



Article

Or-Based Intelligent Decision Support System for E-Commerce

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Abstract: *Aim:* This paper aims to analyze, prepare, and review the general guidelines and rules that govern the development of key factors influencing the enhancement of emotionally supportive networks and selection models using fuzzy logic theory. The researchers have identified eight important components of the information society (IS), representing the computerized economy's growth to explain a realistic framework for medium-term gauges and proposals. *Materials and methods:* A discrete-nonstop opportunity paradigm portrays the creation of the general framework, in which the mutual effects of each of the components are spoken to models within the state-space. The software's mechanical quality offers improvement displayed along these lines that may indicate future interest to programing suppliers. The researchers have given supposed to the developments and interests of information technology (IT) professionals in R&D to provide insightful foundations. For example, this study will demonstrate the development of emotionally supportive networks and recommendations of choices for 3D-web-based businesses and their impact on mechanical advancement, examples of use and social behavior. *Results:* During an IS/IT foreknowledge undertaking completed in Poland in 2019 and sponsored by the Education Research and Development Foundation ERDF, the results were obtained.

Keywords: E-commerce; DSS production; web-based business



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1. Significance of the Study

A decision support system is a computerized system used to help make decisions, judgments and courses of action in companies or organizations [1]. A decision support system (DSS) searches and analyzes large amounts of data and compiles extensive data for problem-solving and decision-making. The standard DSS information includes the actual or estimated profits, revenue and past statistics from different periods, and other stock or administrative details [2]. A network connected with the transmission control protocol/internet protocol (TCP/IP) to the computer server runs a DSS request. The decision support system can be a communication, data-driven, knowledge-driven, model-driven or hybrid-driven Web-based DSS [3]. Any class or type of decision support system may use web technologies. The Web-based DSS means the whole software is deployed with Web technologies; Web-enabled means that the most important parts of a framework such as a server stay in an old system, but a Web-based portion can provide access and display on a Web-based interface [4].

Figure 1 shows the flow chart of the decision support system based e-commerce model. The main aim of using a DSS is to provide the customer with easily understood knowledge [5]. A DSS is useful because many different types of reports can be configured, all based on user preferences [6]. As in the case of a bar chart that is reflecting projected revenue or a written report, the DSS can graphically generate data and generate its information. Data analyzes are not limited to huge, large mainframe computers anymore

as technology continues to progress. As the DSS is essentially an application, it can be indicated either on desktops or laptops on most computer systems. Mobile devices offer certain DSS applications [7–9].

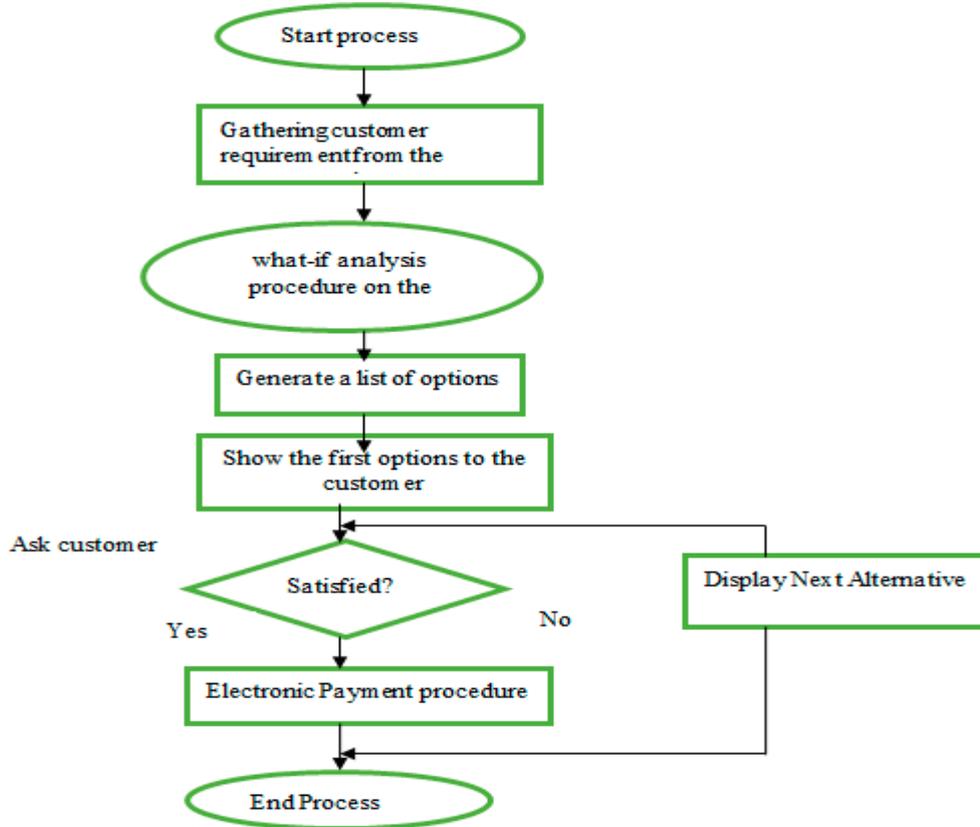


Figure 1. E-Commerce model based on decision support system flow chart.

A DSS can be adapted for all industries, professions or domains, including medical, government agencies, farms, and businesses [10,11]. The DSS can be used by managing operations and other planning divisions of an enterprise to gather and synthesize data and information efficiently. The key use of these systems is mid to top management. In electronic commerce, a decision support system gathers and analyzes data to create comprehensive information about customers. It varies from a normal operations application, the purpose of which is only to collect data, as an information application [12,13].

The distinction between conventional businesses and e-commerce businesses is that the e-commerce approach integrates information technology (IT) and communications and business processes, making it easier for consumers to do business. The process of buying and selling goods and services over the internet is usually electronic commerce. It is one way of sharing the information between individuals and organizations by integrating a variety of processes, including electronic data exchange (EDI), electronic mail, the World Wide Web, and electronic funds transfers (EFT) [14,15]. In the case of appropriate concepts, software techniques and languages, fuzzy logic is seen as a management approach that creates an effective platform for analysis and business regulation [16]. The main contribution of fuzzy to machine learning is its incremental capacity to present gradual concepts and features. Fuzzy definitions in a specific problem domain are used as modelling components [17]. When a problem domain is found in machine learning, it can be broken down gradually.

