



Large-Scale Group Decision-Making Using Analytical Hierarchy Process Based on Bayesian Best Worst Method

Necip Fazıl Karakurt¹ · Gülşah Şahin² · İsmail Buğra Bölükbaşı³ · Esra İlbarhar² · Selcuk Cebi^{2,4}

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Abstract

The most commonly used pairwise comparison method in the literature is the Analytic Hierarchy Process (AHP), with the Best Worst Method (BWM) proposed as an alternative. Both methods can be effectively used in studies with a small number of decision-makers. However, in cases where the number of participants increases, the consistency and applicability of the surveys can sharply decrease. In some instances, it has been observed that the consistency in AHP is considered acceptable up to 10%. In BWM, the Bayesian Best Worst Method (BBWM) is used to address outliers. Therefore, this study aims to address Pairwise Comparison Matrices (PCMs) in multi-criteria decision-making (MCDM) challenges in large group settings by employing an innovative adaptation of BBWM integrated with the AHP. The proposed method starts with the BWM survey, which offers practical comparison opportunities, and then transitions to the AHP matrix. The weights obtained from PCMs show the importance levels of the best and worst criteria in comparison to the other criteria. Normally, these two weights should be consistent, but when they differ, it indicates the indecisiveness of the decision-maker. In both approaches, this indecisiveness is reflected as inconsistency in the matrix, and such evaluations may be disregarded. To prevent this loss of information, in our study, the weights derived from these two PCMs are treated as fuzzy ranges, and fuzzy operations are applied to consider the decision-maker's indecisiveness in producing the final results. The proposed method was applied in the evaluation of mobile shopping applications. The data collected through surveys with 113 users were analyzed using the proposed method, and the rankings of the mobile applications were determined. The obtained rankings were compared with BBWM results to validate the model.

Keywords Large-scale group decision-making · Bayesian best worst method · Analytic hierarchy process · Mobile application features evaluation

1 Introduction

Large-Scale Group Decision-Making (LSGDM) is a process that a large number of individuals or organizations make a joint decision to achieve a goal. Such decisions are often complex, and multi-criteria, requiring a balance between different perspectives (Palomares et al. 2014; Tang et al. 2020; Garcia-Zamora et al. 2022). In this context, LSGDM has become an increasingly important research area in recent years, particularly due to its relevance in real-world large-scale and collaborative decision problems. It is characterized by the participation of a substantial number of decision makers, which amplifies challenges such as handling inconsistent judgments, integrating diverse opinions, and ensuring computational feasibility (Liu et al. 2016; Labella et al. 2018). To address these challenges, several Multi-Criteria Decision-Making (MCDM) methods have been adapted and applied within LSGDM contexts. The Analytic Hierarchy Process (AHP) is a widely used and well-established method for solving multi-criteria decision-making (MCDM) problems by structuring decision criteria into a hierarchical framework and deriving feature weights through pairwise comparisons. However, in large group settings, traditional AHP can struggle to accommodate the variability and subjectivity inherent in human judgment. Pairwise comparison matrices (PCMs) derived from diverse decision-makers often exhibit inconsistencies, leading to challenges in extracting reliable weight estimates. This highlights the need for methodologies capable of managing uncertainty and capturing the collective wisdom of large decision-making groups (Saaty 1977; Olson 1988; Ishizaka and Labib 2009).

The Best Worst Method (BWM) is a relatively new approach in MCDM that has been developed in order to overcome the problems of conventional pairwise comparison methods. In BWM, the information collected from the decision-maker is in the form of identifying the best criterion and the worst criterion. Pairwise comparisons are then made between these two criteria and the other criteria in the decision set. In this way, a minimax optimization problem is defined and solved in order to assess the criteria's weights, and the same procedure is used for the assessment of the alternatives' weights with regard to each criterion. In terms of the number of comparisons needed, this method is quite effective and thus useful in the decision-making process. These enhancements make BWM a viable solution for MCDM problems, especially where the consistency of the results is important. However, like other MCDM methods, BWM is still vulnerable to the effects of outliers or extreme preferences. Outliers or extreme judgments may affect the reliability of the results even if decision-makers are informed about the importance of consistent comparisons. Moreover, the method assumes that the best and worst criteria are easy to determine, which may not always be the case in real-world decision problems, particularly when the problem is complex and dependent on subjective preferences (Rezaei 2015, 2016; Guo and Zhao 2017).

Unlike conventional methods, the Bayesian Best–Worst Method (BBWM) considers variability and enables adaptation to large decision-making groups by handling inconsistent or extreme data points from a probabilistic perspective. This probabilistic framework allows uncertainty to be incorporated directly into the decision-making process (Mohammadi and Rezaei 2020). Decision-making in multi-criteria contexts

often becomes increasingly complex as the number of decision-makers and criteria grows. This complexity is particularly evident in domains such as mobile application development, where features must be evaluated not only for their technical feasibility but also for their perceived value by diverse user groups. LSGDM methods are therefore essential for synthesizing diverse preferences into reliable and comprehensive decision outcomes. Evaluating the effectiveness of mobile applications is inherently a multi-criteria problem, and relying on a small number of participants may not adequately capture the diversity of user preferences. However, conducting large-scale studies using traditional pairwise comparison methods such as AHP and BWM becomes challenging due to the high number of comparisons required. For this reason, this study proposes a novel approach that integrates BBWM with AHP to address these challenges. BBWM is utilized for its efficiency in eliciting consistent judgments by focusing on the best and worst criteria identified by each decision-maker, while AHP contributes a structured pairwise comparison framework. In this integrated approach, two distinct comparison matrices—based on “best” and “worst” evaluations—are constructed and incorporated into a fuzzy modeling framework to capture decision-makers’ uncertainty and indecisiveness.

While AHP allows criteria to be structured hierarchically, BBWM enables weight calculation with fewer inputs, improving consistency and reducing participant fatigue. The combined method also decreases the cognitive load on respondents and simplifies computations for analysts, resulting in an efficient and scalable framework for large-group, multi-criteria decision-making problems such as the evaluation of mobile applications.

The methodological framework of this study begins with collecting judgments from 113 participants regarding four features of mobile sales applications. Each participant’s responses were used to calculate BBWM-derived feature weights, which were then employed to construct PCMs for AHP. To further enhance the reliability of the decision model, each matrix element was normalized relative to either the best or worst feature, resulting in two distinct PCMs. The input-based consistency methodology was employed in order to eliminate inconsistent BBWM expert surveys. Interval weights were calculated for each feature, representing the upper and lower bounds of their importance. These intervals provide a nuanced understanding of feature priorities, accounting for the inherent uncertainty in participant judgments. In this way, this study contributes to the growing body of research on LSGDM by demonstrating the practical application of advanced MCDM techniques in digital platform evaluation. Furthermore, it emphasizes the importance of incorporating uncertainty into decision-making processes, particularly in contexts involving large and diverse participant groups.

The remainder of this paper is structured as follows: Sect. 2 reviews the relevant literature on BBWM, AHP, and LSGDM methodologies and identifies existing research gaps. Section 3 details the proposed hybrid framework. Section 4 presents the application of the proposed framework, including problem definition, data collection, AHPBBWM analysis, comparative analysis with BBWM, and the results and discussion. Finally, Sect. 5 concludes the study by summarizing the main findings, discussing limitations, and suggesting directions for future research.

2 Literature Review

A significant body of research has recently emerged in the field of LSGDM, which concerns the process of decision-making by a large number of participants. The relevant literature on LSGDM is discussed in Sect. 2.

In Sect. 2.2 the fundamental principles of the AHP and significant studies in the literature regarding the development processes of this method have been examined. In Sect. 2.3, the developments on the BWM are analyzed, and the studies in the literature are discussed in this context. Sect. 2.4 indicates the research on the integration of AHP and BWM methods, and gaps in the literature were discussed.

