https://doi.org/10.31891/csit-2025-3-16
UDC 004.89

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MARKETING DECISION SUPPORT SYSTEM BASED ON FUZZY TRAINED ASSOCIATIVE RULES EXPERT SYSTEM

The fuzzy-associative metaheuristic approach addresses the urgent task of developing a marketing decision support system based on a fuzzy trained associative rules expert system, aimed at improving the accuracy and efficiency of consumer preference analysis. The proposed system combines the interpretability of fuzzy logic with data-driven learning via associative rules and parameter identification using an adaptive multi-agent optimization method. To achieve this goal, associative rule learning techniques (Apriori and FP-Growth) were used to extract frequent consumer behavior patterns. A fuzzy expert system was developed, in which the parameters of membership functions are optimized by the Adaptive Vibrating Particle System (AVPS) metaheuristic. Unlike traditional vibrating particle systems, AVPS integrates iteration-dependent control of particle positions, enabling global search in early iterations and local refinement at later stages, thus improving convergence speed and solution precision. The architecture was implemented using Python-based tools (TensorFlow, Keras, Pandas, mlxtend, Scikit-Fuzzy), and validated on the "Consumer Behavior and Shopping Habits" dataset. The fuzzy expert system achieved an accuracy of 0.98, outperforming human experts (0.80), traditional VPS optimization (0.93), and backpropagation-based training (0.90). The system also reduces reliance on manually tuned parameters and increases robustness to data incompleteness and noise. Scientific novelty lies in combining a fuzzy associative rule-learning framework with AVPS-based optimization, offering a scalable and interpretable decision-making mechanism. The developed system contributes to the advancement of intelligent recommendation engines, personalized marketing tools, and decision support systems in consumer-oriented analytics.

Keywords: fuzzy expert system, associative rule learning, adaptive metaheuristics, consumer preferences, marketing decision support systems.

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СИСТЕМА ПІДТРИМКИ ПРИЙНЯТТЯ МАРКЕТИНГОВИХ РІШЕНЬ НА ОСНОВІ НЕЧІТКОЇ ЕКСПЕРТНОЇ СИСТЕМИ, НАВЧЕНОЇ АСОЦІАТИВНИМ ПРАВИЛАМ

У статті запропоновано розв'язання актуальної науково-прикладної задачі створення системи підтримки прийняття маркетингових рішень на основі нечіткої експертної системи, навченої асоціативним правилам. Розроблена система поєднує прозорість нечіткого логічного виводу з можливістю самонавчання на основі закономірностей даних. Ідентифікація параметрів функцій належності здійснюється за допомогою адаптивного мультиагентного метаевристичного методу – адаптивної системи вібруючих частинок (AVPS). Запропонована система адаптує поведінку частинок, залежно від номера ітерації, що забезпечує ефективний загальний пошук на початкових етапах та цільове вдосконалення рішень на фінальних стадіях. Для навчання асоціативним правилам у дослідженні були викристані відомі алгоритми Apriori та FP-Growth, а програмна реалізація здійснена з використанням бібліотек TensorFlow, Keras, Pandas, mlxtend та Scikit-Fuzzy. Експериментальне дослідження, що здійснено на основі масиву даних про споживчу поведінку та клієнтські переваги, підтвердило високу точність запропонованої системи (0.98), що перевищує результати традиційної вібраційної оптимізації (0.93), навчання зі зворотним поширенням помилки (0.90) та оцінки, надані експертом (0.80). Запропонована у статті система стійка до неповноти даних і шумів, а також узагальнює закономірності за такими ознаками, як вік, стать і категорія товару. Наукова новизна дослідження полягає в інтеграції адаптивної метаевристики AVPS у процес навчання нечітких експертних систем. Запропоноване рішення є масштабованим і придатним для застосування в інтелектуальних рекомендаційних системах, персоналізованому маркетингу та прийнятті споживчих рішень.

Ключові слова: нечітка експертна система, асоціативні правила, адаптивні метаевристики, моделювання споживчих уподобань, підтримка прийняття маркетингових рішень.

Received / Стаття надійшла до редакції 09.07.2025
Accepted / Прийнята до друку 29.08.2025

Introduction

Consumer preference decision making systems are being actively developed nowadays. Such decision-making systems based on consumer preferences use machine learning algorithms, big data analysis, and artificial intelligence to personalize services during marketing research.

The aim of the research is to improve the efficiency of decisions about consumer preferences by creating a fuzzy learning associative rules expert system.

To achieve the goal, the following tasks were set and solved:

1. To choose methods of associative rules learning
2. To develop a fuzzy associative rule learning expert system to support decision making about consumer preferences.