This paper proposes an operational research-based intelligent decision support system (OR-IDSS) for e-commerce decision-making using fuzzy logic theory. The decision supports

a system in e-commerce that allows for scheduling and transportation optimization, data collection, improving market operations, conducting a risk analysis, matching buyer to sellers, and assisting in running Business to Consumer (B2C) operations. An important feature called the automatic product recommendation system is required for the online selection of products. As social networks on the internet are becoming more common, users cannot get detailed product or service information using their previous customers' views. The decision-making process has been influenced by reliable people's data and not by consumers' distributors or recommendations.

The main contribution of the paper is:

- Designing the OR-IDSS model for E-commerce utilizing the fuzzy logic theory and machine learning methods.
- Evaluating the mathematical model for decision making in E-commerce.
- The experimental results have been executed, and the proposed model enhances the performance, accuracy, precision and reduces the error rate compared to other existing models.

The article is organized as follows: Sections 1 and 2 explain the existing methods and theoretical study. In Section 3, the mathematical model of an intelligent decision support system has been demonstrated. In Section 4, the experimental results have been discussed. Finally, Section 5 concludes the research paper.

2. Literature Review

Hong Zhou et al. [18] proposed the big data-based intelligent decision support system (B-IDSS) for sustainable regional development. The system is appropriate for advanced planning, cooperation, and management by government agencies and companies. This incorporates state-of-the-art multidisciplinary technologies such as data mining, decision-making artificial intelligence and communications. The system uses large amounts of data from various sources such as non-profit organizations, governments, and companies in numerous forms such as multimedia and text. One possible algorithm to help people in various positions make decisions based on others' behavior is the generalized Kuhn–Tucker approach to bi-level programming.

Chien-Chih Yu et al. [19] introduced the Web-based consumer-oriented intelligent decision support system (CIDSS) for personalized e-services. It facilitates all stages of customer decision-making in e-services applications between businesses and consumers. The system framework's key functional modules include customer and customized management, navigation and browsing, assessments, development, community management, cooperative management, auctioning and payments, transactions and negotiation, performance and input control, and communications distribution of data. Therefore, it can finally lead to customer relationships and bring values and resources into the entire value chain by providing customers with great satisfaction.

Osama sohaib et al. [20] initialized the multi-criteria group decision making (MCGDM) for the E-commerce enterprise decision-making system. They used 2-tuple fuzzy linguistic decision making to address the multi-criteria decision-making problem. The MCGDM is a combination of the MCDM and group decision-making methods that efficiently make a final decision in a group. To define several appropriate requirements, the model proposed is based on a technology-organization-environment (TOE). A small to medium-sized firm uses the approach suggested to promote the evaluation of cloud e-commerce variables and make decisions.

Chang-Shing Lee et al. [21] initialized the meeting scheduling decision support system using an intelligent fuzzy agent (IFA). For the final meeting time, the MSDSS collects the meeting details and sends the meeting host's appropriate time. An intelligent fuzzy agent (IFA) is suggested to carry out an effective meeting schedule selection with a meeting scheduling agency (MNA), a fuzzy inferential agent (FIA) and a genetical learner agent (GLA). The meeting negotiation agent sends information on the meeting, including

the meeting's length, the invitee's names and priorities, meeting the event's importance, and meeting the time requirements with FIA working priorities.

Leung et al. [22] introduced the fuzzy association rule mining approach (FARM) for a pricing decision support system. The business environment of e-commerce mainly reshapes the actions of B2C customers purchasing, not B2B. Although B2B consumers' origin and the purchasing process can all be done through B2B e-commerce sites, B2B customers who make an online application often activate the RFQ process. With the growing number of factors that can be considered in today's B2B e-commerce world, the difficulty in price determination increases.

Pinter et al. [23] suggested the call detail records and hybrid machine learning approach (CDR-HMLA) for modeling real estate prices. The prediction model is based on a multi-layered perceptron (MLP) machine learning system trained with the partial swarm's evolutionary optimization algorithm (PSO). The model's efficiency is assessed employing an MSE, sustainability index and Willmott's index (WI).

In this paper, an operational research-based intelligent decision support system (OR-IDSS) for e-commerce decision-making using fuzzy logic theory has been proposed to overcome these issues. In this paper, general guidelines and rules governing the development of key factors affecting the improvement of emotionally supportive networks and selection models should be analyzed, prepared and reviewed. E-commerce systems are large systems that produce a great deal of data collection, especially concerning customers' behavior. For management and decision support, information may have a high value. Using appropriate tools, the information must be acknowledged, analyzed and properly displayed.

3. Proposed System (Operational Research-Based Intelligent Decision Support System)

In this paper, an operational research-based intelligent decision support system (OR-IDSS) for e-commerce decision making using fuzzy logic theory has been proposed. Fuzzy set theory has become a more common approach to reflect, interact with, and successfully employed in many information technology contexts, including control technology, intelligent decision support system (IDSS) and soft computing. E-commerce is characterized as an attempt to increase transactional efficiency and effectiveness by using current and emerging digital technology in all aspects of the production, design, sales, and marketing of products or services for established and developing markets. In globalization, understanding the adoption by developing ICT countries involving e-commerce is becoming crucial to enhance its adoption. This, in turn, enables more efficient trade between the developed countries and developing countries. Figure 2 shows the basic e-commerce system. The e-commerce system can be described as a web server linked to the information system of the business. The clear concept of the e-commerce system derives from the description of an information system whose fundamental factors are communication systems and information and users. Information systems are specifically designed to support management.

