Advances in Consumer Research
ISSN (Print): 0098-9258
ISSN(Online): 3079-1766

Vol. 2, Issue 4 (2025) https://acr-journal.com/

An Anxiety-Based Multi-Attribute Recommender System Using Interval-Valued Intuitionistic Fuzzy Sets

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Cite this paper as: Eshika Aggarwal, (2025) An Anxiety-Based Multi-Attribute Recommender System Using Interval-Valued Intuitionistic Fuzzy Sets. *Advances in Consumer Research*, 2 (4), 1327-1340

KEYWORDS

Product recommendation, multi-attribute analysis, Interval-Valued Intuitionistic Fuzzy Sets, Anxiety in Decision Making

ABSTRACT

Numerous studies indicate that current recommender systems primarily focus on customer satisfaction, dissatisfaction, and personalized preferences when making product recommendations. However, these systems often neglect the anxiety customers may feel when choosing between similar products. This unease can result in poor decision-making and suboptimal choices. The ideal scenario for customers is to select a product without experiencing anxiety. Our study addresses this gap by incorporating "tranquillity" (or anxiety) as a behavioral factor in the recommendation process. Failing to consider these intuitive customer judgments can lead to the selection of inappropriate products. We propose a unified personalized recommendation approach using interval- valued intuitionistic fuzzy sets, which accounts for uncertain, conflicting criteria and customer behavior. This methodology identifies the best alternative by considering the customer's flexible preferences through an averaging operator. We compare the effectiveness of our approach with existing studies and demonstrate its applicability using a car purchase example in e-commerce.

1. INTRODUCTION

1.1 Background

Ensuring buyer satisfaction is the primary objective for online merchants (Eid, 2011). Also, not all merchants can guarantee complete satisfaction with every product, as customer dissatisfaction also plays a significant role in product purchasing decisions (Fornell & Wernerfelt, 1987). Existing decision support systems recommend a wide variety of products, often making it challenging for buyers to select the right one among many available options (Kumar, Dixit, Javalgi, & Dass, 2016; Gupta & Verma, 2022; Saravanan, Mohanraj, & Senthilkumar, 2019). Additionally, the fierce competition in e-commerce, with a vast array of products featuring varying attributes, makes basing decisions solely on satisfaction and dissatisfaction overwhelming for customers (Albadvi & Shahbazi; Walek & Fojtik, 2020). Although customers can gather product details from various websites, evaluating these products becomes difficult, as their features are often conflicting, non-commensurable, and ambiguous (Gettinger, Kiesling, Stummer, & Vetschera, January 2013; Kabak, Burmaoglu, & Kazancoglu, 2012). Therefore, it is essential to personalize recommendations by considering customer behaviors such as satisfaction, dissatisfaction, and anxiety (bertani, Bianchi, & Costa , 2020; de Campos, Fernandez-Luna, & Huete, 2019; Aggarwal & Mohanty, 2023). This study proposes an approach to address these intuitive judgments by developing a decision support interface that connects customers to e-business platforms.

The customer's uncertainty in ranking products makes it practical for decision support systems to evaluate products using fuzzy information. Moreover, product ranking becomes more robust when customer factors such as satisfaction, dissatisfaction, and tranquillity (anxiety) are integrated into uncertain decision-making scenarios. These uncertainties often arise from a lack of information, expertise, or the inherent indeterminacy of the customer's preferences. Interval-Valued Intuitionistic Fuzzy Sets (IVIFS) (Atanassov & Gargov, 1989; Atanassov K. , Interval-Valued Intuitionistic Fuzzy Sets, 2020) provide an effective method for capturing customer purchasing behavior. IVIFS is particularly useful for handling incomplete, uncertain, or imprecise knowledge, making it well-suited for understanding a customer's perspective on satisfaction, dissatisfaction, and tranquillity (anxiety). Thus, IVIFS is an appropriate approach for managing the insufficient or uncertain knowledge of customers, especially in online business contexts. Based on these factors, the proposed work

ISSN (Print): 0098-9258
ISSN(Online): 3079-1766

introduces a framework for accurately ranking products by considering the customer's cognitive aspects. Several studies on IVIFS can be found in (Atanassov K. , Index Matrices: Towards an Augmented Matrix Calculus, 2014; Aydin & Enginoğlu, 2021; Chen & Li, 2013; Li, 2010; Liang, Wei, & Xia, 2013; Aggarwal & Mohanty, An algorithmic-based multi-attribute decision making model under intuitionistic under intuitionistic fuzzy environment, 2022; Atanassov K. T., 1999).

Current e-business systems fail to truly personalize customer needs, as recommender systems do not account for anxiety in customer satisfaction and dissatisfaction levels involved in selecting products from a wide range of options (Gupta & Mohanty, 2017; Gupta & Verma, 2022; Aggarwal & Mohanty, Hesitant fuzzy sets with non- uniform linguistic terms: an application in multi attribute decision making, 2023). This study aims to develop a methodology that captures the emotional aspects of customers, focusing on their inherent traits of satisfaction, dissatisfaction, and unease when choosing a product. Our work introduces a customer's tranquillity level in product recommendation in e-business (Yager, 1982). With the abundance of products available on websites, customers may experience anxiety when unable to select a product that offers the highest level of tranquillity. Tranquillity refers to the emotional ease a customer feels when choosing a product from a range of options (Yager, 1982). Therefore, it is essential to assess the customer's tranquillity degree in an online environment. Similar to (Yager, 1982), our proposed approach evaluates the tranquillity degree of the customer's vague information regarding satisfaction and dissatisfaction, as well as product features, and subsequently integrates this into the product ranking process.

The proposed study aims to assess the customer's tranquillity (or anxiety) level across all products using the Max- Entropy OWA (MEOWA) operator. The MEOWA operator is employed to maximize information while integrating all product criteria. Additionally, MEOWA accounts for various social characteristics of the customer, such as positive, negative, and compensatory factors [24]. Our work also develops a procedure to determine the customer's risk aptitude, β, further enhancing the personalization of the recommendation process.

