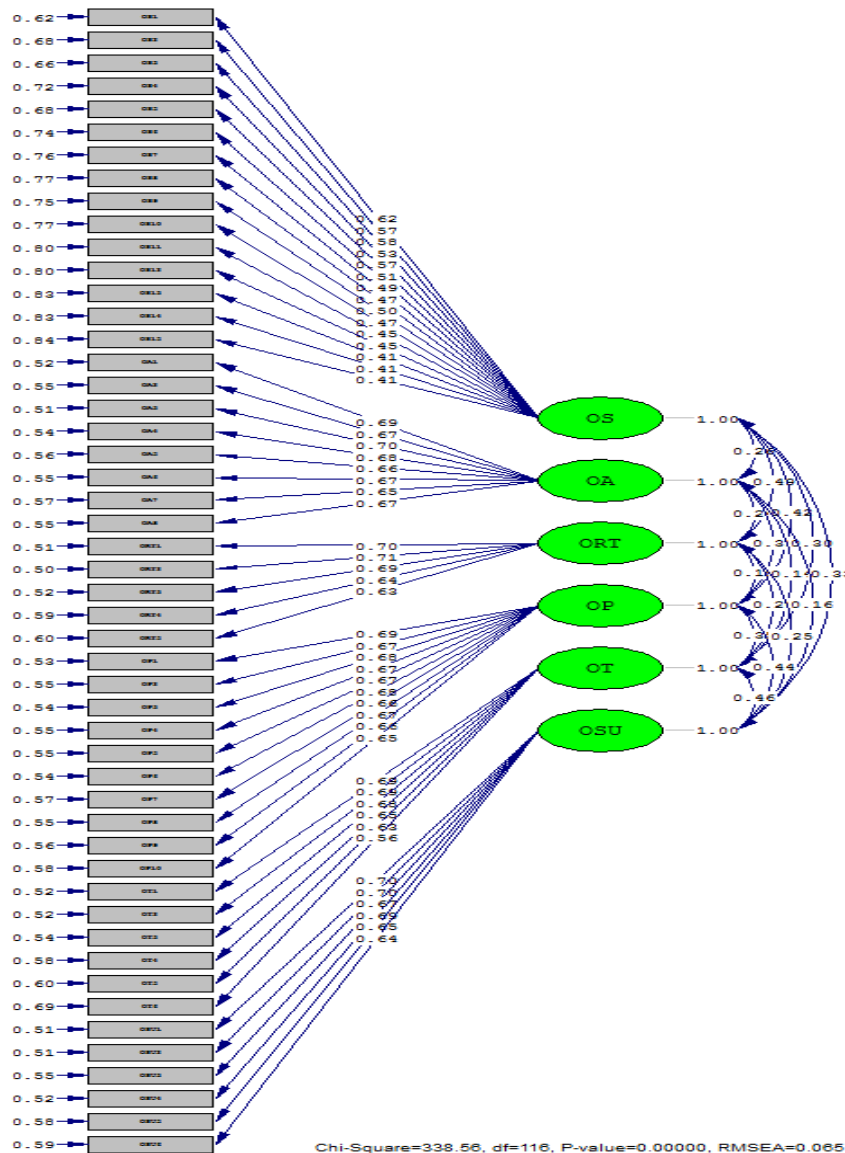


Fig. 2. Standard Factor Loading, Factor Analysis, and Questionnaire Scale

The Cronbach's alpha method was used to measure reliability through SPSS software, the results of which are shown in Table 5. Cronbach's alpha evaluates the internal consistency of the test by examining its various components or items. When the Cronbach's alpha coefficient exceeds 0.70, the test is considered to have acceptable reliability.

**3-3. Calculation of Criteria Weights Using the SWARA Method**

The relative importance of each criterion was evaluated and scored against the main index. In the SWARA method, this value is represented by SJ. The importance of the criteria was determined by a group of experts, and the final weights of the criteria are presented in Table 6.