This research suggests a fuzzy logic based systemic and learning approach to promote price negotiation in e-commerce organizations. This study facilitates the understanding of the one-to-one price problem in the bilateral negotiation. The model is designed to provide the right customer with the right price. Assume that $Y = (y_1, \dots, y_m)$ and the price offered is x , and the problem given is to build the mathematical link between price x and the influencing vector of Y . It is therefore referred to as:

$$x = Q(Y) = Q(y_1, \dots, y_m) \quad (1)$$

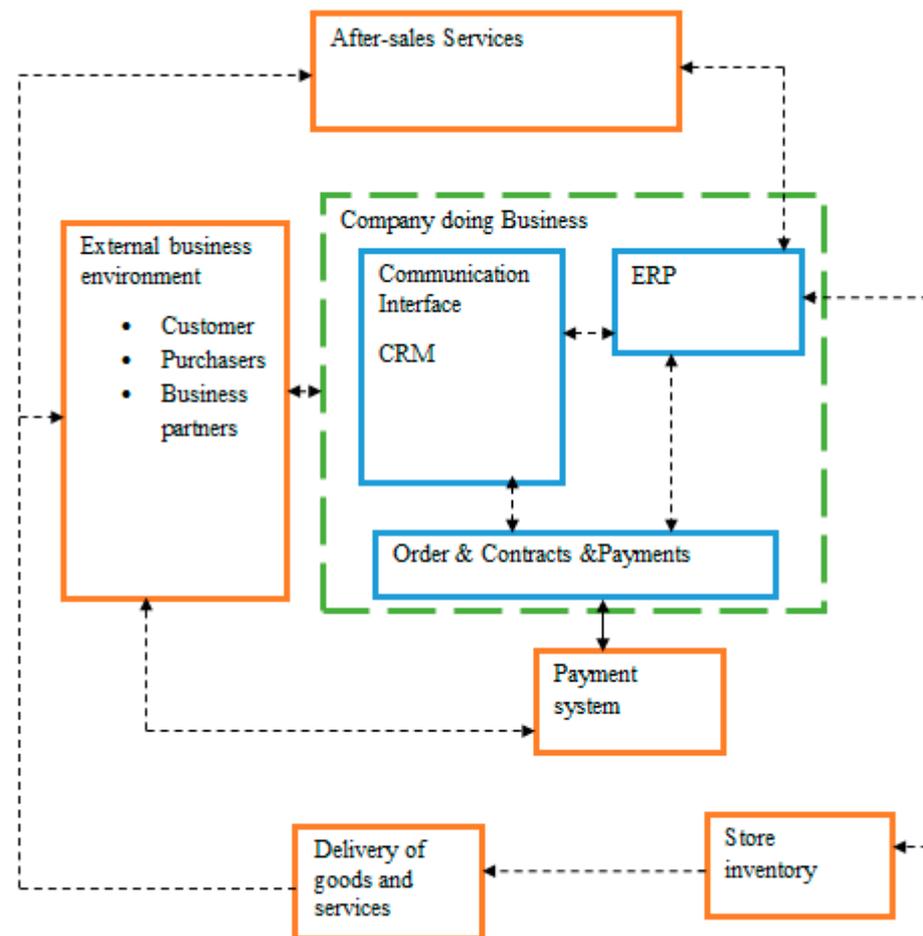


Figure 2. E-commerce system.

Proposition 1: *If the $Q(Y)$ relation can be learned from historical information, then the correct bargaining price can be calculated for each new customer using $Q(Y)$ based on its influential factors' values. As uncertainties are inherent in the pricing of contracts, they may occur concerning influence or the relationship between the factors of influence and the value proposed. A fuzzy logic system solution is, therefore, acceptable and useful.*

The mathematical relationship between the m input variable and one output variable. A complete fuzzy rule base of the standard fuzzy logic system needs $L = \prod_{i=1}^m M_i$ fuzzy rules, where M_i is the number of fuzzy sets of the i th input variable. Given input $Y = (y_1, \dots, y_m)$ and output \hat{x} . The standard fuzzy logic system can be illustrated as the following Equation (2),

$$\hat{x} = f(Y) = \sum_{j_1, \dots, j_m \in J} \left(\prod_{i=1}^m \mu_{j_i}^i(y_i) \right) x_{j_1, \dots, j_m} \tag{2}$$

As shown in Equation (2), where J is the index set that defined as $J = \{j_1, \dots, j_m \mid j_i = 1, 2, \dots, M_i; i = 1, 2, \dots, m\}$, $j_1 j_2, \dots, j_m$ is the index of fuzzy rules and $\mu_{j_i}^i(y_i)$ membership degree of the j th fuzzy set in the i th input variable.

Proposition 2: *Single input and single output standard fuzzy system expressed for the output and various important weight that can be expressed as the following Equation (3),*

$$\hat{x} = \sum_{i=1}^m E_i \left(\sum_{j_i=1}^{M_i} \mu_{j_i}^i(y_i) x_{j_i}^i \right) = \sum_{i=1}^m \sum_{j_i=1}^{M_i} E_i x_{j_i}^i \mu_{j_i}^i(y_i) = \sum_{i=1}^m \sum_{j_i=1}^{M_i} S_{j_i}^i \mu_{j_i}^i(y_i) \tag{3}$$

The hierarchical fuzzy system in this paper represented as the following Equation (3),

$$\begin{aligned} o^{k,a} = x_1^{k+1,b} &= f_{k,a} \left(x_1^{k,a}, \dots, x_{m_{k,a}}^{k,a}, y_1^{k,a}, \dots, y_{n_{k,a}}^{k,a} \right) \\ &= \frac{\sum_{i_1 i_2 \dots i_{m_{k,a}} j_1 j_2 \dots j_{n_{k,a}}} x_{i_1 i_2 \dots i_{m_{k,a}} j_1 j_2 \dots j_{n_{k,a}}}^{k,a} \prod_{l=1}^{m_{k,a}} \mu_{i_l}^{k,a,l} \left(x_l^{k,a} \right) \prod_{l=1}^{n_{k,a}} E_{j_l}^{k,a,l} y_l^{k,a}}{\sum_{i_1 i_2 \dots i_{m_{k,a}} j_1 j_2 \dots j_{n_{k,a}}} \prod_{l=1}^{m_{k,a}} \mu_{i_l}^{k,a,l} \left(x_l^{k,a} \right) \prod_{l=1}^{n_{k,a}} E_{j_l}^{k,a,l} y_l^{k,a}} \end{aligned} \tag{4}$$

The hierarchical fuzzy system contains several standard fuzzy systems. As shown in Equation (4) where $x_1^{k,a}, \dots, x_{m_{k,a}}^{k,a}$ denotes the intermediate attributes, y denotes the original input variable, while x denotes the output of the sub fuzzy system. Figure 3 shows the modified structure of the fuzzy system.

