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A Novel Group Decision Making Model to Compare Online Shopping Platforms

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ABSTRACT

Over the years, E-commerce industry has been witnessing a phenomenal growth, thanks to rapid technological advancement in Industry 4.0. There has been a standout surge in the use of various online shopping platforms (OSP) for daily use. The recent pandemic has accelerated the growth trajectory and made a transformational change in the digital commerce landscape. As a result, there has been a proliferation of OSPs in the competitive domain. It is therefore pertinent to address the questions: How do the customers select their favorite OSP? To what extent the OSPs differ based on consumers' preferences? The present work addresses these questions by proposing a novel group decision making framework. The ongoing study provides several innovative extensions of multi criteria decision making models like Borda count, criteria importance assessment (CIMAS), modified preference selection index (MPSI), and root assessment method (RAM). In this paper, the researchers provide a novel use of the Borda count method, integrated with CIMAS for determining criteria weights utilizing ranking of the criteria. Further, a novel extension of MPSI and RAM has been made with multiple normalizations. In this paper, the authors demonstrate a rare combination of vector and non-linear normalization using the Heron mean. The present paper derives the final criteria weights by combining Borda count, CIMAS and multi-normalization based MPSI (MNMPSI) using Bayesian logic. The criteria are selected based on Uses and Gratification theory (UGT). The findings reveal that interactive app interface and features (C16), user-friendly interface and search (C13), convenience in shopping (C14), product availability and variety (C12) and discounts and offers (C8) exert significant influence in selecting the OSP. Further, it is observed that Flipkart (A2) and Amazon (A1) are the top performers in the eyes of the users. The stability and reliability of the proposed methodology are examined by conducting a sensitivity analysis and comparing with several other models. The robustness of the proposed methodology and practical relevance of the findings of the present work shall provide notable impetus to the analysts and strategic decision-makers.

1. Introduction

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In real life the decision-makers face difficulty in many instances, to select a right course of action or a right alternative because of influences of a set of attributes or criteria that are conflicting to each other. Under such situations of decision-making dilemma, the decision-makers need to trade off the benefits derived out of influence of associated criteria [1,2]. Multi-criteria decision making (MCDM) models help the decision-makers to select an optimum choice or formulate a best possible course of action subject to the impact of several criteria involved in the decision-making process [3-5]. MCDM models compare the available choices based on their performance values with respect to the criteria, represented by a decision matrix [5].

The criteria involved in the decision-making process differ in terms of their range of values, scales, units of measurement and directions. To evaluate the alternatives in a comparable manner, MCDM models often apply the technique of normalization of the decision matrix as an initial step. The extant literature shows a plethora of normalization techniques, linear, non-linear and vector types [6]. However, selection of normalization techniques significantly influences the outcome of an MCDM model, often preventing to obtain an optimum preferential ordering of the alternatives [7,8]. Hence, selection of an appropriate normalization scheme is one of the critical success factors for MCDM applications. Several scholars worked on using different normalization approaches to examine their effects on the ranking provided by different MCDM models [9-18]. In recent time, some scholars have advocated the use of two normalization schemes together for MCDM based ranking of the alternatives for many benefits such as: a) stable decision-making; b) separating closely competitive alternatives; c) withstanding the presence of negative or zero values in the initial decision-matrix and d) examining the sensitivity of the final outcome with respect to the changes in the external conditions [19,20]. There are several novel contributions made in past that used two different normalization schemes in an integrated way to develop new MCDM models such as DNMA [19], AROMAN [20], ALRON [21] among others and for applying in real-life complex problems [22].

1.1. Primary Motivations

In the present paper, the researchers intend to develop a multi-normalization based MCDM framework using modified preference selection index (MPSI) [21] and root assessment method (RAM) [23]. MPSI method provides a number of advantages such as lesser computational complexity, simple applications and stable results [21]. However, it is seen that MPSI method used a linear normalization scheme in its past applications. This stands as a motivation to extend MPSI with multiple normalizations (MN) to develop a new MNMPSI framework for further benefits. RAM works with a unique philosophy to reward the alternatives having superior performances based on beneficial criteria. Unlike the other methods, RAM does not allow an inferior performance on a beneficial criterion to be compensated by a superior performance on a non-beneficial criterion. It uses a simple aggregation function with non-beneficial utility value as index and beneficial utility as radicand. As a result, RAM works fine even with no non-beneficial effect and penalize the higher non-beneficial performance value [23]. However, RAM also depends on a single normalization that might lead to a situation of no effect imposed by non-beneficial criteria. In that case, the final appraisal score will be simple square root of beneficial utility. To avoid such situation, a two-normalization scheme can be helpful. There is no evidence in the literature that modified RAM with double normalizations. Further, the extant literature shows use of similar type of normalizations, for instance, two logarithmic normalizations [21] or vector and linear max-min types [20]. To the best of knowledge of the researchers, there is no prior study that focused on a mix of nonlinear and linear/vector normalization. These gaps motivate to undertake the present work for extending MPSI and RAM with a mix of vector and nonlinear normalizations.

There is another reason for designing the current study. It is evident that several past studies [24-27] used Borda count method [28] to aggregate the results of several ranking methods and/or the findings of different periods applying the same model. Borda count is a simple yet powerful algorithm used for aggregation and consolidate ranking purpose. The original purpose of introducing Borda count method was to aggregate the voting [28]. In line with the fundamental philosophy, Borda count method can be used to calculate weights while aggregating the ranking of the criteria given by a group of decision-makers. But there is no such effort noticed in the past studies. Very recently, CIMAS method [29] has been developed advancing the field of approaches determining criteria weights using objective information like CRITIC. CIMAS provides a number of usefulness such as: a) simple calculation (CIMAS does not require complex steps); b) objective judgement of the criteria using rating by the decision-makers; c) inherent steps to include rating of the decision-makers (this is a crucial step as it requires a careful selection of the decision makers); d) ability to determine weights of a large number of criteria without getting impacted by the decision matrix; e) possibility to include a large group of decision makers without adding to computational complexity. Since, Borda count and CIMAS work with rating/ranking by the decision-makers, it may be an innovative and useful approach to integrate both of them. So far, the literature shows a very limited number of applications and further development of CIMAS [30,31]. Hence, the present research intends to develop a hybrid framework of Borda count and CIMAS methods to determine criteria weights using objective judgements opined by a group of decision makers.

1.2. Case Study

The present work applies the developed methodology for comparing popular online shopping platforms. Online shopping platforms facilitate E-commerce. E-commerce began with the introduction of EDI in 1960s and gained popularity in 1970s and 1980s. Gradually over the years, E-commerce sector (mobile commerce, social commerce) witnessed a phenomenal growth, especially after 2000. Aftermath of Industry 4.0, the trends show proliferation of omnichannel retailing, sustainability, and emerging technologies like AI, AR, and blockchain [32]. The evolution of e-commerce over the has revolutionized the way that consumers buy, with elements such as perceived advantages, risks, purchase intention, trust, and promotional techniques playing a role [33]. The market potential for Indian E-commerce industry is set to reach USD 101.40 Bn by 2029 with a CAGR of 11.45%. The number of consumers for online retail is estimated to reach 375.2 million by 2029 with a penetration rate of 25.5% [34]. There are several past studies that enquired consumers' intention to use online shopping and purchase behavior of the shoppers. However, a handful studies have been made to compare popular online shopping platforms (OSP) based on multiple criteria. Some studies in recent time demonstrated a comparative analysis of OSPs [35-39]. The present study develops a large-scale group decision-making framework with multiple MCDM models for comparing OSPs which is apparently rare in the literature.

1.3. Research Questions

The current work aims to address the following research questions:

RQ 1. How can multiple MCDM models like Borda count, CIMAS and MPSI be integrated to develop a reliable group decision making framework for calculating criteria weights?

RQ 2. How can multiple normalization schemes be aggregated to develop a reliable MCDM framework (using MPSI and RAM) for ranking of alternatives?

