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A New Integrated FUCOM–CODAS Framework with Fermatean Fuzzy Information for Multi-Criteria Group Decision-Making

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Abstract: Smartphones have become an inevitable part of every facet of modern society. The selection of a particular smartphone brand from multiple options that are available is a complex and dynamic decision-making problem, involving multiple conflicting criteria that are associated with imprecise asymmetric information imposed by the uncertainty of the consumers. In this paper, we propose a novel hybrid full consistency method (FUCOM) and a combinative distance based assessment (CODAS) based on the multi-criteria group decision-making (MAGDM) framework in the Fermatean fuzzy (FF) domain for smartphone brand selection. We derive the criteria using the UTAUT2 (unified theory of acceptance and ese of technology) model. A group of 15 decision makers (DMs) participated in our study. We compare 14 leading smartphone brands in India and find that the brands having superior features of a good quality and selling a brand image at a affordable price outperform other smartphones. To check the validity of our framework, we compare the results using extant multi-criteria decision-making (MCDM) models. We observe our model provides a consistent solution. Furthermore, we carry out a sensitivity analysis for ascertaining the robustness and stability of the results generated by our model. The results of the sensitivity analysis show that our proposed framework delivers a stable and robust solution.

Keywords: smartphone brand selection; UTAUT2 (unified theory of acceptance and use of technology) model; full consistency method (FUCOM); combinative distance based assessment (CODAS); Fermatean fuzzy set (FFS); linguistics scale; multi-criteria group decision-making (MAGDM)

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1. Introduction

In the last decade, the world has witnessed the beginning of Industry 4.0, characterized by cyber–physical interaction; internet of things (IoT); the explosion of data (such as, Big Data); advanced computation; analytics driven by artificial intelligence (AI) and Machine learning (ML); the availability of high-performance hardware; and the extensive development in telecommunication. The present decade is experiencing Industry 4.0 in all areas of human life. Consumers are now more informed and knowledgeable and have a wide range of technological applications at their disposal. In the era of Industry 4.0, the world is marching towards the age of Society 5.0, featuring personification and a technology-driven human-centric society aiming to enhance the quality of life for all people [1]. As an effect of the extensive technological developments in Industry 4.0, and the steady transition towards Society 5.0, businesses worldwide have been facing stiff challenges to design and deliver products and services according to the requirements of the global market. Product design is an arduous task for organizations today, and it depends on the optimization of multiple conflicting objectives that are dynamic in nature.

In this context, the smartphone has become an inevitable part of human life. As technology invades daily life, smartphones help people become more mobile, agile, socially connected, and informed. With the transformational growth in internet penetration in households, there has been a quantum increase in smartphone users in India. The smartphone is now necessary for all people, irrespective of age, gender, and educational status [2]. The recent outbreak of COVID-19 has accelerated the use of smartphones. A recent survey [3] estimates that there will be around 973 million smartphone users in India, by 2025. Given this statistical projection and the present scenario, leading smartphone brands are paying more attention to understanding the stated and unstated needs of the consumers for providing appropriate products and services at affordable prices. Studies are being conducted to explore the factors that influence a consumer's buying decision for smartphones. However, as consumer behavior is very complex and dynamic in nature, the decision-making process to buy a smartphone is characterized by many uncertainties and imprecision. Therefore, selecting a brand of choice for high-tech products, such as smartphones, is a complex and dynamic decision-making problem subject to the influences of multiple conflicting criteria.

The primary purpose of MCDM algorithms is to solve the preferential order based on their suitability under the influence of a set of criteria that are different in nature and effect, and in conflict with each other. Thus, any MCDM algorithm depends on two complex aspects: selecting criteria, and deriving their combined effects for each alternative under comparison. In a real-life scenario, any decision-making problem suffers from a considerable degree of uncertainty as an exact interpretation of the combined effect of various attributes is not possible, due to a lack of precise information [4]. Specifically, in the case of an opinion-based evaluation of the alternative options, a significant level of ambiguity and imprecision affects the outcome of the analysis, which often results in an improper decision being made [5–7]. In this regard, Zadeh [8] introduced the most celebrated concept, the fuzzy set (FS), to deal with uncertainties and imprecision in real-life problems that can assign varying degrees of membership or DoM (μ) to the variables, with respect to a set of choices. However, the seminal work of Zadeh [8] overlooked the implications of a degree of non-membership, or DoNM (ϑ). In an extended work, Atanassov [9,10] brought in another celebrated concept of IFS which allowed for the consideration of both DoM and DoNM, subject to the condition $\mu + \vartheta \le 1$. The concept of intuitionistic fuzzy set (IFS) was useful to solve many practical problems over the year, as it gave due importance to indeterminacy [11]. However, the researchers pointed out its inefficiency to deal with uncertainties when the sum of DoM and DoNM exceeds 1. To solve this problem, Yager [12] instituted the concept of the Pythagorean fuzzy set (PyFS). In tune with the previous work, Yager [13] provided an extended generalized version, known as q-rung orthopair fuzzy sets (q-ROFSs), with the condition $\mu^q + \vartheta^q \le 1$.

Advancing from the concepts of IFS and PyFS, Senapati and Yager [14] introduced the concept of FFS as a special case of q-ROFSs (q = 3). In comparison with IFS and PyFS, FFS provides more flexibility and can handle imprecision and uncertainty with greater efficiency [14–17]. As a result, FFS is being increasingly applied to solve many MCDM-related problems. Although FFS can solve some limitations of IFS and PyFS (e.g., consider a case in which the DM opines that DoM $= 0.9$ and DoNM $= 0.6$, which results in $0.9 + 0.6 > 1$ and $0.9^2 + 0.6^2 > 1$), there can be cases (for instance, DoM $= 0.9$ and DoNM $= 0.8$) in which FFS is also limited in its definition. Thus, a q-ROFS provides more flexibility than FFS but offers more complexity, too. FFS, therefore, equips the analysts with reasonable flexibility.

1.1. Motivation of the Research

In this paper, we use a hybrid framework of FUCOM–CODAS to solve a real-life issue, such as the selection of smartphone brands in the FF environment. We consider the theoretical foundation of the UTAUT2 framework as the basis for the identification of the criteria to compare some of the leading smartphone brands in India. The motivation behind our present work stems from the following aspects:

1. The extant literature within our limited search shows a plethora of work that aims to understand consumer behavior in relation to smartphone selection. However, use of a holistic perspective based on MCDM is limited. Previous studies exist that have used MCDM methods for the comparative analysis of smartphones (for example, [18–22]). However, studies on smartphone selection considering the brands based on theoretical perspective, such as UTAUT2, is rare in the literature.
2. In this paper, we use a robust hybrid framework of FUCOM–CODAS. We find that this combination has not been used extensively, especially for brand comparison. CODAS combines two different distance measures, such as Euclidean and taxicab, from two indifference spaces to compare the alternatives, on the basis of optimistic and pessimistic solutions. Therefore, it provides a more rational analysis.
3. For any MAGDM or multi-criteria decision-making (MCDM) framework, the determination of criteria weights is of paramount importance to the analyst. In particular, an opinion-based subjective evaluation of the criteria weights posits more complexities and critically influences the final solution. The subjective evaluation of the relative priorities of the criteria does not provide an accurate estimate, and a deviation from the ideal values occurs. In many cases, it imposes ambiguities to the evaluation [23,24]. For example, in case of a pairwise comparison approach (followed in most of the MAGDM frameworks with subjective information), if X is greater than Y, Y is greater than Z; however, it may not always be the case that X is greater than Z in terms of relative importance, as perceived by the decision makers. Hence, consistency in the decision-making process is a major issue that affects the reliability and accuracy of the final solution. Furthermore, the greater the number of comparison, greater is the likelihood of the inconsistency ([25–27]). To solve this problem, Pamučar et al. [28] developed a new framework FUCOM which provided the following advantages, when compared with other popular algorithms, such as AHP (analytic hierarchy process) or BWM (best worst method).
    - A lesser number of pairwise comparisons (for FUCOM, we need $(n - 1)$ number of comparisons) that reduces the chance of inconsistency due to judgmental bias.
    - Inherent features to check the validity and consistency of the result by calculating and evaluating the value of DFC (deviation from full consistency).

    Pamucar et al. [28] obtained better results by using FUCOM to solve a given problem. Although there are several methods for prioritizing and determining the criteria weights, such as LBWA (level based weight assessment) that is used in many studies (for instance, [29]), the FUCOM algorithm provides more stable results, as it is based on multi-objective optimization. The entropy method is also a widely used method to derive criteria weights for MCDM problems (e.g., [30]). However, in our research, a significant amount of imprecision is involved. Therefore, to reduce likelihood of subjective bias, we selected the FUCOM method in the fuzzy domain.