3. To select the quality criterion for the proposed fuzzy associative rule learning expert system.
4. To create a metaheuristic method based on adaptive vibrating particle system to determine the parameters of the proposed fuzzy associative rule learning expert system.
5. To conduct a numerical study.

To determine the parameters of fuzzy learnable associative rules of expert systems, optimization methods are now actively used.

Existing optimization methods have one or more of the following disadvantages:

- have a high probability of hitting a local extremum;
- have high computational complexity;
- do not guarantee convergence.

This raises the problem of insufficient efficiency of optimization methods, which needs to be solved.

Related works

Regression [1] and autoregressive [2] methods are usually used to create systems for making decisions on consumer preferences based on machine learning.

A knowledge base (most often in the form of product rules) and an inference mechanism are used to create systems for decision-making on consumer preferences based on expert systems [3]. The disadvantages of such systems include the fact that they operate only with quantitative estimates, while the operator is easier to work with qualitative estimates, as well as the lack of automatic selection of rules.

Associative rule learning methods are used for automatic rule selection [4]. The disadvantages of such methods include the fact that there is no provision for working with real features.

Fuzzy expert systems are currently used to simplify the interaction between a human and a computer system. They usually use the fuzzy inference mechanism of Larsen, Mamdani, Tsukamoto and Sugeno [5]. The disadvantages of such systems include the fact that the procedure for determining their parameters is not automated [5].

Metaheuristics (or modern heuristics) are used to find a quasi-optimal solution to optimization problems faster and reduce the probability of hitting a local extremum [6-10]. Metaheuristics extend the capabilities of heuristics by combining heuristics based on a high-level strategy [11-15].

Existing metaheuristics have one or more of the following drawbacks:

- Insufficient accuracy of the method [22];
- only an abstract description of the method is available or the description of the method is focused on solving only a certain problem [16];
- the procedure for determining parameter values is not automated [20];
- the influence of iteration number on the solution search process is not taken into account [17];
- there is no possibility to solve conditional optimization problems [21];
- there is no possibility to use non-binary potential solutions [19];
- convergence of the method is not guaranteed [18].

This raises the problem of constructing efficient metaheuristics for optimization [23,24].

One of the popular metaheuristics is the vibrating particle system [25], which belongs to multi-agent metaheuristics.

Research methods

1. Associative rule learning methods.

Associative rule learning methods (finding relationships) allow us to identify frequent combinations of data elements and use the discovered patterns for decision making. In this paper we propose to use Apriori and FP-Growth based methods

1.1. Learning associative rules based on Apriori method.

The Apriori method [4] can utilize information such as support and validity.

Support *Support (A)* is the ratio of the number of data table rows that contain feature set A to the total number of data table rows, i.e., as the probability of occurrence of data table rows that contain feature set A.

Support $(A \cup B)$ is the ratio of the number of rows of the data table that contain a set of features both A and B to the total number of rows of the data table, i.e., as the probability of occurrence of rows of the data table containing a set of features both A and B.

Confidence (*confidence*) evaluates the mutual dependence of elements A and B and for rules of the type $A \Rightarrow B$ is calculated in the form of

Confidence($A \Rightarrow B$) = Support($A \cup B$)/Support(A)

If the confidence is 0 (i.e., the number of rows in the data table that contain the feature set of both A and B is 0), then A and B are independent. Since rules from $B \not\subset A$ are not considered, Confidence $(A \Rightarrow B) \in [0,1]$. Confidence corresponds to the conditional probability $P(B|A)$.

Instead of credibility are often used:

- lift:

$Lift(A \Rightarrow B) = Support(A \cup B)/(Support(A)Support(A));$

- conviction:

$Conviction(A \Rightarrow B) = (1\text{-}Support(B))/(1\text{-}Confidence(A \Rightarrow B)).$

Threshold settings can be used to adjust the maximum number of features in the feature sets; the minimum confidence for the rule under consideration; and the minimum support for the feature sets under consideration.

The modified Apriori method consists of the following steps:

1. Discretization of feature values.
2. Number of features in the set e=1.
3. Supports are calculated for all sets of e features.
4. The feature sets are selected, whose supports are not less than the minimum support.
5. If e is less than the minimum number of features and there are frequencies of the selected feature sets (number of rows of the data table containing these feature sets) not less than 1, then e=e+1, go to step 3.
6. Validities for all rules formed from the selected feature sets are calculated.
7. The rules whose plausibility are not less than the minimum plausibility are selected.

