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Optimal pricing strategies and decision-making systems in e-commerce using integrated fuzzy multi-criteria method

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Abstract

E-commerce online stores are now virtual platforms for connecting with millions of potential clients worldwide in the age of digitization. The marketing teams develop digital marketing tactics to attract traffic to their e-commerce sites and increase sales volume. With the vast amount of data provided by the cloud, decisions that were previously made with a significant level of intuition based on the knowledge and experience of decision-makers can now be backed using artificial intelligence algorithms. To identify the variables influencing pricing decisions for products launched on e-commerce shopping sites and to develop variable pricing techniques for each product found on an e-commerce site. This paper introduces a novel approach that applies Fuzzy association rule mining (FARM) and Fuzzy TOPSIS MCDM methodology. A B2B e-commerce marketing store based in Hong Kong has created and implemented Smart-Quo, a pricing decision support system for B2B e-commerce retail businesses. After a six-month trial period, there has been a substantial advance in the effectiveness and efficiency of choosing prices for each product. The case study illustrates the viability and potential advantages of implementing artificial intelligence tools in marketing management in the digital era.

KEYWORDS
artificial intelligence, data mining, decision support system, e-commerce, fuzzy theory, market intelligence

1 | INTRODUCTION

With the internet and mobile technologies' increasing popularity (Dogan et al., 2022), e-commerce has gained significant momentum in recent years. To keep up with technological advancements, e-commerce websites have also introduced mobile-friendly applications to facilitate browsing and shopping through mobile devices. B2B, which refers to business-to-business transactions, is the most renowned type of e-commerce that has seen remarkable growth and development in recent years. According to a report, 44% of B2B decision-makers in the US reported increased e-commerce investments in 2020. In 2020, e-commerce sales reached a whopping $4.28 million, experiencing a growth of 27.6% compared to 2019. The sales volume is expected to reach $6.38 trillion in 2024. The proposed theory aims to assist in meeting future demand by making appropriate pricing decisions for products on e-commerce websites.

The surge in business-to-business (B2B) transactions within e-commerce has brought challenges such as competitor pricing, dynamic market conditions, data analysis, implementation, and customer perception (Leung et al., 2019). To develop effective variable pricing strategies for each product, meticulous planning, data analysis, and testing are required. Therefore, businesses must adapt to changing market conditions and customer behaviour while remaining competitive.

Data mining, artificial intelligence, market intelligence, and decision support systems (DSS) are crucial in developing pricing strategies for e-commerce platforms. These features enable businesses to analyse data, predict future trends, and respond to changes in demand and supply. The FARM and Fuzzy TOPSIS of MCDM methods are introduced as new approaches to effectively develop pricing strategies by analysing these features (Kumar et al., 2022; Wang, 2022). For example, businesses can use data mining and AI to analyse customer behaviour and identify pricing trends, use market intelligence to compare their prices with competitors, and adjust their prices accordingly. DSS can simulate the potential impact of different pricing strategies before implementation (Liu, Shi, et al., 2023; Ni et al., 2022; Yuan et al., 2023). These features work together to develop effective pricing strategies. To identify the variables influencing pricing decisions for products launched on e-commerce shopping sites and to create variable pricing techniques for each product established.

The research is motivated by the increasing significance of e-commerce online stores as virtual platforms to connect with a vast global customer base. With the advent of digitization, marketing teams are employing digital tactics to attract traffic and increase sales. The abundance of data in the cloud opens opportunities to utilize artificial intelligence algorithms for data-driven decision-making in pricing strategies. This paper aims to identify variables influencing pricing decisions for e-commerce products and proposes a novel approach using Fuzzy association rule mining (FARM) and Fuzzy TOPSIS MCDM methodology. By developing the Smart-Quo pricing decision support system and implementing it in a B2B e-commerce store in Hong Kong, the research demonstrates the effectiveness and efficiency of artificial intelligence tools in marketing management, showcasing the potential advantages of integrating AI in the digital marketing era.

The pricing and decision-making process in today's B2B business platform is particularly complex (Leung et al., 2019). However, several limitations still exist in this field, such as a lack of accurate data, difficulty in predicting customer behaviour, inability to incorporate dynamic pricing, limited ability to personalize pricing, difficulty in balancing pricing and profitability, and the complexity of the pricing environment. The effectiveness of any pricing strategy depends heavily on the availability of accurate data. However, in some cases, this data may not be available or inaccurate, making it challenging to conduct business transactions. In B2B e-commerce, multiple decision-makers are typically involved in purchasing, and predicting their preferences and behaviour can be difficult. Additionally, current techniques may not personalize pricing based on customer preferences and behaviour. Finally, existing methods may not meet the increasing demands of the B2B business environment (Cheng et al., 2022). The main problem identified to solve by this research is to identify the best decision-making model to analyse the price-influenced variables in the e-commerce market. This helps control the business sector's marketing strategy and control production.

