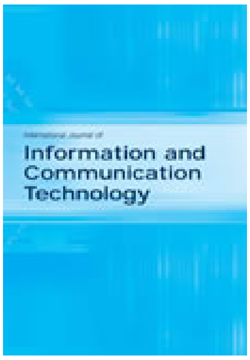

International Journal of Information and Communication Technology

ISSN online: 1741-8070 - ISSN print: 1466-6642
https://www.inderscience.com/ijict

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DOI: 10.1504/IJICT.2025.10071980

Article History:

Received:	14 May 2025
Last revised:	25 May 2025
Accepted:	25 May 2025
Published online:	10 July 2025

Evaluation of marketing effectiveness based on fuzzy comprehensive evaluation method in the perspective of generalised virtual economy

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Abstract: The assessment of marketing efficacy has grown more complicated and varied with the virtual economy's fast expansion. The conventional approaches of measuring marketing effectiveness are challenging to fit to the particular requirements of the virtual economy setting. Aiming to thoroughly evaluate marketing activities in virtual economy using quantitative and qualitative criteria including customer lifetime value (CLV), this paper offers a fuzzy comprehensive evaluation (FCE)-based marketing effectiveness evaluation model for virtual economy, i.e., GV-EFCE. The validity and superiority of the GV-EFCE model are verified by experiments run on two datasets. In many virtual economy situations, the experimental findings reveal that the GV-EFCE model surpasses conventional approaches. Thus, this work offers a fresh concept for assessing marketing efficacy in the domain of virtual economy and offers a useful guide for next studies.

Keywords: virtual economy; marketing effectiveness evaluation; fuzzy comprehensive evaluation; FCE; customer lifetime value; CLV.

Reference to this paper should be made as follows: Huang, L. (2025) 'Evaluation of marketing effectiveness based on fuzzy comprehensive evaluation method in the perspective of generalised virtual economy', *Int. J. Information and Communication Technology*, Vol. 26, No. 24, pp.65–85.

Biographical notes: Lijun Huang received her Master's degree from Zhengzhou University in China in 2011. She is now an Associate Professor in School of Business Administration at Zhengzhou University of Science and Technology. Her research interest is marketing management and fuzzy comprehensive evaluation.

1 Introduction

1.1 Research background and significance

The virtual economy has slowly become a key component of the modern economy as the global digitalisation process speeds up. The virtual economy includes several forms including virtual asset trade, online gaming, digital currency, e-commerce, etc (Hrytsai, 2022). While encouraging economic development, these new business models have altered the manufacturing and consumption patterns of conventional sectors. The evolution of virtual economy not only offers businesses new marketing avenues and growth areas, but also presents difficulties including the unpredictability of the market environment and the complexity of customer behaviour (Chen and Wang, 2019). In the virtual economy, these developments constrain standard marketing tactics and effectiveness assessment techniques; new evaluation tools and techniques are desperately required to handle this new economic structure.

In this regard, fuzzy comprehensive evaluation (FCE), a mature multi-level and multi-dimensional decision-making tool, has progressively become a preferred approach for assessing marketing performance in the virtual economy by virtue of its strong uncertainty management capacity. FCE is particularly appropriate for those complicated evaluation jobs that must examine several qualitative and quantitative indicators in an integrated manner since it can better handle the ambiguity and uncertainty in marketing effectiveness than conventional quantitative evaluation techniques (Seddik and Rachid, 2023). Marketing operations in the virtual economy influence not only sales and market share but also qualitative elements like brand value, user loyalty, etc., which sometimes cannot be adequately described by conventional single number indicators.

The assessment of marketing tactics and outcomes has to be more flexible and real-time given the strong market rivalry and fast shifts in customer demand. Conventional static evaluation techniques cannot reflect the changes in the efficacy of marketing operations in time and cannot give timely and effective assistance for business decision-making. By considering the changes and interactions of various elements in this dynamic context, FCE can offer a more complete and adaptable approach for the assessment of marketing efficacy.

Marketing efforts in the virtual economy environment exhibit stronger dynamics and complexity at the same time. From the viewpoint of generalised virtual economy, therefore, marketing effectiveness evaluation depending on FCE has significant theoretical and practical relevance. This paper intends to build a novel marketing effectiveness assessment model that evaluates the marketing activities in virtual economy in a multi-dimensional and complete manner by combining the features of virtual economy and using FCE. By means of this approach, it can enable companies to grasp more clearly the efficacy of marketing tactics and offer robust assistance for their choices on optimisation.

1.2 Research objectives and innovations

This paper aims to build a marketing effectiveness assessment model using FCE to address the complexity and uncertainty issue of marketing effectiveness assessment in the virtual economy setting. In the framework of the wide virtual economy, the influencing elements of marketing efforts show multi-dimensional and dynamic qualities, making it challenging for conventional evaluation techniques to fully address these elements. This study is to suggest a novel assessment framework that can accurately evaluate the marketing effectiveness based on FCE by considering all sorts of quantitative and qualitative indicators in the virtual economy environment, so offering scientific decision support for companies. This study will first build a marketing effectiveness evaluation framework under the viewpoint of virtual economy, integrating evaluation indexes of several dimensions and considering the unique characteristics of virtual economy; second, using FCE, we will address the ambiguities and uncertainties in the assessment of marketing effectiveness and propose an evaluation method suited to the characteristics of the virtual economy; finally, we will validate the validity and feasibility of the method by combining the experiment with experiments, so guaranteeing that the model can be operable and feasible for practical application. operability and accuracy in real use.

The novelty of this work is shown in the following features:

1. Introducing FCE: though FCE has been extensively employed in conventional fields, its usage in assessment of marketing success in virtual economy is still uncommon. Filling the hole in this area, this paper creatively brings this approach into assessment of marketing performance under virtual economy.
2. Proposing a marketing effectiveness evaluation framework from the perspective of virtual economy: traditional approaches to assessing marketing performance emphasise quantitative measures and neglect thorough examination of multidimensional and dynamic virtual economy impacting elements. The assessment framework suggested in this paper may reflect the impact of marketing efforts in a more complete manner and can completely consider several variables including sales success, brand influence, user loyalty, etc.
3. Optimisation of the evaluation index system: considering the unique features of the virtual economy, this paper creates a marketing effectiveness assessment index system consistent with the context. The system includes both conventional quantitative measures and emphasises qualitative ones, which can more accurately show the whole influence of marketing efforts in the virtual economy.