RQ 3. To what extent do consumers' buying behaviors differ to select an online shopping platform?

RQ 4. To what extent do online shopping platforms differ from each other?

Therefore, the current study intends to develop a crisp MCDM framework (based on group decision) to determine weights of a number of criteria ($j = 1, 2, ..., n$) and rank a set of online shopping platforms ($i = 1, 2, ..., m$).

1.4. Major Contributions

The present work has several contributions such as:

i. From theoretical perspective, the current study provides an extension of application of UGT for comparing OSPs based on multiple perceptual and intention related criteria.
ii. The current work provides an innovative application of CIMAS method in conjunction with Borda count to develop a novel approach for determining criteria weights within a group decision-making framework. In this context, the current work provides a modified approach to calculate the reliability index by using other MCDM models like LBWA or FUCOM or any other that computes criteria weights based on group opinion.
iii. The ongoing work provides a novel extension of MPSI method with multi-normalization scheme (MNMPSI) integrated by Heron mean.
iv. In this study, an innovative combination of a non-linear (Z-score and Sigmoid function based) and vector normalizations is made.
v. The present work provides an innovative way to determine final weights of the criteria. First, it determines the weights of the criteria based on experts' ranking of the criteria. Then, the weights are derived from the decision matrix indicating the rating of the alternatives subject to the criteria. To obtain the final weights, Bayesian logic is applied.
vi. The current study extends RAM with multiple normalization and provides a novel hybrid MNMPSI-RAM framework for decision-making.
vii. A large-scale opinion-based group decision-making framework with multiple models is developed.

The remaining part of the manuscript is organized in a systematic way. In section 2, the theoretical background is narrated briefly. Section 3 revisits the state-of-the-art to substantiate selection of criteria for comparing online shopping sites. Section 4 describes the case study. It describes the research framework and respondents' profile. The proposed methodology is elucidated. Section 5 exhibits key results while section 6 elaborated the inference of the findings along with research implications and some of the possible future scope. Finally, section 7 provides the concluding remarks.

2. Theoretical Background

Uses and Gratifications Theory (UGT) unearths the antecedents influencing customers' choice of a specific media to meet their wants [40]. UGT expresses the functionalist viewpoint on mass media communication, which holds that media consumers actively select the media that best suits their needs and goals rather than being passive consumers [41]. UGT has been widely applied to online activities such as e-shopping, its diverse audience, and its motives for media consumption. UGT has been used to analyze online activities, including the reasons and satisfactions that customers seek out, and it has been applied to a variety of media formats [42]. UGT is utilized to investigate adoption and continuance intention in online shopping, audience motives, and satisfaction in accessing online content. This theory has been instrumental in understanding the impact of various mediums on consumer behavior [43,44]. It reveals how users' characteristics, cognitive, social integrative, personal integrative, and hedonic benefits, influence their participation. This theory also explores the psychological factors driving individuals to seek various forms of gratification, thereby enhancing the overall user experience [45,46], highlights the impact of internet activity on socializing, usefulness, and personal fulfillment. It also delves into the effect of advice, information seeking, and social utility on political environments and voting behavior.

The scholars used UGT to predict the pitfalls of smartphone usage by teenagers [47]. UGT enfolds motivations behind fitness app use, revealing users seek specific gratifications based on platform-based motivations and autonomy. In emergencies like the COVID-19 pandemic, the theory has been applied to analyze the effects of traits like narcissism, time perspective, virtual presence, and hedonic gratification on individuals' disclosure behaviors [48,49]. Understanding consumer behavior—particularly impulsive buying—requires the use of UGT. It facilitates comprehension of the connection between personal attitudes, surfing habits, perceived stimuli, and impulsive purchases in online retail settings. The scholars have also integrated other theories like Stimulus-Organism-Response (S-O-R) with UGT to investigate how gamification affects user happiness and engagement [50,51]. The UGT has been utilized to study customer behavior and gratitude in social commerce settings, focusing on specific gratifications [52,53]. This understanding of user motivations has led to the development of models capturing relationships between gratification, attitudes, learning performance, and intention to use specific applications [54]. UGT theory offers a comprehensive understanding of consumer motivations in the e-commerce industry, highlighting how social and psychological needs influence interactions with online platforms. This theory can enhance the effectiveness of strategies and offerings in the e-commerce industry.

3. Factors influencing consumer behavior for online shopping

E-commerce platforms' strategic business decisions significantly influence consumer interactions and market competition, necessitating a deep understanding of consumer behavior and preferences to effectively tailor their strategies [55]. Consumer perception significantly influences their online shopping choices, with factors like credibility, word of mouth, brand image, and online reviews shaping their behavior. The theory of consumption values helps understand these driving forces [56]. Customers' perceptions are greatly influenced by e-commerce platforms, which in turn affect their purchasing decisions. Trust is built on the provision of transparent communication, privacy protection, and service assurances. Purchase decisions may be impacted by problems like deceptive advertising and delayed deliveries [57,58]. The influence of excessive information on buy motivation and return intents underscores the need of comprehending customer perception when it comes to online purchasing [42]. In this context, Wang *et al.,* [59] emphasized the impact of security and economic capacities on consumers' cognitive processes while formulating promotional strategies. The consumers like to see live videos before they intend to buy. Therefore, online shopping outlets enhance customer engagement [60,61]. Discount pricing is another strategic decision taken by e-commerce platforms to attract the customers and influence their buying process [62]. OSPs conducts Innovative product promotion activities to influence consumers' emotions and thought processes for shaping their attitudes and actions [63].

The positive impact of interactive e-commerce platforms on consumer shopping experiences reflects the importance of user-friendly interfaces and engaging features. Given the notable surge in usage of smartphones (even in rural areas) for online shopping, responsiveness of the service providers is crucial in providing enduring customer shopping experience [33]. UGT emphasizes the importance of user behavior on online platforms, focusing on three types of satisfaction: emotive, convenient, and functional. A seamless user experience evokes positive feelings, motivating consumers to use the site again and strengthening their intention to stay [43]. In e-commerce, research suggests that user satisfaction is significantly influenced by payment options. Users engage with platforms to satisfy specific needs like convenience, entertainment, or information. Convenient payment options simplify the purchasing process, reduce friction, and enhance user experience, aligning with perceived ease of use, a concept often combined with the Technology Acceptance Model (TAM) and UGT theory in online commerce studies [64]. Users seek specific gratifications, which can be enhanced by providing accessible features like screen readers and customizable interfaces. These accessibility options contribute to a more efficient and socially satisfying shopping experience [65,66].

Product availability and diversity play crucial role in shaping customer behavior and happiness in a range of sectors [67]. Another critical factor is comprehension of consumer preferences and motivations, allowing companies to create search features that are quick and straightforward while meeting users' requirements for gratification. This improves user experience and happiness on online platforms [43,68]. In order to retain and satisfy customers, the gratification Theory highlights the significance of simple return policies in e-commerce. Customers are more likely to plan to keep buying when this idea satisfies their needs for comfort and confidence. According to research on consumers' intentions to keep buying, return policies' simplicity of use has a big impact on their behavior and loyalty [43]. The study of [69] recognized the implication of social connections, usability, and high-quality information for understanding consumers' buying decision. Online platforms cater to users' diverse needs, such as information, entertainment, social interaction, and self-expression. By providing detailed product information, these platforms enhance user satisfaction and engagement. The gratifications derived from accessing these platforms are closely linked to the content available, ensuring users seek fulfilment in terms of information, entertainment, or social interaction [70-72].