2.1 Large-Scale Group Decision Making

LSGDM represents a specific category of group decision-making issues, characterized by the involvement of a substantial number of participants in the decision-making process (Liu et al. 2016; Labella et al. 2018)). This setting renders the aggregation of opinions considerably more complex than in traditional small-group decision-making (Garcia-Zamora et al. 2022). In the context of LSGDM events, members of the general public frequently assume a decision-making role (Ding et al. 2024). The limited expertise of these participants often results in assessments that are heterogeneous, ambiguous, and sometimes inconsistent. This causes further complications in the process of obtaining a consensus (Liu et al. 2024). Although the complexities introduced by LSGDM, the literature review reveals the use of several MCDM methods in LSGDM. Some of the MCDM methods used in these processes include the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) (Lourenzutti and Krohling 2016; Song and Li 2019; Mahmoudi et al. 2021; Li 2023; Huang et al. 2024; Li et al. 2024; Wang et al. 2025), AHP (Duleba and Szádoczki 2022; Zhang and Meng 2022; Ágoston et al. 2024; Yu et al. 2025), BWM (Haseli et al. 2021; Heidary-Dahooie et al. 2022; Zhou et al. 2023; Zhang et al. 2024), the Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE) (Han et al. 2025; Ma et al. 2026), PROMETHEE II (Liu et al. 2016; Guo et al. 2021), Multi-Objective Optimization on the basis of a Ratio Analysis plus the full MULTIpllicative form (MULTIMOORA) (Liu et al. 2019; Xiao et al. 2022; Bai et al. 2024; Zhang et al. 2024), Elimination and Choice Translating Reality III (ELECTRE III) (Xiao et al. 2020; Wang et al. 2024; Zhou et al. 2025), RANKing COMparison (RANCOM) (Wieçkowski et al. 2025), VIšekriterijumsko KOmpromisno Rangiranje (VIKOR) (Li et al. 2025), Tomada de Decisão Interativa Multicritério (TODIM) (Chu et al. 2024; Wu et al. 2024; Wang et al. 2025), the Decision Making Trial and Evaluation Laboratory (DEMATEL) (Schulze-Gonzalez et al. 2023; Chen et al. 2023; Du and Shen 2024) and so on. A review of decision-making studies reveals that AHP is one of the most frequently employed methods (Kahraman et al. 2023; Ashour and Mahdiyar 2024; Salehzadeh and Ziaecian 2024; Kriswardhana et al. 2025). In contrast, as seen in the literature review, LSGDM studies demonstrate that AHP is one of the least preferred methods, a consequence of the difficulties that arise when it is applied to large groups.

2.2 AHP Methodology and Historical Developments

AHP is a MCDM methodology introduced by Thomas Saaty in the 1970s (Saaty 1977). A review of the existing literature reveals that the AHP method is widely used by decision-makers and researchers in various contexts (Darko et al. 2019; Liu et al. 2020; Castelló-Sirvent et al. 2022). The fundamental logic of the AHP method involves the establishment of a hierarchical structure, which is initiated by the identification of the main criteria, sub-criteria, and alternatives for a specified purpose. Then, the decision-makers (field experts) make pairwise comparisons according to 9-level scales, assuming that the elements at each level of the hierarchy are independent of each other (Saaty 1990; Kahraman 2018). In the early 1980s, researchers developed fuzzy logic-based AHP approaches in response to the limitations of the classical AHP method in modeling decisions involving uncertainty and subjectivity (Kahraman 2018; Castelló-Sirvent et al. 2022). The purpose of this development was to enhance the effectiveness of the comparison process in dealing with uncertainties. In this context, the first study on the fuzzy AHP method was conducted by Van Laarhoven and Pedrycz (1983). The method in question is based on an approach where calculations are performed using triangular fuzzy numbers. Buckley (1985) developed the geometric mean method for measuring the consistency of fuzzy matrices and calculating criteria weights. Chang (1996) proposed the extended analysis method, a version of the AHP method that makes use of triangular fuzzy numbers. Xu and Liao (2014) applied the intuitionistic fuzzy AHP method to a case study of global supplier development. Unlike other fuzzy AHP methods, this method considers membership, non-membership, and hesitancy values in its calculations. Kahraman et al. (2014) explained that Type-1 fuzzy sets are limited due to the lack of uncertainty in membership functions, and Type-2 fuzzy sets offer the ability to handle the uncertainties in membership functions within the framework of fuzzy set theory. Therefore, they developed an AHP method based on interval type-2 fuzzy sets and applied the proposed method to a supplier selection problem. Abdel-Basset et al. (2017) employed the neutrosophic AHP to address definitive judgments due to insufficient information or disagreements among group decisions. For this purpose, they used triangular neutrosophic numbers in AHP, which have three independent parameters: truth, indeterminacy, and falsity. Each parameter is valued between 0 and 1, and their total can range between 0 and 3, enabling a more flexible modeling of uncertainty and contradictory situations. Ilbahar et al. (2018) introduced the Pythagorean Fuzzy Risk Assessment method, integrating Fine Kinney, the Pythagorean fuzzy AHP, and a fuzzy inference system to evaluate the risks associated with excavation activities at a construction site. Kutlu Gündoğdu and Kahraman (2020) enhanced the classical AHP by developing the spherical fuzzy AHP (SF-AHP) method, illustrating its applicability and validity via a renewable energy site selection case study and a comparative analysis of neutrosophic AHP and SF-AHP. Camci et al. (2022) proposed Fermatean Fuzzy Set (FFS) based AHP, which is a type of q-rung orthopair fuzzy set with $q = 3$. This provided experts with greater flexibility in decision-making and demonstrated its application to a real supplier selection problem in the transition to Industry 4.0. Cebi et al. (2023) proposed the Decomposed Fuzzy AHP (DF-AHP) method in their study in the pharmaceutical industry, integrating Decomposed Fuzzy

Set (DFS) to enhance the reliability of pairwise comparisons in AHP. This method considers the optimistic and pessimistic perspectives of decision-makers and incorporates their individual responses to reciprocal questions under conditions of vagueness and impreciseness, thereby making pairwise comparisons more reliable.

2.3 BWM Methodology and Historical Developments

In the BWM proposed by Rezaei (2015), the best and worst criteria are determined by the decision-makers, and the advantages of the best criterion over all other criteria and the advantages of other criteria over the worst criterion are evaluated. The weights of the alternatives according to different criteria are then obtained using the same process. Compared to other MCDM methods, BWM produces simpler, more accurate, and more consistent results because it obtains the result with fewer pairwise comparisons (Rezaei 2015). Shortly following the aforementioned introduction, Rezaei (2016) proceeded to expand the theoretical underpinnings of BWM. In this study, a linear formula for BWM was proposed to replace the original non-linear formulation. When the number of criteria becomes relatively large, it is recommended to group the criteria into clusters and introduce an additional hierarchical level in the decision structure. For instance, when the number of criteria exceeds nine, the official Best–Worst Method (BWM) solver documentation suggests partitioning the criteria into meaningful subsets and evaluating each subset separately before aggregating the global weights (Rezaei 2017). Afterwards, as the process of decision-making frequently necessitates the involvement of multiple experts, the BWM model has been adapted to encompass group decision-making settings. BBWM was introduced by Mohammadi and Rezaei (2020) to calculate the weight distribution of each participant in the group decision-making process, as well as an aggregated final distribution that reflects the preferences of all participants. In their study, Kazemitash et al. (2021) discussed the integration of rough set theory with the BWM. In the subsequent stages of its development, BWM began to be integrated with other MCDM methods. This tendency is indicative of an emergent awareness that the amalgamation of BWM's efficient weighting capability with the strengths of alternative approaches could enhance the robustness and applicability of decisions across diverse contexts. In their study, You et al. (2017) used BWM and the TOPSIS by hybridizing them. In the study, BWM was used to determine the weights of the criteria, while TOPSIS was used to rank the alternatives. The integrated BWM-Vlsekriterijumska Optimizacija I Kompromisno Resenje (VIKOR) method was proposed in the study by Garg and Sharma (2020). Zolfani et al. (2020) proposed the BWM-Multi-Attributive Ideal-Real Comparative Analysis (MAIRCA) model, which is an integrated Multiple-Attribute Decision- Making (MADM) model. Then, BWM has been used by integrating with many fuzzy sets. Some of these are: hesitate fuzzy sets (Ali and Rashid 2019), triangular fuzzy numbers (Karimi et al. 2020; Moslem et al. 2020b; Dong et al. 2021), interval valued numbers (Qu et al. 2021), trapezoidal interval type-2 fuzzy sets (Wan et al. 2021; Alimohammadlou and Sharifian 2023), intuitionistic fuzzy sets (Mou et al. 2016; Cheng and Chen 2024), Z-number (Aboutorab et al. 2018; Zhang et al. 2023), interval valued intuitionistic fuzzy sets (Dong and Wan 2024). By combining the Fuzzy Inference System (FIS) with BWM, Torbati and Sayadi (2018) suggested