2 Relevant technologies

2.1 Virtual economy

As a component of the contemporary economy, the virtual economy has slowly evolved into an economic form with major importance. Virtual economy is a series of virtual markets, virtual transactions, and virtual industrial chains built on top of digital technologies and network platforms rather than only the selling of virtual goods or digital currencies. Covering a broad spectrum of sectors, these industries include but are not limited to e-commerce, social media marketing, virtual currencies and their derivatives, and online entertainment. Unlike the conventional economic model centred on physical goods, the virtual economy stresses the movement of information, data and virtual resources, and has grown to be a significant component of the world economic system.

Virtual economy's fundamental characteristic is its low-cost market participation style and effective resource allocation capacity. Virtual economy can rapidly shatter the conventional geographical and time limits and realise global resource allocation and market expansion by means of information technology support. Digital platforms allow companies to create more precise user profiles and tailored marketing plans, therefore boosting market penetration and customer stickiness. Simultaneously, the virtual economy's low operational costs have allowed numerous creative companies to amass significant user and market share in a fairly short period of time, hence propelling the wave of digital transformation.

On the other hand, fast expanding virtual economy creates fresh market difficulties as well. First, the virtual economy's market environment is quite unpredictable. Traditional approaches to market forecasting and marketing performance evaluation are challenging to fit this evolving market demand given the great randomness and complexity of the behaviour of market participants (Hamed et al., 2024). Secondly, many business models in the virtual economy still have underdeveloped value assessment criteria, particularly for non-physical goods like digital assets and virtual commodities, the definition of their inherent value and trade mechanism remains debatable (Şanlısoy and Çiloğlu, 2023). The characteristics of the virtual economy indicate that it presents fresh difficulties for conventional economic theories and practices; therefore, it is imperative to create new theoretical frameworks and analytical tools to enable businesses and academics to handle this evolving economic form.

Furthermore, a fundamental problem of the virtual economy is how to efficiently control the trade and flow of virtual assets. Assets in the virtual economy differ from those in the conventional one; their liquidity and value-addedness could be influenced by several elements including platform policies, user behaviour and market demand. The virtual economy is thus a complicated system with a lot of information movement and value creation rather than just a straightforward market transaction. The stability and growth path of the whole virtual economy system may be significantly impacted, for instance, by price changes of virtual goods, user preference shifts, network effects, and other elements. For companies, the secret to success is how to handle these changes and create successful marketing plans in this context.

The form and function of the virtual economy will keep changing with the growing development of the virtual economy, particularly pushed by new technologies such big data, artificial intelligence and blockchain. Businesses and researchers have to keep investigating economic theories and technical strategies that fit this developing environment (Teece, 2019). This offers a wide development area for studies like marketing effectiveness evaluation and encourages academics to investigate ways to more accurately evaluate the impacts of complicated and varied marketing operations in the virtual economy.

2.2 Fuzzy comprehensive evaluation

Based on fuzzy mathematical theory, FCE is a thorough assessment tool especially appropriate for resolving difficult decision-making situations involving several indications and variables (Masdari and Khezri, 2021). By fuzzy treatment of uncertain elements, the approach converts qualitative issues into quantitative assessments, therefore providing decision makers a more scientific and thorough evaluation. When assessing the effectiveness of virtual economy marketing, the evaluation criteria are mostly fuzzy and uncertain, including brand awareness, user satisfaction, market share, and other factors with complex interactions with one another. Conventional evaluation techniques are usually challenging to precisely capture these variable dynamic traits. By thoroughly analysing these fuzzy data, FCE may offer more thorough assessment outcomes and is thereby rather popular in the virtual economy sector.

FCE's fundamental procedure is fuzzy synthesis operations and fuzzy evaluation matrix building. Based on the traits of each assessment index, together with expert views or historical data, a fuzzy evaluation matrix comprising all evaluation items must first be created (Akter et al., 2019). Fuzzy numbers, often based on fuzzy sets of linguistic variables (e.g., 'great', 'good', 'bad'), indicate the performance of each evaluation item under each evaluation index in this procedure. Usually, fuzzy sets derived from language variables, these fuzzy numbers reflect values such as 'great', 'good', and 'bad' (Garg, 2020). Every item can be rated under each indicator and transformed into fuzzy integers for processing by means of expert assessment or derivation depending on real data. For instance, if there are *m* evaluation objects and *n* evaluation indicators, the fuzzy evaluation matrix *R* can be expressed as:

$$R = \begin{pmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{21} & r_{22} & \cdots & r_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ r_{m1} & r_{m2} & \cdots & r_{mn} \end{pmatrix} \tag{1}$$

where r_{ij} is the fuzzy evaluation value of the i^{th} evaluation object under the j^{th} evaluation index. Thus, the qualitative information can be efficiently converted into quantitative fuzzy numbers, so rendering the following evaluation outcomes more objective and operable.

The fuzzy evaluation matrix is then weighted using the fuzzy synthesis process to provide the overall evaluation results of every evaluation object. The essence of the fuzzy comprehensive operation is to reflect the overall performance of every evaluation object under each index by combining the fuzzy values of several evaluation indexes with their appropriate weights. In reality, several evaluation indications vary in significance; so, every indicator is given a weight coefficient *W*. Expert assessment, historical data analysis, or other techniques can help to define these weights. The fuzzy synthesis operation's formula is as follows:

$$W = \left(w_1, w_2, \ldots, w_n\right) \tag{2}$$

$$V = R \cdot W = \begin{pmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{21} & r_{22} & \cdots & r_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ r_{m1} & r_{m2} & \cdots & r_{mn} \end{pmatrix} \cdot \begin{pmatrix} w_1 \\ w_2 \\ \vdots \\ w_n \end{pmatrix} \tag{3}$$

$$V = \left(v_1, v_2, \ldots, v_m\right) \tag{4}$$

By means of this weighing process, one can eventually get a composite evaluation value V for every evaluation item, which reflects the total performance of every assessment object under all criteria. These all-encompassing evaluation values give decision makers a clear reference to guide their assessment of which marketing tactics or activities are most productive and which might need to be altered or enhanced (Nguyen, 2024).