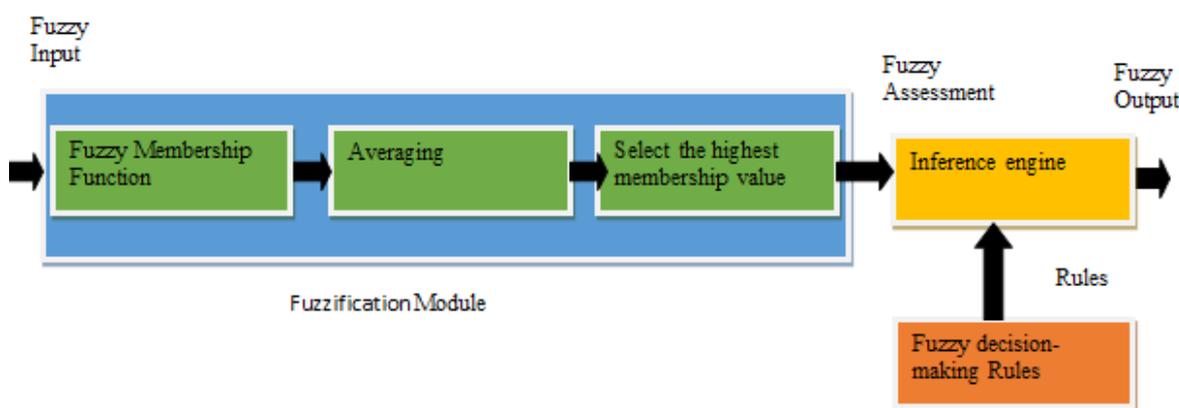


Figure 3. Fuzzy logic system.

By employing the triangular membership function in the hierarchical fuzzy system can be derived as in Equation (5),

$$\sum_{i_1 i_2 \dots i_{m_{k,a}} j_1 j_2 \dots j_{n_{k,a}}} \prod_{l=1}^{m_{k,a}} \mu_{i_l}^{k,a,l} \left(x_l^{k,a} \right) \prod_{l=1}^{n_{k,a}} E_{j_l}^{k,a,l} y_l^{k,a} = 1 \tag{5}$$

Equation (4) can be remodified as in Equation (6),

$$o^{k,a} = \sum_{i_1 i_2 \dots i_{m_{k,a}} j_1 j_2 \dots j_{n_{k,a}}} \left[\prod_{l=1}^{m_{k,a}} \mu_{i_l}^{k,a,l} \left(x_l^{k,a} \right) \prod_{l=1}^{n_{k,a}} E_{j_l}^{k,a,l} \left(y_l^{k,a} \right) \right] x_{i_1 i_2 \dots i_{m_{k,a}} j_1 j_2 \dots j_{n_{k,a}}}^{k,a} \tag{6}$$

The hierarchical fuzzy system can be shown as the number of fuzzy rules,

$$G = \sum_{j=1}^P \left[\sum_{i=1}^{w_j} \left(\prod_{l=1}^{m_{j,i}} M_{j,i}^l \prod_{l=1}^{n_{j,i}} M_{j,i}^l \right) \right] \tag{7}$$

As shown in Equation (7), where P is the number of points in the hierarchy fuzzy system and w_j is the number of sub fuzzy system in the jth level, $m_{j,i}$, and $n_{j,i}$ correspondingly.

Proposition 3: A gradient descent learning algorithm has been used in the fuzzy logic system. The gradient descent algorithm's objective function only reduces the error based on the current information example,

$$h^t = \frac{1}{2}[f(Y_t) - x_t]^2 \tag{8}$$

This algorithm aims to reduce the local error by updating the attributes and implements a standardization step for handling the intermediate variable in the hierarchical fuzzy system. Because of a hierarchical fuzzy system, the final error back propagates from the edge to the lower levels, and the upper-level error is used to change the corresponding low-level parameters. Assume r is the index of the iteration of learning; the final error of a hierarchical fuzzy system is as follows in Equation (9):

$$h_{P,1}(r) = o^{P,1}(r) - x(r) \tag{9}$$

As shown in Equation (9) Where $o^{P,1}(r)$ is the expected output of the top-level sub fuzzy system in the the training iteration, P is the total number of levels in the hierarchical fuzzy system, and while $x(t)$ is the target output of the data set. Provided the structure of the hierarchy. The error is propagated to sub fuzzy system as follows:

$$h_{k,a}(r) = h_{k+1,b}(r) \times \frac{\partial o^{k+1,b}(r)}{\partial o^{k,a}(r)} \tag{10}$$

The $k+1$ and k is omitted for the level index the Equation (10) remodified as in Equation (11),

$$h_a(r) = h_b(r) \times \frac{\partial o^b(r)}{\partial o^a(r)} \tag{11}$$

Therefore, the hierarchical fuzzy system can be simplified as the following Equation (12),

$$o^a_{i_1 i_2} = \left[\prod_{l=1}^{m_a} \mu_{i_l}^{a,1}(x_l^a) \prod_{k=1}^{n_a} E_{j_k}^{a,1}(y_k^a) \right] x_{i_1 i_2 \dots i_{m_a} j_1 j_2 \dots j_{n_a}}^a \tag{12}$$

The output of the sub fuzzy system is illustrated as the following Equation (13),

$$o^a = \sum_{P_a} B_{J_a}^a x_{J_a}^a \tag{13}$$

Equation (11) can be represented as the following Equation (14),

$$\begin{aligned} h_a(r) &= h_b(r) \times \frac{\partial \sum_{P_b} B_{J_b}^b(r) x_{J_b}^b(r)}{\partial o^a(r)} \\ &= h_b(r) \times \sum_{J_b} x_{J_b}^b(r) \frac{\partial B_{J_b}^b(r)}{\partial o^a(r)} \end{aligned} \tag{14}$$

Equation (14) can be remodified as the following Equation (15),

$$\frac{\partial B_{J_b}^b(r)}{\partial o^a(r)} = \frac{B_{J_b}^b(t)}{\mu_{i_1}^{b,1}(o^a, r)} \times \frac{\partial \mu_{i_1}^{b,1}(o^a, r)}{\partial o^a(r)} \tag{15}$$

It is derived from the concept of triangular membership functions and expressed as the following Equation (16),

$$\frac{\partial \mu_{i_1}^{b,1}(o^a, r)}{\partial o^a(r)} = \begin{cases} 1 & o^a \in [s^{il-1}, s^{il}] \\ -1 & o^a \in [s^{il}, s^{il+1}] \\ 0 & \text{otherwise} \end{cases} \tag{16}$$

As shown in Equation (16) where s^{il} denotes the central point of the i th fuzzy set of the l th attribute in sub fuzzy system.