Research Challenges

The existing literature addresses several aspects of customer preferences in e-business. However, there are notable research gaps in understanding certain key elements of customer preferences, such as:

1. Non-consideration of Customer's Tranquillity/Anxiety in Intuitive Judgment of Satisfaction and Dissatisfaction

When customers face difficulty choosing the right product from a wide range of options, it often leads to feelings of unease or anxiety. This sense of anxiety is further exacerbated when the customer cannot evaluate the product solely on satisfaction, especially when confronted with contradictory, non-commensurable, and uncertain product features. Explicitly incorporating customers' inherent characteristics, such as their sense of tranquillity or anxiety, into an e-business platform remains a challenging task.

2. Inability to Measure Maximum Information About Consumer Attitudes

Existing recommender systems fail to capture the full extent of customer attitudes, particularly when customers experience anxiety due to the range of products available with various attributes. Maximizing the understanding of a customer's mindset is crucial, as this information can significantly influence how recommender systems value and suggest products. Therefore, determining and incorporating maximal information about the customer's attitude into decision support tools remains a complex challenge.

Research Contributions

To address the limitations of personalized recommendations in the online marketplace, the proposed work introduces an IVIFS-based recommendation system for e-business, with the following contributions:

1. Our approach objectively calculates the tranquillity associated with both satisfaction and dissatisfaction mindsets of the customer, and effectively integrates this into the decision support tool.
2. The proposed method determines and incorporates the MEOWA aggregation operator to assess the customer's mindset subjectively. Deriving the parametric value β objectively presents a significant challenge in this process.

Structure of the paper

The structure of the paper is: Introduction is mentioned in section 1, literature review in section 2, and preliminary concepts in section 3. In section 4, proposed methodology in product recommendation based on dissatisfaction and uneasiness of choosing products in e-business is described. The concepts of tranquillity and anxiety is mentioned in section 5. The method to compute the MEOWA weights is presented in section 6. In section 7, IOWA for product aggregation is mentioned. In section 8, numerical example is provided. Section 9 compares our work and similar works along with advantages. Section 10 demonstrates the conclusion and future suggestions.

2. LITERATURE REVIEW

Real-world decisions often involve numerous contradictory and non-commensurable product criteria, which can create significant challenges from the customer's perspective (Gettinger, Kiesling, Stummer, & Vetschera, January 2013; Zimmermann, 1978). Multiple Attribute Decision Making (MADM) is a method that assists customers in selecting the best product from a range of options, especially when the product features are conflicting (Gupta & Mohanty, 2017; Kabak, Burmaoglu, & Kazancoglu, 2012; Petkov, Petkova, Andrew, & Nepal, 2007; Kou, Yong, & Wang, 2011; Abdallah, Shehab, & Al-Ashaab, 2022). MADM related to IVIFS has been recognized by experts due to its applicability in various business contexts (Aggarwal & Mohanty, An algorithmic-based multi-attribute decision making model under intuitionistic under intuitionistic fuzzy environment, 2022; Aydin & Enginoğlu, 2021; Cheng, 2018). IVIFS enhances fuzzy set theory by accounting for both satisfaction and dissatisfaction levels across all products, providing a more comprehensive approach to decision-making.

A significant body of literature on recommender systems exists in e-business (Bertani, Bianchi, & Costa, 2020; Park, Kim, Choi, & Kim, 2012; Mishra, Kumar, & Bhasker, 2015; Kwok & Lau, 2019; Walek & Fojtik, 2020; Serrano-Guerrero, Olivas, & Romero, 2020). These systems gather personalized customer information based on past purchase history and comparisons with other customers. Fuzzy approaches in product recommendations are widely used in e-business to make more effective decisions (Gupta & Verma, 2022). Fuzzy set theory captures the underlying ambiguity and uncertainty to determine the rankings in recommender system (de Campos, Fernandez-Luna, & Huete, 2019; Rao, Tiwari, & Mohanty, 1988). (Saravanan, Mohanraj, & Senthilkumar, 2019) uses feature selection method to form deep learning technique based on fuzzy entropy. (Walek & Fojtik, 2020) developed a fuzzy expert system that provide personalized choices in e-business for fuzzy, vague, and ambiguous information. In (Aggarwal & Mohanty, An algorithmic-based multi-attribute decision making model under intuitionistic under intuitionistic fuzzy environment, 2022) confidence level is estimated using IVIFS and MADM. (Mohanty & Aggarwal, 2022/8) gives an algorithmic preference structure based on MADM. (Jia-Wei, Hu-Chen, Xiao-Yue, & Linsen, 2021) recommends assessment of e-learning internet site for fuzzy linguistic evaluations. Establishing utility-based recommender approaches for e-business is done using assessment of preference- elicitation approaches (Huang, 2011). However, rarely these studies capture the different emotional and cognitive aspects of the decision maker such as satisfaction, dis-satisfaction, tranquillity while recommending a product in the e-business. Literature work on hesitant fuzzy sets, probabilistic fuzzy sets, non- uniform linguistic sets, fuzzy graphs etc. and their applications for practitioners and experts are present in (Aydin & Enginoğlu, 2021; Aggarwal & Mohanty, 2022; Aggarwal & Mohanty, 2023; Raut & Pal, 2021)Ranking in proposed work is comparable to other works. This confirms the robustness and superiority of the recommended model to rank and rate products considering satisfaction, dissatisfaction, sense of ease of the buyer. Few limitations in (Wang, Niu, Wu, & Lan, 2014; Gupta & Verma, 2022) are presented here.

1. Although (Wang, Niu, Wu, & Lan, 2014) consider satsifaction and dissatisfaction characteristics of the buyer, it does not consider the emotional ease of the customer to select any product from multiple other products and is unable to integrate the maximal information in various applications. The proposed work removes this gap and establishes a decision support tool that incorporate maximal information of buyer.
2. Although the methodology in (Gupta & Verma, 2022) contemplate the risk taking capabilities and tranquility in product recommendation, it does not consider both satisfaction and dissatisfaction while assessing the products. Our work overcomes these gaps and proposes a emotion based methodology from buyer's perspective.