The computational complexity of the Apriori method is $2^J\text{-}1$ or $O(2^J)$, where J represents the number of columns (features) of the data table and $2^J\text{-}1$ represents the power of the set of all possible feature sets except the empty feature set.

Associative rule learning based on the FP Growth method.

FP-Growth method [4] overcomes the disadvantages of Apriori method by using FP-tree (Frequent Pattern tree) and therefore avoids multiple scans of the data table and building a set of all possible feature sets. On the other hand, the FP-Growth method is more difficult to understand and implement than the Apriori method and also requires storing tree structures.

The FP-Growth method consists of the following steps:

1. Discretization of feature values.
2. Frequency for each trait is calculated (the number of rows in the data table containing that trait).
3. The initial data table is transformed as follows: only those attributes (columns) are selected whose frequency is not less than the minimum frequency, and the attributes (columns) in the new table are ordered by decreasing frequencies.
4. An *FP*-tree is created, which stores information about the sets of selected features and their frequencies, as follows: the features are inserted into the *FP*-tree in the order in the row of the new table, and if a node already exists for a feature in the *FP*-tree, its frequency is incremented, otherwise a new node is created in the *FP*-tree for this feature, the frequency of the new node is set to 1, and the new node is linked to the node of the previous feature of the row of the new table.
5. A Conditional Pattern base is created for each selected feature, which consists of all paths (sequences of nodes in the *FP*-tree) to that feature and the frequencies of those paths.
6. A *CFP* tree (Conditional Frequent Pattern tree) for each selected feature is created, i.e., the *FP*-tree is split into smaller *CFP*-trees, as follows: a *CFP*-tree contains the part of a path that occurs in all paths of the conditional pattern base of that trait, and the frequency of that part of the path, which is computed by summing the frequencies of all paths of the conditional pattern base. There is no *CFP*-tree if there is no common path part.
7. A Frequent Pattern is created for each selected feature by combining that feature with the *CFP*-tree of that feature.
8. Validities are computed for all rules generated from the frequent patterns.
9. Rules whose plausibility are not less than the minimum plausibility are selected.

The computational complexity of the *FP*-Growth method is $O(J^2)$, where J represents the number of columns (features) of the data table, and the maximum *CFP*-tree depth for each feature

2. A fuzzy associative rule learning expert decision support system for consumer preferences

Consumer preference analysis is based on various information including age, gender, product category. A fuzzy associative rule learning expert system is proposed to make decisions about consumer preferences, which involves the following steps:

1. The linguistic variables formation.
2. The fuzzy knowledge base formation.
3. The Mamdani's fuzzy logical inference mechanism formation:

- fuzzification;
- sub conditions aggregation;
- the conclusions activation;
- the conclusions aggregation;
- defuzzification.

4. The parameter identification based on metaheuristics.

2.1 Formation of linguistic variables.

The explicit input variables selected were:

- consumer's age x_1;

- consumer's gender identifier x_2;
- product category identifier x_3.

As linguistic input variables were chosen:

- age of the consumer $\tilde{x}_1$ with its values $\tilde{\alpha}_{11} = young, \tilde{\alpha}_{12} = middle - aged, \tilde{\alpha}_{13} = old$, whose value areas are fuzzy sets $\tilde{A}_{11} = \{(x_1, \mu_{\tilde{A}_{11}}(x_1))\}$, $\tilde{A}_{12} = \{(x_1, \mu_{\tilde{A}_{12}}(x_1))\}$, $\tilde{A}_{13} = \{(x_1, \mu_{\tilde{A}_{13}}(x_1))\}$, ;
- consumer's gender $\tilde{x}_2$with its values $\tilde{\alpha}_{21} = male, \tilde{\alpha}_{22} = female$, for which the areas of values are fuzzy sets $\tilde{A}_{21} = \{(x_2, \mu_{\tilde{A}_{21}}(x_2))\}$, $\tilde{A}_{22} = \{(x_2, \mu_{\tilde{A}_{22}}(x_2))\}$, ;
- product category $\tilde{x}_3$with its values $\tilde{\alpha}_{31} = clothing, \tilde{\alpha}_{32} = footwear, \tilde{\alpha}_{33} = outerwear, \tilde{\alpha}_{34} = accessories$, whose value areas are fuzzy sets $\tilde{A}_{31} = \{(x_3, \mu_{\tilde{A}_{31}}(x_3))\}$, $\tilde{A}_{32} = \{(x_3, \mu_{\tilde{A}_{32}}(x_3))\}$, $\tilde{A}_{33} = \{(x_3, \mu_{\tilde{A}_{33}}(x_3))\}$, $\tilde{A}_{34} = \{(x_3, \mu_{\tilde{A}_{34}}(x_3))\}$;

As a crisp output variable the identifier of the product name was chosen $\tilde{y}$;

As a linguistic output variable was the product name $\tilde{y}$ with its values backpack $\tilde{\beta}_1$ =*backpack*,…, $\tilde{\beta}_{25} = t - shirt$, whose value areas are fuzzy sets $\tilde{B}_1 = \{(y, \mu_{\tilde{B}_1}(y))\}$, …, $\tilde{B}_{25} = \{(y, \mu_{\tilde{B}_{25}}(y))\}$.