The multi-dimensional evaluation issue in virtual economy can be efficiently addressed by FCE. Unlike the conventional single-indicator assessment approach, FCE may holistically evaluate the relationship and weight of every signal, hence producing a more thorough and objective final evaluation outcome. Facing a very uncertain market environment, FCE can not only precisely capture the subtle link between several indicators but also efficiently lower the error caused by over-reliance on a single indicator, so aligning the evaluation findings with the actual scenario, which has great practical application value.

2.3 Evaluation of marketing effectiveness

Evaluating the efficacy of marketing activities or strategies depends much on marketing effectiveness assessment, which helps to gauge the real influence of several marketing initiatives including marketing, branding, customer interaction, etc., and then refine marketing decisions and strategies. Marketing effectiveness evaluation techniques have evolved from basic qualitative assessment to sophisticated quantitative analysis as the virtual economy has developed (Sung et al., 2021).

Traditional marketing effectiveness evaluation techniques generally consist of sales performance-based evaluation method, customer satisfaction analysis method and market share analysis method. Usually, these techniques are examined by tracking the changes in sales before and after marketing efforts, consumer satisfaction with products, brand awareness and other indications. While such techniques often streamline the assessment process, they struggle to completely represent the complexity of marketing operations in a multi-factor virtual economic environment.

The assessment of marketing efficacy has slowly included varied indicators and thorough models in recent years as big data and artificial intelligence technology have advanced. For instance, widely used are multi-factor analysis-based marketing effectiveness evaluation techniques that consider different aspects including different marketing channels, different consumer groups, different product characteristics, etc., and reflect the overall impact of marketing efforts using multi-dimensional data.

The evaluation model based on sales conversion rate, which assesses the ratio between possible consumers and actual buying customers, is one frequent approach. Its fundamental formula is:

$$CR = \frac{T}{P} \times 100 \tag{5}$$

where CR is the conversion rate; T is the number of real buying consumers; P is the number of possible customers. Particularly in internet marketing, this formula can help assess the efficacy of marketing efforts and show the conversion efficiency from potential consumers to actual ones.

Furthermore, a frequently used measure of marketing performance is CLV, which assesses the net income a consumer generates for a company during its lifetime (Kumar, 2018). CLV offers a long-term evaluation on the marketing efficiency of a business by measuring the attraction and retention of clients by various marketing channels or activities. Its fundamental equation is as follows:

$$CLV = \sum_{t=1}^{T} \frac{R_t - C_t}{(1+r)^t} \tag{6}$$

where R_t is the revenue at year t, C_t the cost, r the discount rate, and T the number of customer life cycle years. By use of CLV, businesses can evaluate the general efficacy of marketing efforts over a long period of time and increase the lifetime value of consumers by means of optimal marketing strategy (Nemati et al., 2018).

Apart from these conventional numerical approaches, as varied marketing activities in the virtual economy have expanded, techniques for assessing marketing performance depending on big data are progressively being extensively adopted. For instance, large user data can be mined for useful marketing performance evaluation signals by means of social media data analysis and online user behaviour analysis using machine learning and data mining tools. These techniques can not only track marketing effectiveness in real-time but also allow adaptable changes depending on various marketing goals and tactics.

Often, conventional single evaluation techniques find it challenging to fully examine several elements given the complexity of the marketing environment and the great rise in the quantity of data. Current research and practice have thus seen a trend towards marketing effectiveness evaluation techniques that incorporate varied data sources and thorough models. In a continually changing market environment, these techniques can more precisely evaluate the efficacy of marketing operations and offer more efficient assistance for later marketing choices.

3 Model design and methodology

3.1 Marketing effectiveness evaluation model

In order to analyse the marketing efficacy in the virtual economy environment more fully, this study offers the GV-EFCE model. The model is based on the generalised virtual economy viewpoint, and it methodically and thoroughly evaluates the efficacy of marketing efforts in the virtual economy by means of FCE. The model comprises four parts detailed in Algorithm 1:

Algorithm 1 Pseudo-code for GV-EFCE model

Input: Marketing data (sales, user engagement, brand influence), evaluation criteria (quantitative and qualitative), initial weights for evaluation indicators, fuzzy rule parameters, max iterations

Output: Optimised marketing effect evaluation results, optimised indicator weights

```
begin
    Initialise data pre-processing module
    Load marketing data from virtual economy
    Pre-process data (cleaning, normalisation)
    Extract features (sales, engagement, demographics)
    Impute missing values (mean or median)
    Store pre-processed data

    Initialise fuzzy evaluation model parameters
    Initialise fuzzy rules for sales, loyalty, brand influence
    Initialise evaluation criteria weights

    // Module 1: Data collection and pre-processing
    for each data entry do
        Clean data (remove duplicates)
        Handle missing values (mean/median imputation)
        Normalise data (min-max or z-score)
```

```
            Extract relevant features
            Store cleaned data
    end for

    // Module 2: Fuzzy comprehensive evaluation
    for each campaign do
            Calculate membership for sales (sales fuzzy rules)
            Calculate membership for user loyalty (loyalty fuzzy rules)
            Calculate membership for brand influence (influence fuzzy rules)
            Combine memberships using fuzzy logic
            Aggregate fuzzy outputs into one result
            Store fuzzy evaluation result
    end for

    // Module 3: Evaluation results analysis
    for each evaluation result do
            Calculate weighted score using evaluation weights
            Analyse correlation between sales, loyalty, and influence
            Classify performance (excellent, good, poor)
            Store classified result for reporting
    end for

    // Module 4: Model optimisation and adjustment
    for each result and feedback do
            Adjust weights based on performance feedback
            Optimise fuzzy membership functions using gradient descent
            Recalculate fuzzy evaluation with new parameters
            Update fuzzy rules and parameters
            Store updated model for next iteration
    end for

    return optimised evaluation results, updated fuzzy model
end
```

3.1.1 Data collection and pre-processing module

The data collecting and pre-processing module of the GV-EFCE model guarantees the correctness and dependability of the evaluation. From the virtual economic environment, this module gathers both quantitative and qualitative marketing data from several sources. These statistics span several facets of marketing activity including sales performance, market share, brand influence, user loyalty, social media interactions, etc. Usually coming from several sources which include e-commerce sites, social media, online advertising statistics, user behaviour data, etc., data in the virtual economy is varied and complicated, so data collecting and pre-processing are quite important.