This makes it possible to reflect the propagated error as,

$$h_a(r) = \begin{cases} h_b(r) \times \frac{\sum_{J_b} x_{J_b}^b(r) B_{J_b}^b(r)}{\mu_{i_1}^{b,1}(o^a, r)} o^a \in [s^{il-1}, s^{il}] \\ -h_b(r) \times \frac{\sum_{J_b} x_{J_b}^b(r) B_{J_b}^b(r)}{\mu_{i_1}^{b,1}(o^a, r)} o^a \in [s^{il}, s^{il+1}] \\ 0 \quad \text{otherwise} \end{cases} \quad (17)$$

Because of the previous iteration outcomes, the $x_{J_b}^b(r)$ gradient descent learning algorithm updates the current iteration parameters by iteratively,

$$x_{J_a}^a(r + 1) = x_{J_a}^a(r) - \lambda \times \frac{\partial o^a(r)}{\partial x_{J_a}^a(r)} \times h_a(r) \quad (18)$$

As shown in Equation (18), where λ is the parameter of the learning rate.

$$\frac{\partial o^a(r)}{\partial x_{J_a}^a(r)} = \frac{\partial (\sum_{J_a} B_{J_a}^a(r) x_{J_a}^a(r))}{\partial x_{J_a}^a(r)} = B_{J_a}^a(r) \quad (19)$$

Equation (18) can be remodified as the following Equation (20),

$$x_{J_a}^a(r + 1) = x_{J_a}^a(r) - \lambda \times B_{J_a}^a(r) \times h_a(r) \quad (20)$$

The proposed operational research-based intelligent decision support system for e-commerce decision making using a fuzzy logic system achieves minimum error rate while deciding for the customer. The consumer conceptual model helps to reduce the difficulty level and makes it efficient.

In this paper, the researchers propose a fuzzy logic system on the operational research based on an intelligent decision support system for e-commerce decision making. The gradient descent learning algorithm has been proposed for the hierarchical fuzzy system input and output for the pricing negotiation in e-commerce. Gradient descent is an optimization algorithm used in different machine learning algorithms to minimize the cost function (List on Algorithm 1). It is mainly used to modify the learning model’s parameters. This is a method of downward gradient processing 1 example of training per iteration. Therefore, even after one iteration in which only one instance has been processed, the parameters are modified. This is much slower than the descent of the batch gradient. When the number of training examples is high, only one example is processed, which can be additional overhead for the system as the number of iterations will be quite large.

Algorithm 1: Gradient Descent Learning Algorithm

Input: i, j, l, k, h

Output: $x_{j_a}^a, o^a(r)$

For ($i = 0$)

$$\hat{x} = f(Y) = \sum_{j_1, \dots, j_m \in J} \left(\prod_{i=1}^m \mu_{j_i}^i(y_i) \right) x_{j_1, \dots, j_m}$$

For ($j = 0$)

$$o^{k,a} = \sum_{i_1 i_2 \dots i_{m_{k,a}} j_1 j_2 \dots j_{n_{k,a}}} \left[\prod_{l=1}^{m_{k,a}} \mu_{i_l}^{k,a,l}(x_l^{k,a}) \prod_{l=1}^{n_{k,a}} E_{j_l}^{k,a,l}(y_l^{k,a}) \right] x_{i_1 i_2 \dots i_{m_{k,a}} j_1 j_2 \dots j_{n_{k,a}}}^{k,a}$$

For ($l = 0$)

$$h_a(r) = h_b(r) \times \frac{\partial o^b(r)}{\partial o^a(r)}$$

If ($h = 0$)

$$G = \sum_{j=1}^P \left[\sum_{i=1}^{w_j} \left(\prod_{l=1}^{m_{j,i}} M_{j,i}^l \prod_{l=1}^{n_{j,i}} M_{j,i}^l \right) \right]$$

Else

$$o_{i_1 i_2}^a = \left[\prod_{l=1}^{m_a} \mu_{i_l}^{a,l}(x_l^a) \prod_{k=1}^{n_a} E_{j_k}^{a,l}(y_k^a) \right] x_{i_1 i_2 \dots i_{m_a} j_1 j_2 \dots j_{n_a}}^a$$

End for

End for

End for

End if

End

Return

4. Experimental Results

4.1. Performance Ratio

The complete input conditions, combinations are connected to the standard fuzzy system via fuzzy intersection operators and are expressed in fuzzy laws. It is more reasonable to choose the default fuzzy system if various aspects of negotiation, pricing behaviors in e-commerce need to be emulated and observed. The standard fuzzy system, on the contrary, is a good method for high-dimensional issues with inadequate data samples. The proposed OR-IDSS system achieves a better performance ratio when compared to other existing systems B-IDSS, CIDSS, MCGDM, MSDSS, and FARM. Figure 4 and Table 1 demonstrate the performance ratio of the proposed system.