4. The selection of smartphone brands is a complex decision-making problem, involving multiple criteria that are conflicting in nature. Furthermore, customer choice changes dynamically based on their preferences, demographic factors, and external influences. Therefore, establishing a multivariate model to frame the selection problem requires the consideration of the dynamics of discrete variables of the complex mechanism. Hence, the decision-making problem is associated with a substantial amount of imprecision and uncertainty. In view of this fact, we carry out our analysis using the FFS-based MCDM framework, which is capable of providing rational and robust solutions.

1.2. Contributions of the Research

In this context, the present study aims to contribute a novel and efficient hybrid MCDM framework based on a robust mathematical model that works on asymmetric and imprecise information. We apply this model of mathematical analysis for the evaluation of smartphone brands, using the attributes derived from utilizing the fundamental theory of a frontier technology adoption framework, grounded on the motivations of the consumers. The domain of FS has been an evolving one. In order to include the effect of non-membership, IFS was developed as an advancement of traditional FS. Furthermore, over the years, novel extensions, namely neutrosophic fuzzy sets (NFSs), q-ROFSs, spherical fuzzy sets (SFSs), picture fuzzy sets (PFSs), hesitant fuzzy, and the N-soft set, came into practice for providing the DMs and analysts a better opportunity to handle imprecise information under uncertain domains, to arrive at a better decision-making process through granular analysis. While NFS provides a improved ability to work with varying levels of hesitancy, the others provide a limited independency. There has been a development of q-ROFS as a special case of NFS with the sum of each three-element in (0,3). However, in a real-life scenario, under the constraints of limited time and budget, the lack of physical access to all DMs, and a varying level of understanding and knowledge of the opinion-makers, it is quite difficult to handle the complexities of the above mentioned extensions. FFS has been developed as a special case of q-ROFS (q = 3), which allows a simple interpretation and analysis, when compared with FS, IFS, and PyFS, and more flexibility in handling imprecise information [31–34]. Moreover, FUCOM, due to its inherent advantage of a lesser number of comparisons and its ability to ensure the consistency in its results, allows the analyst to reduce the bias and achieve a reasonable robust and accurate solution. In addition, the CODAS method helps to integrate the best features of two distance measures through a simple mechanism, reduce the chance of instability in the solution, and provide greater flexibility among the distance-based methods. Therefore, we consider the use of the new extension of the FUCOM–CODAS method with FFS.

Hence, to summarize, the main contributions of this study are as follows:

1. The extension of FUCOM and CODAS methods using FFS, where we apply the improved generalized score function (IGSF) as a measure for calculating score values.
2. A novel hybrid FF-based combination of FUCOM and CODAS for MAGDM.
3. The holistic evaluation of smartphone brands from users' perspectives, grounded on the theoretical foundation of the UTAUT2 model.

1.3. Paper Organization

The remainder of this paper is organized as follows: in the subsequent section (Section 2), we summarize some of the related research work; Section 3 presents the research framework in which we provide the computational steps of our new FF FUCOM–CODAS model; Section 4 exhibits a summary of the findings obtained by data analysis; in Section 5, we provide the results of the sensitivity analysis and validation check; Section 6 highlights some of the implications of this study; and Section 7 concludes the paper and provides the future scope of the research.

2. Related Work

In this section, we present a summary of some of the past research related to our work in four sub-sections, such as smartphone selection, development and applications of FFS, CODAS algorithms, and FUCOM algorithms.

2.1. Smartphone Selection

Consumer behavior towards the selection of a brand or product has been a widely accepted subject of research, for many years. In this regard, some of the theories, such as the theory of reasoned action (TRA) [35], the theory of planned behavior (TPB) [36], and the technology acceptance model (TAM) [37] have been prolifically used by researchers and practitioners to explain the antecedents to the selection of a brand, related to various products, from the perspective of the consumers. TRA focuses on the attitudes and subjective norms behind behavioral intention. As an extended version of TRA, TPB includes the perceived ease of the consumers. Apropos of these theories, Davis [37] proposed the concept of TAM, which deals with the perceived ease of use and usefulness of the products or brands, particularly for tech-based items.

There has been a plethora of research in the field of understanding and explaining consumer behaviors, vis-à-vis the purchase of smartphones. For instance, Filieri and Lin [38] adopted a qualitative face-to-face interview-based approach, validated through PLS-SEM, and reported that the design, quality, popularity of the brand, social influence, and culture, influenced the smartphone choice of Chinese consumers. Shieh and Lai [39] understood the importance of brand experience in establishing the brand loyalty among the consumers. Bhalla and Jain [40] reported the influence of the demographic variables on consumers' choices, and the physical attributes and features were major influences, followed by brand, price, serviceability, and social status. Exploring the influencing factors affecting the selection of smartphones in Nepal, Laohakosol and Sharma [41] concluded that their compatibility to various platforms and apps, the features of the product, and social pressure are given more importance by the consumers. Bringula et al. [42] further extended the literature by investigating the influencing factors behind the online purchase of smartphones at three levels, such as company, personal choice, and technical aspects, and noted trust as the most dominant factor.

A general notion is that the young generations (Gen Y) are more conversant in using smartphones. The study conducted by Kiran et al. [43] considered the Gen Y consumers and explored the type of factors that are the catalysts for prompt the decisions to purchase a smartphone, and reported that utilitarian factors, such as features and hardware, are more significant when compared with the hedonic factors. Redda and Shezi [44] conducted a study on South African Gen Y consumers, to recognize the relationship between customer satisfaction and brand loyalty, which precede the buying decision of high-tech products, such as smartphones, and observed a positive association. Martins et al. [45] advocated for the strengthening of promotional activities to entice the buying intention of the customers.

Isa et al. [46] observed a mediation effect of brands on the causal associations of price, promotion, and brand switching of the consumers. Mishra et al. [22] carried out a MCDM-based analysis to address the smartphone selection problem. They compared seven popular smartphones considering three factors, such as the technical features, physical attributes, and user experience, and considered eight criteria, including price; battery power; camera quality; storage capacity; processor type; screen size; ease of use; and the operating system. A study conducted by Kim et al. [47], on the Korean market, confirmed that the brand name was the most significant factor, creating a loyal customer base for smartphone products, and innovation played a crucial role. Mao et al. [48] adopted a flow theory-based analysis, in which they established a relationship among the brand-related underlying constructs, such as image, communication, identity, personality, and purchase behavior of the consumers. Sawaftah et al. [49] stressed the impact of two promotional strategies, such as viral advertising and the electronic word-of-mouth buying decision of the consumers, while examining the moderating role of brand image and age. They reported that viral advertising had a stronger impact on customers' purchase decision, with brand image acting as a strong moderator. We noticed the use of MCDM methods in some of the past studies related to smartphone selection (For example, [18–22]), in which researchers applied frameworks, such as DEMATEL, DANP, MABAC, TOPSIS, and ELECTRE-I in crisp and uncertain domains (using the grey theory and intuitionistic fuzzy sets).

From a methodological perspective, the research, as described above, mostly used parametric statistical analysis and causal models. Table 1 exhibits the summary of the models used in some of the related past work.

Table 1. Examples of methods used in past research.

Contributor(s)	Methodology Used
Filieri and Lin [38]	Qualitative face-to-face interview and Partial Least Square-Based Structural Equation Modeling
Bhalla and Jain [40]	Factor Analysis and Descriptive Analysis
Laohakosol and Sharma [41]	Correlation and Logistics Regression
Bringula et al. [42]	Hierarchical Regression Analysis
Martins et al. [45]	Partial Least Square-Based Structural Equation Modeling
Redda and Shezi [44]	Descriptive Analysis and Logistics Regression
Isa et al. [46]	Partial Least Square-Based Structural Equation Modeling
Mishra et al. [22]	IFS-MABAC
Kim et al. [47]	Mixed Logit
Mao et al. [48]	Partial Least Square-Based Structural Equation Modeling
Sawaftah et al. [49]	Multiple Linear Regression and Analysis of Variance

2.2. Related Work on FFS

Since its first definition, the domain of FFS has been a dynamic and growing field. A substantial number of contributions have been made to this field for defining new properties, aggregation measures, and theorems related to FFS, and extending the basic frameworks of established MCDM methods using FFS. For example, Liu et al. [50] defined linguistic term sets based on FF, and proposed a new combined similarity measure using cosine similarity and Euclidean distance. In a subsequent paper [51], the authors defined the fundamental operations, score, and accuracy functions, and proposed new aggregate operators and distance measures using linguistic terms. Aydemir and Gunduz [7] further extended the growing literature, by providing definitions and properties of Dombi operations-based aggregation operators. Akram et al. [6] used Einstein's norm-based operations for developing some generalized aggregation operators. On the other hand, Garg et al. [52] proposed the further development of aggregation operators by using Yager's t-norm and t-conorm, and contributed to this with six operators. Moreover, Silambarasan [53] introduced some new operators for averaging. Mishra et al. [17] proposed an improved generalized score function. Yang et al. [54] worked on continuous FF functions and related operations, such as subtraction and division, and checked the properties related to continuity, derivatives, and differentials in a non-linear environment.