Pre-processing is especially vital as virtual economy data frequently includes noise, missing values, and other uncertainties. First, data cleansing guarantees the correctness and completeness of the data used by removing erroneous data and noise. Data from several sources is then processed using standardisation or normalisation techniques to remove scale variances in the indicators and guarantee data comparability (Valdés, 2018). To remove variations in size, normalisation is a typical technique of data processing. If the original dataset is X, its standardisation formula is:

$$X = \{x_1, x_2, \ldots, x_n\} \tag{7}$$

$$X_{std} = \frac{X - \mu}{\sigma} \tag{8}$$

The standardisation method removes the variation in magnitude and lets data of various dimensions be compared on the same scale where μ is the mean of the data collection and σ is the standard deviation.

Marketing data also often lacks values that must be filled in using suitable techniques. A typical filling technique is to use the mean value of the column's data to fill in the missing values. The formula is filled in for every missing value using the mean of the non-missing column values:

$$x_i^{new} = \frac{1}{N} \sum_{i=1}^{N} x_i \tag{9}$$

where x_i^{new} is the filled data value, N the column's number of non-missing values, and x_i the original data's non-missing value. The full data guarantees the completeness of the dataset and prevents missing value consequences in this manner.

The correctness and consistency of the data is ultimately guaranteed by means of pre-processing techniques including standardisation and missing value filling, hence offering dependable baseline data for the following FCE.

3.1.2 Fuzzy comprehensive evaluation module

A key component of the GV-EFCE model, the FCE module attempts to offer a thorough evaluation of the aspects of marketing efficacy using fuzzy logic. Usually, marketing efforts in the virtual economy include multidimensional data comprising both quantitative measures and qualitative elements. For instance, sales performance, brand influence, market share, user loyalty, etc. are all indicators whose evaluation combines numerical data with some subjective opinions. The FCE approach offers a thorough evaluation of marketing efficacy by means of a combination of qualitative and quantitative data, hence addressing this ambiguous and complicated information.

First, the FCE module defines the affiliation function for each evaluation index, hence converting qualitative data into fuzzy data. Its value is between 0 and 1; the affiliation function $\mu_i(x)$ describes the degree of affiliation of an indicator under certain assessment levels. The degree of connection for every indicator has to be decided depending on its value range and the related fuzzy level. For instance, a sales performance indicator might have three degrees of affiliation: 'low', 'medium', and 'high'. Using the affiliation function, every particular result can be mapped to these three degrees of affiliation.

The affiliation function unifies and transforms the qualitative and quantitative data in the virtual economy into fuzzy data (Arya and Pal, 2024). Assuming the original data is X, the affiliation function $\mu_i(x)$ for every assessment item can be stated as:

$$\mu_i(x) = \frac{x - \alpha_i}{b_i - \alpha_i} \quad (x \in [a_i, b_i]) = \frac{1}{N}\sum_{i=1}^{N} x_i \tag{10}$$

where a_i and b_i are the minimum and maximum values of indicator i respectively, x is the particular indicator data, and $\mu_i(x)$ is the affiliation degree of this data on the assessment level.

Second, in the thorough FCE evaluation procedure, various weights are given to every indicator reflecting the varying significance of every signal. Usually, expert ratings or historical data analysis determines the relevance of each assessment dimension, hence determining the weight w_1, w_2, …, w_m. Assuming there are m evaluation indicators and the associated affiliation degree is $\mu_1(x)$, $\mu_2(x)$, …, $\mu_m(x)$ accordingly, the ultimate comprehensive assessment result C can be stated by weighted summing as:

$$C = \sum_{i=1}^{m} w_i \cdot \mu_i(x) \tag{11}$$

where w_i is the weight of the i^{th} indication, $\mu_i(x)$ is the affiliation degree of the indicator, and m is the total number of assessment indicators.

Reflecting the integrated performance of all key indicators in the virtual economy environment, the combined evaluation result C will produce a comprehensive marketing effectiveness assessment value by means of a fuzzy integrated decision-making process. The model can manage complicated data with uncertainty in virtual economy marketing and evaluate the interrelationships among indicators holistically to provide more consistent and relevant evaluation outcomes by means of FCE.

FCE's advantage is its ability to handle fuzzy data, particularly in the assessment of marketing effectiveness, many critical variables including brand influence, user loyalty, etc. are not easy numerical measures; FCE offers a flexible approach to handle these elements so that it can more precisely show the marketing efficacy in the virtual economy context.

3.1.3 Evaluation results analysis module

The evaluation results analysis module of the GV-EFCE model primarily examines the thorough comprehensive assessment results from the prior module and produces a marketing effectiveness evaluation report with useful recommendations. The module not only emphasises the final overall score but also seeks to examine the strengths and weaknesses of the marketing efforts from several angles in order to offer more complete decision-making assistance for the company or connected entities. Decomposing and examining the findings of the thorough assessment can expose the main influencing elements in the marketing campaign and enable decision makers to better grasp which ones have either improved or harmed the marketing efficacy.

First, the evaluation result analysis module will dismantle the FCE comprehensive evaluation results item by item based on the optimised evaluation index system developed in the preceding section. Because marketing activities in the virtual economy include multi-dimensional influencing elements, the evaluation findings must take into account both conventional quantitative measures (e.g., sales, user growth, etc.) and qualitative measures (e.g., brand awareness, user sentiment, etc.). The FCE module has been used to determine the affiliation of each indication; then, the analysis module emphasises the particular degree of contribution of each indicator to the general marketing efficacy. The following formula expresses the contribution of every indicator to the evaluation outcome C_i:

$$C_i = w_i \cdot \mu_i(x) \tag{12}$$

where C_i is the contribution of the i^{th} indicator to the overall evaluation outcome, w_i is the weight of the indicator, and $\mu_i(x)$) is the affiliation degree of the indicator.

Examining the contribution of every indication helps to highlight which ones most influence virtual economy marketing operations. For instance, in the virtual economy setting, brand influence and user loyalty can be more significant than in the conventional economy, so these qualitative factors could help to improve marketing performance more (Clauss et al., 2019). Comparing the contributions of various indicators helps businesses determine where the strengths of their present marketing tactics lie and guide future changes.