Given the limitations mentioned earlier, we propose a new, innovative approach that utilizes FARM and Fuzzy TOPSIS methodologies. Fuzzy Association Rule Mining uses fuzzy logic to convert numerical attributes to fuzzy attributes. Integrated FARM and Fuzzy TOPSIS are considered effective methods in pricing strategy because they allow for a more sophisticated and nuanced analysis for pricing decisions. Fuzzy rules can be used to model complex relationships between inputs and outputs, instrumental in pricing decisions. On another side, Fuzzy TOPSIS (techniques for Order of Preference by Similarity to Ideal Solution) is a decision-making tool that can be used to rank alternatives based on multiple criteria. Fuzzy TOPSIS can evaluate pricing strategies based on various criteria, such as profitability, customer satisfaction, and market share. Combining these two methods, the integrated fuzzy rule mining approach and fuzzy TOPSIS method can provide a more comprehensive and accurate analysis of pricing decisions. Below are the comparisons between the existing methodologies and our proposed policy, better suited to meet future demands, as shown in Table 1. The main contribution of the research acknowledges the limitations of traditional pricing analysis methods. It seeks to address them by introducing an innovative approach that leverages the power of FARM and Fuzzy TOPSIS.

The rest of the paper is organized as follows Section 2 presents a literature review related to the work, Section 3 is followed by proposed methodologies Section 4 declares the result and experiments of the proposed method with the existing techniques. Finally, Section 5 gives the conclusions of the study.

2 | LITERATURE REVIEW

The environment of e-commerce (B2B) business transactions is significantly improved nowadays. Undoubtedly the existing techniques and methods lead to good results, but more is needed to meet the future demand in the business; we use some new techniques and methods to

TABLE 1 Comparing existing techniques' disadvantages with the advantages of the proposed method.

S. No	Limitations of the existing methodologies	Advantages of the proposed methodology
1	Lack of accurate data	Accurate data analysis
2	In the ability to incorporate dynamic pricing	Helps with dynamic pricing
3	Limited ability to personalized pricing	Personalized pricing
4	Insufficient consideration of competition	This leads to competitive pricing
5	Difficulty in balancing pricing and profitability	Balancing pricing and profitability
6	The complexity of the pricing environment	Simplifying the pricing environment

develop effective pricing strategies and confident decision-making systems. We thoroughly analysed the existing techniques related to this work belongs to the Fuzzy association rule mining approach to identify e-commerce product association considering sales amount (Dogan et al., 2022), Using the fuzzy weighted association rule mining approach to develop a customer satisfaction product form (Kang et al., 2020), B2B flexible pricing decision support system for managing the request for quotation process under e-commerce business environment which Leung early discussed, K. H., Luk, C. C., Choy (Leung et al., 2019), Using the Association Rule Mining and Machine Learning Algorithm (Kumar et al., 2022), B2B flexible pricing decision support system for managing the request for quotation process under e-commerce business environment (Cheng et al., 2022), Due to the pandemic period e-commerce transactions increase its volume (Zhang, Peng, et al., 2023), optimal pricing strategy and techniques (Xu et al., 2022).

Research on Fuzzy Temporal Event Association Mining Model and Algorithm (Zhang, Huang, et al., 2023), An Overview Of Temporal Data Mining (Li, Tan, et al., 2021), big data and decision making: a case study in urban path planning (Li et al., 2022), temporal association rules mining in customer relationship management systems (Li, Wang, et al., 2023), Cluster-based membership function acquisition approaches for mining fuzzy temporal association rules (Li, Fan, et al., 2023). Fuzzy neural networks and neuro-fuzzy networks (Zhu et al., 2022), Application of neuro-fuzzy methods for stock market forecasting: (Yang et al., 2022), Fuzzy clustering based on feature weights for multivariate time series (Li & Sun, 2020), Performance Evaluation of Fuzzy Association Rule Mining Algorithms (Xie et al., 2023). Time-series forecasting with deep learning (Li et al., 2020; Wu et al., 2022), A new fuzzy time series forecasting method (Li, Zhou, & Huang, 2021), Fuzzy Temporal Data Mining Algorithms (Poli, 2020; Sharmila & Vijayarani, 2021), and Application of neuro-fuzzy methods for stock market forecasting (Cao et al., 2020). A comprehensive review of fuzzy multi-criteria decision-making methodologies for energy policy-making (Huang et al., 2021), Multi-criteria decision-making methods in fuzzy decision problem (Zheng et al., 2023). Assessing the human resource in science and technology for Asian countries: Application of fuzzy AHP and fuzzy TOPSIS (Chou et al., 2019).