3. PRELIMINARIES

3.1 IVIFS

(Atanassov & Gargov, 1989; Atanassov K. , Interval-Valued Intuitionistic Fuzzy Sets, 2020; Atanassov K. , Intuitionistic fuzzy sets, 1986) Let $A = \{a_1, a_2 \ldots a_n\}$ is a set containing n number of elements. An IVIFS 'X' on A is stated as $X = < \mu_X(a), \nu_X(a), \pi_X(a) | a \in A >$

Where $\mu_X(a) = [\mu_X^l(a), \mu_X^u(a)]$, $\nu_X(a) = [\nu_X^l(a), \nu_X^u(a)]$, and $[\pi_X^l(a), \pi_X^u(a)]$ are satisfaction, dissatisfaction, and neutral values in interval forms of IVIFS 'X'.

$$\mu_X^u(a) + \nu_X^u(a) \le 1;$$
$$0 \le \mu_X^l(a) \le \mu_X^u(a) \le 1,$$
$$0 \le \nu_X^l(a) \le \nu_X^u(a) \le 1,$$
$$0 \le \pi_X^l(a) \le \pi_X^u(a) \le 1$$

Following (Wang, Niu, Wu, & Lan, 2014), the neutral degree $\pi_X(a)$ can be combined with satisfaction $\mu_X(x)$ and dissatisfaction $\nu_X(a)$, resulting in IVIFS 'B' in satisfaction and dissatisfaction values as presented in equation (1).

$$B(a) = < [m^l_B(a), m^u_B(a)], [n^l_B(a), n^u_B(a)], a \in A> \quad (1)$$

As given in (Cheng, 2018), the score value of B(a) is shown in equation (2):

$$S(B(a)) = \frac{m^l_B(a) - n^l_B(a) + m^u_B(a) - n^u_B(a)}{2} + 1 \quad (2)$$

$S(B(a)) \in [0,2]$.

3.2 Tranquillity and Anxiety (Yager, 1982)

Let $A = ((a, S(B(a_1))), (a_2, S(B(a_2))), \ldots (a_n, S(Ba_n))))$ is a fuzzy set and $S(B(a_i))$ is score values (i=1,2,…,n). T (A) is tranquillity level described as:

$$T(A) = \int_0^{\varsigma} \frac{1}{L(X_\varsigma)} \, d \propto \quad (3)$$

Where $\varsigma = \max\,(S(B(a_1)), S(B(a_2)), \ldots, S(B(a_k)))$ and $L(X_\varsigma)$ is cardinality of ς for A.

3.3 MEOWA weights (Yager, 2009)

Let $(w_1, w_2, \ldots, w_n)$ be the MEOWA weights, then as shown in equation (4)

$$w_j = m(M_j) - m(M_{j-1}) \quad (4)$$

Where $M = \sum_{k=1}^{j} \varphi_\kappa$ is sum of preference of attributes conforming to j highest values as defined in equation (5):

$$m(x) = \frac{(1-e^{-\beta x})}{1-e^{-\beta}}, \beta \in (-\infty, \infty) \quad (5)$$

β is a parameter to judge the mindset of customer. For any change in weight, the preferential weights also change subsequently. Further reference in (Yager, 2009).

3.4 Linguistic Quantifier

Following the procedure (Kacprzyk & Yager, 1984), the linguistic quantifier "most" can be specified based on score values of IVIFS (most, $S(B(a))_{most}$) as follows:

$$(\text{most}, S(B(a))_{most}) = \begin{cases} 1 & a \geq 0.8 \\ (2a - 0.6) & 0.3 \leq a \leq 0.8 \\ 0 & a \leq 0.3 \end{cases} \quad (6)$$

In equation (6), parameter 'a' represents the number of entities. If a ≥ 0.8, it means the assertion "most" is 100% fulfilled. If a ≤ 0.3, the statement "most" is 0% fulfilled. In 0.3≤ a ≤ 0.8, the satisfaction for "most" remains in between as shown in equation (6).

Note: parameters for "most" (0.8 and 0.3) can be modified according to different circumstances.

3.5. IOWA Operator (Yager, Induced aggregation operators, 2003)

An IOWA : $[0,1]^n \rightarrow [0,1]$ is n dimension set of vector $W = (w_1, w_2, \ldots, w_n)$ is connected such that $w_j \in [0,1]$, $\sum_{j=1}^{n} w_j = 1$ as shown inequation (7) as:

$$IOWA(\,(x_1, u_1), \ldots, (x_n, u_n)) = \sum_{i=1}^{n} w_i p_i \quad (7)$$

where X=(x_1, x_2, ... x_n) are aggregated values of attributes and $W = (w_1, w_2, \ldots, w_n)$. $U = [u_1, u_2, \ldots u_n]$ is an ordered vector defining the order of elements for vector X that is to be combined. In equation (7), the vector $[p_1, p_2, \ldots, p_n]$ is permutation vector X reorganized as per vector U in such a way that p_i is the i_{th} element connected with i_{th} greatest among values $u_1, u_2, \ldots u_n$.

4. PROPOSED FRAMEWORK TO RANK PRODUCTS

As businesses increasingly operate on e-commerce platforms, product recommendation has become a significant challenge, especially when customer preferences are based on satisfaction derived from product assessments (Gupta & Verma, 2022). However, in today's highly competitive environment, where survival and customer loyalty are crucial, it is essential to understand both customer satisfaction and dissatisfaction levels (Lu, Lu, & Wang, 2012; Eid, 2011; Fornell & Wernerfelt, 1987). To fully recognize a customer's expectations in the online marketplace, it is vital to consider the buyer's behavioral aspects, including satisfaction, dissatisfaction, and their sense of ease [38]. Unfortunately, to the best of our knowledge, these aspects related to a customer's sense of ease are often overlooked in current e-business practices (Huang, 2011). Unfortunately, to the best of our knowledge, these aspects related to a customer's sense of ease are often overlooked in current e-business practices (Gupta & Verma, 2022). For instance, when a buyer is looking to purchase a second-hand car, they may feel a sense of satisfaction to some extent, yet simultaneously experience dissatisfaction. Moreover, due to the availability of similar products in the market, the buyer may also feel uneasy. As a decision support tool, a customer may express their needs as:

Price: The needs of buyer can be stated in the form of satisfaction in the range of (0.3- 0.7) and dissatisfaction (0.1-0.2). Thus, price can be expressed as:

$$(\text{price}, \mu_{price}, \nu_{price}) = \left\{ \frac{[0.3-0.7, 0.1-0.2]}{30000}, \frac{[0.1-0.3, 0.3-0.5]}{40000}, \frac{[0.3, 0.4-0.6]}{15000}, \frac{[0.4-0.6, 0.2-0.3]}{50000}, \frac{[0.2-0.5, 0.2-0.3]}{20000} \right\} \quad (8)$$

In equation (8), for 'price', a buyer gets satisfied with the car a_1 30%-70% but dissatisfied 10-20%. Similarly, the same can be done for other criteria as explained in section 8.

To address the impact of a customer's sense of unease on their purchase decisions in e-commerce, it is essential to develop a decision support system that incorporates the emotional aspects of satisfaction, dissatisfaction, and unease. The use of interval-valued intuitionistic fuzzy sets provides an effective approach to considering these emotional factors in the decision-making process.

Let 'n' are number of products $\{P_1, P_2, P_3, ..., P_n\}$ available in e-commerce market. Let P_{ij} is the selected value of i^th product in j^th criteria.

Step1: Find the emotion-based needs of a customer in terms of satisfaction and dis-satisfaction for a product in each criteria as shown below:

$$\{(a_{a1}, (|m^l_{a1}, m^u_{a1}|, |n^l_{a1}, n^u_{a1}|))\}, \{(a_{a2}, (|m^l_{a2}, m^u_{a2}|, |n^l_{a2}, n^u_{a2}|))\}, \ldots, \{(a_{ai}, (|m^l_{aj}, m^u_{aj}|, |n^l_{aj}, n^u_{aj}|))\} \quad (9)$$

Step2: Evaluate the current products according to customer's needs for every product criterion. Let $(a_{a1}, (|m^l_{a1}, m^u_{a1}|, |n^l_{a1}, n^u_{a1}|))$ indicates satisfaction, dissatisfaction with which product P_i match to preferences of customer.

Step3: Find the score value of the customer in each product criteria based on equation(2)

$$(\text{price}, score_{price}) = \left\{ \frac{0.35}{30000}, \frac{0.8}{40000}, \frac{0.8}{15000}, \frac{0.25}{50000}, \frac{0.1}{20000} \right\} \quad (10)$$

5. TRANQUILLITY AND ANXIETY

In e-business, it is crucial to understand the cognitive aspects of the customer, such as tranquillity (or anxiety), satisfaction, and dissatisfaction, in order to achieve better outcomes. Tranquillity (or anxiety) refers to the degree of ease a customer feels when selecting a product, especially when multiple similar options are available. The ideal scenario is when the customer can choose a product without any anxiety. However, when the criteria are contradictory, incompatible, and uncertain, customers often experience confusion, which leads to a sense of unease. This anxiety can result in selecting an inappropriate product. Therefore, our approach recommends a product by incorporating tranquillity (or anxiety) as a cognitive characteristic in the decision support system. By calculating product values and scores, we can reflect the sense of unease in the customer's mind, helping guide them to a more informed choice.

For example, let criteria of 'price' of car is:

$$(\text{price}, score_{price}) = \left\{ \frac{0.35}{30000}, \frac{0.8}{40000}, \frac{0.8}{15000}, \frac{0.25}{50000}, \frac{0.1}{20000} \right\}$$

Using equation (3), the tranquillity level for 'price' is:

$$Q_{price} = \mathrm{T}(\mathrm{C}_1) = \int_{0} \frac{}{5} d\alpha + \int_{0.1} \frac{}{4} d\alpha + \int_{0.25} \frac{}{3} d\alpha + \int_{0.35} \frac{}{2} d\alpha = 0.316$$

It can be inferred that $A_{price} = 1 - Q_{price}$
$= 1 - 0.316 = 0.684$

Step 4: Using equation (3), T (A) is the tranquillity level of a criteria is expressed as:

$$T(A) = \int_{0} \frac{}{L(X_\varsigma)} d \propto$$

Where $\varsigma = \max(S(B(a_1)), S(B(a_2)), \ldots, S(B(a_k)))$ and $L(X_\varsigma)$ is the cardinality of ς for A.

Step 5: If T^{α} is the aggregated tranquillity among attributes (Kosko, 1986), we have

$$T^{\alpha} = \begin{cases} 1 - x + y & if\ x \geq \frac{1}{2}(1+y) \\ x & if\ x \leq \frac{1}{2}(1+y) \end{cases} \quad (11a)$$

Where l and b are smallest & maximum tranquillity of product attributes as shown in equations (11b) and (11c).

$$y = Min_j T_j \quad (11b)$$

$$x = Max_j T_j \quad (11c)$$

6. OBJECTIVE DETERMINATION OF MEOWA WEIGHTS

Let $(w_1, w_2, \ldots, w_n)$ be the MEOWA weights, then as shown in equation (4)

$$w_{j=} \ m(M_j) - m(M_{j-1})$$

Where $M = \sum_{k=1}^{j} \varphi$ is sum of preference of attributes conforming to j highest values as defined in equation (5):

$$m(x) = \frac{(1-e^{-\beta x})}{1-e^{-\beta}}, \beta \in (-\infty, \infty) \ |$$

β is a parameter to judge the mindset of customer. For any change in weight, the preferential weights also change subsequently. Further reference in (Yager, 2009).

Follow steps 1 to 5 mentioned in Section 5,

Step 6: MEOWA weights (w_j) are defined by applying equations (4) & (5).

$$w_{j=} \ m(M_j) - m(M_{j-1})$$

where $m(x) = (1 - e^{-\beta x})/(1 - e^{-B})$. β value is obtained from α value from the table in (Yager, 2009).