Security and gratification theories are intertwined in e-commerce, promoting a secure and gratifying shopping experience. By protecting user data and privacy, platforms enhance trust, satisfaction, and loyalty. Moreover, catering to user gratifications through personalized offerings deepens customer engagement, drives repeat purchases, ensures market competitiveness and maintaining brand competitiveness [73,74]. Gratification towards online shopping also depends on product classification on online marketplaces. This strategy adheres to the theory's tenets by guaranteeing precise and consistent product details. Online platforms improve user experience and happiness by offering recommendations on how to get nutritional information and standardize costs. By meeting informational demands, this strategy enhances the online platform user experience [75,76]. The Gratification theory emphasizes the importance of an intuitive interface in an online platform, enhancing user satisfaction and engagement. A simple, easy-to-understand interface is crucial for a wide range of users, especially those with visual impairments, as it reduces the learning curve and improves navigation. Incorporating diverse search filters in e-commerce platforms enhances user experience and satisfaction. These filters, including price range, brand, size, color, and customer ratings, provide a personalized shopping experience, meeting modern consumer expectations [74,77,78]. Gratification underscores the importance of accurate order fulfillment for customer satisfaction and loyalty. It involves efficiently processing orders, selecting correct items, securely packing, and delivering them promptly, influencing consumer behavior and purchase intentions [43,72]. Gratification theory highlights the importance of intact delivery in e-commerce platforms, highlighting the role of user gratification, immersion, and product involvement in shaping consumer behavior. This theory underscores the significance of understanding consumer gratification in enhancing customer satisfaction and loyalty [79]. Customer satisfaction is significantly influenced by timely delivery in e-commerce platforms, which offer a convenient and efficient shopping experience. Optimizing delivery processes to reduce missed deliveries is crucial for enhancing customer satisfaction in e-commerce [80,81].

4. Materials and Method

In this section we delineate the formulation of the comparison matrix (i.e., alternatives and criteria), respondents' profile and methodological steps.

4.1. Criteria description

Based on the past studies, in this paper we consider a set of criteria (Table 1) to compare the OSPs. The selection of criteria is grounded on UGT.

4.2. Alternatives

The present paper identifies five popular OSPs from E-commerce industry for comparison purpose. These five OSPs are identified considering views of several websites and through informal discussion with a focus group of 30 customers who frequently do online shopping. The list of alternatives (i.e., OSPs) is mentioned in Table 2.

Table 1
Description of the criteria

S/L	Criteria	Description	Desired goal
C1	Credibility and image	Trustworthiness of the OSP, social image and reviews by users	Maximize
C2	Customer relationship management	Responsiveness to the queries, after sales support	Maximize
C3	Order Fulfilment	Sufficiency of the product items	Maximize
C4	Quality of delivery	Reliable product delivery on time with right item and packaging	Maximize
C5	Data security and privacy	Confidentiality of the information and reliable platform	Maximize
C6	Price	Higher price than the actual worth of the product	Minimize
C7	Product/service quality	Features and performance of the products/service experience	Maximize
C8	Discounts and offers	Promotional offers and discount pricing	Maximize
C9	Accessibility and interoperability	Accessibility of the app through any device (smartphone, laptop etc.)	Maximize
C10	Ease of payment	Easy way to pay the requisite amount and availability of a lot of options	Maximize
C11	Difficulty in return	Difficulty in returning unwanted and damaged or poor	Minimize
C12	Product variety and Availability	Availability of a wide range of products	Maximize
C13	User-friendly interface and search	Easy access and navigation, variety of search filters	Maximize
C14	Convenience in shopping	Shopping is possible anytime, anywhere	Maximize
C15	Product details	Detailed product information, categorization	Maximize
C16	Interactive App Interface and features	Immersive experience, features, fast operation	Maximize
C17	Information availability	Availability of detailed information	Maximize

Table 2
List of online shopping platforms

S/L	Name of the platform	S/L	Name of the platform
A1	Amazon	A4	India Mart
A2	Flipkart	A5	Snapdeal
A3	Myntra		

4.3. Research administration and respondents' profile

The current study could organize a cohort of 262 respondents who are using OSPs for at least two years and are well-versed with E-commerce. The respondents were approached as per convenience and using snow ball mechanism. Initially, we approached 350+ respondents but 298 of them took part in the study. After obtaining the responses, we checked for missing values. Finally, we recognized 262 valid and complete responses. The responses were obtained both using online and offline process. The respondents were requested to rank the criteria and rate the alternatives subject to their performance based on the criteria. The rating of the alternatives was done on a scale of 1 to 5 (Table 3). Respondents' profile is given in Table 4.

Table 3
Description of the rating scale

Value	Linguistic description
1	Very Bad
2	Bad
3	Fair
4	Good
5	Very Good

Table 4
Respondent profile

Classifier	Numbers	Classifier	Numbers
Gender		Qualification	
Male	122	Below graduation	5
Female	139	Graduation	131
Others	1	Post-graduation	126
Total	262	Total	262
Experience of use		Profession	
2 to 3 years	5	Service	142
3 to 4 years	89	Business	80
4 to 5 years	90	Self-employed	39
More than 5 years	78	Others	1
Total	262	Total	262

4.4. Proposed methodology

The present work uses several methods to develop a novel decision-making framework. In what follows are the methodological steps described under different stages.

Stage 1. Calculation of criteria weights using Borda count-CIMAS-approach (BCC) with modified reliability index

Step 1.1. Obtain the ranking of the criteria by the respondents

Let, $C_j\,(j=1,2,...,n)$ represents the set of criteria and $r_{j(k)}$ is the rank ($r_{j(k)}=1,2,..,n$) of the j^{th} criterion as voted by the $k^{th}(k=1,2,...,k)$ respondent.

The next two steps are related to Borda count method [28].

Step 1.2. Obtain the rank-based score of the criteria for each respondent

According to Borda count method, the criterion with $r_{j(k)}=1$ is the most significant one and is followed by the remaining ($n-1$) criteria. Hence, the most significant criterion obtains the rank-based score $s(r_{j(k)})\big|_{r_{j(k)}=1}=(n-1)$. In the similar manner, the rank-based scores for all criteria are obtained corresponding to the opinion of each respondent.

Step 1.3. Aggregate the opinions of the respondents and obtain the Borda count score of the criteria

The Borda count score of the criteria are obtained as

$$s_j = \sum_{k=1}^{k} s(r_{j(k)}) \in [0, k(n-1)] \tag{1}$$

Now we use the steps of the CIMAS method [29] to determine the criteria weights.

Step 1.4. Rating of the respondents

The respondents are assigned with relative priorities based on their experience. Suppose, φ_k is the weight of the k^{th} respondent.

Step 1.5. Formation of the input data matrix (IDM)

Combining the rank-based scores of the criteria, obtained by using the ranking given by $E_k(k = 1, 2, .., k)$ respondents, the input data matrix is formulated as follows.

$$\begin{array}{c} \\ E_1 \\ E_2 \\ \ldots \\ E_k \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \ldots\ldots \; \ldots\ldots\ldots\ldots & C_n \end{array} \\ \begin{pmatrix} s(r_{1(1)}) & s(r_{2(1)}) & \ldots & s(r_{n(1)}) \\ s(r_{1(2)}) & s(r_{2(2)}) & \ldots & s(r_{n(2)}) \\ \ldots & \ldots & \ldots & \ldots \\ s(r_{1(k)}) & s(r_{2(k)}) & \ldots & s(r_{n(k)}) \end{pmatrix}_{k \times n} \end{array} \tag{2}$$

Step 1.6. Normalization of IDM

Using the linear sum-based normalization scheme, IDM is normalized (NIDM) as per equation (3) given below.

$$s^*(r_{j(k)}) = \frac{s(r_{j(k)})}{s_j} \tag{3}$$

Step 1.7. Formulate weighted NIDM

The weighted NIDM is found by multiplying each element of NIDM with corresponding respondent's weight. Accordingly, the elements of the weighted NIDM are found as

$$v_{j(k)} = s^*(r_{j(k)})\varphi_k;\; j = 1, 2, ..n; k = 1, 2, ..., k \tag{4}$$

Step 1.8. Identify the reference points (maximum and minimum values) for each criterion in NIDM

The maximum and minimum values for each criterion C_j are obtained as

$$v_j^+ = \max_k (v_{j(k)});\; j = 1, 2, ..., n \tag{5}$$

$$v_j^- = \min_k (v_{j(k)});\; j = 1, 2, ..., n \tag{6}$$

Step 1.9. Obtain the difference between maximum and minimum values

At this step, CIMAS method seeks to find the range of values for each criterion as follows.

$$\Delta_j = (v_j^+ - v_j^-);\; j = 1, 2, ..., n \tag{7}$$

Step 1.10. Determine the importance of each criterion

The criterion importance indicates the weight of the corresponding criterion. CIMAS method argues that the criterion with a higher proportional range value is the significant one. Therefore, criterion importance score is calculated as

$$I_j = \frac{\Delta_j}{\sum_{j=1}^{n} \Delta_j} \tag{8}$$

Step 1.11. Obtain the reliability index

As per the classical CIMAS method, the respondents are supposed to once again rate the criteria on a percentage scale (1 to 100) such that the sum of rating = 100%. Let, the rating for the j^{th} criterion is denoted as p_j. Then, the reliability index (RI) is computed as

$$RI = \frac{\sum_{j=1}^{n} \left| I_j \times 100 - p_j \right|}{100} \tag{9}$$

The developers [29] recommended the value of RI < 0.1 to consider the reliability of the calculated weights.