The article (Forouzandeh et al., 2021) proposes a novel recommendation system for the tourism industry, combining the Artificial Bee Colony (ABC) algorithm and the fuzzy TOPSIS model to optimize the system. Using the real TripAdvisor dataset, the improved ABC algorithm and TOPSIS efficiently handle multi-criteria decision-making for hotel recommendations based on user preferences. The research demonstrates the high accuracy and effectiveness of the proposed method in assisting tourists' accommodation selection process. The paper (Forouzandeh et al., 2022) presents a novel recommendation system for the tourism industry, combining the artificial bee colony (ABC) algorithm and Fuzzy TOPSIS for optimizing the system and suggesting travel recommendations to tourists. Data from a 1015 online questionnaire were used, and the two-stage process involving TOPSIS and ABC algorithm effectively recommends the best tourist spots based on user preferences.

The researcher explored a range of pricing strategies and decision-making techniques utilizing diverse methodologies, with their efficacy substantiated by their past performance in meeting market demand. After evaluating these various techniques and methods, we have identified a novel solution that yields superior outcomes in pricing decisions.

3 | SYSTEM MODEL

The proposed methodology has been identified as a highly effective approach for developing optimal pricing strategies and decision-making systems in e-commerce transactions. While previous research has yielded effective methods for achieving better results, there are still limitations to obtaining optimal outputs. To address these limitations, we propose an integrated Fuzzy Association Rule Mining Approach (FARM) (Dogan et al., 2022) and Fuzzy TOPSIS MCDM methods (Huang et al., 2021; Wang, 2022). Dogan et al. (2022) proposed a more effective version of the traditional Association Rule Mining (ARM) by integrating Fuzzy set theory, resulting in the FARM algorithm. Following this, we apply multi-criteria decision making (MCDM) techniques such as Fuzzy TOPSIS to refine our analysis (Chou et al., 2019) further. The proposed system architecture is illustrated in Figure 1.

3.1 | The structure of the proposed model performs under the following steps

This involves clearly defining the problem that needs to be addressed and outlining the objectives of the analysis. Data is collected from various sources related to pricing strategy, customer reviews, and market trends. This data is crucial in providing insights into the problem and developing a suitable solution. Natural Language Processing (NLP) techniques are applied to pre-process the collected data, including cleaning, normalization, and transforming raw data into a format suitable for analysis. This step may involve data cleansing, data integration, and data transformation. FARM involves extracting fuzzy association rules related to pricing strategy, which is done by applying techniques such as fuzzy itemset, calculating unclear support and confidence (Wu et al., 2020). Fuzzy TOPSIS ranks pricing strategies based on their similarity to the ideal solution. This step involves identifying the perfect pricing strategy and assessing the suitability of the other pricing strategies based on their proximity to the perfect solution (Wang, 2022).

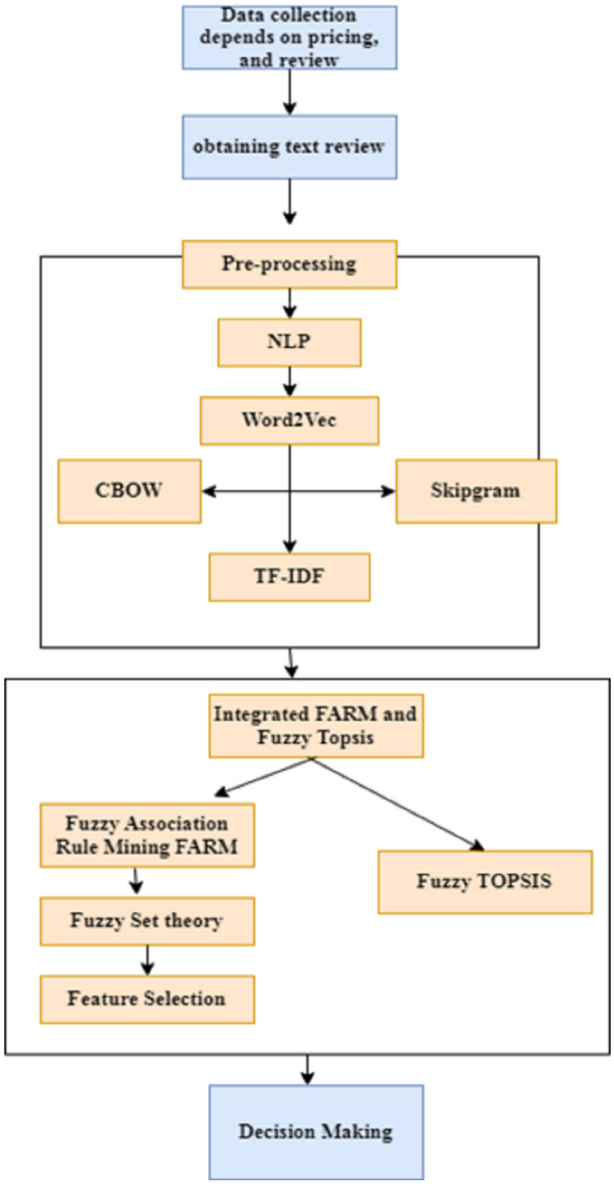


FIGURE 1 Structure of the proposed model.