2.2 Formation of a fuzzy knowledge base.

Fuzzy knowledge is represented in the form of the following fuzzy rules, which contain a linguistic output variable:

R^n: IF $\tilde{x}_1$ is $\tilde{\alpha}_{1i}$ AND $\tilde{x}_2$ is $\tilde{\alpha}_{2j}$ AND $\tilde{x}_3$ is $\tilde{\alpha}_{3k}$ THEN $\tilde{y}$ is $\tilde{\beta}_m$

These fuzzy rules are formed on the basis of the method of inventing associative rules.

2.3. Formation of Mamdani's Fuzzy Inference Mechanism.

2.3.1. Fuzzification.

The degree of truth of each sub-condition of each rule is determined using the membership function $\mu_{\tilde{A}_{ik}}(x_i)$.

As membership functions for the subconditions, we selected those based on the density function of the symmetric generalized Gaussian distribution (excluding the normalization factor), i.e.

$$\mu_{\tilde{A}_{ik}}(x_i) = exp\left(-\frac{|x-\mu_{ik}|^{\beta_{ik}}}{s_{ik}^{\beta_{ik}}}\right), i \in \overline{1,3},$$

where s_{ik} – is a scale parameter, $s_{ik} > 0$, μ_{ik} – is a localization parameter, β_{ik} – is a shape parameter, $\beta_{ik} > 0$.

$s_{ik}, \mu_{ik}, \beta_{ik}$ – are membership functions parameters.

This function, with the appropriate selection of parameters, can be a *U*-shaped membership function, an *S*-shaped membership function, or a *Z*-shaped membership function.

2.3.2. Aggregation of subconditions.

Membership functions of the condition for each rule R^n are determined based on the minimum value method:

$$\mu_{\bigcup_{i=1}^{4} \tilde{A}_{i,f(n,i)}}(x_1, x_2, x_3) = \underset{i\in\overline{1,3}}{min}\left\{\mu_{\tilde{A}_{i,f(n,i)}}(x_i)\right\},$$

where f – is a function that returns the value index of the *i*-th linguistic input variable of the *n*-th rule and is defined based on association rule learning.

2.3.3. Activation of conclusions.

membership functions of the conclusion for each rule R^n are determined, based on the minimum value method:

$$\mu_{\tilde{B}'_{g(n)}}(y) = min\left\{\mu_{\bigcup_{i=1}^{4} \tilde{A}_{i,f(n,i)}}(x_1, x_2, x_3), \mu_{\tilde{B}_{g(n)}}(y)\right\},$$

where g – is a function that returns the value number of the linguistic output variable of the *n*-th rule and is determined based on learning association rules. A piecewise linear triangular function was chosen as the membership functions of the conclusions, i.e.

$$\mu_{\tilde{B}_m}(y) = \begin{cases} 0, & y \le e_m \\ \frac{y-e_m}{u_m-e_m}, & e_m \le y \le u_m \\ \frac{v_m-y}{v_m-u_m}, & u_m \le y \le v_m \\ 0, & y \ge v_m \end{cases}, m \in \overline{1,25},$$

where e_m, u_m, v_m – are a membership function parameters.

In the case of such a membership function, the kernel of each fuzzy set $\tilde{B}_m$ is is defined as:

$$\widetilde{ker\,B}_m = \{y \in Y | \mu_{\tilde{B}_m}(y) = 1\} = \{u_m\}.$$

2.3.4. Aggregation of conclusions

The membership functions of the final conclusion, which includes the linguistic output variable, were determined based on the maximum value method:

$$\mu_{\tilde{B}}(y) = \max_{n}\{\mu_{\tilde{B}'_{g(n)}}(y)\}.$$

2.3.5. Defuzzification

The product name identifiers were determined based on the maximum membership principle:

$$y^* = \frac{\sum_{y\in Y}\mu_{\tilde{B}'}(y)y}{\sum_{y\in Y}\mu_{\tilde{B}'}(y)},\ Y = \{1,\ldots,25\}.$$