FFS has been used to solve various kinds of problems from engineering, social science, and business management domains, such as the selection of suppliers for green construction [55]; capital budgeting [56]; the selection of sanitizer for preventing the spread of COVID-19 [6]; the selection of COVID-19 testing labs [52]; and the evaluation of third-party reverse logistics providers for sustainability [17]. In the process of extending the concept of FFS, the researchers used several existing MCDM algorithms for the demonstration of the applications. Table 2 summarizes some of the extensions of MCDM algorithms using FFS.

Table 2. Examples of MCDM methods using FFS.

MCDM Algorithm	Reference(s)
TOPSIS (The Technique for Order of Preference by Similarity to Ideal Solution)	[6,7,50–52]
TODIM (Tomada de Decisão Interativa Multicritério)	[50]
WASPAS (Weighted Aggregated Sum Product Assessment)	[55]
SMART (Simple Multi-Attribute Rating Technique)	[55]
CRITIC (Criteria Importance Through Inter-Criteria Correlation)	[17]
EDAS (Evaluation Based on Distance from Average Solution)	[17]
WPM (The Weighted Product Model)	[16]

2.3. Related Work on CODAS

The CODAS algorithm was introduced by combining two distance measures, such as the Euclidean (primary measure) and taxicab (secondary measure), to solve the issues related to the TOPSIS method [57]. Since then, CODAS has drawn attention from a substantial number of researchers and practitioners. Over the years, the fundamental procedure of the CODAS method has undergone a number of extensions, using FS [58], IFS [59]; interval valued IFS [60]; NFS [61]; linguistic PyFS [62]; 2-tuple LPyFS [63]; Z-fuzzy sets [64]; probabilistic uncertain linguistic information [65]; PFS [66]; and SFS [67]. Researchers have also conducted several experiments to develop hybrid frameworks by using the CODAS method in conjunction with other MCDM algorithms, for instance, AHP [68] and SWARA [69]. CODAS is one of the MCDM frameworks that has been widely used to solve numerous problems pertaining to engineering, sociology, biology, and management domains. The following table (see Table 3) presents some of the application areas in which the CODAS method has been applied in recent times.

Table 3. Some of the recent applications of CODAS method.

Application Area	Reference(s)
Financial performance assessment and management	[60]
Selection of renewable energy sources	[61]
Supplier selection	[58,64,65]
Facility location selection	[66,70]
Assessment of quality of living	[67]
Maintenance management	[68]
Evaluation of organizational performance	[71]
Comparing energy storage technologies	[59]
Personnel selection	[72]
Investment decision-making	[73]
Material selection	[69]
Performance evaluation of banks	[74]

2.4. Related Work on FUCOM

The extant literature shows the wide applications of FUCOM in determining criteria weights, in recent times. In this sub-section, we present some of the recent extensions and applications of FUCOM. Table 4 provides a summary of some of the recent works using FUCOM.

Table 4. Summary of some of the extensions and applications of FUCOM.

Problem Statement	Methodology	Reference(s)
Selection of side-loading forklift	FUCOM–WASPAS	[75]
Supplier selection for sustainable supply chain management	FUCOM	[76]
Comparative performance assessment of airlines in Libya	FUCOM–AHP	[25]
Facility location selection for the construction of single span baily bridge	FUCOM–MABAC	[26]
Renewable energy management: supplier selection for the installation of solar panels	SWARA–FUCOM–GRA–EDAS	[77]
Material classification (ABC analysis)	IRDWGAO, FUCOM, Interval Rough CoCoSo	[78]
Sustainable supplier selection	FUCOM–Interval Rough SAW	[79]
Path planning for multi-robot, using the cloud technology: evaluation of efficiency	FUCOM	[80]
Facility location selection for the logistics center in an urban development project	DEA, Rough FUCOM, and Rough CoCoSo	[81]
Facility location selection for solid waste landfill for municipality	FUCOM-CODAS	[82]

Table 4. *Cont.*

Problem Statement	Methodology	Reference(s)
Transportation management for an urban mobility project in Istanbul	Dombi BonferroniBased Fuzzy FUCOM	[83]
Sustainable supplier selection for the lime production unit	FUCOM–Rough SAW	[84]
Comparison of non-traditional manufacturing process	FUCOM, Fuzzy TOPSIS, and Fuzzy WASPAS	[85]
Defence system: location selection for combat operations	FUCOM–Z-number–Based MABAC	[86]
Green supplier selection	Fuzzy FUCOM	[87]
Performance appraisal for human resource management and the determination of compensation	FUCOM-MARCOS	[88]
Comparative assessment of risk and safety for traffic system	CRITIC, Fuzzy FUCOM using Fuzzy Bonferroni Mean, Fuzzy MARCOS, and DEA	[89]
Multi-objective optimization for the enhancement of the efficiency of a water management system	FUCOM–VIKOR	[90]
Multi-objective optimization for a mineral potential mapping problem	FUCOM, MOORA, and MOOSRA	[91]

3. Materials and Methods

In this section, we elucidate the research framework presented in this paper, where we discuss the selection of criteria for comparing smartphone brands, and our proposed FF-based hybrid FUCOM–CODAS methodology.

3.1. Criteria Selection

In the present research, we used the theoretical foundation of the UTAUT2 model (an extended version of UTAUT) to frame the criteria for evaluating the smartphone brands under consideration. The fundamental UTAUT model was derived from TAM. The UTAUT stands on four intrinsic drivers with the intention to adopt mobile technology, such as the performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC) [92]. Venkataraman and Ramasamy [93] recognized the applicability of the UTAUT in explaining users' intentions behind adopting mobile technology. Grounded on the foundation of UTAUT, Venkatesh et al. [94] proposed the extended version (UTAUT2) by incorporating three additional constructs, such as hedonic motivation (HM), price value (PV), and habit (HA). According to the UTAUT2 model, all seven independent constructs (PE, EE, SI, FC, HM, PV, and HA) influenced the dependent outcome, such as use behavior (UB) (in our study, the selection of a particular smartphone brand from the available choices), under the moderating effect of behavioral intention (BI). In a later study, Venkatesh et al. [95] reported that the UTAUT2 model could explain 74% of BI. Recent literature [96] mentioned that the use of the UTAUT2 model was still limited in its understanding of the UB of students (user group), vis-à-vis mobile technology. In recent literature [97], we noticed evidence of the use of the UTAUT2 model for explaining the BI of students pursuing higher education in Greece, related to the use of smartphones as learning aids. Therefore, in the present study, we found it appropriate to embrace the UTAUT2 model apropos of the basis for criteria selection. Table 5 provides brief clarifications of all seven independent constructs of the UTAUT2 model, while Table 6 exhibits the criteria considered in this paper for comparing leading smartphone brands in India. Figure 1 presents the steps constituting the research framework of this study.

In this context, BI is the derived intention of the users to avail the technology, while UB is defined as the extent to which the technology is actually being used by the users [92,94].

In the present study, 15 DMs have participated in the survey and given their opinions. These respondents have substantial experience of using smartphones or dealing with smartphone buyers. Table 7 describes the profiles of the DMs.