A fuzzy logic-based approach is used to integrate the results obtained from FARM and Fuzzy TOPSIS, which comprehensively evaluates the pricing strategies and helps identify the optimal ones. The integrated FARM and Fuzzy TOPSIS model results are used to make informed decisions about the optimal pricing strategy. This step may involve evaluating the ranked pricing strategies, selecting the best strategy based on specific business objectives, and implementing the chosen strategy.

3.2 | Natural language pre-processing

Natural language pre-processing (NLP) is used to extract the feature data for evaluation (Wang, 2022). Applying the NLP pre-processing method to the proposed Integrated FARM and TOPSIS method can help extract relevant information from the text data and provide insights into patterns and trends. It helps to prepare the text data for analysis (Cheng et al., 2017; Lu et al., 2023) by removing noise, normalizing text, and extracting relevant features. Data can be proceeded by machines based on natural language processing (Forouzandeh et al., 2018; Liu, Zhou, et al., 2023; Sheikhpour et al., 2023). For representing adequate data, we used the most prominent method Word2Vec (Wang, 2022) was developed by Google's Tomas Mikolov. This method is used to describe a word as vectors. The basic idea behind word2vec is to train a neural network on a large corpus of text data to learn distributed representations of words. The network is trained to predict the probability of a given word appearing in the context of other words. The key innovation of word2vec is using an external neural network with a hidden layer that learns the distributed representations of words. Two main types of word2vec models exist Continuous Bag of Words (CBOW) and Skip-gram.

1. CBOW predicts a target word based on the context of surrounding words.
2. Skip-gram predicts the context words given a target word.

Both models learn to predict the probability of a given word appearing in the context of other words, and the weights of the hidden layer represent the learned vector representations of the words. Finally, evaluate each data through TF-IDF (Term Frequency-Inverse Document Frequency). It works under TF (Term Frequency) measures the frequency of a term in a document, and is calculated as the number of times the term appears in the document divided by the total number of terms in the document.

IDF (Inverse Document Frequency) measures the rarity of a term across all documents in the corpus and is calculated as the logarithm of the total number of documents in the corpus divided by the number of documents containing the term. This helps to identify the most relevant words in a document or corpus and is commonly used for tasks such as keyword extraction, document classification, and search engine ranking.

For a set of D containing M data, use the respective tool to segment the data into the set D and remove the stop words further, use TF-IDF to calculate weight $\mathrm{TF}-\mathrm{IDF}_{ij.}$

Represents weight of word t_i in the data $D_j=(1,2,3,\ldots M)$ calculated in equation (1)

$$\mathrm{TF}-\mathrm{IDF}_{ij}=\mathrm{TF}_{i,j}\times \mathrm{IDF}_i \tag{1}$$

Here $n_{i,j}$ represents the number of times the term i appears in the document j, while $\sum_k n_{k,j}$ represents the total number of terms in the document j in equation (2)

$$\mathrm{TF}_{i,j}=\frac{n_{i,j}}{\sum_k n_{k,j}} \tag{2}$$

Total number of data text in the corpus $\{j:t_i\in D_j\}$ contains the number of text of the word t_i which is the number of texts with the $n_{i,j}\neq 0$ if the word is not in corpus it results zero. Therefore, $1+|\{j:t_i\in D_j\}|$ is used in equation (3)

$$\mathrm{IDF}_i=lg\frac{|D|}{|\{j:t_i\in D_j\}|} \tag{3}$$

Here the word vector converted by the skip gram model of Word3Vec, it takes a w_t As input and tries to predict the word w_{t+i} around it, through input–output selects the random index value I from the skip gram program c randomly sample k times and the sample value of I of input w_t comes from j. Shows in equation (4)

$$\frac{i}{T_i}\sum_{t=1}^{T}\sum_{\forall i\in J}\log p(w_{t+i}|w_t) \tag{4}$$

3.3 | Proposed integrated fuzzy association rule mining approach (FARM) and fuzzy TOPSIS

3.3.1 | Fuzzy association rule mining FARM approach

Fuzzy association rule mining (FARM) is a method that incorporates Fuzzy set theory into association rule mining (ARM). Traditional methods of ARM are not suitable for products that belong to multiple classes, as they cannot handle these multi-class situations. Therefore, fuzzy association rule mining provides an improved approach that is effective in addressing this issue and achieving the desired outcome.

3.3.2 | Fuzzy sets theory

In fuzzy set theory, each element in a universal set X is assigned a degree of membership through a membership function, which defines a fuzzy set. This function distinguishes individuals in X as either members or non-members of a crisp set. The function's output is a value that represents the degree of membership.