3. Quality criterion for the proposed fuzzy associative rule learning expert system.

As the quality criterion, the objective function F was chosen to represent system accuracy as the probability of correct decisions about consumer preferences:

$$F = \frac{1}{P}\sum_{p=1}^{P}[y_p = d_p] \to \max_{\theta},$$

$$[p = q] = \begin{cases}1, & p = q\\ 0, & p \neq q\end{cases},$$

where d_p – are the test identifiers of the product,

y_p – are the identifiers of the product name obtained as a result of fuzzy logical inference,

P – are the number of test implementations,

$\theta = (s_{11}, \mu_{11}, \beta_{11}, \ldots, s_{34}, \mu_{34}, \beta_{34}, e_1, u_1, v_1, \ldots, e_{25}, u_{25}, v_{25})$ – is a parameter vector of the membership functions.

4. A Metaheuristic Method Based on an Adaptive Vibrating Particle System for Determining the Parameters of the Proposed Fuzzy Associative Rule-Based Expert System.

In contrast to the traditional vibrating particle system, this method adjusts the particle position based on the iteration number, allowing for controlled convergence speed. This approach ensures global search capabilities during initial iterations and enables local search during the final stages. The parameter vector of the membership functions θ corresponds to the position vector of a single particle x. The objective function used is the quality criterion (1).

1. Initialization.

1.1. Specification of the constant α (typically 0.05), the probability p, the probability p^{HMCR} for selecting the harmony generation strategy (the harmony is either chosen from the harmony memory or generated randomly); the probability $p^{PAR}$for controlling the modification of a harmony selected from memory (the harmony is either modified or left unchanged); the parameter δ used to generate a new position; and the relative importance weights w_1, w_2, w_3 (typically 0.3, 0.3, and 0.4), with the conditions $0 < \delta < 1$ and$w_1 + w_2 + w_3 = 1$.

1.2. Specification of the maximum number of iterations N, the population size K, the harmony memory size K^M, the length of the particle position vector M (corresponding to the length of the parameter vector of the membership functions), and the minimum and maximum values of the position vector $x_j^{min}, x_j^{max}, j \in \overline{1,M}$.

1.3. Setting the cost function (objective function)

$$F(x) \to \min_{x}$$

where x – is the particle position vector.

1.4. Creating the initial population P

1.4.1. Particle number $k = 1$, $P = \emptyset$

1.4.2. Randomly generating the position vector x_k

$x_k = (x_{k1}, \ldots, x_{kM})$, $x_{kj} = x_j^{min} + (x_j^{max} - x_j^{min})U(0,1)$,

where $U(0,1)$ is a function returning a standard uniformly distributed random number.