a fuzzy expert model. Criteria weights were determined using BWM, then alternative evaluation and ranking were carried out employing FIS. Khanmohammadi et al. (2019) presented a fuzzy BWM that includes a novel method for obtaining weight vectors from fuzzy pair comparison matrices. It involves solving the nonlinear optimization model and then extracting crisp weights from fuzzy pairs. This allows more consistency to be achieved with fewer comparisons. A two-stage model consisting of BWM and type-2 fuzzy TOPSIS techniques was presented by Yucesan et al. (2019). In their study, Karakurt et al. (2021) combined expert opinions using Borda count and arithmetic mean techniques, and they employed fuzzy BWM.

2.4 Studies Using Integrated AHP and BWM Methodology and Research Gaps

In the literature there are several studies in which AHP and BWM have been employed concomitantly. Ajrina et al. (2018) aimed to evaluate the potential suitable areas for mining in Kediri Regency. In this regard, the researchers obtained results by applying the AHP and the BWM methods separately. Moslem et al. (2020a) adopted an integrated AHP-BWM approach to analyze and categorize significant driver behavior factors related to road safety. Due to the challenges associated with implementing AHP in large-scale problems, AHP was used for 4×4 and smaller matrices, while BWM was used for 5×5 and larger matrices. Akbari et al. (2021) integrated AHP and BWM methods to generate maps of groundwater potential recharge in Iran's Sarakhs Plain. 10 criteria were defined in the study. In order to facilitate a comparative analysis of the areas and numbers of wells in different groundwater potential recharge areas, the results of the methods were presented separately. Bathrinath et al. (2022) used a variety of techniques to identify sustainability risks in their study, and they then used AHP to rank these risks. After that, the AHP results were verified using BWM. Foroozesh et al. (2022) evaluated the development sustainability of Taraj city in Iran. Accordingly, criteria and sub-criteria were determined with various methods, then they were weighted with Group Fuzzy BWM and AHP methods. Then, the results of the two methods were evaluated comparatively and it was revealed that both of them determined the employment criterion as the most important criterion. In their studies, Sharma et al. (2022) applied various methods and revealed 28 lean supply chain enablers (LSCEs), which they categorized into five groups. Subsequently, the weights of the criteria were determined by applying AHP and BWM separately in order to ascertain the priority weights and to rank the LSCEs. The calculation of the global weight and the final prioritization of the LSCEs was then conducted. Badi et al. (2023) used BWM and AHP in an integrated manner in their study. The objective of the study was to assess the most suitable site for the establishment of a wind farm. Initially, the criteria weights were determined using BWM, followed by AHP. The final weight values used in the study were then calculated based on these results. The study, conducted by Tan et al. (2023), was concerned with the rational expansion of *P. notoginseng* cultivation areas and agricultural layout planning in Yunnan Province, China. Accordingly, the study determined the criteria and sub-criteria weights for the evaluation of ecological suitability. These were obtained through the separate application of the AHP and BWM, and then, the results were compared. Should an investigation be conducted on the utilization of BBWM and AHP in unison, the

advent of ship automation systems constituted the foundational basis for the study carried out by Xiang et al. (2024). In accordance with the aforementioned points, BBWM establishes the ideal weights for all layers and permits the comparison of elements within each layer. The system reliability index, the variables that affect it, and the relative significance weights between units are all determined using AHP. The calculated optimal weights are then transformed into allocation factors.

When the studies in the literature where AHP and BWM are used together are examined, it is seen that they are generally used for comparison purposes. In a few studies, a hybrid method is used by combining the weights found separately with the two methods to obtain a common weight. In a mentioned study, a hybrid method of using BWM for small groups and AHP for large groups has been put forward. However, to the best of our knowledge, no information has been collected using the BWM survey, and its solution has been carried out with AHP. It can be said that there is a deficiency in the literature on this subject. In BWM, excessive variation in decision-maker ratings can have a significant impact on overall outcomes. BBWM addresses the uncertainty and inconsistency inherent in decision-maker responses by employing a probability-based framework, thereby ensuring more balanced outcomes (Mohammadi and Rezaei 2020). Studies using BBWM and AHP together in a way that takes these problems into account are quite few and such a hybrid use has not been encountered. Considering the necessity of making pairwise comparisons for each parameter in AHP applications, AHP applications become difficult in cases where the number of decision-makers is high. As the number of participants increases, the surveys become more difficult to complete, and the consistency of the results decreases significantly. For this reason, when examining the literature, it can be seen that AHP applications are carried out with fewer expert opinions, and some examples of studies are presented in Table 1. Accordingly, there is a deficiency in the literature in terms of the ability to use the AHP method for LSGDM.

3 Proposed Methodology

The proposed methodology combines AHP and BWM. AHP, developed by Thomas L. Saaty in the 1970s, is a widely used decision-making tool for complex problems involving multiple criteria, where subjective judgments are needed to rank alternatives. By integrating both qualitative and quantitative analyses, AHP helps decision-makers prioritize options systematically. It employs pairwise comparisons to evaluate the relative importance of criteria, and consistency is checked using the consistency ratio (CR), with 0.1 as the common threshold (Saaty 1977, 1980, 1990).

Table 1 Number of experts in some of the AHP studies in the literature

References	Expert number
Kutlu Gündoğdu and Kahraman (2020)	3
Büyüközkan et al. (2021)	4
Camci et al. (2022)	3
Cebi et al. (2023)	3
Ayyildiz et al. (2023)	5
Dağıdır and Özkan (2024)	5

However, AHP has drawbacks in LSGDM. As the number of criteria and alternatives increases, the exponential growth of pairwise comparisons makes the process time-consuming and cognitively demanding. Moreover, results can become unstable when small input changes occur. To address these limitations, Jafar Rezaei developed BWM in 2015 (Rezaei 2015). BWM reduces the number of comparisons by focusing only on the best and worst criteria, thereby enhancing consistency and avoiding redundancy (Rezaei 2016). Nevertheless, BWM also faces challenges: it assumes independence among criteria and may still be cumbersome in large-scale problems. In group settings, reaching consensus on best and worst criteria can be difficult.