**Table 5. Results of the Validity and Reliability of the Questionnaire by Variables**

Factor Loading	statement	Factor Loading	Statement	Cronbach's Alpha	Dimensions	Cronbach's Alpha	Structure
0/50	9	0/62	1	0/981	Online services	0/930	Viral Marketing
0/47	10	0/57	2				
0/45	11	0/58	3				
0/45	12	0/53	4				
0/41	14	0/57	5				
0/41	15	0/51	6				
0/41	16	0/49	7				
		0/47	8				
0/66	23	0/69	19	0/983	Online attractiveness	0/930	Viral Marketing
0/67	24	0/67	20				
0/67	25	0/70	21				
0/67	26	0/68	22				
0/64	30	0/70	27	0/968	Online risk-taking	0/930	Viral Marketing
0/63	31	0/71	28				
0/68	39	0/69	29				
0/66	40	0/69	34	0/980	Online Persuasion	0/930	Viral Marketing
0/67	41	0/67	35				
0/66	43	0/68	36				
0/65	44	0/67	37				
		0/67	38	0/953	Online trust	0/930	Viral Marketing
0/65	48	0/69	45				
0/63	50	0/69	46				
0/56	51	0/68	47				
0/69	56	0/70	52	0/971	Online support	0/930	Viral Marketing
0/65	58	0/70	53				
0/64	59	0/67	54				

**Table 6. Normal Weights of Main Criteria**

Prioritization	Normal Weight wj	Calculation of the initial weight of each index qj	Calculation of the coefficient KJ	Average relative importance of each index SJ	Research Index
1	0/366	1	1	1	Online attractiveness
2	0/232	0/633	1/58	0/580	Online persuasion
3	0/162	0/443	1/43	0/430	Online trust
4	0/113	0/307	1/44	0/440	Online support
5	0/077	0/209	1/47	0/470	Online services
6	0/050	0/138	1/52	0/520	Online risk-taking

According to Table 6, the criteria for online attractiveness with a weight of 0.366, online encouragement with a weight of 0.232, online trust with a weight of 0.162, online support with a weight of 0.113, online services with a weight of 0.077, and online risk-taking with a weight of 0.050 are ranked from first to sixth, respectively. Based on the SWARA calculations, the final weights of the sub-criteria were calculated and presented in Table 7.

Based on Table 7, the final priority of the sub-criteria is presented in Table 8.

**Table 7. Final Weights Under the Criteria**

Final weight	Branch Weight		Initial weight	
0/024	0/478	Reluctance and harassment		
0/015	0/306	Saving	0/050	Online risk-taking
0/011	0/216	Risk aversion		
0/084	0/362	Public fame and word-of-mouth advertising		
0/059	0/255	Encouragement and motivation		
0/042	0/182	10-hour shopping	0/232	Online persuasion
0/028	0/121	Social capital and standardization		
0/018	0/079	Exaggerating		
0/094	0/578	Trust and Quality	0/162	Online trust
0/068	0/422	Authenticity and warranty		
0/068	0/602	Support and comparison capability	0/113	Online support
0/045	0/398	Technology-centric and abundance of information		
0/028	0/364	Leadership in the market		
0/019	0/251	Mellifluous		
0/014	0/182	Customer satisfaction and loyalty	0/077	Online services
0/009	0/120	Customer bargaining power		
0/006	0/084	Complimentary gifts and free services		
0/180	0/491	Website appeal and ease of access		
0/123	0/336	Reputation	0/366	Online attractiveness
0/063	0/173	Abundance and diversity of goods and brands		
0/042	0/115	Attention to detail in purchasing		