At this step, the present study infuses an innovative approach. we use the procedural steps of LBWA method [82] and FUCOM [83] to obtain the weights (ω_j) of the criteria based on rating of the criteria (on a scale 1 to 5). We select these methods as they require only $(n-1)$ number of pairwise comparisons. We use the values of aggregated rating of the criteria as input to LBWA and FUCOM and recalculate the weights (ω_j). Then we compute the modified RI as follows.

$$RI^* = \sum_{j=1}^{n} \left| I_j - \omega_j \right| \tag{10}$$

If $RI^* < 0.1$ then we consider the calculated weight (by BCC) reliable.

Stage 2. Calculation of criteria weights using modified preference selection index method with multiple normalization (MNMPSI)

At this stage, we further extend the modified preference selection index (MPSI) method [21] with multiple normalizations. The scholars advocated for using multiple normalizations to avoid the effect of selection of a particular scheme on the final outcome and for true representation of the decision matrix [29,84]. In this study, we use a unique combination of vector normalization and non-linear statistical normalization using z-score and sigmoid function [85]. To obtain the final normalized values, Heron mean (HM) is applied for integrating two normalization approaches. HM offers a unique approach using both arithmetic (sum) and geometric (product) operations [86]. In what follows are the computational steps.

Step 2.1. Formulation of the decision matrix

Let, $A_i (i = 1, 2, ..., m)$ are the alternatives to be compared subject to their performance with respect to the criteria $C_j (j = 1, 2, ..., n)$. The performance values are obtained by aggregating the rating of the alternatives (subject to each criterion) given by the respondents $E_k (k = 1, 2, ..., k).$ Let, $x_{ij(k)}$ is the rating (on a Likert scale 1 to 5) of i^{th} alternative subject to j^{th} criterion, opined by the respondent E_k. Then, the elements of the decision matrix (DM) are obtained as

$$x_{ij} = \frac{1}{k} \sum_{k=1}^{k} \varphi_k x_{ij(k)} \tag{11}$$

Accordingly, DM looks like

$$X = \begin{pmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{pmatrix}_{m \times n} \tag{12}$$

Step 2.2. Normalization of the decision matrix

The normalized decision matrix (NDM) is formulated as under.

Step 2.2(a). Normalization 1. Vector normalization

The first scheme is applying the vector normalization [87]. Vector normalization has been used in several MCDM applications [20,22,88] and it shows lesser dependency on the extreme values [89,90]. The elements of NDM using vector normalization [90,91] are obtained by using Eq. (13) as below.

$$\eta_{ij(1)} = \begin{cases} \dfrac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}; \; j \in B \\ 1 - \dfrac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}; \; j \in NB \end{cases} \tag{13}$$

Step 2.2(b). Normalization 2. Non-linear normalization using z-score and sigmoid function

At this step, we use sigmoid function (Sgm(Z)) that converts Z-score values to (0, 1). Use of z-score and then Sgm(Z) allows the decision-maker to have a NDM without containing any negative or zero value while putting reward to the performing alternatives [85]. The elements of NDM are derived as

$$\eta_{ij(2)} = \frac{1}{1+e^{-3Z_{ij}}} \tag{14}$$

Here, $$\underset{\substack{i=1,2,..,m \\ j=1,2,...,n}}{Z_{ij}} = \frac{x_{ij} - \overline{x_j}}{\sigma_j} = \frac{x_{ij} - \overline{x_j}}{\sqrt{\frac{1}{m}\sum_{i=1}^{m}\left(x_{ij} - \overline{x_j}\right)^2}}; \overline{x_j} = \frac{1}{m}\sum_{i=1}^{m} x_{ij} \tag{15}$$

Step 2.2(c). Aggregated final normalization

At this step, two normalizations, Eq. (13) and Eq. (14), are aggregated by using HM as follows

$$\eta_{ij} = (1-\xi)\sqrt{\eta_{ij(1)}\eta_{ij(2)}} + \xi \frac{\eta_{ij(1)} + \eta_{ij(2)}}{2} \tag{16}$$

Here, ξ is a coefficient that helps to integrate two normalizations while providing a flexibility in selecting a varying level of influence of two schemes and provides an opportunity to examine the sensitivity of the outcome to normalization for checking the stability of the result.

Stage 3. Calculation of criteria weights using MNMPSI

Following the steps of [21] we find out the criteria weights from the decision matrix. This paper uses multiple normalization (using two step normalization as stated at step 2.2, Eq. (13) to Eq. (16). The steps to calculate criteria weights are described below.

Step 3.1. Find out the average of normalized performance values for each criterion

The average values are obtained as

$$\overline{\eta_j} = \frac{1}{m}\sum_{i=1}^{m} \eta_{ij}; \; j = 1, 2...n \tag{17}$$

Step 3.2. Obtain the preference variation values for the criteria

The preference variation values are computed as

$$\gamma_j = \sum_{i=1}^{m} (\eta_{ij} - \overline{\eta_j})^2; \; j = 1, 2, ...n \tag{18}$$

Step 3.3. Compute criteria weights

The criteria weights are calculated as under

$$\varpi_j = \frac{\gamma_j}{\sum_{j=1}^{n} \gamma_j}; \varpi_j \geq 0; \sum \varpi_j = 1 \tag{19}$$

Stage 4. Final calculation of criteria weights by integrating BCC and MNMPSI methods

By using Bayesian logic [92,93] we aggregate the calculated weights by applying BCC (I_j) and MNMPSI (ϖ_j) methods. The final weights of the criteria are obtained as follows

$$w_j = \frac{I_j \varpi_j}{\sum_{j=1}^{n} I_j \varpi_j}; w_j > 0; \sum_{j=1}^{n} w_j = 1 \tag{20}$$

Stage 5. Ranking of the alternatives by using RAM with multiple normalizations

This is the final stage where we use the normalized decision matrix (Eq. (16)) and weights of the criteria (Eq. (20)) to determine the appraisal scores (ψ_i) of the alternatives by following the procedural steps of RAM [23]. The developers of RAM used a sum-based linear normalization scheme. The present work provides an innovative extension of RAM with multiple normalization. The steps are given below.

Step 5.1. Formulate the weighted NDM

The weighted NDM (WNDM) is formulated by multiplying each element of NDM (Eq. (16)) with corresponding criteria weights (Eq. (20)). Thus, the elements of WNDM are obtained as

$$\upsilon_{ij} = \eta_{ij} w_j \tag{21}$$

Step 5.2. Obtain the total weighted normalized scores of beneficial and non-beneficial criteria for each alternative

The total weighted normalized score of i^{th} alternative corresponding to beneficial and non-beneficial criteria is computed as

$$\psi_i^+ = \sum_{j=1}^{n} \upsilon_{+ij}; j \in B \tag{22}$$

$$\psi_i^- = \sum_{j=1}^{n} \upsilon_{-ij}; j \in NB \tag{23}$$

Step 5.3. Find the overall appraisal scores of the alternatives

The overall appraisal scores are computed as follows.

$$\psi_i = \left(2 + \psi_i^+\right)^{\frac{1}{\left(2+\psi_i^-\right)}} \tag{24}$$

Decision rule: The higher is the value of ψ_i, the preferred is the corresponding alternative.