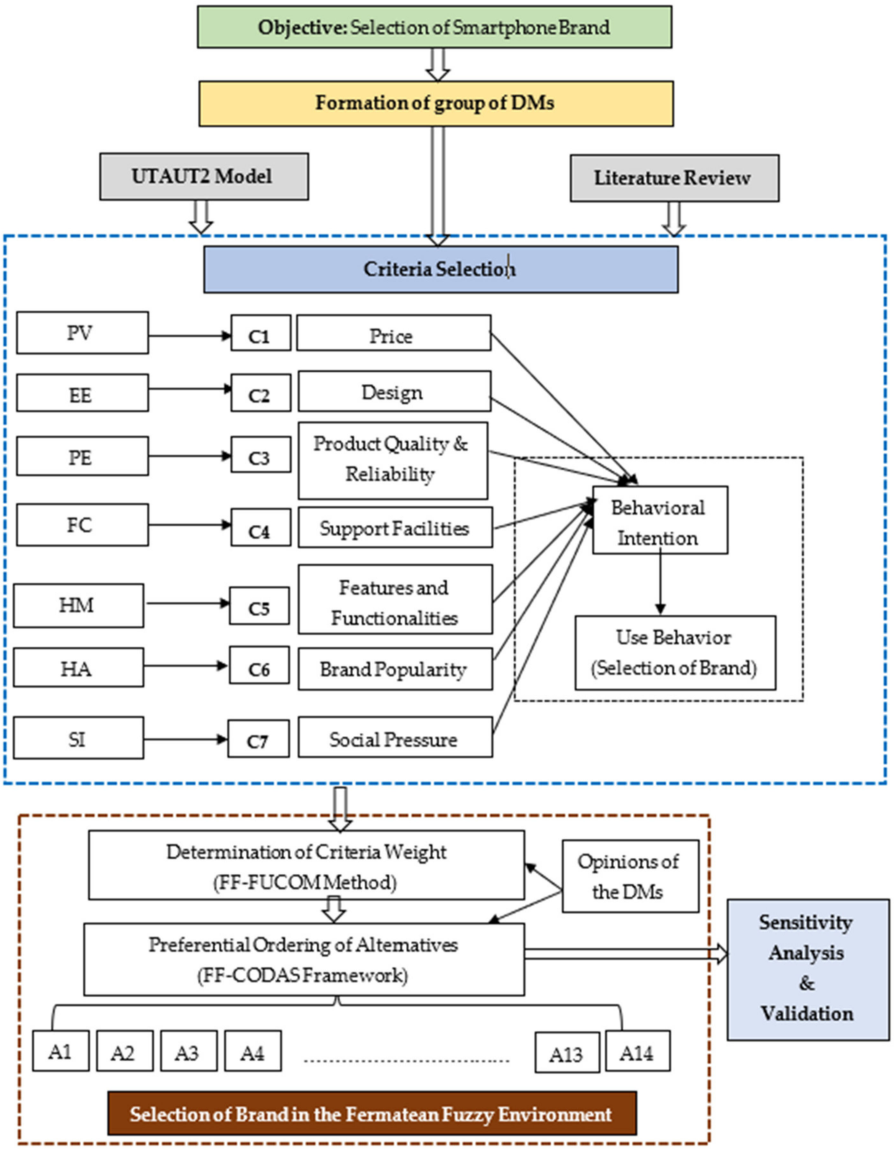


Figure 1. Research framework (source: authors).

Table 5. Description of the constructs of the UTAUT2 model.

Description of the Constructs	References
PE: Expectation of the user of the performance of the system/technology that helps to meet the desired purpose behind the use	[92,94,98]
EE: Expected ease with which the user can use the technology, i.e., the level of effort to be given and complexity involved	[92,94,99]
SI: The degree to which the users perceive that the use of technology shall satisfy the concerns and opinions of the reference group, consisting of family members, friends, and other acquaintances	[92,94,100]
FC: The user's perception of the requirement of the organizational and technical infrastructure to facilitate the use of the technology	[92,94]
HM: The intrinsic value or benefits derived by using the technology, which provides pleasure of use to the users and strengthens their attachment to the product	[94,101]
PV: Perceived value of the technology/product in terms of desired attributes, against the price paid for achieving the same	[94,102]
HA: Behavioral nature, prior experiences, and learning of the users influencing the natural use of the echnology	[94,103]

Table 6. Criteria description.

	Criteria	Description	Effect Direction
C1	Price	Price range of the models (affordability)	(−)
C2	Design	Aesthetics, weights, and attractiveness, etc., of the models	(+)
C3	Product Quality and Reliability	Performance of models, reliability of the manufacturers, and technical specifications of the hardware	(+)
C4	Support Facilities	After sales service, availability of the auxiliary items and spare parts, and customer care	(+)
C5	Features and Functionalities	Range of applications, utilities, ease of use, technical aspects, security and privacy, compatibility, and speed of operations	(+)
C6	Brand Popularity	Brand image, awareness of the company, availability of information, word of mouth, and availability of the models	(+)
C7	Social Image	Peer use and reference, personal choice factors, and esteem value	(+)

Table 7. Respondents' profiles.

Years Using Smartphones		Nature of Job	
Less than 5 years	03	Service	04
5–10 years	11	Business	02
More than 10 years	01	Dealers	09
Total	15	Total	15

It can be observed in Table 7, that out of 15 DMs, the majority (9) is made up of smartphone dealers who have adequate experience in dealing with a large number of users or buyers having different demographic and professional backgrounds. In other words, these dealers are treated as experts while the remaining 6 DMs are considered as users. Therefore, our respondent group has a satisfactory level of variety in demographical background. We selected 14 popular smartphone brands in India as decision making units (DMUs), for comparison purposes. These 14 DMUs attain approximately 75% of the market share in India. To avoid any commercial dispute, and statutory and regulatory violations, confidentiality of identity is maintained. Hence, in the present study, the DMUs are referred to as B1, B2, . . . , and B14.

3.2. Preliminaries of FFS

Definition 1 (IFS [9,10])**.** *An IFS $\widetilde{A}^{I}$ in the universe of discourse U is defined as the following:*

$$\widetilde{A}^{I} = \left\{ \langle x,\ \mu_{\widetilde{A}^{I}}(x), \vartheta_{\widetilde{A}^{I}}(x) \rangle\ : x \in U \right\}$$

where $\mu_{\widetilde{A}^{I}}(x) : U \rightarrow [0,1]$ *and* $\vartheta_{\widetilde{A}^{I}}(x) : U \rightarrow [0,1]$ *represent the DoM and DoNM, respectively, so that* $0 \le \mu_{\widetilde{A}^{I}}(x) + \vartheta_{\widetilde{A}^{I}}(x) \le 1;\ \forall\, x \in U$ *(the equality holds for the traditional FS).*

Definition 2 (PyFS [12,13])**.** *A PyFS $\widetilde{A}^{P}$ in the universe of discourse U is defined as the following:*

$$\widetilde{A}^{P} = \left\{ \langle x,\ \mu_{\widetilde{A}^{P}}(x), \vartheta_{\widetilde{A}^{P}}(x) \rangle : x \in U \right\}$$

where $\mu_{\widetilde{A}^{P}}(x) : U \rightarrow [0,1]$ *and* $\vartheta_{\widetilde{A}^{P}}(x) : U \rightarrow [0,1]$ *are DoM and DoNM, respectively, so that* $0 \le \left(\mu_{\widetilde{A}^{P}}(x)\right)^2 + \left(\vartheta_{\widetilde{A}^{P}}(x)\right)^2 \le 1;\ \forall\, x \in U$*; the degree of indeterminacy (DoI) is given as:*

$$\pi_{\widetilde{A}^{P}}(x) = \sqrt{1 - \left(\mu_{\widetilde{A}^{P}}(x)\right)^2 - \left(\vartheta_{\widetilde{A}^{P}}(x)\right)^2}\ ;\ \forall\, x \in U \quad (1)$$

Senapati and Yager [14–16] have provided the definitions, theorems, and properties of FFS, which are described below.

Definition 3 (Fundamental definition of FFS)**.** *A FFS $\widetilde{A}^F$ in the universe of discourse U is defined as the following:*

$$\widetilde{A}^F = \left\{ \langle x,\ \mu_{\widetilde{A}^F}(x), \vartheta_{\widetilde{A}^F}(x) \rangle\ : x \in U \right\}$$

where $\mu_{\widetilde{A}^F}(x) : U \ \to [0,1]$ *and* $\vartheta_{\widetilde{A}^F}(x) : U \ \to [0,1]$ *are DoM and DoNM, respectively, so that* $0 \le \left(\mu_{\widetilde{A}^F}(x)\right)^3 + \left(\vartheta_{\widetilde{A}^F}(x)\right)^3 \le 1;\ \forall\, x \in U$*; the DoI is given as:*

$$\pi_{\widetilde{A}^F}(x) = \sqrt{1 - \left(\mu_{\widetilde{A}^F}(x)\right)^3 - \left(\vartheta_{\widetilde{A}^F}(x)\right)^3};\ \forall\, x \in U \tag{2}$$

For simplicity, let us consider that an FFS is denoted by F = (μ_f,ϑ_f)*, with the usual definitions being presented in the form provided above. The following figure (Figure 2) depicts the difference among IFS, PyFS, and FFS, in terms of membership degrees (MD).*

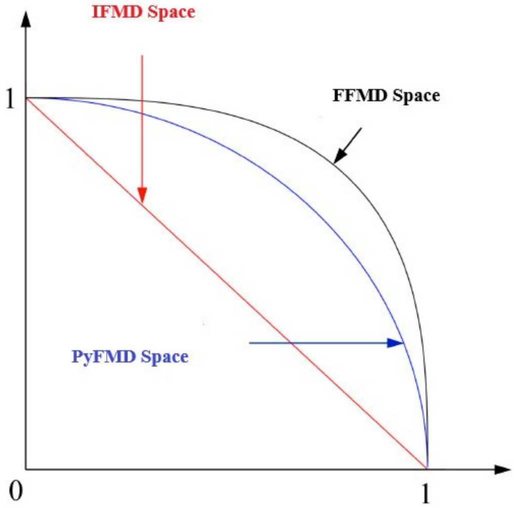


Figure 2. Difference among IFS, PyFS, and FFS based on spaces related to MD.