**Table 8. Final Priority of Sub-Criteria**

Final prioritization of sub-criteria	Final Weight	Sub-criterion	Row
1	0/180	Website appeal and ease of access	1
2	0/123	Reputation	2
3	0/094	Trust and quality	3
4	0/084	Public fame and word-of-mouth advertising	4
5	0/068	Authenticity and warranty	5
5	0/068	Support and comparison capability	6
6	0/063	Abundance and diversity of goods and brands	7
7	0/059	Encouragement and motivation	8
8	0/045	Technology-centric and abundance of information	9
9	0/042	10-hour shopping	10
9	0/042	Attention to detail in purchasing	11
10	0/028	Social capital and standardization	12
10	0/028	Leadership in the market	13
11	0/024	Reluctance and harassment	14
12	0/019	Mellifluous	15
13	0/018	Exaggerating	16
14	0/015	Saving	17
15	0/014	Customer satisfaction and loyalty	18
16	0/011	Risk aversion	19
17	0/009	Customer bargaining power	20
18	0/006	Complimentary gifts and free services	21

### 3-4. Preprocessing

In scientific research and investigations, it may not be possible to measure one or more variables for certain observations or cases under study, or even to retrieve the information related to those observations in a readable and recordable manner. Such cases will lead to the recording of missing data (Momeni, 2017). In this research, all system and user missing values have been identified and reviewed using SPSS software. The questionnaire utilized a 1-to-5 Likert scale. To prepare the data for the genetic algorithm, responses were dichotomized: scores below 2.5 were classified as 'unfavorable,' and scores 2.5 and above were classified as 'favorable.'

### 3-5. Optimal Modeling of Viral Marketing Using a Metaheuristic Algorithm and Decision Tree

#### 3-5-1. Genetic Algorithm

In this study, the initial population of chromosomes, which is composed of a strand of genes, is considered to be 20. Each dimension or characteristic is equivalent to a gene. The value of each gene can be assigned a binary number of zero or one. Zero means not selecting that dimension, and one means selecting that dimension. The optimization goal in this research is to obtain the best decision tree with the least error and the highest accuracy. Therefore, the fitness function is proposed based on

the criteria of precision, recall, and the accuracy of the test data according to Equation 9. To implement the genetic algorithm, the WEKA software was used. To achieve the best chromosome with the best features at each stage, the decision tree is designed using the C5 algorithm. The fitness function is constructed based on the training data of the model and then evaluated using the test data of the designed decision tree, resulting in the fitness function. If the fitness function is not suitable, a new generation of chromosomes is produced using mutation, crossover, and roulette wheel operators, and this process continues until the optimal decision tree model is reached. In this algorithm, the two-point crossover operator and the binary mutation operator are used, with a mutation rate of 10% and a crossover rate of 90%. Table 9 presents the factors or components identified in the qualitative part of the research. If a component is included in the genetic algorithm’s chromosome, it is assigned a value of 1; otherwise, it is assigned a value of 0. In other words, the values 0 and 1 indicate the absence or presence of a component in the decision tree, respectively.

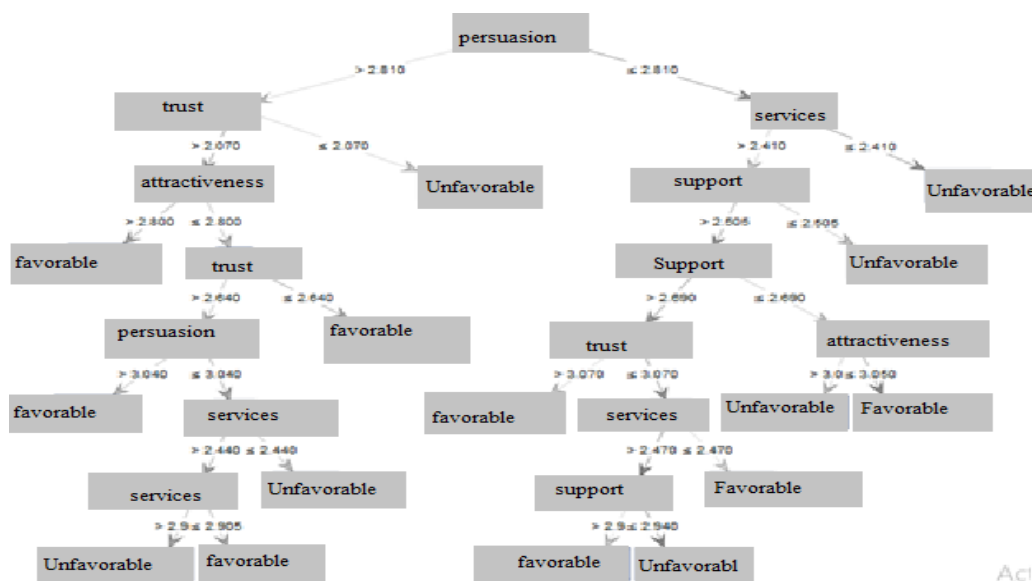
**Table 9. Definition of Chromosome in Genetic Algorithm**