$\mu A(X)$ to each $x \in X$ (Wu et al., 2020).

$$\mu A(x) = \begin{cases} 1 \text{ if and only if } x \in A \\ 0 \text{ if and only if } x \in A \end{cases}$$

Function depicts the element of the universal set including 0 and 1.

3.3.3 | Algorithm for FARM

Step 1: Association Rules represented as $X \rightarrow Y$ X and Y are consider as the item set

It refers that X appears in a condition that Y also apply with the high probability. In some times the approach of association rules would be consider by a real world researchers by using fuzzy set theory to avoid unnatural boundaries and partitioning (Wu et al., 2020). For instance if there is a dataset with two attributes B_1 and B_2 and three linguistic levels (LOW, MEDIUM and HIGH)

Possible mined fuzzy association rule will be (B_1 is LOW $\rightarrow$ B_2 is HIGH) (Wu et al., 2020), support and confidence are features that are commonly used to obtained association rules. Here we use the same concept of X and Y. measurements if X and Y relations support and confidence would be

Step 2:

$$\text{Support}(R) = \frac{\sum_{X_{P \in D}} \mu R(X_P)}{|D|} \tag{5}$$

Step 3:

$$\text{Confidence}(R) = \frac{\sum_{X_P \in D} \mu R(X_P)}{\sum_{X_P \in D} \mu X(X_P)} \tag{6}$$

Step 4: In equation (2) $\mu X(X_P)$ is the matching degree of the rule pattern X_P with rule antecedents $\mu R(X_P)$ is the matching degree of rule pattern X_P with rule antecedents and consequent $|D|$ is the cardinality of the dataset

// *Using Fuzzy Lift Measurement* //

Step 5: Fuzzy Association Rule mining uses the Lift measurement to represent the ratio between confidence ratio and expected confidence ratio of each rule.

Step 6:

$$\text{Lift}(R) = \frac{\text{Confidence}(R)}{\sum_{X_{P \in D}} \mu Y(X_P) / |D|} \tag{7}$$

Step 7: In equation (3), $\mu X(X_P)$ is the matching degree of X_P with the rule consequent Measure detects the item rule with negative dependence (Lift < 1), independence (Lift = 1) or positive dependence (Lift > 1).

The FARM (fuzzy association rule mining) algorithm is a method that utilizes fuzzy set theory to mine association rules from datasets containing fuzzy attributes. It represents association rules in the form of $X \to Y$, where X and Y are item sets showing the co-occurrence of items with high probability. The algorithm calculates support and confidence to measure the frequency and strength of the rules in the dataset. Additionally, it uses fuzzy lift to detect item rules with negative, independent or positive dependence. By employing fuzzy logic, FARM provides a more nuanced analysis, particularly suitable for real-world scenarios with imprecise or uncertain data, enabling the discovery of meaningful relationships between items in complex datasets.

By utilizing both support and confidence rules in the FARM algorithm, the research aims to strike a balance between frequency and strength of associations. High support ensures that the discovered rules are statistically significant, while high confidence ensures that the relationships between X and Y are robust and meaningful. Together, these measures contribute to the algorithm's ability to provide a more comprehensive and accurate analysis of pricing decisions or other applications, particularly when dealing with complex datasets with fuzzy attributes, ultimately enhancing the effectiveness of the FARM method.

3.3.4 | Using fuzzy TOPSIS model

Fuzzy TOPSIS is used to find a positive ideal solution (PIS) and (NIS) negative ideal solution at the comparison criteria for each choice. By comparing the Euclidean Distance between the ideal solution and alternatives, the closest alternatives will obtain the Pros and Cons of the alternative are ranked, further, calculate the fuzzy rating.

Step 1: If the fuzzy rating of the k-th decision maker is $\tilde{x}_{ijk} = (a_{ijk}, b_{ijk}, c_{ijk)}$ the aggregate fuzzy rating of each new sample is (Wang, 2022)

$$\tilde{x}_{ijk} = (a_{ijk}, b_{ijk}, c_{ijk}); \tag{8}$$

Step 2: Where $a_{ij} = \min\{a_{ijk}\}$;

$$b_{ij} = \frac{1}{k}\sum\nolimits_{k=1}^{k} b_{ijk};$$

$$c_{ij} = \max\{c_{ijk}\};$$

Step 3: Thus the standardized fuzzy decision matrix can be

$$\tilde{R} = [\tilde{r}_{ij}]_{m \times n} \tag{9}$$

$$\tilde{r}_{ij} = \left(\frac{a_{ij}}{c_j+}, \frac{b_{ij}}{c_j+}, \frac{c_{ij}}{c_j+}\right), j \in B \tag{10}$$

$$\tilde{r}_{ij} = \left(\frac{a_J-}{c_{ij}+}, \frac{a_j-}{b_{ij}+}, \frac{a_j-}{a_{ij}+}\right), j \in C \tag{11}$$

$$C_j* = \max(c_{ij}), j \in B \tag{12}$$

$$C_j* = \max(c_{ij}), j \in C \tag{13}$$

Step 4: Where B and C represents the set of cost criteria.