In the above diagram, IFMD space consists of all the points with $0 \le \mu_{\widetilde{A}^I}(x) + \vartheta_{\widetilde{A}^I}(x) \le 1$*; the PyFMD space covers all points with* $0 \le \left(\mu_{\widetilde{A}^P}(x)\right)^2 + \left(\vartheta_{\widetilde{A}^P}(x)\right)^2 \le 1$*; and the FFMD space represents the points with* $0 \le \left(\mu_{\widetilde{A}^F}(x)\right)^3 + \left(\vartheta_{\widetilde{A}^F}(x)\right)^3 \le 1$*. Therefore, the set of FFMDs is larger than PyFMD, which is, again, larger than IFMD.*

Consider now, that $\mathcal{F} = (\mu_f,\ \vartheta_f)$*;* $\mathcal{F}_1 = (\mu_{f1},\ \vartheta_{f1})$*; and* $\mathcal{F}_2 = (\mu_{f2},\ \vartheta_{f2})$ *are three FFS. The following definitions and theorems are, subsequently, appropriate:*

Definition 4 (Basic operations (3))**.**

$$\begin{aligned}
\mathcal{F}^c &= (\vartheta_f,\ \mu_f) \\
\mathcal{F}_1 \cup \mathcal{F}_2 &= (\max(\mu_{f1},\ \mu_{f2}), \min(\vartheta_{f1}, \vartheta_{f2})) \\
\mathcal{F}_1 \cap \mathcal{F}_2 &= (\min(\mu_{f1},\ \mu_{f2}), \max(\vartheta_{f1}, \vartheta_{f2})) \\
\mathcal{F}_1 \boxplus \mathcal{F}_2 &= \left(\sqrt[3]{\mu_{f1}{}^3 + \mu_{f2}{}^3 - \mu_{f1}{}^3\mu_{f2}{}^3}, \vartheta_{f1}\vartheta_{f2}\right) \\
\mathcal{F}_1 \boxtimes \mathcal{F}_2 &= \left(\mu_{f1}\mu_{f2},\ \sqrt[3]{\vartheta_{f1}{}^3 + \vartheta_{f2}{}^3 - \vartheta_{f1}{}^3\vartheta_{f2}{}^3}\right) \\
\mathcal{F}_1 \boxminus \mathcal{F}_2 &= \left(\sqrt[3]{\frac{\mu_{f1}{}^3 - \mu_{f2}{}^3}{1-\mu_{f2}{}^3}}\ ,\ \frac{\vartheta_{f1}}{\vartheta_{f2}}\right); \text{if } \mu_{f1}\ \geq \mu_{f2} \text{ and } \vartheta_{f1} \leq \min\left\{\vartheta_{f2},\ \frac{\vartheta_{f2}\pi_{f1}}{\pi_{f2}}\right\} \\
&= (0,1),\ \text{otherwise} \\
\mathcal{F}_1 / \mathcal{F}_2 &= \left(\frac{\mu_{f1}}{\mu_{f2}}, \sqrt[3]{\frac{\vartheta_{f1}{}^3 - \vartheta_{f2}{}^3}{1-\vartheta_{f2}{}^3}}\right); \text{if } \mu_{f1} \leq \min\left\{\mu_{f2},\ \frac{\mu_{f2}\pi_{f1}}{\pi_{f2}}\right\} \text{ and } \vartheta_{f1} \geq\ \vartheta_{f2} \\
\alpha\mathcal{F} &= \left(\sqrt[3]{1-(1-\mu_f{}^3)^{\alpha}}, \vartheta_f{}^{\alpha}\right); \alpha \text{ is a constant} \\
\mathcal{F}^{\alpha} &= \left(\mu_f{}^{\alpha},\ \sqrt[3]{1-(1-\vartheta_f{}^3)^{\alpha}}\right)
\end{aligned} \tag{3}$$

Definiton 5 (Score function (SF) of FFS)**.** *The SF of any FFS $\mathcal{F}$ is given as:*

$$\mathfrak{H}(\mathcal{F}) = \ \mu_f{}^3 - \vartheta_f{}^3\ ;\ \mathfrak{H}(\mathcal{F}) \in [-1,1] \tag{4}$$

However, $\mathfrak{H}(\mathcal{F}) = 0$ if $\mu_f = \vartheta_f$

Definition 6 (Accuracy function (AF) of FFS)**.**

$$\mathbb{A}(\mathcal{F}) = \ \mu_f{}^3 + \vartheta_f{}^3 \tag{5}$$

Here, $0 \leq \mathbb{A}(\mathcal{F}) \leq 1$; $\mathbb{A}(\mathcal{F}) \in [0,1]$; $\pi_f{}^3 + \mathbb{A}(\mathcal{F}) = 1$, *which suggests that the lower the DoI, the higher is the accuracy of FFS.*

Theorem 1. Ranking of FFS based on SF and AF values

$$\begin{aligned}
&\mathfrak{H}(\mathcal{F}_1) < \mathfrak{H}(\mathcal{F}_2) \text{ implies } \mathcal{F}_1 \prec \mathcal{F}_2 \\
&\mathfrak{H}(\mathcal{F}_1) > \mathfrak{H}(\mathcal{F}_2) \text{ implies } \mathcal{F}_1 \succ \mathcal{F}_2 \\
&\text{If } \mathfrak{H}(\mathcal{F}_1) = \mathfrak{H}(\mathcal{F}_2) \text{ then} \\
&\mathbb{A}(\mathcal{F}_1) < \mathbb{A}(\mathcal{F}_2) \text{ implies } \mathcal{F}_1 \prec \mathcal{F}_2 \\
&\mathbb{A}(\mathcal{F}_1) > \mathbb{A}(\mathcal{F}_2) \text{ implies } \mathcal{F}_1 \succ \mathcal{F}_2 \\
&\mathbb{A}(\mathcal{F}_1) = \mathbb{A}(\mathcal{F}_2) \text{ implies } \mathcal{F}_1 \approx \mathcal{F}_2
\end{aligned} \tag{6}$$

Definition 7 (Positive SF of FFS)**.** *Considering the possibility of a negative value, Keshavarz-Ghorabaee et al. [55] modified the score function as given below:*

$$\mathfrak{H}^P(\mathcal{F}) = \mathfrak{H}(\mathcal{F}) + 1 \tag{7}$$

Definition 8 (IGSF of FFS)**.** *In order to avoid the possibility of $\mathfrak{H}(\mathcal{F}) = 0$, in a recent work, Mishra et al. [17] proposed a new IGSF for FFS. The definition of the IGSF is given as:*

$$\mathfrak{H}^*(\mathcal{F}) = \mu_f{}^3\Big[1 + (\delta_1 + \delta_2)\Big(1 - \mu_f{}^3 - \vartheta_f{}^3\Big)\Big] \tag{8}$$

here, $\delta_1 + \delta_2 = 1$ and $\delta_1, \delta_2 > 0$ signify the weighted average of the indeterminacy between DoM and DoNM. This definition of IGSF provides an improved ranking of FFS than the definition of SF provided by Senapati and Yager [14].

Theorem 2. *Properties of IGSF [17].*

$$\mathfrak{H}^*((0,1)) = 0 \text{ and } \mathfrak{H}^*((1,0)) = 1 \tag{9}$$

$\mathfrak{H}^{*}(\mathcal{F})$ *increases monotonically with respect to* μ_f *and decreases monotonically with respect to* ϑ_f

Definition 9 (Average operator on FFS)**.**

$$\mathcal{A}(\mathcal{F}_1, \mathcal{F}_2) = \left(\frac{{\mu_{f1}}^3 + {\mu_{f2}}^3}{2}, \frac{{\vartheta_{f1}}^3 + {\vartheta_{f2}}^3}{2}\right) \tag{10}$$

Definition 10 (Fermatean fuzzy weighted average (FFWA) operator)**.**

$$\mathrm{FFWA}\left(\mathcal{F}_i\right) = \left(\sum_{i=1}^{n} w_i \mu_{fi}, \sum_{i=1}^{n} w_i \vartheta_{fi}\right) \tag{11}$$

here, $i = 1, 2, \ldots, n$ *is the number of FFS, and* w_i *is the weight of the* ith *FFS and* $\sum_i w_i = 1$.

Definition 11 (Distance measures between the FFS)**.** *Following the definition for PyFSs [104], the taxicab distance (TD) of FFS are given as:*

$$d_T(\mathcal{F}_1, \mathcal{F}_2) = |\mu_{f1} - \mu_{f2}| + |\vartheta_{f1} - \vartheta_{f2}| + |\pi_{f1} - \pi_{f2}| \tag{12}$$

Aydemir and Gunduz [7] provided a modified definition of Euclidean distance (ED), extending the work of Ke et al. [105]. The definition of ED between the FFS is given as:

$$d_E(\mathcal{F}_1, \mathcal{F}_2) = \frac{1}{n}\sum_{i=1}^{n}\sqrt{\left(\frac{\mathfrak{H}(\mathcal{F}_1)}{2} - \frac{\mathfrak{H}(\mathcal{F}_2)}{2}\right)^2 + \frac{1}{3}\left(\frac{\mathbb{A}(\mathcal{F}_1)}{2} - \frac{\mathbb{A}(\mathcal{F}_2)}{2}\right)^2} \tag{13}$$

3.3. FUCOM Algorithm

The algorithm of FUCOM [28] is described below.

Step 1. Ranking of the criteria by the DMs according to their relative importance.

Suppose that $C = \{C_1, C_2, C_3, \ldots., C_n\}$ is the set of criteria, and following is the order of the criteria as per the preference of the DMs.