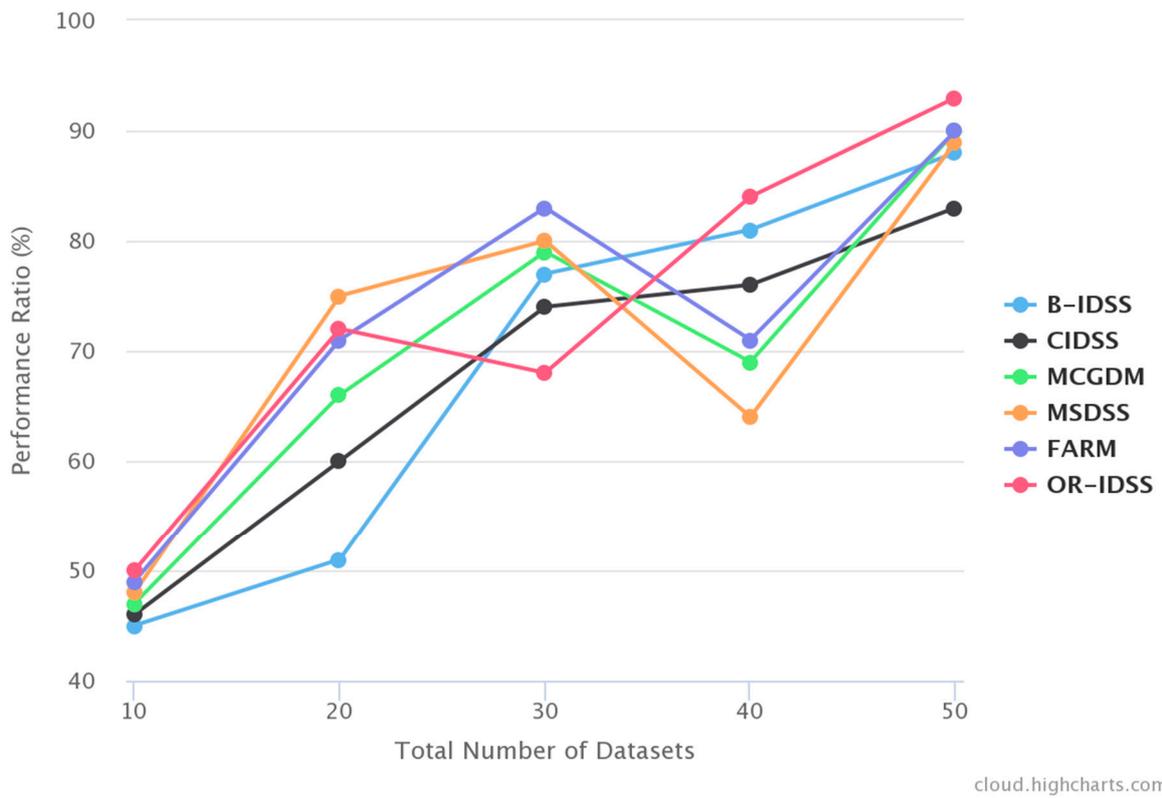


Figure 4. Performance ratio.

Table 1. Performance ratio.

Total Number of Datasets	B-IDSS	CIDSS	MCGDM	MSDSS	FARM	OR-IDSS
10	45	46	47	48	49	50
20	51	60	66	75	71	72
30	77	74	79	80	83	68
40	81	76	69	64	71	84
50	88	83	90	89	90	95

4.2. Accuracy

In this analysis, the root means square error and average absolute percentage error were used to calculate the accuracy and performance of results. This output depends on how well the training data protects the partitioned sub fuzzy system [24]. Consider the case where the m input variable exists and where n subspaces partition each attribute's input space to evaluate this argument. As such, the generic fuzzy system and the sub fuzzy system-single input and single output model, respectively, have separated sub-spaces between nm and n^m . Figure 5 and Table 2 show the accuracy ratio of the proposed system OR-IDSS.

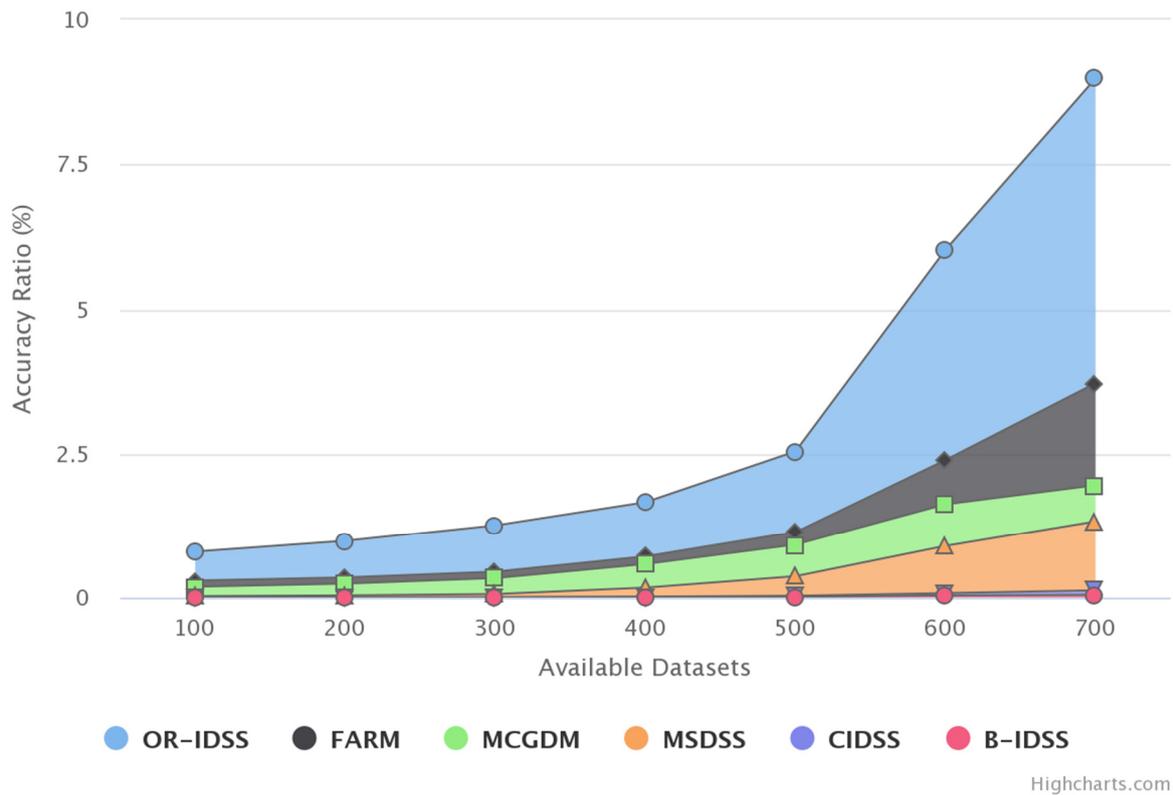


Figure 5. Accuracy ratio.