7. IOWA IN AGGREGATION OF PRODUCT ATTRIBUTES

When numerous products are available in the market, the buyer looks for the product in totality rather than in isolation to do comparison of several products. To identify this emotional aspect of customer, it is vital to find a decision support system that evaluates the products relatively as well as absolutely. Averaging operator, IOWA determines the feelings of the customer with relative preference and recommends the products in totality as explained below:

Step 7: Determine the average score of the alternatives in each attribute.

$$Av_j = \sum_{k=1}^{j} S(B(a))_j \quad (12)$$

Step8: Calculate the degree based on which products is mostly satisfied M_j with the j[th] product feature as it helps to generalize the products in entirety:

$$M_j = S(B(Avj))_{most}) \quad (13)$$

These steps show the benefit of IVIFS and fuzzy linguistic quantifier "most" in e-commerce platform to conclude the ranking and rating of products considering the emotional aspects of the customer.

Step 9: Using the criteria, determine the customer's satisfaction and dissatisfaction level for the attributes in the products in search engine depending on the score value as

$$R_{ij} = \begin{cases} Yes & if\ M_j \geq Avj) \\ No & if\ M_j \leq Avj) \end{cases} \quad (14)$$

Only the attribute values with minimum core value greater than the average score value is considered

Step 10: Reorder vector R_{ij} as an index to combine the attributes as present in equation (15) for product Pi

$$IOWA(S(B(a))_{ij}, R_{ij}) = w_1(S(B(a))_{i1}) + w_2(S(B(a))_{i2}) + \cdots + w_m(S(B(a))_{im}) \ \ldots \quad (15)$$

where $w_j(S(B(a))_{ij})$ signifies the score value of attribute a_{ij} corresponding to j[th] largest amongst R_{ij} (j=1,2….,m)

Example 1.2: Let the product P has score values based on satisfaction and dissatisfaction of the buyer as $[0.35, 0.7, 0.1, 0.55, 0.5, 0.75]$ and derived weights in addition to reorder vector are $w = [0.31, 0.13, 0.34, 0.11, 0.09, 0.03]$ and r = [Yes, Yes, No, No, Yes, Yes] respectively.

Considering the satisfaction level of the buyer with minimum competency in which only satisfied valued of "Yes" is considered and discarding the "No" values as they did not satisfied the minimum competency level of the buyer, we have

IOWA ((0.35, Yes), (0.7, Yes), (0.1, No), (0.55, No), (0.5, Yes), (0.75, Yes)) = 0.31 × 0.75 + 0.13 × 0.7 + 0.34 × 0.5 + 0.11 × 0.35 + 0.09 × 0 + 0.03 × 0 = 0.532

The combined product value achieved is 0.532 as per preference index of the buyer.

PersonalizedRecomm_IVIFS() is developed to explain the methodology established in four different modules as shown in Figure 1:

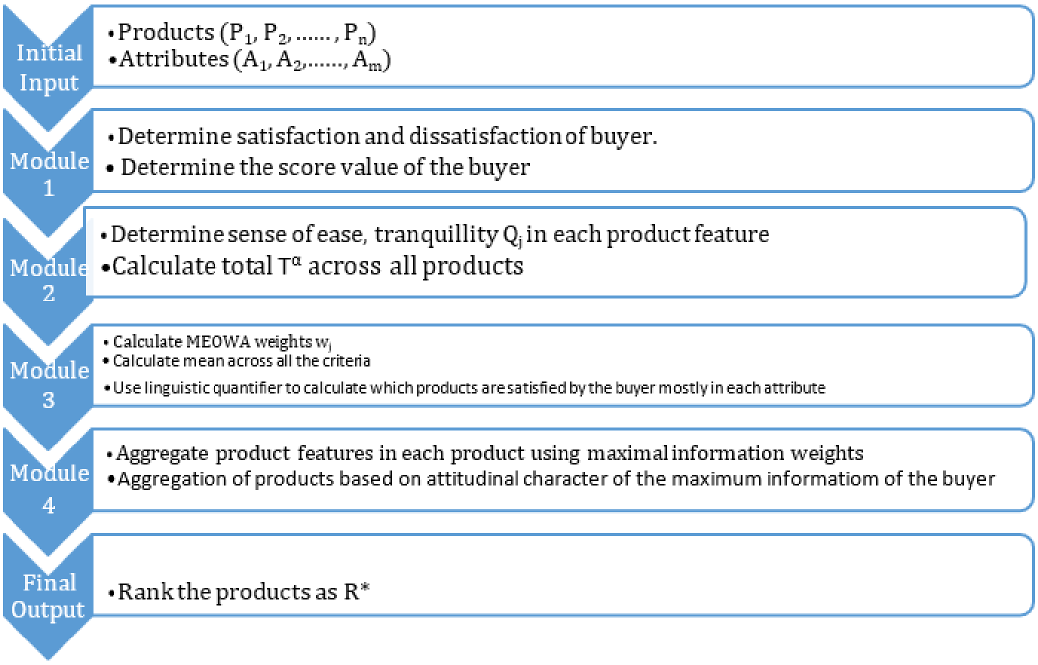

Fig. 1 Proposed Methodology

The notations in PersonalizedRecomm_IVIFS() algorithm are shown below:

P_i: Set of products A_j: Set of product $[m_{ij}^l, m_{ij}^u]$=interval form of satisfaction of $[n_{ij}^l, n_{ij}^u]$= interval form of dis-satisfaction of $B_{ij} = \{[m_{ij}^l, m_{ij}^u],[n_{ij}^l, n_{ij}^u]\}$:intutionistic fuzzy form) $I(h_{ij})$) : (ij); ij ε N = {0,1,2,...} T(A): Tranquility level associated with each product feature. ϱ_j: weight of set of product feature Q^{φ}: Overall tranquillity β: Beta value