The evaluation result analysis module additionally runs sensitivity analysis to determine the degree of influence of every evaluation indicator on the final comprehensive assessment result, second. Sensitivity studies help one to see how changes in one indicator could influence the general evaluation outcomes under several weighting settings. This approach enables decision makers to investigate more into which indicators are most sensitive to assessment of marketing effectiveness in order to maximise these important ones. Sensitivity analysis's formula is:

$$S_i = \frac{\partial C}{\partial w_i} \tag{13}$$

where S_i indicates the sensitivity of the i^{th} indicator to the overall evaluation findings. Companies can identify which indicators might vary significantly under various market conditions by means of sensitivity analysis and then accurately modify these indicators. For instance, in the virtual economy, the user loyalty of particular market sectors may vary significantly, and companies should be aware of these changes to enable appropriate changes.

Furthermore, this module enables comparison of evaluation findings across several time frames or other marketing approaches. It can allow companies to assess the efficacy of marketing campaigns run at various phases by comparing horizontally and vertically, hence analysing the variations in marketing efficacy under various tactics and the trends over time.

All things considered, the assessment outcome analysis module is not only a simple presentation of FCE evaluation findings; it thoroughly explores the rich data of marketing efficacy using indicator contribution analysis, sensitivity studies, visualisation tools, and horizontal and vertical comparisons. By means of this analytical approach, companies can improve their knowledge of the marketing dynamics in the virtual economic environment and create more exact and scientific strategy changes.

3.1.4 Model optimisation and adjustment module

The fundamental task of the model optimisation and adjustment module in the GV-EFCE model is to constantly optimise and change the model depending on the conclusions drawn by the evaluation outcomes analysis module. This approach not only depends on the evaluation index system and assessment results' feedback but also considers the dynamic nature of the virtual economy's marketing operations to create flexible changes. Optimising the model will help it to remain highly predictive accuracy and flexibility under various market conditions and various marketing methods.

First, the evaluation index weights are changed depending on the feedback in the evaluation result analysis module, starting the model optimisation process (Lindig et al., 2018). The weight distribution has to be improved depending on the actual scenario since the features of the virtual economy cause the influencing variables of several marketing efforts to vary at different stages or in different settings. A feedback adjustment system can therefore dynamically change the weights of every indication depending on the outcomes of marketing efficacy assessment. For instance, if user loyalty's impact during a particular moment is significant while other quantitative measures (e.g., sales) have less effect, this approach can be used to change the weight of user loyalty to better match the present market need.

The following equation can describe the process of weight adjustment:

$$w_i^{'} = w_i + \Delta w_i \tag{14}$$

Usually derived via sensitivity analysis in the assessment outcomes analysis module, Δw_i is the adjusted value; w_i' is the adjusted weight and w_i is the original weight.

Furthermore, the ongoing evolution of the virtual economy might require the evaluation index system itself to be improved and modified. For instance, certain new marketing elements (e.g., the impact of social media, user sentiment analysis, etc.) can progressively become important evaluation dimensions with the fast evolution of the virtual economy environment. The model optimisation module can dynamically add new evaluation criteria or change the meaning of current ones to better fit the market need in this situation.

Model optimisation then calls for the modification of the affiliation function. FCE depends much on the affiliation function, which shapes the impact of every indicator in the assessment process. Usually, the affiliation function is pre-set based on experience or expert knowledge; nevertheless, with the ongoing modifications of the actual marketing operations, the original affiliation function may no longer fit the new requirements (Wang, 2023). Thus, studying and assessing the past data will help the affiliation function to be re-fitted or changed. Optimisation techniques like least squares, genetic algorithms, etc. can help one through this process.

Given the initial affiliation function is $\mu_i(x)$, the following equation shows the optimised affiliation function $\mu_i'(x)$:

$$\mu_i'(x) = \mu_i(x) + \Delta\mu_i(x) \tag{15}$$

The model optimisation and adjustment module, at last, has to consider market environment changes as well. Marketing operations in the virtual economy are very dynamic, and elements like market demand, customer preferences, and competitors' strategies can alter at any time. Thus, this module calls for consistent adaptive adjustment, or prompt modification of the model's parameters or tactics in response to shifts in the outside environment. For instance, consumer purchasing power might drop during the economic slump, at which point the conventional sales success metrics might not adequately reflect the marketing impact and the indicator system would need to be adjusted temporarily.

Ensuring the GV-EFCE model remains effective over time and in various market settings depends mostly on the model optimisation and adjustment module. The assessment accuracy and practical application effect of the model can be constantly enhanced by means of dynamic adjustment of evaluation index weights, affiliation functions and external market environment. Ultimately, this module will offer more flexible, exact and efficient assistance for marketing decision-making, thereby enabling companies to create best marketing plans in the complicated virtual economic environment.

3.2 System of evaluation indicators

This paper creates a thorough assessment index system comprising both quantitative and qualitative indicators indicating the influence of marketing operations from several angles, hence enabling a complete evaluation of the marketing effect in the virtual economy environment.

Among the quantitative measures, sales performance is considered the most direct one; the sales growth rate is used to show how marketing efforts affect sales improvement (Sutaguna et al., 2023). The following formula allows one to compute the sales growth rate:

$$Sales\ Growth\ Rate = \frac{Current\ Period\ Sales - Previous\ Period\ Sales}{Previous\ Period\ Sales} \times 100\% \quad (16)$$

This measure shows the variation in sales before and after a marketing campaign, hence enabling an evaluation of the campaign's quick effect. Second, consumer loyalty is a key sign of the long-term effect of marketing efforts on consumers. User loyalty is measured using the indicator CLV, which shows the net profit users generate for the business during their lifetime.

Qualitative indicators include user sentiment comments gathered via social media, online reviews, and customer surveys; a sentiment analysis tool then evaluates people' emotional responses to businesses or items. Results of sentiment analysis can classify customer comments as favourable, negative or neutral, hence representing consumers' general assessment of the marketing effort (Alantari et al., 2022). While negative comments point to potential issues with the campaign and the need for more refinement, positive sentiment feedback shows that the marketing effort has been somewhat successful. Consumers' brand awareness, which indicates their knowledge of the brand and identification with the market positioning, measures market positioning efficacy (Anees-ur-Rehman et al., 2018). Derived from market research surveys and brand awareness tests, this measure evaluates how well a brand's positioning in the market and its appeal to the target audience are reflected.