1.4.3. If $x_k \notin P$, то $P = P \cup \{x_k\}$, $k = k + 1$

1.4.4. If $k \leq K$, then go to step 1.4.2

1.5. To sort P by the objective function, i.e. $F(x_k) < F(x_{k+1})$

1.6. To slect the best (first) K^M harmonies from P into the P^Mharmonies memory.

1.7. To determine the particle that is best by the objective function:

$k^* = \arg\min_{k} F(x_k)$, $k \in \overline{1,K}$, $x^* = x_{k^*}$

2. Iteration number n=1.

3. Calculating of the decay function (considered to be analogous to$exp(-\gamma n)$)

$$D(n) = \left(\frac{n}{N}\right)^{-\alpha}$$

4. Calculating of good and bad particles by the objective function

4.1. To order P by the objective function, i.e. $F(x_k) < F(x_{k+1})$

4.2$l^{good} = round(1 + (K/2 - 1)U(0,1))$, $x^{good} = x_{l^{good}}$

4.3. $l^{bad} = round(K/2 + 1 + (K/2 - 1)U(0,1))$, $x^{bad} = x_{l^{bad}}$,
where $round()$ is a function that rounds a number to the nearest integer.
5. Modification of position based on free vibration
5.1. Particle number k=1
5.2. $\lambda = U(0,1)$, $w_3 = \begin{cases} 0, & p < \lambda \\ 0.4, & p \geq \lambda \end{cases}$, $w_2 = 1 - (w_1 + w_3)$
5.3. Calculating the initial amplitude of oscillations
$A_k = w_1(x^* - x_k) + w_2(x^{good} - x_k) + w_3(x^{bad} - x_k)$.
5.4. Modifying the position
5.4.1. $r_{1kj} = U(0,1)$, $r_{2kj} = U(0,1)$, $r_{3kj} = U(0,1)$,
$x_{kj} = w_1(D(n)A_{kj}r_{1kj} + x_j^*) + w_2(D(n)A_{kj}r_{2kj} + x_j^{good}) + +w_3(D(n)A_{kj}r_{3kj} + x_j^{bad})$, $j \in \overline{1,M}$
5.4.2. $x_{kj} = max\{x_j^{min}, x_{kj}\}$, $x_{kj} = min\{x_j^{max}, x_{kj}\}$
5.5. If $k < K$, then $k = k + 1$, go to step 5.2
6. Modification of positions based on harmony memory.
6.1. Particle number $k = 1$
6.2. Component number $j = 1$
6.3. If $x_{kj} \in [x_j^{min} - x_j^{max}]$, then go to step 7.8
6.4. If $\lambda > p^{HMCR}$, then $x_{kj} = x_j^{min} + (x_j^{max} - x_j^{min})U(0,1)$, go to step 6.8
6.5. Harmonyx_m is randomly selected from the harmony memory, and
$m = round(1 + (K^M - 1)U(0,1))$.
6.6. If $U(0,1) > p^{PAR}$, then $x_{kj} = x_{mj}$, go to step 6.8
6.7. Generate component j of position x_k from component j of harmony x_m
6.7.1. $x_{kj} = x_{mj} + \delta(x_j^{max} - x_j^{min})(-1 + 2U(0,1))$
6.7.2. $x_{kj} = max\{x_j^{min}, x_{kj}\}$, $x_{kj} = min\{x_j^{max}, x_{kj}\}$
6.8. If $j < M$, then $j = j + 1$, go to step 7.3
6.9. If $k < K$, then $k = k + 1$, go to step 7.2
7. Positions are placed in the harmony memory

$$P^M = P \cup P^M.$$

8. To order$P^M$by the objective function, i.e. $F(x_k) < F(x_{k+1})$, and keep in the harmony memoryK^Mbest (first) harmonies.
9. To determine the best particle by the objective function

$$k^* = arg \min_k F(x_k),\ k \in \overline{1,K}$$

10. To determine the global best position

$$\text{If } F(x_{k^*}) < F(x^*), \text{ then } x^* = x_{k^*}$$

11. If $n < N$, then $n = n + 1$, go to step 3
The result is x^*.

Experiments

The numerical study of the proposed approach was conducted using the «Keras» submodule of «TensorFlow». The Pandas library was employed to fill in missing values via linear interpolation, as well as to perform input/output operations for tabular data. The «mlxtend» library was used to train association rules, while the «Scikit-fuzzy» library facilitated the creation of the fuzzy expert system.

To evaluate the effectiveness of decision-making regarding consumer preferences, the proposed fuzzy expert system was tested using the «Consumer Behavior and Shopping Habits Dataset» (https://www.kaggle.com/datasets/zeesolver/consumer-behavior-and-shopping-habits-dataset). Dataset features related to consumer age, gender, and product category were utilized. The original sample size consisted of 3,900 observations.

For the proposed adaptive vibrating particle system, the constants were set as follows: the value of α was 0.05; the probability p was 0.7; the probability p^{HMCR} for selecting the harmony generation method was 0.95; and the probability $p^{PAR}$for controlling the modification of harmonies selected from the harmony memory was 0.1. The parameter δ, used for generating a new position, was set to 0.1. The relative importance weights w_1, w_2, w_3 were 0.3, 0.3, and 0.4, respectively. The maximum number of iterations N was set to 1500; the population size K was 20; the harmony memory sizeK^M was 10% of the population; and the particle position vector length M corresponded to the length of the parameter vector of the membership functions.

The results of the comparison between the proposed fuzzy learning associative expert system and the human operator are presented in Table 1.

Table 1

Comparison between the proposed fuzzy rule-based expert system and a human operator

Accuracy	
fuzzy associative rule learning expert system	operator
0.98	0.8

The results of the comparison between the proposed fuzzy associative rule-learning expert system, the proposed metaheuristic based on the Adaptive Vibrating Particle System (AVPS), and the traditional Vibrating Particle System (VPS) metaheuristic are presented in Table 2.

Table 2

Comparison of the proposed fuzzy associative rule-learning expert system with AVPS-based and traditional VPS metaheuristics

Accuracy	
VPS	AVPS
0.93	0.98

Figure 1 illustrates the accuracy of the proposed fuzzy associative rule-learning expert system trained using both the proposed Adaptive Vibrating Particle System (AVPS) metaheuristic and the traditional Vibrating Particle System (VPS) metaheuristic.