PersonalizedRecomm_IVIFS() (P_i, A_j, Hij)
Input: Products $\{P_1,P_2,\ldots P_m\}$ Attributes $\{A_1,A_2,\ldots A_n\}$ IVIFS Values $H_{ij} = \{[m_{ij}^l, m_{ij}^u],[n_{ij}^l, n_{ij}^u]\}$
Output: Ranking of products in R*
begin

1. For i=0,1, 2, ..., m-1 ; j=0,1, 2, ..., n-1

begin

2. Set $H_{ij} \leftarrow \{(m_{ij}^l, m_{ij}^u),(n_{ij}^l, n_{ij}^u)\}$
3. Set $S_{ij} \leftarrow \frac{(\tilde{m}_{ij}^l - \tilde{n}_{ij}^l + \tilde{m}_{ij}^u - \tilde{n}_{ij}^u)}{2} + 1$
4. $T_j = \{\ \}$
5. $AV_j = \{\ \}$
6. for feature in A_j:

begin

7. $T_j\,[A_j] \leftarrow$ calculate_ tranquility $((Comp)_{ij})$

end

8. if max(T_j) > ((1+min(T_j))/2), do

9. Q^{φ}= 1-max(T_j)+min(T_j)
10. else Q^{φ}=max(T_j)
11. Set α = Q^{φ}
12. Get β ⟵Table[α] //infer β value corresponding to α from a table given in Yager (2009)
13. R_p = { }
14. w_j = { }
15. ϱ_i= {A_1: ϱ_1, A_2: ϱ_2, … … A_j: ϱ_j}
16. sort(N_j, sort_order = descending)
17. def meowa_f(float a,float b):
18. m=(1-exp(-b*a))/(1-exp(-a))
19. return (m)
20. for k in range(0, A_j), do

begin

21. if k>0:
22. R_p [k]= ϱ_i[N_j [k]]+ ϱ_i[N_j [k-1]]
23. w*= meowa_f(R_p[k], β)-meowa_f(R_p[k-1], β)
24. else:
25. S_p [k]=Aw[N_j [k]]
26. w* =meowa_f(R_p[k], β)-meowa_f(0, β)
27. w_j [k] = w* End
28. C_{ij}= { }
29. u_{ij} = { }
30. L_{ij} = distinct count of μ_j
31. sort distinct list of μ_j in descending order for every attribute j
32. P_{ij} = position of μ_{ij} in the sorted distinct list for attribute j
33. C_{ij} = L_{ij} - P_{ij} + 1
34. For product in P_i

begin

35. k = 0
36. for attribute in A_j

begin

k = k + C_{ij}[product][attribute]

end

37. $U_{ij} = C_{ij}/k$

end

38. for product in list P_i, do

begin

39. sort(U_{ij} [product][attribute], sort_order = descending)
40. Set r = 0
41. for k in range (0, A_j)

begin

42. r = r + U_{ij} [k] [μ_{ij}]* w_i[k]

end

43. IOWA [P_i]= r

end

44. R*=Rank(IOWA)

8. NUMERICAL EXAMPLE

A numerical example is provided to validate the robustness and superiority of the proposed methodology. In this example, a customer seeking to purchase a second-hand car from five different models in the online market is considered. The online platform recommends a car based on the customer's satisfaction and dissatisfaction levels regarding the features of each car.

The customer's preferences are based on six key attributes: 'price,' 'maintenance,' 'mileage,' 'color,' 'resale value,' and 'age.' The information on these car features as mentioned in online platform is shown in the Table 1 below:

Table 1: Data of used cars

	Price (Rs)	Maintenance Cost (Rs)	Mileage	Colour	Resale-value (Rs)	Age
Car_1	**300000**	**1000**	**19**	**Dark grey**	**1000**	**5**
Car_2	**400000**	**500**	**25**	**Black**	**1500**	**4**
Car_3	**150000**	**5000**	**12**	**Light Grey**	**500**	**6**
Car_4	**500000**	**1500**	**25**	**Dark grey**	**2000**	**5**
Car_5	**200000**	**3000**	**17**	**Black**	**750**	**7**

The subsequent steps describe the method of recommending the available cars according to satisfaction and dis- satisfaction of the customer's inclinations. As mentioned in Sections 7 and 8, the steps are explained below: **Step 1:** Let the decision support interface collects preferences of customer on each car attribute across all the cars according to satisfaction and dissatisfaction of buyer. Table 2 shows the preference of the customer for each car attributes across all the car models in satisfaction and dis-satisfaction in interval form.

Table 2: Preferences of customer in satisfaction and dissatisfaction level

	Price	Maintenance	Mileage	Colour	Resale-value (Rs)	Age
Car_1	[0.3,0.7], [0.1,0.2]	[0.1,0.1], [0.3,0.5]	[0.3,0.6], [0.3,0.4]	[0.4,0.9], [0.1, 0.1]	[0.5,0.8], [0.1, 0.2]	[0.8,0.9], [0.1, 0.1]
Car_2	[0.1,0.3], [0.3, 0.5]	[0.7,0.9], [0.1, 0.1]	[0.0,0.0], [0.2, 0.4]	[0.6,0.8], [0.1, 0.2]	[0.4,0.7], [0.1, 0.2]	[0.8,0.8], [0.1, 0.2]
Car_3	[0.3,0.3], [0.4, 0.6]	[0.6,0.9], [0.1, 0.1]	[0.4,0.7], [0.2, 0.3]	[0.8,0.9], [0.1, 0.1]	[0.3,0.7], [0.1, 0.2]	[0.5,0.7], [0.1, 0.2]
Car_4	[0.4,0.6], [0.2, 0.3]	[0.3,0.5], [0.3, 0.4]	[0.4,0.8], [0.1, 0.2]	[0.5,0.7], [0.1, 0.3]	[1.0,1.0], [0, 0]	[0.3,0.7], [0.2, 0.3]
Car_5	[0.2,0.5], [0.2, 0.3]	[0.7,1.0], [0, 0]	[0.4,0.7], [0.1, 0.3]	[0.6,0.9], [0, 0.1]	[0.4,0.6], [0.2, 0.3]	[0.8,0.8], [0.1, 0.2]