The proposed method proceeds through a series of structured steps. Initially, the decision problem is defined, and the hierarchical framework including the goal, criteria, and alternatives is established. Once the hierarchy is constructed, two parallel workflows are executed to derive and validate the weights. The overall workflow of the proposed methodology is presented in Fig. 1. In the BBWM workflow, expert evaluations are obtained through pairwise comparisons between the best and worst criteria using the BBWM. These weights are subsequently verified through internal consistency analysis to ensure their robustness and reliability. In the AHPBBWM workflow, pairwise comparison matrices are developed in accordance with the AHP. Eigenvector and consistency calculations are performed, after which fuzzy weights are generated to capture uncertainty in expert opinions. These fuzzy weights are aggregated with the criteria and alternative weights, then defuzzified and normalized to obtain the final AHPBBWM weights. Finally, the results of both workflows are compared and validated to ensure coherence and methodological soundness. This integrated approach combines the hierarchical rigor and consistency analysis of AHP with the efficiency and reduced comparison burden of BBWM, while fuzzy modeling enhances the method's ability to address uncertainty and ambiguity in decision-making.

The detailed steps of the proposed methodology given by Fig. 1 are as follows:

Step 1. Define the Problem and Structure the Hierarchy: The decision problem is structured into a hierarchical framework. The hierarchy starts with the main goal at the top, followed by criteria, sub-criteria, and alternatives at the lower levels.

Step 2. Select the Best and Worst Criteria: The decision-maker selects the most important criterion (the "best" criterion, denoted as C_B) and the least important criterion (the "worst" criterion, denoted as C_W) for each hierarchy. The best and worst criteria are chosen based on their importance relative to the goal of the decision-making problem.

Step 3. Pairwise Comparison of the Best Criterion with Other Criteria:

The decision-makers perform pairwise comparisons between the best criterion (C_B) and each of the other criteria. These comparisons are made using a scale (e.g., 1 to 9) reflecting the relative importance of $[C_B]$ compared to (C_j) . The relative importance of the C_B to any other C_j criteria is denoted as $a_{B,j}$ (Eq. (1)).

$$a_{B,j} = [a_{B1} \ a_{B2} \ \dots \ a_{Bj}] \quad (1)$$

The values $a_{B,j}$ are typically between 1 and 9 (e.g., 1 if C_B and C_j are equally important, 9 if C_B is extremely more important than C_j).

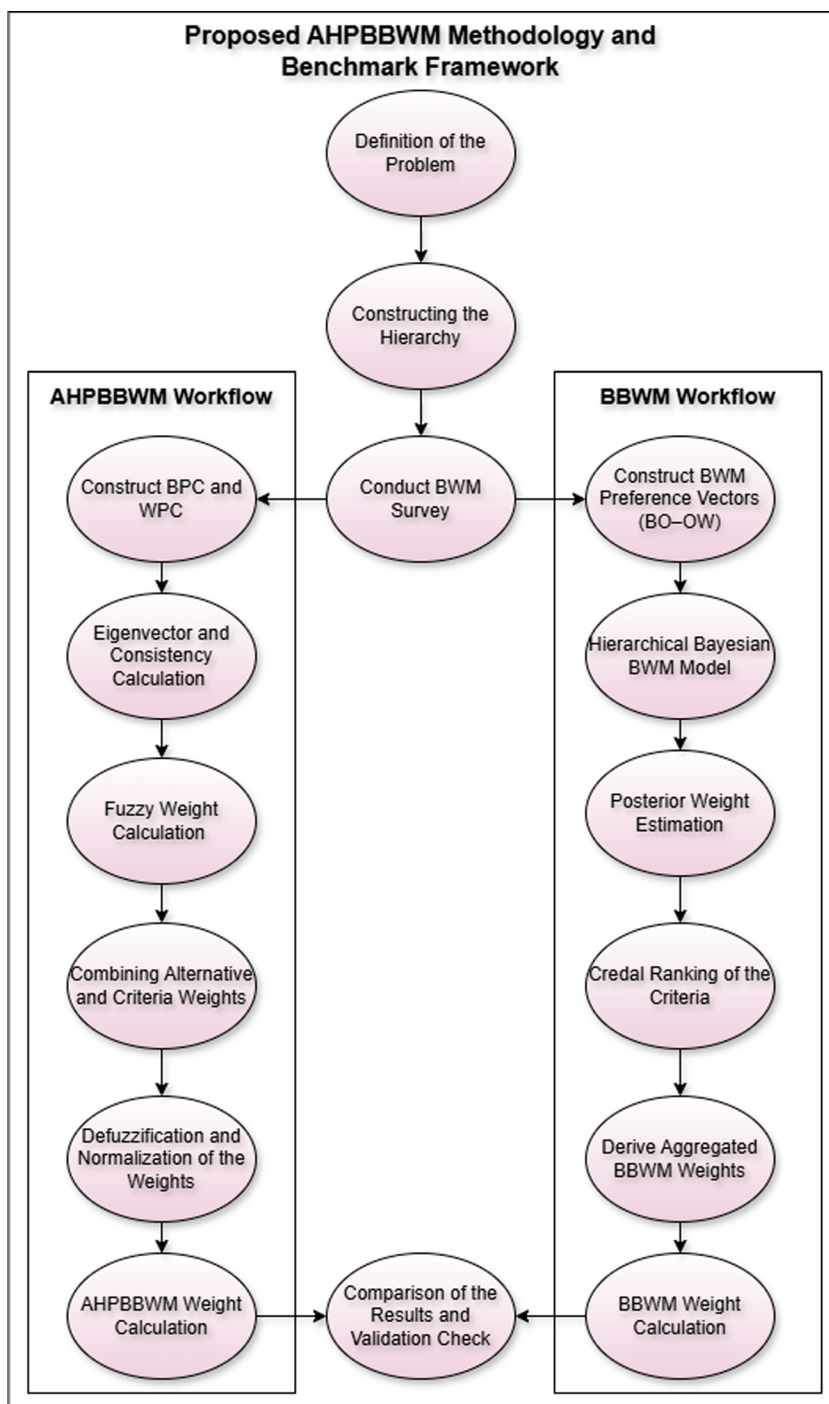


Fig. 1 Flowchart of the proposed AHPBBWM methodology and benchmark BBWM framework

Step 4. Pairwise Comparison of the Other Criteria with Worst Criteria: Similarly, the decision-makers perform pairwise comparisons between the worst criterion (C_W) and each of the other criteria for each hierarchy. The relative importance of the criterion (C_j) compared to the worst criterion (C_W) is denoted by a_{jW} (Eq. (2)).

$$a_{jW} = [a_{1W} \ a_{2W} \ \dots \ a_{jW}] \quad (2)$$

Step 5. Construct the Best Pairwise Comparison Matrix: For each level of the hierarchy, Best Pairwise Comparison (BPC) matrices are constructed to evaluate their relative importance or preference of criteria, as described in Eq. (3). In this matrix, for $1 \leq m \leq j$, the m^{th} row represents the level of importance of criterion $j = m$ (C_m) relative to the other criteria (C_j). While determining the elements of the m^{th} row, the relative importance degrees of the criterion C_m with respect to all criteria C_j are obtained by dividing each element of the a_{Bj} vector by the value of a_{Bm} , respectively. The underlying rationale is that the ratios of a_{Bj} relative to the a_{Bm} value provide a_{mj} , which represents the relative importance of C_m with respect to each C_j .

$$\text{BPC} = \begin{bmatrix} \frac{a_{B1}}{a_{B1}} & \frac{a_{B2}}{a_{B1}} & \dots & \frac{a_{Bj}}{a_{B1}} \\ \frac{a_{B1}}{a_{B2}} & \frac{a_{B2}}{a_{B2}} & \dots & \frac{a_{Bj}}{a_{B2}} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{a_{B1}}{a_{Bj}} & \frac{a_{B2}}{a_{Bj}} & \dots & \frac{a_{Bj}}{a_{Bj}} \end{bmatrix} \quad (3)$$