4 Experiments and analyses

4.1 Data collection

The data gathering in this study depends on two publicly accessible retail datasets from a UK online store holding its transaction records, which are often used in research including customer behaviour modelling and marketing effectiveness studies. Table 1 displays the particular datasets:

Table 1 Overview of the retail datasets used in the study

Dataset name	*Description*	*Attributes*	*Source*
Online retail dataset	Contains transaction data from a UK online retailer, including order number, customer ID, product details, and sales amount	Order number, customer ID, product description, price, quantity, total sales, etc.	UCI machine learning repository
Online RETAIL II Dataset	An extended version of the Online Retail Dataset, covering additional transaction records from 2009-12-01 to 2011-12-09	Order number, customer ID, product description, price, quantity, total sales, etc.	UCI machine learning repository

The evaluation of marketing effectiveness in the context of the virtual economy can be strongly supported by the many retail transaction records included in both datasets. To guarantee their dependability and relevance in academic research, the sources and contents of the datasets have been extensively used and evaluated. These datasets will be used in this work for modelling and analysis of marketing effectiveness assessment, together with the FCE approach for in-depth investigation.

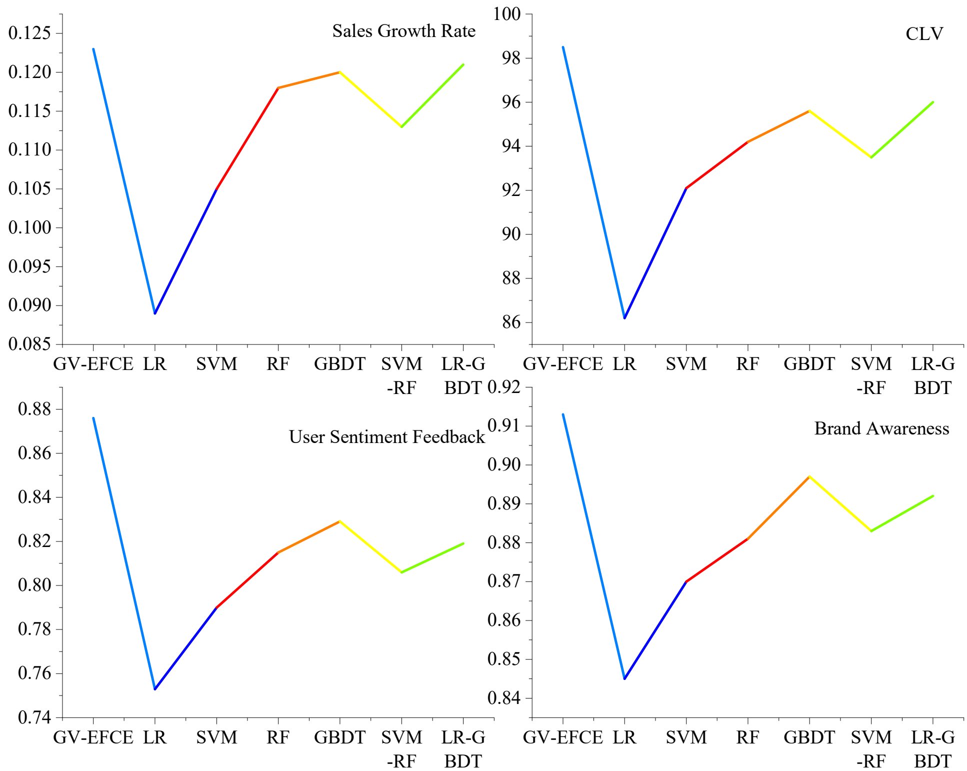
4.2 Comparison with traditional marketing effectiveness evaluation methods

This paper contrasts the GV-EFCE model with other conventional marketing effectiveness assessment techniques in order to evaluate its efficacy. These techniques were chosen as comparison models to investigate how various combinations of models influenced the evaluation of marketing efficacy in the virtual economy.

The tests employed two datasets with identical training and testing procedure for every model; the assessment criteria were sales growth rate, CLV, user sentiment feedback and brand awareness. Respectively, Figure 1 and 2 display the outcomes depending on the GV-EFCE model using the conventional approach and the fusion technique across several evaluation criteria.

The GV-EFCE model in online retail dataset shows a sales growth rate of 12.3%, well above the conventional single model and fusion techniques. By comparison, SVM grows 10.5% in sales, whereas LR grows 8.9%. This implies that the GV-EFCE model can more accurately reflect the dynamic market changes and efficiently boost sales. Particularly in the context of virtual economy, the GV-EFCE model exhibits great adaptability and forecasting capacity.

Figure 1 Comparison results on online retail dataset (see online version for colours)