$C_j(1) \succ C_j(2) \succ C_j(3) \succ \ldots\ldots C_j(r)$, where r is the rank of the particular criterion. However, there can be the possibility that any two criteria hold the same rank (in that case, an "=" can be used).

Step 2. Deriving the comparative priority of the criteria.

The comparative priority (CP) of the criterion $C_j(r)$ when compared with $C_j(r+1)$ is given as $\Phi_{r/(r+1)}$.

The CP can be defined in two ways: (a) based on the DM's defined way, and (b) based on a predetermined scale.

The first ranked criterion, being the most significant, will be compared with itself, which leads to a total of (n − 1) number of comparisons.

Step 3. The calculation of the final values of the weight coefficients of the criteria.

The final weight values are calculated based on the following two conditions:

$$\frac{w_r}{w_{r+1}} = \Phi_{r/(r+1)} \tag{14}$$

Mathematical transitivity:

$$\frac{w_r}{w_{r+2}} = \Phi_{r/(r+1)} \bigotimes \Phi_{(r+1)/(r+2)} \tag{15}$$

Step 4. Constructing the final model.

The full consistency or maximum possible consistency can be achieved if DFC (χ) is at a minimum and subject to the satisfaction of both the conditions, as is mentioned in Step 3. The final model is given by

$$\begin{gathered} \text{Min } \chi \\ \text{s.t.} \\ \left| \frac{w_{j(r)}}{w_{j(r+1)}} - \Phi_{r/(r+1)} \right| \leq \chi, \forall j \\ \left| \frac{w_{j(r)}}{w_{j(r+2)}} - \Phi_{r/(r+1)} \otimes \Phi_{(r+1)/(r+2)} \right| \leq \chi, \forall j \\ \sum w_j = 1, \ w_j \geq 0, \ \forall j \end{gathered} \tag{16}$$

3.4. CODAS Algorithm

The CODAS method uses two types of distance measurements, such as the Euclidean (primary, with l^2-norm indifference space) and taxicab (secondary, with l^1-norm indifference space), combined by a threshold value for comparing the DMUs based on their distances from the anti-ideal solution [57].

Suppose that $X = \left[x_{ij}\right]_{m \times n}$ represents the decision matrix (DMTR), where $i = 1, 2, \ldots m$ is the number of DMUs (i.e., alternatives under comparison) and $j = 1, 2, \ldots n$ are the number of criteria. The computational steps are described below.

Step 1: Normalization.

Suppose that $X^N = \left[x_{ij}{}^N\right]_{m \times n}$ is the normalized decision matrix (NDMTR), where

$$x_{ij}{}^N = \frac{x_{ij}}{\max\limits_i x_{ij}} \text{ When } j \in j^+ \tag{17}$$

$$x_{ij}{}^N = \frac{\min\limits_i x_{ij}}{x_{ij}} \text{ When } j \in j^- \tag{18}$$

Step 2: Construction of the weighted normalized decision matrix (WNDMTR).

The WNDMTR is given as $X^{N*} = \left[x_{ij}{}^{N*}\right]_{m \times n}$, where

$$x_{ij}{}^{N*} = w_j \, x_{ij}{}^N \tag{19}$$

where w_j denotes the weight of the jth criterion. $(\sum_{j=1}^{n} w_j = 1)$

Step 3: Derives the anti-ideal or pessimistic solution.

$$S^- = \left[s_j^-\right]_{1 \times n} \tag{20}$$

$$s_j^- = \min_i x_{ij}{}^{N*} \tag{21}$$

Step 4: Calculation of the distances from the anti-ideal solution.

The ED (E_i) and TD (T_i) of the DMUs from the anti-ideal solution are calculated as

$$E_i = \sqrt{\sum_{j=1}^{n} \left(x_{ij}{}^{N*} - s_j^-\right)^2} \tag{22}$$

$$T_i = \sum_{j=1}^{n} \left| x_{ij}{}^{N*} - s_j^- \right| \tag{23}$$

Step 5: Formation of relative assessment matrix $R_a = [h_{ik}]_{m \times m}$, where

$$h_{ik} = (E_i - E_k) + (\psi\,(E_i - E_k) \times (T_i - T_k)) \tag{24}$$

where k = 1,2, . . . , m; ψ denotes a threshold function, where

$$\psi(d) = 1, \text{ if } |d| \geq \tau;\ 0, \text{ otherwise} \tag{25}$$

d is the difference between the ED of the two alternatives and τ is a threshold parameter that determines the use of the distance measure (τ = 0.02, as suggested by [57]).

Step 6: Calculation of the assessment score (H_i).

$$H_i = \sum_{k=1}^{m} h_{ik} \tag{26}$$

The alternative with a higher H_i value is given higher priority than others, as it stands farthest from the anti-ideal solution.

3.5. Proposed FF–FUCOM–CODAS Methodology

The proposed methodology consists of the following steps:

Step1: Rating of the criteria by the DMs using a pre-defined linguistic scale.

Suppose that $t = 1, 2, \ldots k$ is the number of DMs. Then, the linguistic weight matrix for the criteria is given as

$$\varphi^t = \begin{array}{c} C_1 \\ C_2 \\ \vdots \\ C_n \end{array} \begin{bmatrix} \varphi_1^t \\ \varphi_2^t \\ \vdots \\ \varphi_n^t \end{bmatrix} \tag{27}$$

Here, $\varphi_j^t = \left(\mu_{fj}{}^t, \vartheta_{fj}{}^t\right)$ is the relative importance (in the FF linguistic scale), given by the tth DM for the criterion C_j (where, $j = 1, 2, \ldots n$). The linguistic scale is presented in Table 8. We use the scale defined by [55].

Table 8. FF linguistic scale for criteria rating.

Linguistic Scale	FFN	Linguistic Scale	FFN	Linguistic Scale	FFN
Very Very Low (VVL)	(0.1, 0.9)	Medium Low (ML)	(0.4, 0.5)	High (H)	(0.7, 0.2)
Very Low (VL)	(0.1, 0.75)	Medium (M)	(0.5, 0.4)	Very High (VH)	(0.8, 0.1)
Low	(0.25, 0.6)	Medium High (MH)	(0.6, 0.3)	Very Very High (VVH)	(0.9, 0.1)

Step 2. Deriving the relative importance (i.e., weights) of the DMs.

In this step, the expert panel gave weights to different DMs in terms of the FFS-based linguistic scale, as described above. Suppose that $\mathcal{F}_t = (\mu_{ft}, \vartheta_{ft})$ is the aggregated weight for tth DM, as given by the expert panel. Then, the weight of each DM is calculated as [17]

$$\omega_t = \frac{\mathfrak{H}^*(\mathcal{F}_t)}{\sum_{t=1}^{k} \mathfrak{H}^*(\mathcal{F}_t)} \tag{28}$$

where $\mathfrak{H}^*(\mathcal{F}_t)$ is calculated using the expression (8) and $\delta_1 + \delta_2 = 1;\ \delta_1, \delta_2 > 0$.

In this paper, we considered all DMs as equally important and, hence, the weight for each DM = 1/k.

Step 3. Aggregation of the opinions of the DMs for formulating the criteria matrix.

The criteria matrix is given as $\mathbb{C} = [C_j]_{1 \times n}$, where $C_j = \left(\mu_{fj}, \vartheta_{fj}\right)$.

The application of the FFWA operator for the aggregation of the opinions of the DMs (assuming equal importance for the DMs) as per expression (11), we obtain the following:

$$C_j = \left(\frac{1}{k}\sum_{t=1}^{k} \mu_{fj}{}^t,\ \frac{1}{k}\ \sum_{t=1}^{k} \vartheta_{fj}{}^t\right) \tag{29}$$

Step 4. Calculation of the score values of C_j and priority ordering.

We use the expression (8) to calculate the score values (IGSF) and then we set the preferential order as per score values.

Step 5. Calculation of criteria weights w_j.

Use Steps 2–4 of the FUCOM method (refer to Section 3.3) to calculate the criteria weights. We used Lingo 19 software for this purpose.

Step 6. Formation of the FF–DMTR.

In this step, first, the DMs rate the DMUs with respect to the criteria, using the FFlinguistic scale. In this study, we have one cost type criterion (lower the better) and six profit type criteria (higher the better). We use the linguistic scale, described in Table 1, for rating the DMUs, with respect to the cost type criterion. However, for the profit type criteria, we slightly modified the description of the linguistic scale (see Table 9) for the rating of DMUs, while keeping the FFS values the same.

Table 9. FF linguistic scale for DMU rating (profit type criteria).