Step 6. Construct Worst Pairwise Comparison Matrix: For each level of the hierarchy, the Worst Pairwise Comparison (WPC) matrices are constructed to evaluate the relative importance or preference of the criteria, as defined in Eq. (4). In this matrix, for $1 \leq m \leq j$, the m^{th} row represents the importance level of the $j = m$ criterion C_m relative to the other criteria C_j . To calculate the elements of the m^{th} row, the importance degree of C_m relative to C_W is obtained by dividing a_{mW} by a_{jW} vector, which represents the relative importance degrees of all C_j criteria with respect to C_W . The rationale here is that the relative importance degrees derived from the ratio of a_{mW} to the a_{jW} vector yield the a_{mj} vector, which constitutes the m^{th} row of the WPC matrix.

$$\text{WPC} = \begin{bmatrix} \frac{a_{1W}}{a_{1W}} & \frac{a_{2W}}{a_{1W}} & \dots & \frac{a_{jW}}{a_{1W}} \\ \frac{a_{1W}}{a_{2W}} & \frac{a_{2W}}{a_{2W}} & \dots & \frac{a_{jW}}{a_{2W}} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{a_{jW}}{a_{1W}} & \frac{a_{jW}}{a_{2W}} & \dots & \frac{a_{jW}}{a_{jW}} \end{bmatrix} \quad (4)$$

Step 7. Calculate the Eigenvector: In this step, the normalized eigenvector is calculated to obtain the weights (priorities) of the criteria or alternatives. The calculation is performed separately for the two pairwise comparison matrices derived from the BPC and WPC perspectives for each expert. The eigenvector for each matrix is calculated using the standard AHP eigenvalue method as given by Eq. (5) and Eq. (6).

$$\lambda_{\max}^W = (WPC \cdot w^W) \oslash w_i^W \quad (5)$$

$$\lambda_{\max}^B = (WPC \cdot w^B) \oslash w_i^B \quad (6)$$

where w^W and w^B are the weight vectors for the WPC and BPC matrices, respectively, and $\lambda_{\max}^W$ and $\lambda_{\max}^B$ are their corresponding maximum eigenvalues. The vectors w^W and w^B contain the relative weights of the criteria or alternatives, as in classical AHP.

After calculating the eigenvectors for both matrices, normalization is applied by dividing each element of the weight vector by the sum of all elements, ensuring that the resulting weights sum to 1. The relevant formulas shown in Eq. (7) and Eq. (8).

$$w_j^W = \frac{w_j^W}{\sum_j w_j^W} \quad (7)$$

$$w_j^B = \frac{w_j^B}{\sum_j w_j^B} \quad (8)$$

This step is performed for each expert individually, resulting in two sets of normalized weights per participant. These weights are subsequently used in the fuzzy modeling framework to account for indecisiveness and uncertainty across decision-makers.

Step 8. Check the Consistency: A key feature of AHP is the consistency check, which helps ensure the judgments made during the pairwise comparisons are logical and consistent. This is achieved by calculating the Consistency Index (CI) and Consistency Ratio (CR), defined as:

$$CI^W = \frac{\lambda_{\max}^W - n}{(n - 1) \cdot RI} \quad (9)$$

$$CI^B = \frac{\lambda_{\max}^B - n}{(n - 1) \cdot RI} \quad (10)$$

$$CR = \frac{CI}{RI} \quad (11)$$

where n is the number of criteria or alternatives and RI is a random index value which are presented in Table 2. CR^W and CR^B are the consistency ratios for the WPC and the BPC, respectively. If the CR is less than or equal to 0.1, the consistency is acceptable.

Step 9. Construct the Fuzzy Weight Matrix: In Step 9, the fuzzy representation of the weights is constructed using an interval-valued fuzzy number. Specifically, for

Table 2 RI indices from randomly generated matrices

n	1	2	3	4	5	6	7	8	9	10
RI	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49

each criterion j , two weights are obtained independently from BPC and WPC pairwise comparison matrices, denoted as w_j^B and w_j^W . The fuzzy weight is then defined as the interval. The formula shown in Eq. (12).

$$\tilde{w}_j = [\min(w_j^W, w_j^B), \max(w_j^W, w_j^B)] \quad (12)$$

The fuzzy weight for each criterion j is thus represented as an interval-valued fuzzy number:

$$\tilde{w}_j = [l_j, u_j], \quad l_j = \min(w_j^W, w_j^B), \quad u_j = \max(w_j^W, w_j^B)$$

and it can be interpreted as an interval set $\{x \in \tilde{w}_j \mid l_j \leq x \leq u_j\}$. This formalization clarifies that each $\tilde{w}_j$ defines the range of possible weight values bounded by the best-case and worst-case evaluations. This interval-valued fuzzy set reflects the uncertainty and indecisiveness of the decision-maker. If the judgments were fully consistent, the best-based and worst-based weights would converge to the same value, yielding a crisp weight. In practice, however, differences occur because the weights are derived with respect to two different references ("best" and "worst"). The closer the two values are to each other, the lower the uncertainty in the decision-making process. Both bounds always lie within the range $[0, 1]$, with the upper bound exceeding or equaling the lower bound. All subsequent operations on the interval weights are performed following standard fuzzy interval arithmetic.

Step 10. Synthesize the Results: After completing the pairwise comparisons and consistency checks, the next step is to synthesize the results. This process integrates the calculated weights of the criteria with the pairwise comparisons of the alternatives to determine their final ranking. For each alternative, an overall score is computed by multiplying the criteria weights by the performance ratings of the alternatives and summing the resulting values:

$$\tilde{S}_j = \sum_{i=1}^n (\tilde{w}_i \cdot \tilde{p}_{ij}) \quad (13)$$

where $\tilde{S}_j = [S_j^l, S_j^u]$ is the fuzzy score for alternative j , $\tilde{w}_i$ is the fuzzy weight of criterion i , $\tilde{p}_{ij}$ is the fuzzy performance rating of alternative j , and n is the number of criteria, respectively.

Step 11. Rank the Alternatives: Since the obtained scores are represented in fuzzy form, a defuzzification procedure is required to convert them into comparable crisp values for ranking purposes. The proposed formulation is designed to preserve both the central tendency and the uncertainty embedded in the fuzzy evaluations. Specifically, the expression incorporates the lower and upper bounds of the fuzzy score and reflects the dispersion between them, which represents the decision-makers' hesitation and uncertainty. By combining the midpoint of the fuzzy interval with a correction term that accounts for the spread of the fuzzy bounds, the method produces a representative crisp score while maintaining the information contained in the fuzzy representation. The resulting scores are then normalized to ensure compa-

rability among alternatives and to guarantee that the total weight sums to one. The defuzzified score for alternative j is calculated as follows:

$$S_j = \frac{\frac{S_j^l + S_j^u + (S_j^l - S_j^u) \cdot (1 - S_j^l / S_j^u)}{2}}{\sum_{j=1}^n S_j} \quad (14)$$

where S_j is the overall score for alternative j . The division by the sum of S_j values for all j in the denominator is for normalization purposes. Equation (14) ensures that the sum of the obtained weights equals 1, and the criteria are then ranked according to overall scores.

4 Application

4.1 Problem Definition

This study examines the design features of mobile sales applications through a hybrid methodology that integrates two widely used MCDM techniques: AHP and BBWM. While AHP provides a structured hierarchical analysis, its application to large datasets can be challenging due to the complexity involved in constructing and maintaining consistent PCMs. In contrast, BBWM streamlines the process by requiring only comparisons between the best and worst criteria, making it a more practical and scalable approach for large-scale data collection.