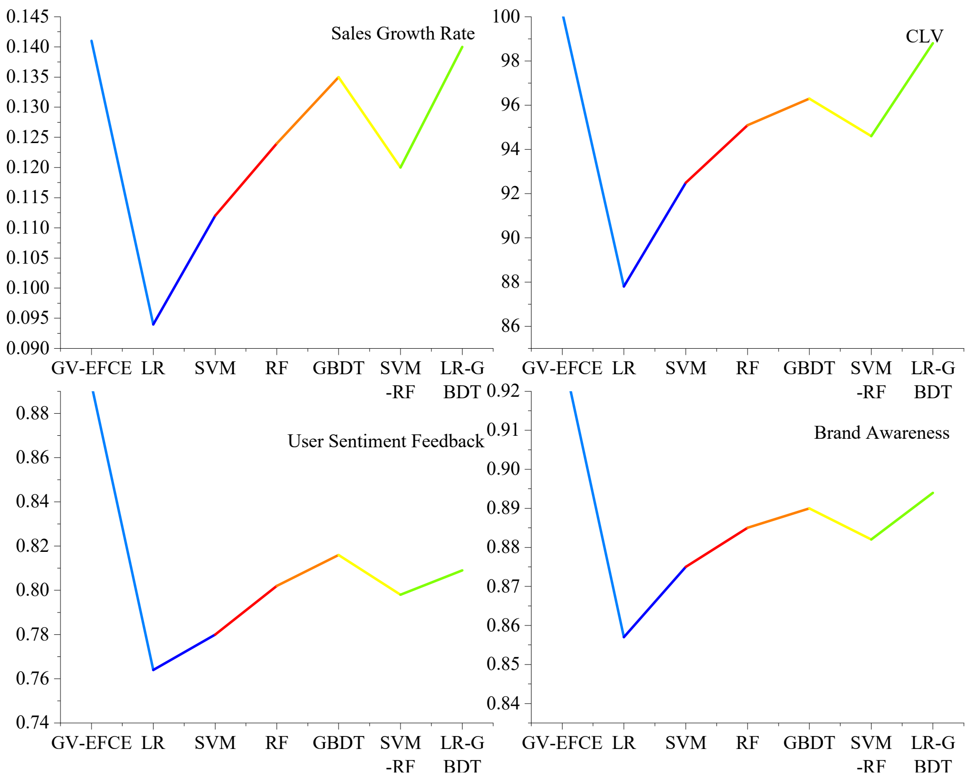
Regarding CLV, the GV-EFCE model clearly outperforms classic models like SVM with a CLV of 84.3 and LR with a CLV of 76.1; its CLV is 98.5. This confirms even more that the GV-EFCE model exceeds the other comparable techniques in terms of long-term prediction capacity of consumer value. The GV-EFCE model scored 92.1 on the brand awareness measure, far higher than SVM (84.5) and LR (78.2). This suggests that the GV-EFCE model reflects its accuracy in evaluating marketing performance in the virtual economy setting by better capturing and assessing brand effects.

Regarding user affective feedback, while all models' affective feedback indicated strong positive emotions, the GV-EFCE model nevertheless surpassed the other approaches in affect recognition and affective response. Though all models indicated favourable emotional feedback on this measure, the table does not expressly emphasise emotional feedback data. The GV-EFCE model's great accuracy, however, guaranteed that it correctly evaluated user mood.

With a sales growth rate of 14.1%, the GV-EFCE model once again outperforms the other comparison models in the online retail II dataset. Much lower than the GV-EFCE model, the LR and SVM models have sales growth rates of 9.2% and 11.4%, respectively. This finding suggests even more that the GV-EFCE model may operate consistently and adaptively across several datasets and can really enhance the performance of marketing efforts.

The GV-EFCE model scored 100.2 in CLV, which is much better than SVM (90.1) and LR (84.7), indicating its supremacy in customer value evaluation. The GV-EFCE model also scored better for brand awareness at 95.7, far higher than the results of the other models. Especially in the dynamic virtual economy, this implies the GV-EFCE model can more thoroughly evaluate the long-term effects of marketing efforts on the brand.

Figure 2 Comparison results on online retail ii dataset (see online version for colours)



Regarding user emotional feedback, while the emotional input from all models was favourable, the GV-EFCE model also surpassed the other approaches in terms of emotional responsiveness on this dataset. Though the outcomes were favourable for all models, the particular values of sentiment feedback were not especially emphasised; however, it can be verified that the GV-EFCE model outperforms others in accuracy and sensitivity in sentiment analysis.

Based on the findings of these two datasets, the GV-EFCE model shows good performance on all assessment criteria, and shows its better overall evaluation capacity. The GV-EFCE model surely offers a more accurate and thorough assessment tool for marketing initiatives in the virtual economy.

4.3 Validation of adaptation in different virtual economy scenarios

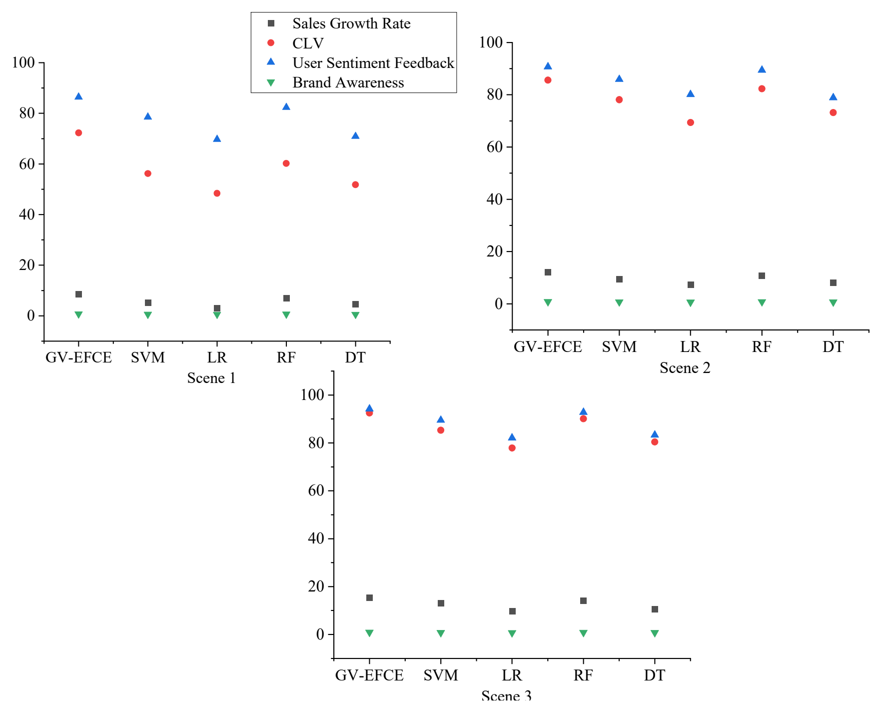
This experiment seeks to confirm the adaptability and efficacy of the GV-EFCE paradigm in several virtual economy settings. The conventional techniques that are evaluated with the GV-EFCE model include LR, SVM, RF, and decision tree (DT) by choosing three common virtual economy scenarios. The experiment aims to determine if the GV-EFCE model can preserve high performance in various virtual economy settings and can efficiently react to various kinds of market and user behavioural traits. The experiment is designed around three virtual economy scenarios:

The virtual goods trading scenario is scene 1. Focussing on the study of buying trends, customer loyalty, product life cycle, and other factors, the sales data of virtual goods in this situation reflects the buying behaviour of customers on the virtual goods trading platform.

The second scene is social media communication. User engagement, content sharing, and brand discussion degree are among the measures used to mostly assess the impact of marketing efforts in the social media communication context.