Table 2. Accuracy ratio.

Available Datasets	B-IDSS	CIDSS	MCGDM	MSDSS	FARM	OR-IDSS
100	4.5	4.6	4.7	4.8	4.9	5.0
200	5.1	6.0	6.6	7.5	7.1	7.2
300	7.7	7.4	7.9	8.0	8.3	6.8
400	8.1	7.6	6.9	6.4	7.1	8.4
500	8.8	8.3	9.0	8.9	9.0	9.5

4.3. Computational Cost

The computational cost of this analysis concerns both the complexity of time and space. For spatial consistency, the input matrix must be built by both the regular fuzzy system and sub fuzzy system. In the proposed solution, triangular membership functions are chosen to accomplish interpretability and computation efficiency [25]. The triangular membership functions are essentially linear and are easy to evaluate. The proposed OR-IDSS using a fuzzy logic system achieves low computational cost when compared to other existing methods. Figure 6 shows the computational cost of the proposed OR-IDSS approach.

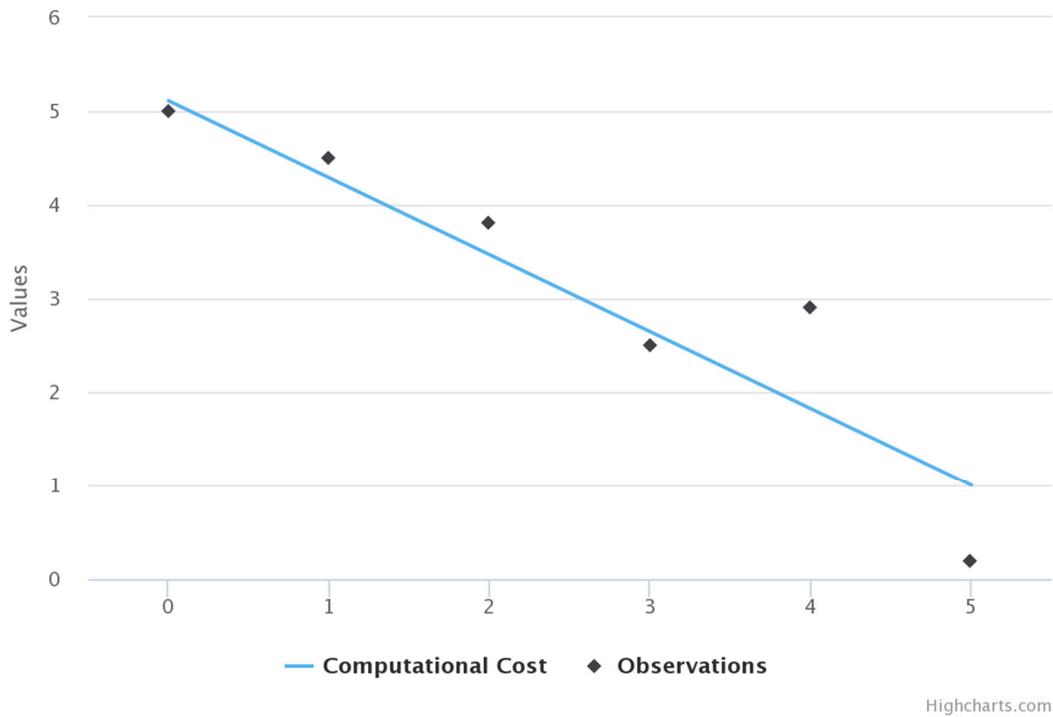


Figure 6. Computational cost.

4.4. Precision Ratio

The system can provide a suggested negotiation price/discount to help the pricing model when a new payment is made. The client must manually insert the details of a new transaction in the prediction screen and then press the predict button. The predicted cost will be shown. This proposed price can be utilized in price negotiation as a point of resistance or baseline. The proposed OR-IDSS achieves a high precision ratio when compared to other existing systems. Figure 7 shows the precision ratio of the proposed OR-IDSS method.

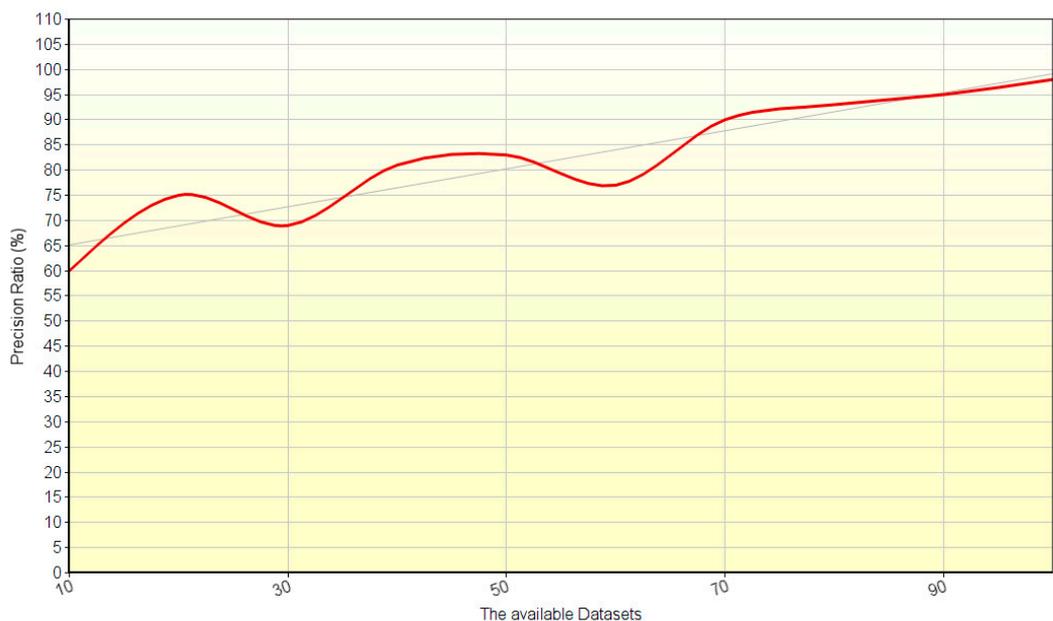


Figure 7. Precision ratio.