To overcome the limitations of each method, this study combines their strengths within a unified AHPBBWM framework. Data collection is carried out through BBWM surveys administered to a group of 113 participants, allowing for an efficient and structured assessment while mitigating the challenges associated with traditional AHP surveys. The results obtained from the BBWM process are then utilized to construct PCMs for AHP. As outlined in Step 1, this approach follows a hierarchical structure that decomposes the decision problem into multiple levels, ensuring a systematic evaluation of criteria and alternatives. The integration of these methods enables AHP to retain its hierarchical robustness while leveraging the computational efficiency of BBWM, resulting in a reliable framework for evaluating key features of mobile sales applications.

The proposed methodology further enhances the analytical process by introducing two separate matrices—Best Pairwise Comparison (BPC) and Worst Pairwise Comparison (WPC)—rather than a single PCM, which is traditionally used in AHP. These matrices generate interval fuzzy weights that capture both the uncertainty in expert evaluations and the level of inconsistency in responses. By incorporating input-based consistency checks, the AHPBBWM approach enables a clearer assessment of how inconsistencies affect the final results. The study presents both the consistent dataset and the full dataset, which includes both consistent and inconsistent responses, allowing for a comprehensive comparison of the BBWM and AHPBBWM methodologies in terms of their sensitivity to inconsistencies.

This hybrid approach not only simplifies implementation through BBWM but also improves result interpretation by incorporating fuzzy representations of inconsistency within AHP. Furthermore, it eliminates the necessity for complex optimization and probabilistic tools often required in BBWM, making the methodology more adaptable and accessible for LSGDM scenarios.

The study assesses widely used mobile applications in the Turkish market—Getir, Trendyol, Hepsiburada, Amazon, Yemeksepeti, and n11—based on key usability factors: ease of use, ease of learning, memorability, and satisfaction. A hierarchical evaluation framework, illustrated in Fig. 2, is employed to systematically assign weights to these criteria and analyze the overall performance of each application. This structure provides a transparent and organized decision-making process.

BBWM is initially used to determine rankings based on the derived criteria weights and application performance. These rankings are then compared with the outcomes of the proposed AHPBBWM approach, which incorporates BBWM-derived inputs to address the scalability issues associated with traditional AHP. Additionally, the results are validated against alternative evaluation methods to ensure reliability.

By integrating these methodologies, this study establishes a well-founded ranking of mobile applications while demonstrating the applicability and robustness of the AHPBBWM framework in handling complex decision-making problems. This comprehensive evaluation not only underscores the advantages of the hybrid model but also illustrates its potential for use in diverse assessment contexts.

4.2 Data Collection

The survey for this study was conducted online during the final quarter of 2024, with participation from 113 respondents. Its primary goal was to evaluate the features of mobile sales applications using the BBWM. While BBWM is effective in deriving relative importance weights, its complexity—requiring participants to simultaneously

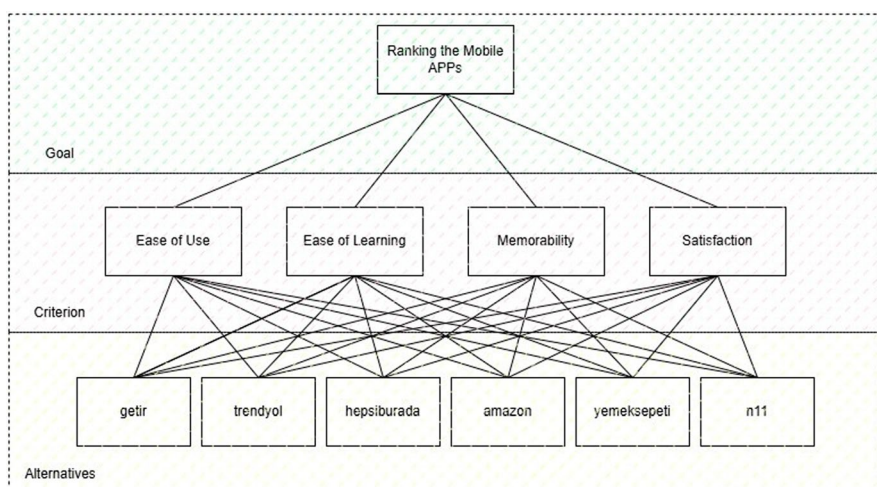


Fig. 2 Hierarchy of the problem

consider both the best and worst comparisons—can challenge participants' understanding and impact the consistency of responses.

To address this, the survey design incorporated conditional questioning, dynamically adapting based on participants' prior responses to enhance clarity and engagement. The survey was organized into five groups, each targeting different aspects of the evaluation framework:

- **Group 1:** Participants compared and weighted four fundamental criteria for evaluating mobile applications.
- **Groups 2 to 5:** Each group evaluated six Turkish mobile applications through pairwise comparisons across all identified criteria.

The AHPBBWM method is structured around the BBWM survey, following an 11-step framework as outlined in the previous section. The initial stages of the process, corresponding to Steps 1, 2, 3, and 4, were implemented during the survey phase. In accordance with Step 1, the problem was first defined and structured hierarchically. Step 2 involved problem identification and group segmentation, after which the survey was distributed to participants via online channels.

For each group, the selection of the best and worst alternatives or criteria was conducted, leading to the formulation of pairwise comparison vectors. These comparisons were designed based on BBWM principles (Steps 3 and 4), allowing for a bidirectional evaluation where the best criterion was compared against others and all criteria were evaluated against the worst. This structured approach provided a more comprehensive understanding of the relationships among criteria and alternatives.

The data collected through the survey were then processed to construct PCMs, which served as inputs for the AHP phase. This transformation was carried out using Eq. (3) and Eq. (4), as detailed in Steps 5 and 6. The weight values were subsequently determined using the eigenvector method, as described in Eq. (5-8) within Step 7. Here, priority vectors were derived and normalized to ensure consistency in the weighting process.

Following this, Step 9 introduced an interval-based fuzzy representation of the weight values for each alternative or criterion, utilizing Eq. (12). In Step 10, arithmetic operations were applied to these interval fuzzy numbers to compute the overall scores using Eq. (13). Finally, Step 11 involved defuzzification and normalization, refining the results into crisp values with the aid of Eq. (14).

While the study primarily focuses on analyzing the complete dataset to maintain the integrity and relevance of a large-scale study, a parallel evaluation of consistent responses is also included. This additional analysis—using input-based consistency checks proposed by Liang et al. (2020)—serves as a robustness assessment to determine the impact of inconsistencies on the results. Specifically:

- **Group 1:** 102 inconsistent responses excluded
- **Group 4:** 103 inconsistent responses excluded
- **Groups 2, 3, and 5:** 107 inconsistent responses excluded

Although a filtering process is applied, the primary analyses are conducted using the complete dataset, as the study is designed to address large-scale decision-making scenarios where inconsistencies are naturally present. This approach ensures that the results accurately represent real-world conditions and yield insights that can be broadly generalized.

To provide a comparative perspective, a subset consisting of only consistent responses is included as supplementary information. This allows readers to examine the differences between the full dataset and the subset with consistent responses. The inclusion of both datasets not only demonstrates the robustness of the AHPBBWM framework in handling inconsistencies but also reinforces its applicability to LSGDM problems.

By integrating conditional questioning with consistency-driven robustness assessments, the survey design enhances data reliability while preserving its large-scale applicability. This methodological approach establishes a strong foundation for meaningful feature prioritization and aligns with the study's overarching objectives.

4.3 AHPBBWM Analysis

To enhance the robustness of the pairwise comparison process, the proposed AHPBBWM method integrates both AHP and BBWM principles within an interval-based fuzzy framework. This approach allows for a more flexible representation of decision-makers' judgments while accounting for inconsistencies and uncertainty in LSGDM.