Step 5: The weighted normalized fuzzy decision matrix

$$\tilde{V} = [\tilde{v}_{ij}]_{m\times n}, i = 1, 2..., n; \tag{14}$$

$$\tilde{v}_{ij} = \tilde{r}_{ij}(.)\tilde{w}_j$$

Step 6: Fuzzy optimal ideal solution A^+ and the fuzzy worst ideal solution $A^=$ can be defined a

$$A^+ = \left(\tilde{V}_1^+, \tilde{V}_2^+, ..., V_n^+\right), \tilde{v}_j = \max\{v_{ij3}\} \tag{15}$$

$$A^+ = \left(\tilde{V}_1^-, \tilde{V}_2^-, ..., V_n^-\right), \tilde{v}_j = \min\{v_{ij1}\} \tag{16}$$

Step 7: For each new sample distance between the candidate solution and the optimal solution A^+ and worst solution A^- is defined as

$$d_i^+ = \sum_{j=1}^{n} d_v\left(\tilde{v}_{ij}, \tilde{v}_j^+\right), i = 1, 2..., m \tag{17}$$

$$d_i^- = \sum_{j=1}^{n} d_v\left(\tilde{v}_{ij}, \tilde{v}_j^-\right), i = 1, 2..., m \tag{18}$$

Step 8: Where

$$d_v(\tilde{m}, \tilde{n}) = \sqrt{\frac{1}{3}\sum_{i=1}^{3}(m_i - n_i)^2} \tag{19}$$

Step 9: Then, the relative closeness of each new sample to the ideal solution is calculated,
Step 10: Finally,

$$CC_i = \frac{d_i^-}{d_i^+ + d_i^-}, i = 1, 2, ..., m. \tag{20}$$

Step 12: Finally the new sample are arranged according to the descending order of closeness,
Step 13: At last the new sample are ranked first is the best solution (which is closest to the optimal solution and farthest to the worst solution).

By applying fuzzy logic, the research converts numerical attributes into fuzzy attributes, allowing for a more nuanced representation of complex relationships between inputs and outputs. The fuzzy TOPSIS multi-criteria decision-making methodology further enables the ranking and evaluation of pricing strategies based on multiple criteria, such as profitability, customer satisfaction and market share. This ensures that the pricing decisions are comprehensive and consider various important factors simultaneously. Customized Pricing Techniques: The Smart-Quo system allows for the development of variable pricing techniques for each product on the e-commerce site. Instead of applying a one-size-fits-all pricing approach, the system tailors pricing strategies to the specific characteristics and demands of individual products. This customization ensures that each product's pricing is optimized for maximum profitability and competitiveness.

4 | RESULTS AND DISCUSSIONS

4.1 | Data description

This article explores the dataset of smart capsule coffee machines by collecting reviews from two popular e-commerce websites (Taobao and Jingdong). The most recent year's transactions were used to select reviews related to smart capsule coffee machines, pricing strategies and market trends as a test sample. (Wang, 2022; Wu et al., 2020). A total of 127,765 words and user reviews were exported to a text file for text analysis. Evaluate the extract features using the keywords good, very good, neutral, bad and very bad using Equation (1) and the rule of descending weight values, feature words were extracted from the word segmentation results, as represented in Table 2.

Table 2 presents an analysis of the overall reviews collected over the past 5 years on the pricing decisions of the smart capsule coffee machine. The analysis involved evaluating the reviews using the following keywords: good, very good, neutral, bad and very bad. The keywords were assigned weights and ranks based on their frequency of occurrence in the reviews. The keyword 'good' was found to have the highest weight of 0.30 and rank of 9 among all the keywords analysed. Therefore, the pricing decision was based on this keyword. The other keywords, namely very good, neutral, bad and very bad, were also assigned weights and ranks based on their frequency of occurrence in the reviews. Keyword representation for graph is shown in Table 3.

4.2 | Performance of metrics in our proposed model

In this study we used the metric measures of accuracy, precision, recall and F1 score with existing techniques and our proposed model.

Accuracy

Term accuracy (ACC) is used for the exact prediction.

$$\text{Accuracy} = \frac{\text{TP}+\text{TN}}{\text{TP}+\text{TN}+\text{FP}+\text{FN}} \times 100 \tag{21}$$

Precision

$$\text{Precision} = \frac{\text{TP}}{\text{TP}+\text{FP}} \times 100 \tag{22}$$

Recall

$$\text{Recall} = \frac{\text{TP}}{\text{TP}+\text{FN}} \times 100 \tag{23}$$

F1 score

TABLE 2 Weight and rank of the keywords regarding smart capsule coffee machine collected from overall reviews of past 5 years.