F1	F2	F3	F4	F5	F6
Support	Trust	Persuasion	Risk-taking	Services	Attractiveness
0 and 1	0 and 1	0 and 1	0 and 1	0 and 1	0 and 1

**3-4-2. Decision Tree**

In this research, the C5 algorithm in the RAPIDMINER software was used for designing and pruning the decision tree. This algorithm first creates a full tree based on the Gini index and entropy so that the subsets contain records more homogeneous than their parent. Then, this algorithm employs an incremental tree pruning method to reduce the classification error caused by noise or excessive details in the training data. Pruning occurs by replacing an internal node with a leaf node, thereby reducing the percentage or amount of error. In this article, two favorable and unfavorable classes are proposed, and during the implementation of the decision tree, 70% of the statistical data was used for training, and 30% was used for testing. Figure 3 shows the decision tree model output from MATLAB software, using the information acquisition criterion. After pruning, all five features contribute to the decision-making process. The confusion matrix for this tree is presented in Table 9. According to this table, both the accuracy and precision of the model are 100%. In other words, this decision tree correctly and precisely predicts all 455 training data instances.

The optimal decision tree model is shown in Figure 3. In this model, the higher the index and the closer it is to the root, the higher the priority in forming the tree. Moreover, the closer a component or index is to the branch and to the end of the model, the less important it is in writing the rules. The confusion matrix for the test data of the optimal decision tree has been calculated, as shown in Table 10.



**Fig. 3. Decision Tree Formed Based on Information Gain Criterion**

The rules for determining favorable viral marketing, based on information utility criteria and considering the specified genetic algorithm components, are as follows: If online persuasion exceeds 2.81, online trust surpasses 2.07, and online appeal is greater than 2.8, then viral marketing is deemed favorable. Additional rules, consistent with the first mentioned rule, are stated in Table 11.

**Table 10. Confusion Matrix for the Test Data of the Optimal Decision Tree**

	true Unfavorable	true favorable	class precision
<b>Pred. Unfavorable</b>	39	0	100.00%
<b>pred. favorable</b>	0	6	100.00%
<b>class recall</b>	100.00%	100.00%	