The steps of the research methodology are depicted in the flow diagram (Figure 1).

5. Findings

In this section we exhibit key findings of data analysis. The responses were obtained through online and offline interactions. The responses were obtained for two purposes such as ranking of the criteria and rating of the alternatives (on a scale 1 to 5) subject to the effect of the criteria. The responses are given in the supplementary file (Table S1 and S2) for the readers.

In what follows are the step-by-step major findings of the data analysis. Based on the ranking of the criteria, we find rank-based scores of the criteria using Borda count method (step 1.2). Now, we calculate the Borda count scores of the criteria (step 1.3) using Eq. (1). Table 5 provides the Borda count scores of the criteria.

Next, we assign weights to the respondents as per their priorities (step 1.4). The weights are assigned in terms of rating of the respondents on a scale 1 to 4 (Table 6). The rating of the respondents is done based on their experience in using online shopping. We did not consider any respondent with experience less than two years. Table S3 (supplementary file) provides the rating of the respondents.

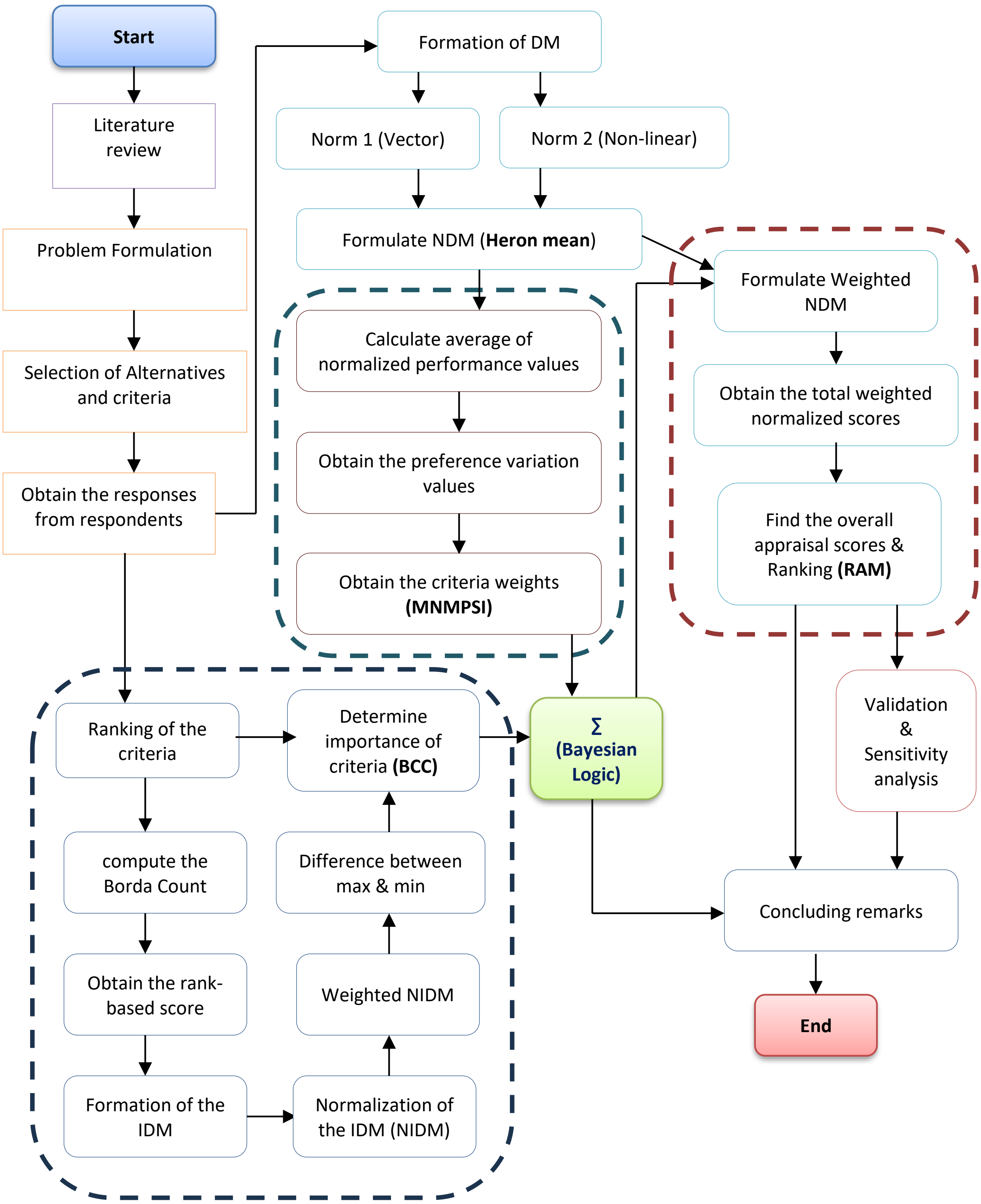

Fig. 1. Flow diagram of research methodology

Then, we formulate IDM using the rank-based scores (step 1.5 and Eq. (2)) given in Table S4 (supplementary file). After that we normalize IDM (step 1.6) to obtain the NIDM (Eq. (3)). Next, the elements of NIDM are multiplied with the priority weight values of the respondents (Eq. (4)). The weighted NIDM (step 1.7) is given in the supplementary file (Table S5). Now, we find the reference points (maximum and minimum values) for all criteria (step 1.8). Using Eq. (5) and Eq. (6) we obtain the reference points given in Table 7.

Table 5
Calculated Borda count scores of the criteria

Criteria	C1	C2	C3	C4	C5	C6	C7	C8	C9
Borda count score	3012	2991	2863	2772	2632	2461	2309	2170	1991
Criteria	C10	C11	C12	C13	C14	C15	C16	C17	
Borda count score	1890	1745	1535	1438	1362	1446	1484	1446	

Table 6
Rating of the respondents

Years of experience	Rating
2 to 3 years	1
3 to 4 years	2
4 to 5 years	3
More than 5 years	4

Table 7
Maximum and minimum values for the criteria

Criteria/ Reference points	C1	C2	C3	C4	C5	C6	C7	C8	C9
v_j^+	0.0212	0.0214	0.0224	0.0231	0.0243	0.0244	0.0260	0.0276	0.0321
v_j^-	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Criteria/ Reference points	C10	C11	C12	C13	C14	C15	C16	C17	
v_j^+	0.0317	0.0367	0.0417	0.0445	0.0470	0.0443	0.0431	0.0443	
v_j^-	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	

Next, by using Eq. (7) and Eq. (8) (step 1.9 and step 1.10) criteria importance (i.e., weights of the criteria) are calculated (Table 8). After that, we move on to examine the reliability of the calculated weights at step 1.11. We use aggregated rating values of the criteria to recalculate the weights by using LBWA and FUCOM methods. Then, by using Eq. (10) we calculate the modified RI scores (Table 9). It is seen that RI scores are well within the prescribed reference value. Hence, BCC method provides a reliable calculation of criteria weights.

Table 8
Calculated criteria importance (weights) using BCC method

Criteria	C1	C2	C3	C4	C5	C6	C7	C8	C9
Δ_j	0.0212	0.0214	0.0224	0.0231	0.0243	0.0244	0.0260	0.0276	0.0321
I_j	0.0382	0.0385	0.0402	0.0415	0.0437	0.0439	0.0468	0.0497	0.0578
Criteria	C10	C11	C12	C13	C14	C15	C16	C17	
Δ_j	0.0317	0.0367	0.0417	0.0445	0.0470	0.0443	0.0431	0.0443	
I_j	0.0571	0.0660	0.0750	0.0801	0.0845	0.0796	0.0776	0.0796	

Table 9
Calculation of reliability index

Approach	Modified RI
BCC and LBWA	$RI^*=0.0632 < 0.1$
BCC and FUCOM	$RI^*=0.011 < 0.1$

Now, we proceed to stage 2 to calculate criteria weights using MNMPSI approach. Using Table S2 (rating of the alternatives) and Table S3 (rating of the respondents) as given in the supplementary file, we first formulate the decision matrix (DM) by applying Eq. (11) (step 2.1). Accordingly, the decision matrix is given in Table 10.