Keywords	Good	Very good	Neutral	Bad	Very bad
Weight	0.30	0.26	0.25	0.11	0.08
Rank	9	10	11	12	13

TABLE 3 Keyword representation table for graph.

Keywords
Good-1
Very good-2
Neutral-3
Bad-4
Very bad-5

The F-Measure, also known as the F1 score, is the harmonic mean of precision and recall.

$$\mathrm{F-Score} = \frac{2 \times \mathrm{Precision} \times \mathrm{Recall}}{\mathrm{Precision} + \mathrm{Recall}} \tag{24}$$

Figure 2 presents the precision levels of various existing pricing methods, including FARM, FL (fuzzy logic), and FWARM (fuzzy weighted association rule mining), as well as the FDM (fuzzy Delphi method). The table shows the precision of the keyword 'good' in existing methods to be 91%, whereas the proposed method achieves a precision of 93%. Similarly, the precision of the keyword 'very good' in existing methods is 86%, whereas the proposed method achieves a precision of 88%. For the keyword 'neutral', the existing methods achieve a precision of 81%, whereas the proposed method achieves a precision of 84%. For the keyword 'bad', the existing methods achieve a precision of 74%, whereas the proposed method achieves a precision of 80%. Finally, for the keyword 'very bad', the existing methods achieve a precision of 68%, whereas the proposed method achieves a precision of 70%.

Figure 3 displays the Recall percentages of various existing pricing methods, including FARM, FL (fuzzy logic), and FWARM (fuzzy weighted association rule mining), as well as the FDM (fuzzy Delphi method). The table shows the recall of the keyword 'good' in existing methods to be 93%, whereas the proposed method achieves an accuracy of 96%. Similarly, the recall of the keyword 'very good' in existing methods is 88%, whereas the proposed method achieves recall of 89%. For the keyword 'neutral', the existing methods achieve recall of 83%, whereas the proposed method achieves recall of 85%. For the keyword 'bad', the existing methods achieve recall of 78%, whereas the proposed method achieves recall of 82%. Finally, for the keyword 'very bad', the existing methods achieve recall of 76%, whereas the proposed method achieves recall of 81%.

Table 4 displays the F1 score percentages of various existing pricing methods, including FARM, FL (fuzzy logic), and FWARM (fuzzy weighted association rule mining), as well as the FDM (fuzzy Delphi method). The table shows the F1 score of the keyword 'good' in existing methods to be 96%, whereas the proposed method achieves an F1 score of 98%. Similarly, the F1 score of the keyword 'very good' in existing methods is 89%,

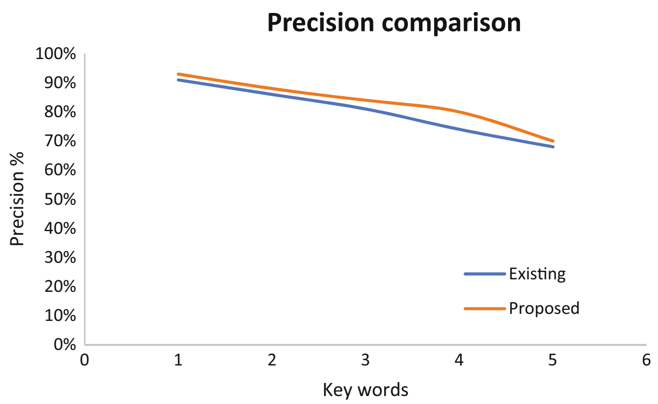


FIGURE 2 Precision of existing methods and proposed method.

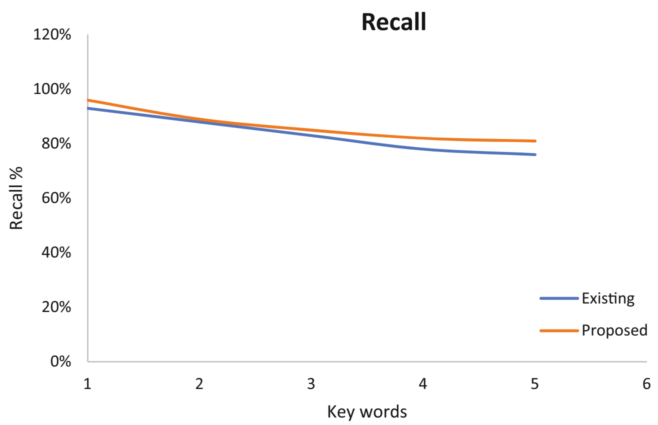


FIGURE 3 Recall of existing methods and proposed method.

TABLE 4 F1 score of existing methods and proposed method in %.

Keywords	F1 score of keywords using (FARM-FL) and FWARM-FDM) method	Proposed method (FARM and F-TOPSIS MCDM)
Good	96%	98%
Very good	89%	89%
Neutral	84%	87%
Bad	78%	82%
Very bad	78%	82%

TABLE 5 Accuracy obtained with the keyword 'good'.