**Table 11. Extracted Rules for Viral Marketing from the Decision Tree**

Component Rule	Online persuasion	Online trust	Online attractiveness	Online services	Online support	Viral Marketing
1	> 2.810	> 2.070	> 2.800	-	-	Favorable
2	> 3.040	> 2.640	≤ 2.800	-	-	Favorable
3	≤ 3.040 encouragement <2.810	> 2.640	≤ 2.800	≤ 2.440	-	Unfavorable
4	≤ 3.040 encouragement <2.810	> 2.640	≤ 2.800	> 2.9	-	favorable
5	≤ 3.040 encouragement<2.810	> 2.640	≤ 2.800	≤ 2.905	-	Unfavorable
6	> 2.810	≤2.640 trust < 2.070	≤ 2.800	-	-	Favorable
7	> 2.810	2.070 ≤	-	-	-	Unfavorable
8	≤ 2.810	-	-	> 2.410	-	Unfavorable
9	≤ 2.810	-	-	> 2.410	≤ 2.505	Unfavorable
10	≤ 2.810	-	> 3.050	> 2.410	≤2.690 Support<2.505	Unfavorable
11	≤ 2.810	-	≤ 3.050	> 2.410	≤2.690 Support<2.505	Favorable
12	≤ 2.810	> 3.070	-	> 2.410	> 2.690	Favorable
13	≤ 2.810	≤ 3.070	-	> 2.470	> 2.940	Favorable
14	≤ 2.810	≤ 3.070	-	> 2.470	≤2.940 Support<2.690	Unfavorable
15	≤ 2.810	≤ 3.070	-	≤ 2.470 services< 2.410	> 2.690	Favorable

#### 4. Discussion and Conclusion

Viral marketing refers to a strategy that encourages individuals to send advertising messages to one another, thereby spreading the advertising message like a virus among people. As mentioned in the introduction, there has been little research in the field of viral marketing, which refers to dimensions and components that are similar in most studies, and no new components are observed. Additionally, there are very few cases in the optimization section as well. For this purpose, this research initially attempts to identify and examine the new components and dimensions of viral marketing using a mixed-methods approach (qualitative-quantitative). Following the confirmation of the identified indicators, we employed the SWARA decision-making method to rank them based on expert assessments of their relative importance. Subsequently, we utilized a metaheuristic algorithm to identify the most influential indicators, which then served as the foundation for discovering viral marketing optimization rules through a decision tree analysis.

The results in the qualitative section showed that there are six new components, one of which is a fundamental element of viral marketing for online services, including being a pioneer, offering free products and services, product delivery, and personalized recommendations. The online attractiveness component, identified as the second component in this research, can be attributed to product variety,

brand diversity, and appealing design. The third component discovered based on the mixed approach is online persuasion, which can be identified in the development of viral marketing in online businesses through indicators such as freedom in purchasing, meeting individual standards, and aligning with user opinions. Online risk-taking is another identified component of viral marketing, with distrust in advertisements and exaggeration also representing it. Online support, which includes indicators such as brand comparison, product returns, and assistance throughout the purchasing process, can be considered in this regard. The latest identified component of online viral marketing has been trusted, including product quality, authenticity verification, and warranty among its indicators.

In the next section, the SWARA decision-making findings were as follows: the criteria of online attractiveness with a weight of 0.366, online persuasion with a weight of 0.232, online trust with a weight of 0.162, online support with a weight of 0.113, online services with a weight of 0.077, and online risk-taking with a weight of 0.050 were ranked from first to sixth priority, respectively. In the following section, five components were identified as the most influential in the genetic algorithm, and the online risk-taking component was removed. Leveraging a decision tree algorithm for data mining, we optimized viral marketing by pinpointing the strategy most likely to reach the final goal. The findings clearly indicate that high levels of ‘online persuasion’ and ‘online trust’ are the primary drivers for an optimal or favorable viral marketing status. In the absence of online encouragement and trust, two components—attractiveness and online services—can be replaced, leading to the optimization of viral marketing. If online businesses do not possess these four components, that is, even if they are at an unfavorable level, by increasing online support, they can nurture their viral marketing. Ultimately, the most important components are online trust and encouragement, while online support can serve as the final component in this regard. The data collected in this study may be affected by limitations arising from the different conditions under which interviews were conducted with experts and questionnaires were completed by consumers. Variations in environmental or situational factors could introduce bias and affect the overall data quality.

To enrich the current research and conduct further studies, there are some recommendations for future researchers:

- Using all decision tree methods and comparing them
- Examining the research topic in other economic sectors
- Using other metaheuristic algorithm methods and comparing them with the method employed in the present study

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