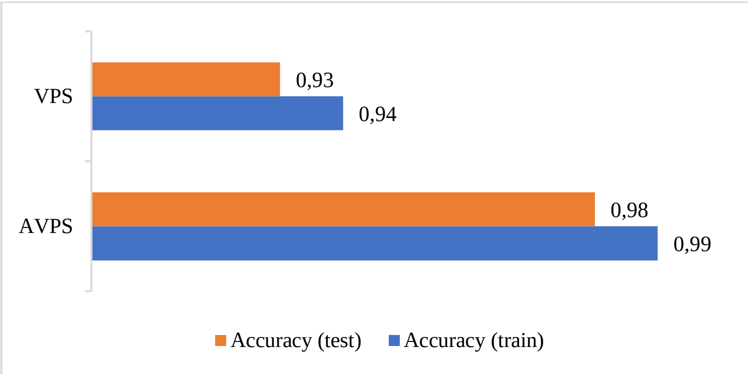

Fig. 1 Accuracy of the proposed fuzzy associative rule-learning expert system trained using the VPS and AVPS metaheuristics

Table 3 presents a comparison between the proposed expert system trained using the Back Propagation (BP) method and the same system trained using the AVPS-based metaheuristic.

Table 3

Comparison results of the proposed fuzzy associative rule-learning expert system trained using the Back Propagation method and the proposed metaheuristic

Accuracy	
BP	AVPS
0.90	0.98

Figure 2 illustrates the accuracy of the proposed fuzzy association rule-learning expert system trained using both the Back Propagation (BP) method and the proposed Adaptive Vibrating Particle System (AVPS) metaheuristic.

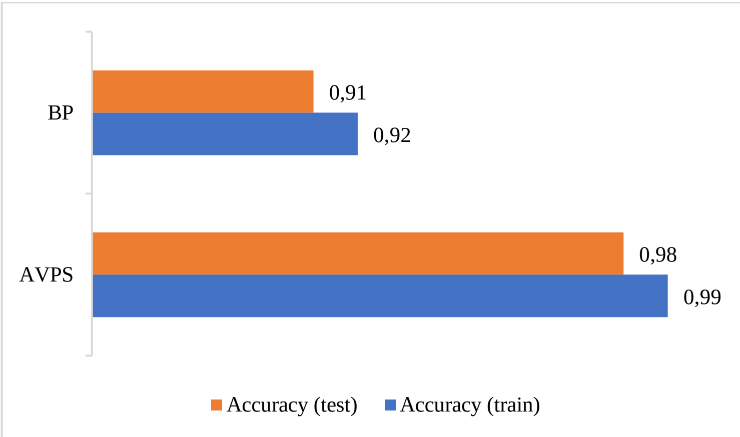

Fig.2 Accuracy of the proposed fuzzy associative rule-learning expert system trained using the BP and AVPS metaheuristics

The traditional non-automated approach to evaluating the effectiveness of decision-making regarding consumer preferences reduces the accuracy of correct assessments (Table 1). The proposed method eliminates this limitation.

The traditional Vibrating Particle System (VPS) metaheuristic does not account for the iteration number when calculating particle positions, which decreases solution accuracy (Table 2); requires a large number of parameters. These limitations are addressed by the proposed method.

The traditional approach to training a fuzzy associative rule-based expert system using the Back Propagation (BP) algorithm also reduces the accuracy of correct assessments (Table 3). The proposed method overcomes this drawback as well.

Conclusions

Within the scope of decision-making technology for modeling consumer preferences, relevant expert systems and optimization methods were analyzed. The results of the study demonstrate that fuzzy expert systems trained using associative rules – whose parameters are identified through multi-agent metaheuristic techniques – are currently among the most effective approaches. A fuzzy associative rule-based expert system was developed to support decision-making related to consumer preferences. The proposed system simplifies interaction between the operator and the computer system through the use of quality indicators, and it enables automatic parameter identification via the proposed multi-agent metaheuristic framework.

A quality criterion was introduced that accounts for the specific structure of the fuzzy associative rule-based expert system and enables the assessment of the accuracy of decisions generated by the system.

A novel multi-agent metaheuristic method based on an adaptive vibrating particle system was developed. It enables dynamic control of the convergence rate by incorporating global search at early iterations and local refinement at later stages through adaptive adjustment of particle positions. The proposed optimization method, in conjunction with the fuzzy associative rule-based expert system, contributes to the advancement of intelligent decision-making technologies for consumer preference modeling. Future research will focus on evaluating the proposed expert system and metaheuristic method across a broader range of test datasets.