Method	Accuracy obtained with the keyword 'good'
FARM-FL	88%
FWARM-FDM	94%
Proposed	98%

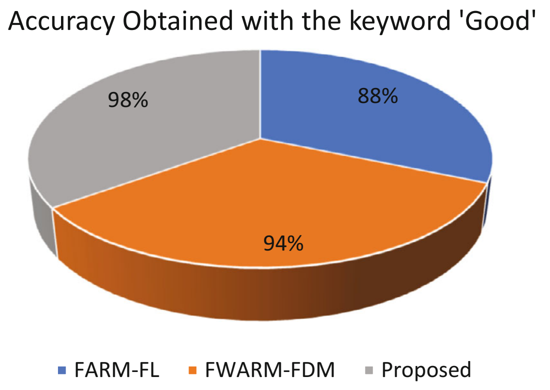


FIGURE 4 Percentage of accuracy obtained from the overall reviews using the keyword 'good'.

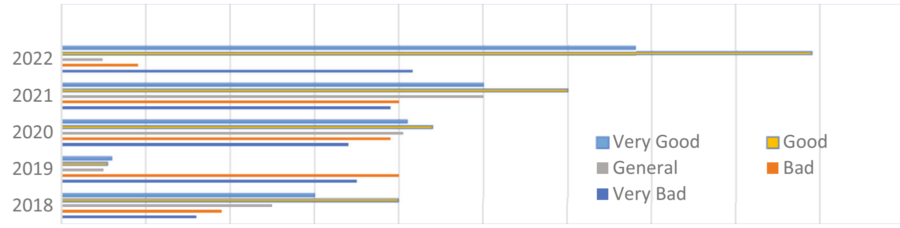
whereas the proposed method achieves F1 score of 89%. For the keyword 'neutral', the existing methods achieve F1 score of 84%, whereas the proposed method achieves F1 score of 87%. For the keyword 'bad', the existing methods achieve F1 score of 78%, whereas the proposed method achieves F1 score of 82%. Finally, for the keyword F1 score 'bad', the existing methods achieve F1 score of 78%, whereas the proposed method achieves F1 score of 82%.

Table 5 illustrates the overall accuracy achieved by three different methods: the previous approach of FARM-FL resulted in 88% accuracy, FWARM-FDM yielded 94%, and the proposed model achieved 98%. Figure 4 pie chart represents the percentage derived from the keyword 'good'. To analyse review ratings for a smarter pricing strategy and decision-making for smart capsule coffee machines, the keyword "good" was used.

Figure 5 displays the frequency rate of the keyword "good" in pricing and decision reviews for smart capsule coffee machines over the past 5 years. This highlights the effectiveness of the proposed method in achieving an optimal pricing strategy and decision-making system for future e-commerce transactions.

4.3 | Result discussion

The focus of our study was on the e-commerce pricing strategy and decision-making system, and we proposed the use of the integrated fuzzy association rule mining and fuzzy TOPSIS method to relate pricing strategy with the current market trend. The algorithm's performance was based



	2018	2019	2020	2021	2022	
Very Good	0.6	0.12	0.82	1	1.36	
Good	0.8	0.11	0.88	1.2	1.78	
General	0.5	0.1	0.81	1	0.098	
Bad	0.38	0.8	0.78	0.8	0.182	
Very Bad	0.32	0.7	0.68	0.78	0.832	

FIGURE 5 Keyword frequency rate in past 5 years.

on reviews and pricing data from the last 5 years, categorized according to keywords such as good, very good, bad, general and very bad. To implement this method, we first applied NLP pre-processing to collected reviews and used the FARM methodology to calculate fuzzy support and confidence while extracting fuzzy association rules related to pricing strategy. We then proceeded with fuzzy TOPSIS to rank pricing strategies based on their similarity to the ideal solution. Finally, we integrated both methods to find the optimal pricing and decision solution. Our study aimed to overcome the limitations of existing methods in pricing strategy and decision-making systems in the e-commerce environment.

5 | CONCLUSION

To overcome the limitations of existing optimal pricing decision systems in B2B e-commerce sites, this study utilized the fuzzy association rule mining and fuzzy TOPSIS MCDM method. The study provides valuable insights into e-commerce environments, helping to identify the best solution for optimal pricing strategies and decision-making systems. Going forward, similar research could lead to even better results, resulting in more satisfying pricing decisions. The performance is evaluated using precision, recall, F1-score and accuracy using mentioned equations. Then the values are formulated using graphs and tables. The obtained graphs and tables clearly show that proposed integrated technique makes better decision by predicting the keywords on pricing strategy. This helps the e-commerce platform to make timely decision on pricing the products and improve the business strategy. In future, deep learning-based prediction and analysis for dynamic pricing will be used to improve performance of current strategy.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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