Linguistic Scale	FFN	Linguistic Scale	FFN	Linguistic Scale	FFN
Very Very Poor (VVP)	(0.1, 0.9)	Medium Poor (MP)	(0.4, 0.5)	Good (G)	(0.7, 0.2)
Very Poor (VP)	(0.1, 0.75)	Medium (M)	(0.5, 0.4)	Very Good (VG)	(0.8, 0.1)
Poor (P)	(0.25, 0.6)	Medium Good (MG)	(0.6, 0.3)	Very Very Good (VVG)	(0.9, 0.1)

We subsequently aggregated the opinions of the DMs using the same method followed in Step 3 (i.e., using FFWA and assuming equal importance for each DMs), to formulate the FF–DMTR. The FF–DMTR is given as

$$\check{X} = \left[\tilde{x}^{F}{}_{ij}\right]_{m\times n} \tag{30}$$

where $\tilde{x}^{F}{}_{ij} = \left(\mu_{fij},\ \vartheta_{fij}\right)$ is an FFS itself.

Step 7. Deriving FF–NDMTR

In the classical CODAS method, we used linear max-min normalization. In the work of Keshavarz-Ghorabaee et al. [55], it is mentioned that since, in case of FFS, the elements belong to the range of 0 to 1, there is no need to change the scale. Therefore, for normalization, we used the following scheme to formulate the NDMTR $\check{N} = \left[\tilde{\eta}^{F}{}_{ij}\right]_{m\times n}$, where

$$\tilde{\eta}^{F}{}_{ij} = \begin{cases} \tilde{x}^{F}{}_{ij};\text{if } C_j \text{ is profit type} \\ \left(\tilde{x}^{F}{}_{ij}\right)^{c};\text{if } C_j \text{ is cost type} \end{cases} \tag{31}$$

To find out the complement values, we use Definition 4 (i) (see expression (3))

Step 8. Construction of the WNDMTR.

The WNDTMR $\check{N}^{*} = \left[\tilde{\eta}^{F*}{}_{ij}\right]_{m\times n}$ is given as

$$\tilde{\eta}^{F*}{}_{ij} = w_j\tilde{\eta}^{F}{}_{ij} \tag{32}$$

We use property 4 (viii) (see expression (3)) for to construct the WNDMTR.

Step 9. Finding out the anti-ideal solution.

For finding out the anti-ideal solution, we first formulated the score matrix corresponding to $\check{N}^{*}$ using expression (8). Then, based on the score values, we discovered the anti-ideal solution, which is given below

$$\check{S}^{-} = \left[\check{s}_j^{\,-}\right]_{1\times n} \tag{33}$$

Here, $\check{s}_j^{\,-}$ is the corresponding $\tilde{\eta}^{F*}{}_{ij}$ whose score value is the minimum, with respect to the criterion C_j, as per Theorem 1 (see expression (6)).

Note: In our study, we did not observe any equality of the score values between the two FFS and, hence, we do not need to use accuracy values for comparison.

Step 10. Calculation of distances from the anti-ideal solution.

In this step, we first calculated the score and accuracy values, the degree of indeterminacy for the anti-ideal solution, and the WNDMTR, using definitions 8 and 6 (see expressions (8) and (5)) and expression (2). Subsequently, we calculated the Euclidean (E_i) distances of the DMUs from the anti-ideal solution by using expression (13) (see Definition 11). To calculate the taxicab (T_i) distance, we used expression (12) (see Definition 11).

Step 11. Formation of relative assessment matrix $R_a = [h_{ik}]_{m \times m}$.

We followed step 5 of the classical CODAS method (see expressions (24) and (25))

Step 12. Calculation of the assessment score (H_i).

We followed step 6 of the classical CODAS method (see expression (26)).

The alternative with a higher H_i value was given a higher priority than the others, as it was the farthest from the anti-ideal solution.

4. Results

In this section, we provide the results of the data analysis using our proposed FF-FUCOM-CODAS framework, for the problem of the selection of a smartphone brand, in a step-by-step manner, as described in the previous section (see Section 3.5)

Step 1. Rating of the criteria.

In our study, we used 15 respondents (DMs). In tune with the extant literature survey, we found seven criteria based on the UTAUT2 model for comparing the smartphone brands under consideration (see Table 6). We used a nine-point FF linguistic scale, as described in Table 8, for prioritizing the criteria according to their relative importance, as presented by the DMs. The responses received from the respondents or DMs are expressed in Table 10.

Table 10. Rating of the criteria by DMs.

Decision Maker	Rating of the Criteria						
	C1	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**
DM1	H	H	H	H	H	MH	VH
DM2	VH	VH	VVH	VH	VH	VH	VVH
DM3	H	H	H	H	H	H	H
DM4	M	M	H	H	VH	VH	VH
DM5	H	VVH	VVH	VH	VH	VH	VVH
DM6	H	VVH	VVH	VVH	VVH	VH	VH
DM7	M	MH	VH	VH	H	VH	VH
DM8	H	H	H	M	M	M	M
DM9	M	H	H	VH	VH	H	H
DM10	H	VH	H	VH	VVH	MH	M
DM11	MH	H	VH	M	VH	VVH	VVH
DM12	H	VH	VH	VH	VH	H	VH
DM13	H	H	H	H	H	H	H
DM14	MH	H	VVH	MH	VVH	VH	MH
DM15	MH	VH	VVH	VH	VH	VH	VVH

(Green color: beneficial, and red color: non-beneficial criteria).

It can be noted that we have one criterion (C1) for cost type (i.e., non-beneficial) and six other criteria (C2 to C7) for profit type (i.e., beneficial), for the users, while they are considering a smartphone brand.

Step 2. Deriving the relative weights of the DMs.

In our study, we considered the opinions given by all DMs as equally important, as they were a blend of users and dealers with substantial experience. Therefore, expression (28) was not applicable, in our case. The weights for all the DMs are equal to $\omega_t = \frac{1}{15}$ (since 15 DMs participated in our study).

Step 3. The formation of the criteria rating matrix after aggregating the responses of the DMs. In this step, we aggregated the opinions of the DMs using expression (29), to construct the criteria rating matrix. Note that each element in the criteria rating matrix is also an FFS.

Step 4. We then calculated the score values of the elements in the criteria rating matrix by using the IGSF (see expression (8)), and presented the criteria in a descending order based on the score values.

Step 5. In the next step, we calculated the criteria weights following the procedural algorithm of the FUCOM method (see Section 3.3). The final model for determining the criteria weights is expressed below (see expression (34)).

Tables 11–13 show the results of the step-by-step calculations of the criteria weights. Table 11 provides the aggregated criteria rating matrix and IGSF values. In Table 12, the calculations for comparative priorities are given and in Table 13 the derived final weights of the criteria (by solving the expression (34) using the Lingo 19 solver) are listed. It is worth noting that the value for DFC (χ) is very negligible and close to zero, which suggests the validity of the results given by the FF–FUCOM method. We observed that the criteria weights were appropriately distributed, while C3 (product quality and reliability), C5 (features and functionalities), and C7 (social image) were given more preference by the DMs. In other words, HM, PE, and SI were found to be dominant constructs. The criteria weight calculation using FF-FUCOM method is demonstrated in Tables 11–13.

Table 11. Score Value of the Criteria.

Criteria	μ	ν	**IGSF Value**
C1	0.6467	0.2533	0.4633
C2	0.7333	0.1800	0.6309
C3	0.7867	0.1467	0.7351
C4	0.7267	0.1800	0.6180
C5	0.7733	0.1467	0.7096
C6	0.7333	0.1733	0.6312
C7	0.7533	0.1733	0.6700

Table 12. Comparative Priority.

Criteria	**Priority**	$\varnothing_{\frac{k}{k+1}}$	$\frac{\mathbf{W_k}}{\mathbf{W_{k+1}}}$	$\frac{\mathbf{W_k}}{\mathbf{W_{k+2}}}$
C3	0.7351	1.03593	1.0359	1.09711
C5	0.7096	1.05906	1.0591	1.12431
C7	0.6700	1.06161	1.0616	1.06203
C6	0.6312	1.00039	1.0004	1.02137
C2	0.6309	1.02097	1.0210	1.36173
C4	0.6180	1.33375	1.3338	
C1	0.4633			

Table 13. Final Weights.

Criteria	**Weight**
C1	0.1039
C2	0.1415
C3	0.1649
C4	0.1386
C5	0.1592
C6	0.1416
C7	0.1503
Sum	1.0000

$$\text{Min } \chi$$
$$\text{S.T}\begin{cases} \left|\frac{w_3}{w_5}\right| - 1.03593 \leq \chi;\ \left|\frac{w_5}{w_7}\right| - 1.05906 \leq \chi;\ \left|\frac{w_7}{w_6}\right| - 1.06161 \leq \chi;\ \left|\frac{w_6}{w_2}\right| - 1.00039 \leq \chi; \\ \left|\frac{w_2}{w_4}\right| - 1.02097 \leq \chi;\ \left|\frac{w_4}{w_1}\right| 1.33375 \leq \chi \\ \left|\frac{w_3}{w_7}\right| - 1.09711 \leq \chi;\ \left|\frac{w_5}{w_6}\right| - 1.12431 \leq \chi;\ \left|\frac{w_7}{w_2}\right| - 1.06203 \leq \chi;\ \left|\frac{w_6}{w_4}\right| - 1.02137 \leq \chi; \\ \left|\frac{w_2}{w_1}\right| - 1.36173 \leq \chi \\ \sum_{j=1}^{7} w_j = 1;\ w_j \geq 0\ \forall\, j \end{cases} \quad (34)$$

Step 6. In this step, we constructed the FF–DMTR. First, we took the ratings of the DMUs (i.e., 14 alternatives considered in our study) subject to the 7 criteria of each DM, using the FF linguistic scales given in Tables 8 and 9. The responses of the DMs are summarized in Appendix B and the FF–DMTR after aggregating individual responses of the DMs is given in Table 14.