The resulting normalized weight values, calculated by dividing the smoothed values by their total, were as follows: 0.1381 for A1, 0.2819 for A2, 0.1706 for A3, 0.1610 for A4, 0.1604 for A5, and 0.0881 for A6.

When the same procedure was applied to the consistent dataset, the normalized weight values were: 0.1410 for A1, 0.3092 for A2, 0.1614 for A3, 0.1364 for A4, 0.1598 for A5, and 0.0923 for A6. As seen, when considering all surveys, the intervals become even wider. This serves as a good indicator of the uncertainty in the experts' evaluations. Upon examining Tables 3 and 4, it can be observed that the AHPBBWM approach is slightly sensitive to inconsistent results.

Although there is a slight change in the ranking, the overall order of importance remains the same when considering all surveys: A2, A3, A4, A5, A1, A6. This consistency reinforces the reliability of the findings, with the Trendyol application (A2) continuing to dominate across both the full and consistent datasets.

4.4 Comparative Analysis with BBWM

The validity of the AHPBBWM method was assessed by comparing it with the BBWM approach to ensure consistency in the findings. The comparison aimed to evaluate whether the rankings obtained through AHPBBWM aligned with those derived from BBWM, reinforcing the reliability of the proposed framework. A standard BBWM analysis was conducted using the responses from all 113 participants. While the primary analysis incorporated the complete dataset, a parallel evaluation was carried out on a subset containing only consistent responses to assess the model's robustness

Table 3 AHPBBWM total weights

Total	Min	Max	Defuzzification	Normalized Defuzzification	Rank
getir (A1)	0.0703	0.1241	0.0856	0.1381	5
trendyol (A2)	0.1516	0.2179	0.1747	0.2819	1
hepsiburada (A3)	0.0863	0.1569	0.1057	0.1706	2
amazon (A4)	0.0870	0.1231	0.0997	0.1610	3
yemeksepeti (A5)	0.0821	0.1418	0.0994	0.1604	4
n11 (A6)	0.0468	0.0703	0.0546	0.0881	6

Table 4 AHPBBWM consistent weights

Consistent	Min	Max	Defuzzification	Normalized Defuzzification	Rank
getir (A1)	0.0799	0.1172	0.0926	0.1410	4
trendyol (A2)	0.1823	0.2359	0.2030	0.3092	1
hepsiburada (A3)	0.0923	0.1313	0.1060	0.1614	2
amazon (A4)	0.0772	0.1135	0.0895	0.1364	5
yemeksepeti (A5)	0.0945	0.1215	0.1050	0.1598	3
n11 (A6)	0.0548	0.0694	0.0606	0.0923	6

against inconsistencies. The identified criteria weights were computed using Python, followed by the calculation of alternative weights relative to these criteria. The final overall weights were then obtained by multiplying the alternative weights by their corresponding criteria weights. The results, including criteria weights, alternative weights based on each criterion, and the overall alternative weights, are presented in Table 5.

This structured representation provides a comprehensive view of the relative significance of both criteria and alternatives within the evaluation framework. According to BBWM, across all surveys, the mobile applications were ranked by their importance as perceived by the participants, in descending order: A2, A3, A5, A4, A1, A6. The corresponding weights for these rankings are 0.2328, 0.1716, 0.1676, 0.1620, 0.1501, and 0.1115, respectively.

For the subset of consistent survey responses, the ranking of applications by importance remains the same: A2, A3, A5, A4, A1, A6. However, the corresponding weights slightly differ, with values of 0.2795, 0.1616, 0.1607, 0.1484, 0.1441, and

Table 5 BBWM total weights

BBWM total	Ease of use (C1)	Ease of learning (C2)	Memorability (C3)	Satisfaction (C4)	Overall weights
	$w = 0.3124$	$w = 0.1969$	$w = 0.1581$	$w = 0.3325$	
getir (A1)	0.1457	0.1529	0.1586	0.1484	0.1501
trendyol (A2)	0.2412	0.2378	0.2262	0.2251	0.2328
hepsiburada (A3)	0.1765	0.1768	0.1779	0.1745	0.1761
amazon (A4)	0.1543	0.1501	0.1538	0.1801	0.1620
yemeksepeti (A5)	0.1695	0.1660	0.1754	0.1631	0.1676
n11 (A6)	0.1128	0.1165	0.1081	0.1088	0.1115

Table 6 BBWM consistent weights

BBWM consistent	Ease of use (C1)	Ease of learning (C2)	Memorability (C3)	Satisfaction (C4)	Overall weights
	$w = 0.3303$	$w = 0.2251$	$w = 0.1520$	$w = 0.2836$	
getir (A1)	0.1350	0.1504	0.1623	0.1401	0.1441
trendyol (A2)	0.2580	0.2653	0.2413	0.3371	0.2795
hepsiburada (A3)	0.1669	0.1635	0.1889	0.1393	0.1616
amazon (A4)	0.1605	0.1549	0.1598	0.1226	0.1484
yemeksepeti (A5)	0.1743	0.1551	0.1717	0.1431	0.1607
n11 (A6)	0.1054	0.1108	0.0760	0.1180	0.1057

0.1057, respectively (Table 6). These results indicate that, considering the criteria of Ease of Use, Ease of Learning, Memorability, and Satisfaction, the Trendyol application (A2) stands out significantly as the most preferred option among decision-makers. This strong performance highlights its dominant position in the evaluated usability aspects compared to other applications.

In addition to the group weights, Credal Ranking representations for these groups are illustrated in Fig. 3. In Credal Ranking, the alternatives (A1, A2, A3, A4, A5, A6) or criteria (C1, C2, C3, C4) are depicted using a network diagram, where nodes represent the alternatives or criteria, and arcs indicate pairwise relative importance relationships. Each arc is assigned a confidence level, which quantifies the extent to which the decision-making group (DMs) favors one criterion or alternative over another. These confidence levels are expressed as numerical values between 0 and 1, with values closer to 1 reflecting stronger and more definitive preferences. The direction of the arcs signifies relative importance, with the originating node being considered more significant than the node it points to.

It is essential to note that the numerical values displayed on the arcs do not directly correspond to the computed weights. Instead, they represent relative importance derived from pairwise comparisons. However, these values remain proportional to the calculated weights, providing additional insights into the decision-making patterns within the group.

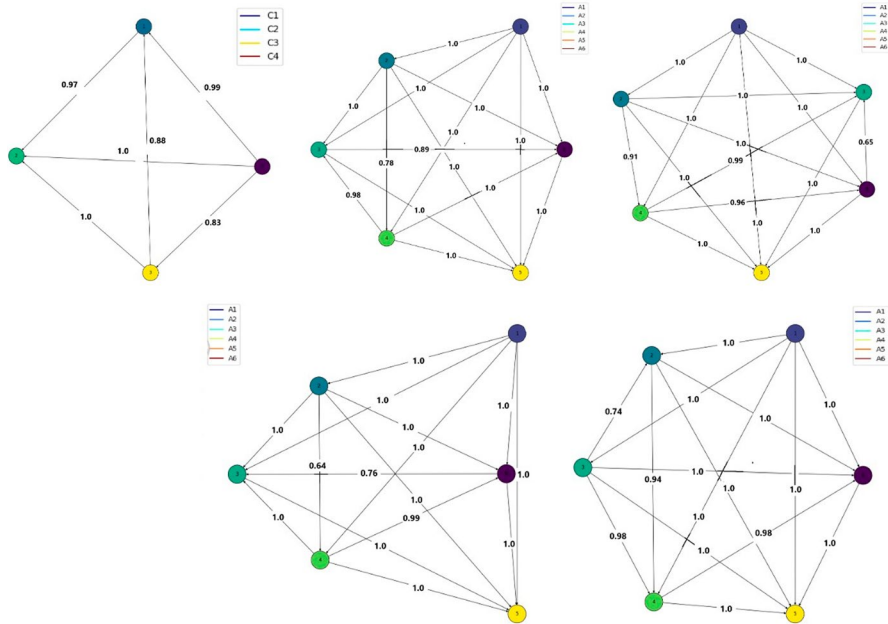


Fig. 3 Credal rankings of group 1–5

Table 7 Framework comparison

Apps	BBWM weights	Rank	AHPBBWM weights	Rank
getir (A1)	0.1501	5	0.1381	5
trendyol (A2)	0.2328	1	0.2819	1
hepsiburada (A3)	0.1761	2	0.1706	2
amazon (A4)	0.1620	4	0.1610	3
yemeksepeti (A5)	0.1676	3	0.1604	4
n11 (A6)	0.1115	6	0.0881	6

The results above show that the BBWM method is less affected by inconsistencies, whereas the proposed AHPBBWM method is more sensitive to inconsistencies. Since this study focuses on a large group scale, the analysis continued by incorporating all survey responses, including those with inconsistencies.