Table 10
Decision matrix for comparison of alternatives

Criteria/ Alternative	C1	C2	C3	C4	C5	C6	C7	C8	C9
A1	12.752	11.733	12.790	12.763	13.256	8.172	12.603	11.779	12.107
A2	11.847	13.191	12.248	12.084	13.065	8.523	11.958	13.469	12.641
A3	8.046	13.084	9.019	8.603	10.458	12.931	9.160	10.359	8.985
A4	7.656	10.042	8.481	7.977	10.370	11.519	8.557	6.149	8.412
A5	7.943	7.412	8.885	8.424	5.908	12.198	8.889	5.698	8.927
Criteria/ Alternative	C10	C11	C12	C13	C14	C15	C16	C17	
A1	11.580	10.248	11.977	11.664	12.519	8.874	11.935	8.939	
A2	11.179	8.725	13.275	12.095	11.664	13.141	13.427	8.641	
A3	8.580	11.584	10.214	12.176	9.027	8.905	13.248	9.172	
A4	8.107	11.603	5.943	8.546	8.302	8.370	8.511	9.252	
A5	8.164	11.672	5.737	8.950	8.634	8.324	7.370	9.198	

It may be noted that criteria C6 and C11 are non-beneficial in nature. Now, we proceed for normalization of the decision matrix (step 2.2). Using Eq. (13) to Eq. (15) we obtain two different types of normalization (Tables 11 and 12). After that, we apply Eq. (16) to combine vector and non-linear normalizations to arrive at the final normalized decision matrix (NDM) as given in Table 13. The value for the coefficient ξ is set to 0.5 for the initial case [21].

Table 11
Normalized decision matrix (Vector normalization)

Criteria/ Alternative	C1	C2	C3	C4	C5	C6	C7	C8	C9
A1	0.576	0.464	0.547	0.561	0.542	0.663	0.543	0.528	0.522
A2	0.536	0.522	0.524	0.531	0.534	0.649	0.516	0.604	0.545
A3	0.364	0.518	0.386	0.378	0.428	0.467	0.395	0.464	0.388
A4	0.346	0.397	0.363	0.351	0.424	0.525	0.369	0.276	0.363
A5	0.359	0.293	0.380	0.370	0.242	0.497	0.383	0.255	0.385
Criteria/ Alternative	C10	C11	C12	C13	C14	C15	C16	C17	
A1	0.537	0.577	0.540	0.483	0.550	0.409	0.477	0.442	
A2	0.518	0.640	0.598	0.501	0.513	0.606	0.537	0.427	
A3	0.398	0.522	0.460	0.504	0.397	0.411	0.530	0.454	
A4	0.376	0.521	0.268	0.354	0.365	0.386	0.340	0.458	
A5	0.379	0.518	0.259	0.370	0.379	0.384	0.295	0.455	

Table 12
Normalized decision matrix (Non-linear normalization)

Criteria/ Alternative	C1	C2	C3	C4	C5	C6	C7	C8	C9
A1	0.986	0.708	0.983	0.984	0.952	0.021	0.985	0.903	0.960
A2	0.953	0.948	0.961	0.958	0.941	0.036	0.955	0.980	0.983
A3	0.100	0.940	0.113	0.117	0.457	0.970	0.130	0.700	0.112
A4	0.061	0.189	0.050	0.050	0.432	0.787	0.049	0.037	0.046
A5	0.088	0.006	0.093	0.092	0.005	0.913	0.085	0.024	0.103
Criteria/ Alternative	C10	C11	C12	C13	C14	C15	C16	C17	
A1	0.983	0.206	0.922	0.863	0.987	0.256	0.777	0.207	
A2	0.963	0.005	0.977	0.934	0.945	0.997	0.954	0.005	
A3	0.136	0.894	0.682	0.943	0.148	0.266	0.944	0.851	
A4	0.059	0.899	0.033	0.018	0.047	0.131	0.054	0.943	
A5	0.065	0.914	0.027	0.037	0.081	0.122	0.014	0.890	

Table 13
Final normalized decision matrix ($\xi = 0.5$)

Criteria/ Alternative	C1	C2	C3	C4	C5	C6	C7	C8	C9
A1	0.768	0.580	0.750	0.758	0.733	0.230	0.748	0.703	0.725
A2	0.729	0.719	0.726	0.729	0.723	0.247	0.718	0.780	0.748
A3	0.211	0.713	0.229	0.229	0.442	0.696	0.245	0.576	0.229
A4	0.174	0.284	0.171	0.166	0.428	0.649	0.172	0.129	0.167
A5	0.201	0.096	0.212	0.208	0.079	0.689	0.207	0.109	0.221
Criteria/ Alternative	C10	C11	C12	C13	C14	C15	C16	C17	
A1	0.743	0.368	0.718	0.659	0.753	0.328	0.618	0.313	
A2	0.723	0.189	0.776	0.700	0.713	0.790	0.731	0.131	
A3	0.250	0.695	0.566	0.706	0.258	0.334	0.722	0.637	
A4	0.183	0.697	0.122	0.132	0.168	0.242	0.166	0.678	
A5	0.190	0.702	0.113	0.160	0.203	0.235	0.110	0.654	

Moving forward to stage 3 (step 3.1 to 3.3), we determine the criteria weights using MNMPSI method (Eq. (17) to Eq. (19)). Table 14 provides calculated weights using MNMPSI method.

Table 14
Calculation of criteria weights (MNMPSI)

Criteria	C1	C2	C3	C4	C5	C6	C7	C8	C9
γ_j	0.3686	0.3078	0.3440	0.3558	0.2882	0.2334	0.3344	0.4079	0.3406
ϖ_j	0.0673	0.0562	0.0628	0.0650	0.0526	0.0426	0.0611	0.0745	0.0622
Criteria	C10	C11	C12	C13	C14	C15	C16	C17	
γ_j	0.3346	0.2273	0.4124	0.3545	0.3333	0.2126	0.3757	0.2436	
ϖ_j	0.0611	0.0415	0.0753	0.0648	0.0609	0.0388	0.0686	0.0445	

Next, we apply Bayesian logic (Eq. (20)) to find out the final weights of the criteria (stage 4) as given in Table 15.

Table 15
Final criteria weights (combining BCC and MNMPSI)

Criteria	C1	C2	C3	C4	C5	C6	C7	C8	C9
w_j	0.0440	0.0370	0.0432	0.0462	0.0394	0.0320	0.0488	0.0634	0.0615
Criteria	C10	C11	C12	C13	C14	C15	C16	C17	
w_j	0.0597	0.0468	0.0966	0.0887	0.0880	0.0529	0.0911	0.0606	

It is observed that product availability and variety (C12), interactive app interface and features (C16), user-friendly interface and search (C13), convenience in shopping (C14) and discounts and offers (C8) hold the higher preferences. The next task is to rank the online shopping platforms using RAM with multiple normalizations (stage 5). To this end, first we obtain the weighted normalized decision matrix (WNDM) by using Eq. (21) (step 5.1) given in Table 16.