Step 2: Obtain the score value for the car features across all the cars as shown in Table 3

Table 3: Score values of customer's preferences

	Price (Rs)	Maintenance Cost (Rs)	Mileage	Colour	Resale-value (Rs)	Age
Car_1	0.35	*-0.3*	0.1	0.55	0.5	0.75
Car_2	*-0.2*	0.7	*-0.3*	0.55	0.4	0.65
Car_3	*-0.2*	0.65	0.3	0.75	0.35	0.45
Car_4	0.25	0.05	0.45	0.4	1	0.25
Car_5	0.1	0.85	0.35	0.7	0.25	0.65

Since few score functions obtained have negative value (shown in italics). To get corresponding positive value, 1 is added to those values as shown in table 4

Table 4: Modified Score values of customer's preferences

	Price (Rs)	Maintenance Cost (Rs)	Mileage	Colour	Resale-value (Rs)	Age
Car_1	0.35	*0.7*	0.1	0.55	0.5	0.75
Car_2	*0.8*	0.7	*0.7*	0.55	0.4	0.65
Car_3	*0.8*	0.65	0.3	0.75	0.35	0.45
Car_4	0.25	0.05	0.45	0.4	1	0.25
Car_5	0.1	0.85	0.35	0.7	0.25	0.65

Step 3: Using equation (11), the tranquillity level of car features across all the car models are shown below:

$$T(C_1) = \int_{0}^{0.1}\frac{1}{5}d\alpha + \int_{0.1}^{0.25}\frac{1}{4}d\alpha + \int_{0.25}^{0.35}\frac{1}{3}d\alpha + \int_{0.35}^{0.8}\frac{1}{2}d\alpha = 0.316$$

$$T(C_2) = \int_{0}^{0.05}\frac{1}{5}d\alpha + \int_{0.05}^{0.65}\frac{1}{4}d\alpha + \int_{0.65}^{0.7}\frac{1}{3}d\alpha + \int_{0.7}^{0.85}\frac{1}{1}d\alpha = 0.326$$

$$T(C_3) = \int_{0}^{0.1}\frac{1}{5}d\alpha + \int_{0.1}^{0.3}\frac{1}{4}d\alpha + \int_{0.3}^{0.35}\frac{1}{3}d\alpha + \int_{0.35}^{0.45}\frac{1}{2}d\alpha + \int_{0.45}^{0.7}\frac{1}{1}d\alpha = 0.386$$

$$T(C_4) = \int_{0}^{0.4}\frac{1}{5}d\alpha + \int_{0.4}^{0.55}\frac{1}{4}d\alpha + \int_{0.55}^{0.7}\frac{1}{2}d\alpha + \int_{0.7}^{0.75}\frac{1}{1}d\alpha = 0.242$$

$$T(C_5) = \int_{0}^{0.25}\frac{1}{5}d\alpha + \int_{0.25}^{0.35}\frac{1}{4}d\alpha + \int_{0.35}^{0.4}\frac{1}{3}d\alpha + \int_{0.4}^{0.5}\frac{1}{2}d\alpha + \int_{0.5}^{1}\frac{1}{1}d\alpha = 0.641$$

$$T(C_6) = \int_{0}^{0.25}\frac{1}{5}d\alpha + \int_{0.25}^{0.45}\frac{1}{4}d\alpha + \int_{0.45}^{0.65}\frac{1}{3}d\alpha + \int_{0.65}^{0.75}\frac{1}{1}d\alpha = 0.266$$

Step 4: Using equations (11a,11b, & 11c), the merged tranquillity considering all attributes is $T\alpha = 0.601$.
Step 5: Implying the tranquillity $T\alpha$ as customer's level of risk-taking ability, $\alpha = 0.601$.
Step 6: Applying equations (4 & 5), determine weights (wj) of MEOWA.
The β value equivalent to $\alpha = 0.601$ is 1.2 [18].

Weights for product feature price ϱ_{price}, maintenance cost $\varrho_{maintCost}$, mileage $\varrho_{mileage}$, colour ϱ_{colour}, resalevalue $\varrho_{resalevalue}$, age ϱ_{age} are 0.2, 0.1,0.35,0.15,0.15, and 0.05 respectively.
The MEOWA weights $(w_1, w_2, w_3, w_4, w_5, w_6)$ are: (0.31,0.13,0.34,0.11,0.09,0.03)

Mean of the criterion as shown in equation (12) obtained is in table 5:

Table 5: Mean of the criterion.

	Price (Rs)	Maintenance Cost (Rs)	Mileage	Colour	Resale-value (Rs)	Age
Mean	0.46	0.59	0.38	0.59	0.5	0.55

Define the $\mu_{most}(x)$ as :
1 if $x \geq 0.8$
$\frac{x-0.3}{0.8-0.3}$ if $0.3 < x < 0.8$
0 if $x \leq 0.3$
Calculating the $\mu_{most}(x)$ for all the criterion as shown in table 6 using equation (13):

Table 6: Satisfaction of products among most of the products across all criteria

	Price (Rs)	Maintenance Cost (Rs)	Mileage	Colour	Resale-value (Rs)	Age
$\mu_{most}(x)$	0.32	0.58	0.16	0.58	0.4	0.5

Mean of $\mu_{most}(x) = 0.423$

Using the criteria, products fulfilling the preference level of the buyer using equation(14) are shown in the table 7 below:

Table 7: Products fulfilling the preference level of buyer.