In terms of methodology validity and comparison, the results obtained from the surveys in BBWM and from the AHPBBWM framework are presented in Table 7. A high level of agreement is observed between the weights derived from BBWM and those obtained from AHPBBWM. The R^2 value for this agreement is 98.15%. Furthermore, when examining the rankings, the results are largely similar to those derived from the classic BBWM method, with the exception of the rankings of alternatives A4 and A5, which have swapped places. This is considered a minor change. This similarity is further supported by the Spearman's rho coefficient of 0.943 ($p = 0.005$), indicating a strong positive correlation between the rankings obtained from BBWM and AHPBBWM. Therefore, it can be concluded that the proposed frame-

work offers a consistent alternative to BBWM, demonstrating its robustness and reliability in LSGDM scenarios.

The consistency observed in the rankings further supports the conclusion that, based on the criteria of Ease of Use, Ease of Learning, Memorability, and Satisfaction, the Trendyol application consistently outperforms its competitors and remains the most preferred choice among decision-makers. The higher weight assigned to Trendyol within the consistent-response subset suggests that its leading position remains stable even when inconsistencies are excluded.

A comparison between the results from the full dataset and those derived from the consistent subset reveals that the rankings remain largely unaffected by inconsistencies. This finding underscores the robustness of the methodology and reinforces the reliability of the study's conclusions.

4.5 Results and Discussion

The evaluation conducted through both the BBWM and AHPBBWM frameworks has provided meaningful insights into the usability of Turkish mobile sales applications, including Getir, Trendyol, Hepsiburada, Amazon, Yemeksepeti, and n11. The study assessed these applications based on four key usability dimensions: Ease of Use, Satisfaction, Ease of Learning, and Memorability, ranking them according to participant preferences.

One of the most notable findings is Trendyol's (A2) consistent dominance across all datasets, maintaining its top position regardless of whether inconsistent responses were included. The ranking order remained largely unchanged, with Hepsiburada (A3) and Amazon (A4) following behind, reinforcing the robustness of the methodology in handling variability in expert judgments.

Examining the weight distribution of the usability criteria, Ease of Use emerged as the most influential factor, followed by Satisfaction, while Ease of Learning and Memorability played a comparatively smaller role. This result aligns with previous research emphasizing that users prioritize intuitive navigation and an effortless interaction experience over memorability when engaging with mobile sales platforms (Gao et al. 2024; Okonkwo 2024). The lower impact of Memorability suggests that once users become accustomed to an application, efficiency and ease of interaction take precedence, supporting the idea that usability is more about fluid interaction rather than recall-based familiarity. Based on the positively classified studies retrieved from literature, several research articles emphasize Ease of Use and Satisfaction as key usability attributes in mobile applications.

Specifically, Ease of Use (C1) has been positively classified in the studies conducted by Weichbroth (2020), and Ammar (2019), highlighting the importance of intuitive design and effortless interaction in mobile usability evaluations. Similarly, Satisfaction (C4) has been recognized as a crucial usability dimension in Weichbroth (2020), Baharuddin et al. (2013), and Alturki and Gay (2019), reinforcing the significance of user experience and perceived enjoyment in mobile application assessments. These classifications align with the findings of this study, where Ease of Use and Satisfaction emerged as the most influential factors in user decision-making, further emphasizing their role in mobile application usability.

These findings contribute to the broader research on e-commerce usability evaluation, confirming that user-centered design principles significantly impact application success. Future studies could further explore how additional features, such as personalized recommendations, AI-driven search optimization, and interactive customer support, influence user satisfaction and decision-making in mobile sales applications.

5 Conclusion

In this study, a BWM-based AHP method has been proposed, and the effectiveness of the AHPBBWM framework has been demonstrated in evaluating mobile sales applications based on usability criteria. The results highlighted Trendyol as the top-rated application across multiple dimensions, with consistent rankings achieved through both full and consistent survey data. The proposed methodology's ability to handle large-scale datasets while maintaining consistency and reliability reinforces its potential for complex decision-making tasks in diverse fields.

The AHPBBWM framework, by integrating BBWM's dual comparison approach with the hierarchical structure of AHP, provided a comprehensive evaluation tool for assessing mobile applications. The findings suggest that AHPBBWM is not only effective in terms of consistency and reliability but also robust enough to account for inconsistencies and uncertainty in expert evaluations. The interval values derived from the full dataset provided a deeper understanding of these inconsistencies, highlighting the framework's ability to quantify and reflect the variability in expert opinions.

While the study offers valuable insights, it is not without limitations. The sample size of 113 participants limits the generalizability of the findings. Although the participant pool was large enough for the scope of this study, a larger and more diverse group could provide more nuanced insights, especially when considering different demographics or user groups. Future studies could expand the survey to include a broader participant base, potentially improving the generalizability of the results.

Another limitation is the focus on a specific set of mobile sales applications in the Turkish market. While this context provides useful information, the methodology could benefit from being applied to a broader range of applications across different regions and industries. Extending the analysis to global or cross-industry comparisons would enable researchers to assess the universality of the findings and further refine the framework.

Moreover, future research could explore the use of other advanced decision-making techniques in conjunction with AHPBBWM to further enhance its robustness and scalability, especially in more dynamic environments with varying decision criteria.

Despite these limitations, the study validates the AHPBBWM framework as a robust alternative to traditional methods for evaluating mobile applications. The strong correlation between the results of BBWM and AHPBBWM, along with the high degree of reliability demonstrated by both methods, underscores the utility of the proposed approach in LSGDM problems. By incorporating both consistency checks and sensitivity to inconsistencies, the AHPBBWM framework provides a powerful

tool for evaluating complex systems, making it a valuable asset for future research in the field of multi-criteria decision analysis.

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

Declarations

Conflict of interest The authors declare no conflict of interest.

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Authors and Affiliations

Necip Fazıl Karakurt¹ · Gülşah Şahin² · İsmail Buğra Bölükbaşı³ · Esra İlbarhar² · Selcuk Cebi^{2,4}

✉ Necip Fazıl Karakurt
nfkarakurt@cumhuriyet.edu.tr

Gülşah Şahin
gulsah.sahin@yildiz.edu.tr

İsmail Buğra Bölükbaşı
ismail.bolukbasi@yaloiva.edu.tr

Esra İlbarhar
eilbahar@yildiz.edu.tr

Selcuk Cebi
scebi@yildiz.edu.tr

¹ Industrial Engineering Department, Sivas Cumhuriyet University, Sivas, Turkey

² Industrial Engineering Department, Yıldız Technical University, Istanbul, Turkey

³ Industrial Engineering Department, Yalova University, Çınarcık, Turkey

⁴ Industrial Data Analytics and Decision Support Systems Center, Azerbaijan State University of Economics, Baku, Azerbaijan