Table 16
Weighted normalized decision matrix

Criteria/ Alternative	C1	C2	C3	C4	C5	C6	C7	C8	C9
A1	0.034	0.021	0.032	0.035	0.029	0.007	0.037	0.045	0.045
A2	0.032	0.027	0.031	0.034	0.028	0.008	0.035	0.049	0.046
A3	0.009	0.026	0.010	0.011	0.017	0.022	0.012	0.037	0.014
A4	0.008	0.011	0.007	0.008	0.017	0.021	0.008	0.008	0.010
A5	0.009	0.004	0.009	0.010	0.003	0.022	0.010	0.007	0.014
Criteria/ Alternative	C10	C11	C12	C13	C14	C15	C16	C17	
A1	0.044	0.017	0.069	0.058	0.066	0.017	0.056	0.019	
A2	0.043	0.009	0.075	0.062	0.063	0.042	0.067	0.008	
A3	0.015	0.033	0.055	0.063	0.023	0.018	0.066	0.039	
A4	0.011	0.033	0.012	0.012	0.015	0.013	0.015	0.041	
A5	0.011	0.033	0.011	0.014	0.018	0.012	0.010	0.040	

Next, by using Eq. (22) to Eq. (24) (stage 5.2 and stage 5.3) we derive the final appraisal scores of the alternatives and rank them (Table 17). We notice that leading e-commerce giants like Flipkart (A2) and Amazon (A1) perform at the top.

Table 17
Appraisal scores and ranking of the alternatives

Alternative	ψ_i^+	ψ_i^-	ψ_i	Rank (RAM)
A1	0.6083	0.0246	1.6056	2
A2	0.6422	0.0168	1.6189	1
A3	0.4130	0.0548	1.5353	3
A4	0.1952	0.0534	1.4665	4
A5	0.1813	0.0549	1.4616	5

5.1. Comparison with other MCDM models

MCDM models often are constrained by variability of outcome because of changes in various underlying assumptions like criteria and alternative set, selection of normalization scheme, criteria weights and others [94,95]. To ascertain the reliability of the outcome, the extant literature [96-98] demonstrated the use of comparative analysis of ranking results of several MCDM models. In this work, we carry out a comparison of our proposed method (RAM with multiple normalizations) with various other MCDM models like SAW, MABAC, CRADIS, COPRAS, and PIV. Then, we carry out

Spearman's Rank correlation test (SRCT) to examine statistical significance of their correlations. Table 18 exhibits the result of SRCT while Figure 2 depicts the ranking of the alternatives obtained by using different MCDM models including RAM. It is observed that our model maintains statistically significant and high correlation with all other methods.

Table 18
Comparison of MCDM models: Spearman's rank correlation test

Method	SAW	MABAC	CRADIS	COPRAS	PIV
RAM (with multiple normalization)	1.000*	1.000*	1.000*	1.000*	0.9*

(*Significant at 0.05 level, two-tailed)

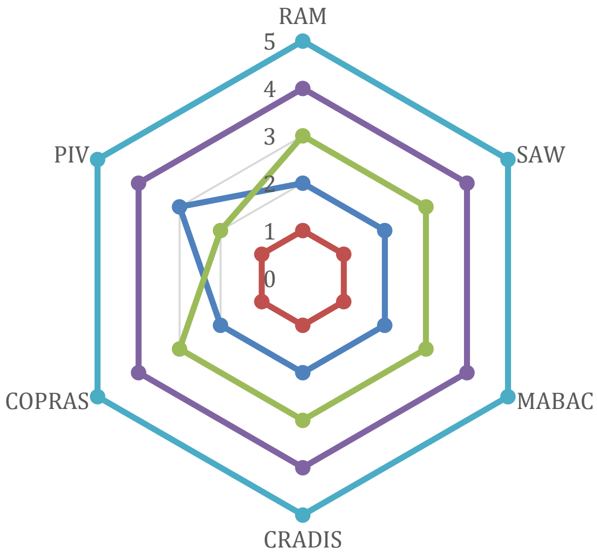

Fig. 2. Comparison of MCDM models for ranking of alternatives

5.2. Sensitivity analysis

Many a times MCDM models suffer from the issue of instability of the ranking result because of changes in the values of the parameters used in aggregation and/or model construction, inclusion/exclusion of criteria and alternative set, changes in criteria weights, use of different normalization schemes and various other reasons [99-102]. Sensitivity analysis is conducted to figure out the sensitivity of the final outcome to the changes in the underlying conditions [103-105]. In this work, we change the coefficient value (ξ) to simulate several experimental cases and rank the alternatives under such cases (Table 19). Table 20 exhibits the appraisal scores of the alternatives under various experimental cases. Figures 3 and 4 showcase the result of sensitivity analysis (ranking of the alternatives under various experimental cases) which confirms that our approach provides a stable result.

Table 19
Ranking of alternatives under experimental cases (sensitivity analysis)

Cases	Initial	Exp 1	Exp 2	Exp 3	Exp 4	Exp 5	Exp 6	Exp 7	Exp 8
Aggr. Coeff/ Alternatives	$\xi = 0.5$	$\xi = 0.1$	$\xi = 0.2$	$\xi = 0.3$	$\xi = 0.4$	$\xi = 0.6$	$\xi = 0.7$	$\xi = 0.8$	$\xi = 0.9$
A1	2	2	2	2	2	2	2	2	2
A2	1	1	1	1	1	1	1	1	1
A3	3	3	3	3	3	3	3	3	3
A4	4	4	4	4	4	4	4	4	4
A5	5	5	5	5	5	5	5	5	5

Table 20
Appraisal scores of alternatives under experimental cases (sensitivity analysis)

Cases	Initial	Exp 1	Exp 2	Exp 3	Exp 4	Exp 5	Exp 6	Exp 7	Exp 8
Aggr. Coeff/ Alternatives	$\xi = 0.5$	$\xi = 0.1$	$\xi = 0.2$	$\xi = 0.3$	$\xi = 0.4$	$\xi = 0.6$	$\xi = 0.7$	$\xi = 0.8$	$\xi = 0.9$
A1	1.6011	1.5973	1.5983	1.5992	1.6002	1.6020	1.6030	1.6039	1.6049
A2	1.6149	1.6102	1.6114	1.6126	1.6137	1.6160	1.6171	1.6183	1.6194
A3	1.5262	1.5235	1.5241	1.5248	1.5255	1.5269	1.5276	1.5282	1.5289
A4	1.4611	1.4541	1.4558	1.4576	1.4593	1.4628	1.4646	1.4664	1.4682
A5	1.4557	1.4485	1.4503	1.4521	1.4539	1.4575	1.4593	1.4611	1.4629

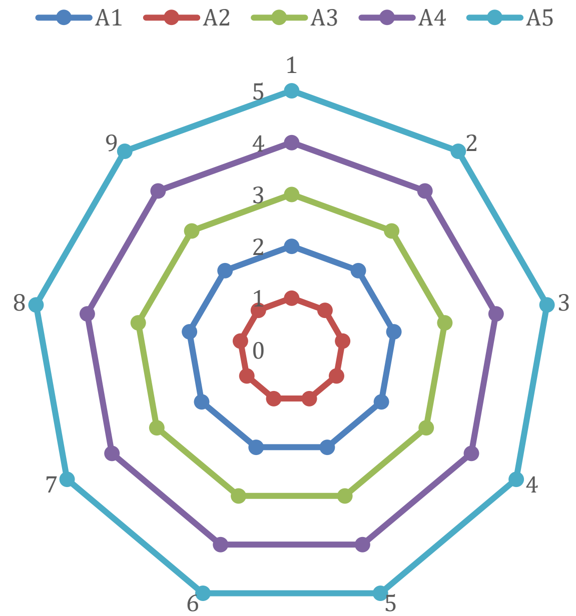

Fig. 3. Ranking of alternatives for different experimental cases (sensitivity analysis)