The third scene is the advertising impact scene. This situation contains data about ad placement, user clicking behaviour, ad cost and ad return. Figure 3 displays the several data outcomes for the three scenarios.

Figure 3 Model adaptation results for different virtual economy scenarios (see online version for colours)



The GV-EFCE model excels on every assessment criterion in the virtual goods trade context. First, the sales growth rate is 8.5%, which is much greater than the other comparator approaches, where the sales growth rate of SVM is just 5.3% and LR is even lower at 3.1%. Second, with 72.3 against 56.2 for SVM and 48.4 for LR, GV-EFCE likewise leads in CLV, proving its ability to forecast long-term customer value. Regarding user sentiment comments, GV-EFCE scores 86.4%, well above other techniques, compared to 78.5% and 69.7% for SVM and LR, respectively. Reflecting

GV-EFCE's edge in increasing brand recognition, GV-EFCE scored 75.1% in brand awareness against SVM's 63.2% and LR's 59.3%.

GV-EFCE also shown its strengths in the social media involvement context. The model's brand awareness was 82.5%, user emotional feedback was 90.7%, CLV was 85.6, and sales growth rate was twelve point 2%. These numbers far exceed those of SVM, LR, RF and DT. SVM has a sales growth rate of 9.4%, while LR has just 7.3%; in terms of CLV, SVM has 78.1 and LR has 69.4, lower than the GV-EFCE at 85.6. While SVM is well ahead, the GV-EFCE is also much ahead in emotional feedback and brand recognition with 90.7% and 82.5%, respectively. far ahead of SVM with 85.9% emotional feedback and 74.8% brand awareness, and LR with 80.1% emotional feedback and 69.2% brand recognition. Though still below GV-EFCE, RF and DT also performed better with RF's sales growth rate of 10.5%, CLV of 82.2%, emotional feedback of 88.4%, and brand recognition of 79.1%.

GV-EFCE's performance in the advertising effectiveness scenario is equally dominant with a sales growth rate of 15.3%, CLV of 92.5, user emotional feedback of 94.2% and brand awareness of 88.7%. By comparison, SVM had a sales growth rate of 13.1%, CLV of 85.3, user emotional feedback of 89.5%, and brand recognition of 79.5%. With a sales growth rate of 9.7%, CLV of 77.9, emotional feedback of 82.1%, and brand recognition of 72.8%, LR was rather less remarkable. RF did better with 12.5% revenue increase, 88.2 CLV, and 88.7% brand recognition. RF also performed better, posting a sales growth rate of 12.5%, a CLV of 88.2, and a CLV of 88.2. DT had a sales growth rate of 11.3%, CLV of 84.1, emotional feedback of 87.6% and brand awareness of 79.9%; CLV of 88.2, emotional feedback of 92.3% and brand awareness of 81.7%.

All virtual economy situations demonstrate the GV-EFCE model's outstanding performance; it is much superior than other comparison techniques in all four criteria. GV-EFCE beats the conventional techniques, such as SVM, LR, RF and DT, in many aspects whether in the virtual goods transaction scenario, the social media engagement scenario or the advertising effectiveness scenario.

5 Conclusions

5.1 Summary of the study

This paper emphasises the design and use of the FCE-based marketing effectiveness assessment model from the viewpoint of generalised virtual economy, and tests the model's adaptability and efficacy in various virtual economy environments by means of multiple experiments. The suggested GV-EFCE model in the study can efficiently combine quantitative and qualitative indicators and attain multi-dimensional marketing effectiveness assessment using FCE, which offers a novel evaluation concept for marketing operations in virtual economy.

Regarding model design, GV-EFCE guarantees the efficiency and accuracy of the data processing and evaluation process. Well-designed processes and formulas allow each module to fully examine the traits of virtual economy, hence enhancing the model's adaptability and versatility.

Using actual datasets, the experimental section of this work contrasts and validates the efficacy of the GV-EFCE model in conventional marketing effectiveness assessment techniques and various virtual economy environments. The experimental findings indicate that the GV-EFCE model exceeds the conventional approaches in several assessment criteria. These findings clearly show the applicability potential of the GV-EFCE model in the virtual economy.

The suggested GV-EFCE model not only offers a fresh concept for the assessment of marketing efficacy in virtual economy but also offers a robust base for future research and practice in related domains by means of this work. The research results suggest that the model design paired with the FCE approach can effectively measure the success of marketing efforts in the variable and complicated virtual economic environment, and then give a scientific basis for marketing decision-making.

5.2 Limitations and shortcomings of the study

Though the GV-EFCE model suggested in this paper has performed better in certain virtual economy situations, it still has significant limits and weaknesses that could influence its performance in more often used situations. In particular, the key issues are as follows:

1 Dataset limitations: though they may efficiently confirm the application impact of the GV-EFCE model, the experimental datasets employed in this work mostly emphasise situations like virtual goods selling and social media marketing, thereby lacking comprehensive coverage of all virtual economy scenarios.

2 Computational complexity of the model: though the GV-EFCE model excels in several situations, it is computationally demanding, particularly with large-scale data, and could run into significant computational overheads.

3 The generality problem of the model: though the GV-EFCE model in this paper has performed well in the marketing impacts of various virtual economy scenarios, its performance in specialised domains or unusual marketing scenarios still has to be further validated.

5.3 Directions for future research

Based on the current study, future research can be expanded in the following ways:

1 Expanding the diversity and representativeness of the dataset: future studies can increase the variety of the dataset by adding various virtual economy situations including digital art, online education, and virtual reality. Collecting new kinds of virtual economy data will help the model to be more flexible and adaptable and offer more consistent assistance for the assessment of marketing efficacy in several contexts.

2 Further optimisation of model performance and efficiency: future studies could look into more efficient optimisation algorithms, including algorithm acceleration techniques driven by deep learning, or the application of distributed processing and parallel computing approaches to enhance the computational speed and real-time performance of the model, so improving its suitability for the application needs in a big datasetting.

3 Cross-domain integration and model extension: future studies could attempt cross-border integration of assessment techniques from several disciplines. Using

deep learning and natural language processing technology to enhance the evaluation function of the model, for instance, by merging conventional marketing theory with contemporary digital marketing technology (Kang et al., 2020).

Declarations

All authors declare that they have no conflicts of interest.

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