References

1. Milovanović D., Marković N. Strategic decision making and influence of economic freedoms on foreign direct investment (FDI) in Bosnia and Herzegovina. *Strategic Management.* 2022. Vol. 27. No. 2. P. 44–56.
2. Kurecic P., Kokotovic F. The relevance of political stability on FDI: A VAR analysis and ARDL models for selected small, developed, and instability threatened economies. *Economies.* 2017. Vol. 5. No. 3. P. 1–21.
3. Yi. Shen, D. Zhao, Ya. Li, X. Hu, Yu. Chen, B. Liu. Development of fuzzy rule-based models in the presence of the big data environment. *Applied Soft Computing*. 2025. Vol. 184. Part B. 113869
4. J. Chen, H. Ma, H. Ren. Reasonable capture: Community detection based fuzzy rule discovery. *Fuzzy Sets and Systems*. 2025. Vol. 519. 109537
5. T. de Silva. Determinants of college mismatch in a rule-based admission system: The case of Sri Lanka. *International Journal of Educational Development*. 2025. Vol. 118. 103405
6. B. Teixeira, G. Santos, D. Araújo, L. Gomes, Z. Vale. Semantic rule-based approach for automated energy resource management in buildings. Applied Energy. 2025. Vol. 401. Part A. 126675
7. M. Diaz, L. Sante, J. Perca, J.V. da Silva, N. Ferreira, J. Poco. STRive: An association rule-based system for the exploration of spatiotemporal categorical data. *Computers & Graphics*. 2025. Vol. 132. 104410
8. Nakib A., Talbi El-G. Metaheuristics for Medicine and Biology. Berlin: Springer-Verlag. 2017. 211 p.
9. Yang X.-S. Nature-inspired Algorithms and Applied Optimization. Cham: Springer. 2018. 330 p.
10. Subbotin S., Oliinyk A., Levashenko V., Zaitseva E. Diagnostic Rule Mining Based on Artificial Immune System for a Case of Uneven Distribution of Classes in Sample. *Communications.* 2016. Vol. 3. P. 3–11.
11. Blum C., Raidl G. R. Hybrid Metaheuristics. Powerful Tools for Optimization. Cham: Springer. 2016. 157 p.
12. A. Melman, O. Evsutin. Hybrid metaheuristic algorithms for image watermarking: An experimental study. *Swarm and Evolutionary Computation*. 2025. Vol. 99. 102163
13. Yang X.-S. Optimization Techniques and Applications with Examples. Hoboken, New Jersey: Wiley & Sons. 2018. 364 p.
14. Martí R., Pardalos P. M., Resende M. G. C. Handbook of Heuristics. Cham: Springer. 2018. 1289 p.
15. Gendreau M., Potvin J.-Y. Handbook of Metaheuristics. New York: Springer. 2010. 640 p.
16. Ya. Fu, J. Dong, K. Gao, P.N. Suganthan, M. Huang, L. Zhu. A review on metaheuristics for solving home health care routing and scheduling problems. Applied Soft Computing. 2025. Vol. 182. 113560
17. Bozorg-Haddad O., Solgi M., Loaiciga H. Meta-heuristic and Evolutionary Algorithms for Engineering Optimization. Hoboken, New Jersey: Wiley & Sons. 2017. 293 p.
18. Chopard B., Tomassini M. An Introduction to Metaheuristics for Optimization. New York: Springer. 2018. 230 p.
19. Radosavljević J. Metaheuristic Optimization in Power Engineering. New York: The Institution of Engineering and Technology. 2018. 536 p.
20. Grygor O., Fedorov E., Utkina T., Lukashenko A., Rudakov K., Harder D., Lukashenko V. Optimization method based on the synthesis of clonal selection and annealing simulation algorithms. *Radio Electronics, Computer Science, Control.* 2019. No. 2. P. 90–99.
21. Fedorov E., Lukashenko V., Utkina T., Lukashenko A., Rudakov K. Method for parametric identification of Gaussian mixture model based on clonal selection algorithm. *CEUR Workshop Proceedings.* 2019. Vol. 2353. P. 41–55.
22. F. Zito, El-Gh. Talbi, C. Cavallaro, V. Cutello, M. Pavone. Metaheuristics in automated machine learning: Strategies for optimization. *Intelligent Systems with Applications*. 2025. Vol. 26. 200532
23. Du K.-L., Swamy M. N. S. Search and Optimization by Metaheuristics. Techniques and Algorithms Inspired by Nature. Cham: Springer. 2016. 434 p.
24. Brownlee J. Clever Algorithms: Nature-Inspired Programming Recipes. Melbourne: Brownlee. 2011. 436 p.
25. Kaveh A., Ghazaan M. I. A new meta-heuristic algorithm: vibrating particles system. *Scientific Iranica. Transactions A: Civil Engineering.* 2017. Vol. 24. No. 2. P. 551–566.

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