	Price (Rs)	Maintenance Cost (Rs)	Mileage	Colour	Resale-value (Rs)	Age
P_1	Yes	*Yes*	No	No	Yes	Yes
P_2	*Yes*	Yes	*Yes*	No	Yes	Yes
P_3	*Yes*	Yes	Yes	Yes	No	No
P_4	No	No	Yes	No	Yes	No
P_5	No	Yes	Yes	Yes	No	Yes

For P_1: $w_1 \times 0.75 + w_2 \times 0.7 + w_3 \times 0.5 + w_4 \times 0.35 + w_5 \times 0 + w_6 \times 0$

$= 0.31 \times 0.75 + 0.13 \times 0.7 + 0.34 \times 0.5 + 0.11 \times 0.35 + 0.09 \times 0 + 0.03 \times 0 = 0.532$

Similarly,

For P_2: $w_1 \times 0.8 + w_2 \times 0.7 + w_3 \times 0.7 + w_4 \times 0.65 + w_5 \times 0.4 + w_6 \times 0 = 0.685$ For P_3: $w_1 \times 0.8 + w_2 \times 0.75 + w_3 \times 0.65 + w_4 \times 0.3 + w_5 \times 0 + w_6 \times 0 = 0.6$ For P_4: $w_1 \times 1 + w_2 \times 0.45 + w_3 \times 0 + w_4 \times 0 + w_5 \times 0 + w_6 \times 0 = 0.369$

For P_5: $w_1 \times 0.85 + w_2 \times 0.7 + w_3 \times 0.65 + w_4 \times 0.35 + w_5 \times 0 + w_6 \times 0 = 0.614$

The overall ranking of all car models is shown in Table 8.

Table 8: Total performance of car models

Mobile phone	Overall Ranking
Car_1	0.53
Car_2	0.69
Car_3	0.60
Car_4	0.37
Car_5	0.61

The final ranking for car models is:

$Car_2 > Car_5 > Car_3 > Car_1 > Car_4$

In this ranking, Car_2 is identified as the best car model according to the customer's expectations, taking into account emotional aspects such as satisfaction, dissatisfaction, and anxiety. Similarly, the other car models are ranked accordingly. This ranking highlights the robustness, effectiveness, and consistency of the proposed approach, as it aligns well with the customer's purchase intentions.

9. COMPARISON WITH RELATED WORKS

The approach of (Wang, Niu, Wu, & Lan, 2014; Gupta & Verma, 2022) is studied and data from Table 2 is obtained. The outcome is shown in Table 9 below and figure 2 below:

Table 9 Comparison with related works

Car model	Proposed Methodology	Wang et all 2014	Gupta & Verma 2022
P_1	4	4	4
P_2	1	1	1
P_3	3	3	2
P_4	5	5	5
P_5	2	2	3

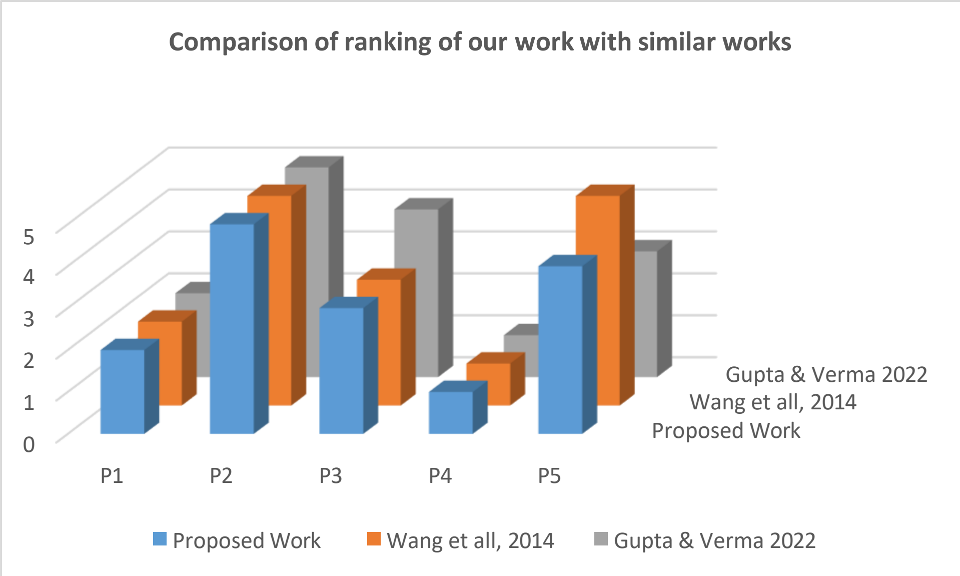

Fig. 2 Comparison of ranking of proposed and related works

Ranking in proposed work is comparable to other works. This confirms the robustness and superiority of the recommended model to rank and rate products considering satisfaction, dissatisfaction, sense of ease of the buyer. Few limitations in (Wang, Niu, Wu, & Lan, 2014; Gupta & Verma, 2022) are presented here.

1. Although (Wang, Niu, Wu, & Lan, 2014) consider satsifaction and dissatisfaction characteristics of the buyer, it does not consider the emotional ease of the customer to select any product from multiple other products and is unable to integrate the maximal information in various applications. The proposed work removes this gap and establishes a decision support tool that incorporate maximal information of buyer.
2. Although the methodology in (Gupta & Verma, 2022) contemplate the risk taking capabilities and tranquility in product recommendation, it does not consider both satisfaction and dissatisfaction while assessing the products. Our work overcomes these gaps and proposes a emotion based methodology from buyer’s perspective.

10. CONCLUSION AND SCOPE FOR FUTURE RESEARCH

Numerous studies have highlighted that buyers consider a range of factors when choosing a product in e-business. However, few websites offer personalized preferences that address customer satisfaction, dissatisfaction, and unease when evaluating similar products. This study presents a unified personalized recommendation approach that incorporates these intuitive elements of customer judgment through IVIFS (Interval-Valued Intuitionistic Fuzzy Sets). Our research makes valuable contributions to the fields of decision support systems, Multi-Criteria Decision Making (MADM), and e-commerce. We propose a practical decision support tool for e-business that ranks products based on the buyer’s experiences when comparing similar products. By factoring in the buyer’s sense of tranquility and unease regarding product features, this approach provides a more nuanced understanding of the buyer's mindset during the decision-making process.

Future research could explore additional behavioral factors that influence buyer decisions, such as confusion when recommending products on e-commerce platforms. Emotional and psychological experiments using various techniques may also be explored to further improve product recommendations.

Competing Interests: The authors of this publication declare there are no competing interests

Funding: This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors. Funding for this research was covered by the author(s) of the article.

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