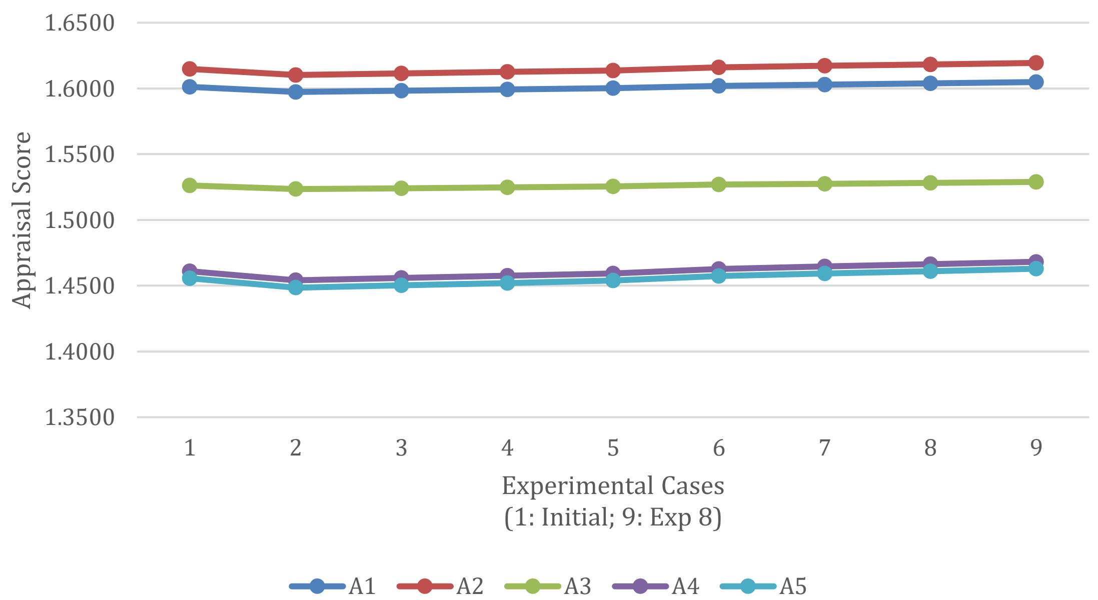

Fig. 4. Appraisal scores of the alternatives for different experimental cases (sensitivity analysis)

5.3. Rank reversal test

Due to unforeseen changes in the assumptions behind MCDM models, sometimes variations in the initial ranking order are noticed. This phenomenon is known as rank reversal (RR). Therefore, for a reliable outcome, MCDM models must not suffer from any RR phenomenon [106]. In this work, we make experimentation of step wise removal of alternatives and examine the ranking order of the rest (Table 21). It is observed that there is no RR phenomenon.

Table 21
Result of rank reversal test

Experimental case	Ranking order
Initial case (all alternatives)	$A_2 \succ A_1 \succ A_3 \succ A_4 \succ A_5$
Case 1 (removal of A_2)	$A_1 \succ A_3 \succ A_4 \succ A_5$
Case 2 (removal of A_2, A_1)	$A_3 \succ A_4 \succ A_5$
Case 3 (removal of A_2, A_1, A_3)	$A_4 \succ A_5$
Case 4 (removal of A_2, A_1, A_3, A_4)	A_5

6. Discussion

The present study provides a comprehensive analysis of OSPs using an innovative MCDM framework. The study reveals a number of interesting findings. Overall, experience of use (interactive app interface and features (C16), user-friendly interface and search (C13), convenience in shopping (C14)), economies of scope (product availability and variety (C12)) and economic benefits (discounts and offers (C8)) emerge as prominent influencer of selection of OSPs. Taking all these findings together, it may be contended that customers want variety, convenience, quality service and memorable shopping experience with economic benefits. It is evident that the finding is in tune with the philosophy of UGT. The finding provides a significant impetus to strategic decision-making for the firms to improve their promotional efforts and better position their platforms in a competitive market.

From the ranking it is observed that Flipkart (A2) and Amazon (A1) perform at the top. It is interesting to note that A1 performed well than its closest competitor A2 for most of the criteria (10 out of 17 criteria), yet stands second. A2 beats A1 with respect to its performance based on seven criteria such as C2, C6, C8, C9, C12, C15 and C16. However, the differences in performance values are much higher for these criteria. The results show that A2 provides superior customer service at an affordable price with a lot of discounts and offers and product variety. The app provides an immersive experience to the customers. The findings reinstate the need to focus on affordability, variety, transparency, service quality and creating long lasting customer experience. Essentially, the ranking result reflects the cornerstones of UGT.

The present work demonstrates notable methodological advances. It showcases innovative application of Bayesian logic to integrate two different perspectives of calculating criteria weights. It integrates MNMPSI (calculates criteria weights based on performance rating of the alternatives obtained from the decision-matrix) and BCC methods (compute the weights using voting/ranking of the criteria and rating of the decision-makers) with Heron mean to provide a reliable approach. Use of two normalizations enhances the dependability of the framework enabling a more detailed understanding of how various factors affect consumers' decisions. Further, use of the concept of root value to determine the ranking of the alternatives (RAM) helps to delineate the best performers while penalizing the effect of non-beneficial criteria. The methodology used in this paper provides a reliable analysis in a group decision making scenario yet not resorting to uncertain modelling that adds computational complexities.

In a nutshell, the present research has far-reaching implications across managerial, social, and technical domains. By leveraging these insights, stakeholders can enhance decision-making processes, improve consumer experiences, and drive innovation in the e-commerce sector. The study not only contributes to academic literature but also provides practical guidance for managers and policymakers aiming to navigate the complexities of the digital marketplace.

However, there are several scopes for further extensions. First, it may be a useful extension of the proposed methodology with fuzzy, rough or grey numbers to capture the subjective bias. Since, this work involves a large group size, the extension may be useful for complex decision-making problems. Secondly, alongside MCDM based analysis, formulation and testing of statistical hypotheses may also be thought of. Thirdly, the current work has not considered any causal analysis. Based on the findings of the present work, a causal model can be developed and examined to unveil the effect of dominant criteria on selection of OSPs. Thereafter, the impact of those criteria on buying decisions using the OSPs can be examined. Fourthly, a mixed lens of UGT and other relevant theories like CX, UX and self-determination theories can also be designed to address the stated problem. Fifth, the present work uses a quantitative analysis. In a future research, one can design a mixed methodology by incorporating qualitative statements of the users. In that case, a comparative study of quantitative and qualitative can be made. Seventh, a diverse geographical and demographic respondent profile may also be interviewed vis-à-vis the current problem. In addition, external factors like economic conditions, cultural differences, or technological advancements may also be included. Acknowledging these factors could provide a more comprehensive understanding of the dynamics at play. Eighth, it may be interesting to examine the impact of technology on the selection of OSPs. Ninth, sustainability and ethical considerations are subdued in the present work. In a future study those aspects may also be included.

7. Conclusion

The current study provides notable contributions in the field of MCDM by developing a novel framework of group decision-making to compare popular OSPs in the E-commerce industry. The present paper provides a novel integration of Borda count and CIMAS models for determining criteria weights based on ranking and experience of the decision-makers. The present study showcases a new application of Borda count in determining criteria weights other than aggregation of various results or preferences. The study offers a novel extension of MPSI method by using double normalizations integrated by Heron mean. By doing so, the proposed method enables to have true representation of the decision matrix for determinization of criteria weights. The use of Bayesian logic to combine the ranking and rating based weight calculations further enhances the comprehensibility and dependability of the model. The ongoing work further enhances the usability and robustness of RAM by using two normalizations. The case study presented in this work addresses a topical issue of comparison of OSPs. The present work compares five popular OSPs in India on the basis of 17 criteria indicating the perception and intention of the users. The application of UGT provides a comprehensive theoretical ground for criteria selection. The analysis highlights a number of notable observations. It is seen that affordability, variety, transparency, service quality and customer experience stand as order winning criteria for the OSPs. The results indicate the dominance of two E-commerce giant Flipkart and Amazon as popular choices. The sensitivity analysis proves the stability of MCDM framework while comparison of several models confirms the reliability of the outcome. This innovative approach not only addresses the complexities of decision-making in a competitive online environment but also emphasizes the collaborative nature of consumer preferences through a group decision-making lens.

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Conflicts of Interest
The authors declare no conflicts of interest.

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