4.5. Error Rate

The learning algorithm and specified parameters are used to learn the fuzzy rules from the training dataset. The results of the learning and the rules produced will then be seen. As a result, the created fuzzy rules further validate the built model in conjunction with the test dataset. The test results are shown in Figure 8, including target values, predictive value, error, average absolute percentage error, and RMSE [26]. The target value plot and expected value provide a simple and intuitive view of the system’s output to the user. The proposed OR-IDSS error rate is very less when compared to other existing methods. Figure 8 demonstrates the error rate of the proposed system.

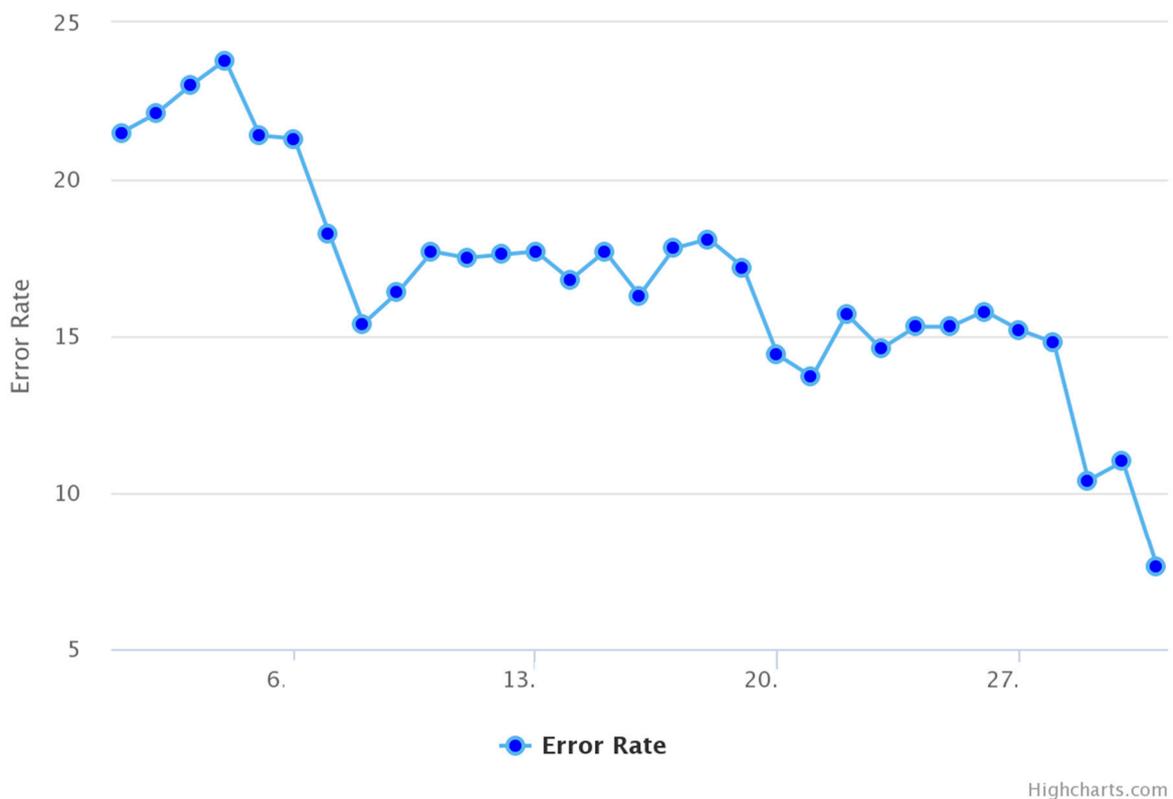


Figure 8. Error rate.

The above discussion analyzes the proposed operational research-based intelligent decision support system (OR-IDSS) for e-commerce decision making using fuzzy logic theory outer forms compared to existing methods.

5. Conclusions

This paper presents an operational research-based intelligent decision support system for e-commerce decision making. Online shopping is central to e-commerce systems. Such programs concentrate on the requirements of consumers. E-commerce systems are massive data that collect enormous quantities of data, especially customers’ behavior. Data can have great value for management and support for decision-making. As social networks are becoming increasingly popular on the internet, consumers who cannot have comprehensive product or service information frequently use their opinions from previous customers. Data from reliable people and not the consumer supplier or recommendation systems have affected the customer decision-making process. The social influence of high-quality checks by previous customers can be direct, positive, and spread across a social network to potential consumers. E-commerce companies are well-positioned to use social influence among customers as an instrument of decision-making aid by enabling a customer to

determine the adequacy of guidelines and reviews. The proposed system OR-IDSS achieves better performance when compared to other existing methods. An e-commerce firm should consider combining data of the customer preference found in the matrix of product ratings and the user preference similarities matrix and details of social impact included in the user engagement matrix and user faith matrix. This will be one of the success points for the help systems for e-commerce decisions. Moreover, a potential field of study is an important method in combining user preferences and social impact in e-commerce. In future work, this study will focus on basic issues and challenges in E-commerce research.

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Abbreviations

DSS	Decision Support System
IT	Information Technology
Or	Operational Research
E-commerce	Electronic Commerce
EFT	Electronic Funds Transfers
EDI	Electronic Data Exchange
OR-IDSS	Operational research-based Intelligent Decision Support System
ICT	Information and Communication Technology
B-IDSS	Big data-based Intelligent Decision Support System
CIDSS	Consumer-oriented Intelligent Decision Support System
MCGDM	Multi-Criteria Group Decision Making
IFA	Intelligent Fuzzy Agent
GLA	Genetical Learner Agent
FARM	Fuzzy Association rule mining approach
B2B	Business-to-Business

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