Table 14. FF–DMTR for evaluations of the alternatives.

Criteria	0.1039	0.1039	0.1415	0.1415	0.1649	0.1649	0.1386	0.1386	0.1592	0.1592	0.1416	0.1416	0.1503	0.1503
	C1		C2		C3		C4		C5		C6		C7	
Brands														
B1	0.6767	0.2267	0.7267	0.1933	0.7467	0.1667	0.7267	0.1867	0.7400	0.1733	0.7533	0.1667	0.7667	0.1667
B2	0.5867	0.3267	0.6667	0.2400	0.6933	0.2133	0.6867	0.2267	0.7200	0.2000	0.6867	0.2367	0.7200	0.1933
B3	0.7133	0.2067	0.7800	0.1600	0.7800	0.1533	0.7600	0.1667	0.7933	0.1400	0.8000	0.1400	0.7933	0.1400
B4	0.8000	0.1667	0.8333	0.1267	0.8467	0.1267	0.8067	0.1400	0.8200	0.1333	0.8467	0.1200	0.8467	0.1267
B5	0.6067	0.2967	0.6867	0.2267	0.6600	0.2400	0.6533	0.2533	0.7067	0.2133	0.6867	0.2200	0.6867	0.2200
B6	0.6000	0.2967	0.6800	0.2200	0.6567	0.2400	0.6333	0.2667	0.6800	0.2333	0.6933	0.2133	0.7000	0.2133
B7	0.4700	0.4167	0.5567	0.3367	0.5367	0.3567	0.5500	0.3467	0.5367	0.3667	0.5733	0.3267	0.5533	0.3433
B8	0.4600	0.4300	0.5600	0.3367	0.5667	0.3300	0.5267	0.3667	0.5733	0.3333	0.5867	0.3067	0.5667	0.3300
B9	0.4933	0.3967	0.5533	0.3533	0.5200	0.3700	0.5067	0.3833	0.5333	0.3667	0.5133	0.3767	0.5000	0.3867
B10	0.5533	0.3500	0.5467	0.3467	0.5800	0.3267	0.5733	0.3167	0.5833	0.3200	0.6400	0.2600	0.5867	0.3100
B11	0.4933	0.3933	0.5467	0.3567	0.5067	0.4000	0.4733	0.4200	0.5033	0.3967	0.5300	0.3633	0.5333	0.3567
B12	0.3533	0.5267	0.4400	0.4567	0.4233	0.4833	0.4567	0.4533	0.4700	0.4400	0.4633	0.4300	0.4433	0.4567
B13	0.4733	0.4167	0.5300	0.3800	0.5100	0.4000	0.4433	0.4467	0.5300	0.3700	0.6033	0.2933	0.5467	0.3500
B14	0.5800	0.3167	0.6800	0.2200	0.6800	0.2200	0.6433	0.2533	0.6933	0.2067	0.6800	0.2200	0.6933	0.2067

Step 7. In this step, using the expression (31) we formulated the FF–NDMTR after normalization. Appendix B provides the FF-NDMTR for further proceedings.

Step 8. Next, we multiplied the values of the FF–NDMTR with the respective criteria weights, using expression (32) and property 4 (viii) (see the expression (3)) to construct the FF–WNDMTR. The FF–WNDMTR is given in Appendix B.

Step 9. We proceeded to determine the anti-ideal solutions $\check{S}^{-} = \left[\check{s}_j^{-}\right]_{1\times n}$. Here, $\check{s}_j^{-}$ is the corresponding $\widetilde{\eta}^{F*}{}_{ij}$ whose score value is minimum, with respect to the criterion C_j as per Theorem 1 (see expression (6)). Table 15 provides the anti-ideal solutions in the FFN, and Table 16 gives the score (IGSF), accuracy, and DoI values, calculated using expressions (8), (5), and (2), respectively.

Table 15. Anti-ideal solution.

	C1		C2		C3		C4		C5		C6		C7	
$\check{s}_j^{-}$	0.1672	0.9356	0.2322	0.8950	0.2347	0.8870	0.2324	0.8943	0.2586	0.8775	0.2451	0.8874	0.2387	0.8889

Table 16. Score, accuracy, and DoI values of the anti-ideal solution.

$\check{s}_j^{-}$	C1	C2	C3	C4	C5	C6	C7
Score	0.0055	0.0159	0.0167	0.0160	0.0226	0.0189	0.0175
Accuracy	0.8235	0.7295	0.7108	0.7278	0.6929	0.7134	0.7159
DoI	0.5609	0.6467	0.6613	0.6481	0.6746	0.6593	0.6574

Step 10–12. In these steps, we performed three types of calculations:

Calculation of distances from the anti-ideal solution;

Formation of relative assessment matrix;

Calculation of assessment score (Hi) to rank the alternatives (considering τ= 0.02).

We used the procedural steps mentioned in Section 3.5; definitions 8 and 6 (see expressions (8) and (5)); expression (2); expression (12); expression (13) (see Definition 11); and expressions (24), (25), and (26) to arrive at the final ranking. Tables 17–22 describes the step-by-step activities to derive the final ranking order of the alternatives. It is worth noting that higher represents the Hi value, and more preferred is the alternative.

We noticed that B4 > B3 > B1 > B2 > B14 > . . . . > B13 > B11 > B12, as per their performances in the context of the DMs. Furthermore, it can be observed that there are large variations in the appraisal scores (see Table 22, which is not an aberration as far as subjective opinion-based studies are concerned. Subsequently, we conducted a validation test and sensitivity analysis for further confirmation of the reliability of our results, which is addressed in the next section.

Table 17. Score values (FF–WNDMTR).

	C1	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**
B1	0.0504	0.0951	0.1277	0.0933	0.1181	0.1106	0.1264
B2	0.0294	0.0682	0.0950	0.0743	0.1050	0.0757	0.0987
B3	0.0614	0.1265	0.1514	0.1115	0.1569	0.1420	0.1471
B4	0.0974	0.1691	0.2137	0.1431	0.1795	0.1820	0.1932
B5	0.0334	0.0761	0.0789	0.0616	0.0974	0.0766	0.0821
B6	0.0322	0.0740	0.0776	0.0551	0.0841	0.0795	0.0881
B7	0.0139	0.0355	0.0375	0.0332	0.0357	0.0393	0.0373
B8	0.0129	0.0362	0.0453	0.0286	0.0450	0.0429	0.0406
B9	0.0163	0.0345	0.0337	0.0251	0.0350	0.0269	0.0264
B10	0.0241	0.0333	0.0489	0.0386	0.0479	0.0587	0.0459
B11	0.0164	0.0331	0.0305	0.0198	0.0287	0.0299	0.0329
B12	0.0055	0.0159	0.0167	0.0174	0.0226	0.0189	0.0175
B13	0.0142	0.0296	0.0311	0.0160	0.0343	0.0473	0.0357
B14	0.0285	0.0740	0.0885	0.0585	0.0917	0.0740	0.0857

Table 18. Accuracy values (FF–WNDMTR).

	C1	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**
B1	0.6674	0.5640	0.4971	0.5625	0.5124	0.5431	0.5319
B2	0.7287	0.5941	0.5303	0.5923	0.5353	0.5961	0.5445
B3	0.6575	0.5464	0.4962	0.5517	0.4953	0.5304	0.5108
B4	0.6439	0.5311	0.5025	0.5395	0.5018	0.5301	0.5248
B5	0.7106	0.5864	0.5480	0.6093	0.5451	0.5795	0.5623
B6	0.7097	0.5779	0.5470	0.6170	0.5574	0.5746	0.5595
B7	0.7725	0.6564	0.6278	0.6686	0.6457	0.6509	0.6450
B8	0.7793	0.6569	0.6104	0.6806	0.6244	0.6367	0.6363
B9	0.7628	0.6689	0.6362	0.6903	0.6451	0.6809	0.6714
B10	0.7400	0.6627	0.6101	0.6485	0.6149	0.6064	0.6231
B11	0.7608	0.6705	0.6582	0.7126	0.6645	0.6730	0.6526
B12	0.8235	0.7295	0.7108	0.7335	0.6929	0.7134	0.7159
B13	0.7728	0.6857	0.6587	0.7278	0.6473	0.6284	0.6494
B14	0.7211	0.5779	0.5332	0.6070	0.5335	0.5777	0.5503

Table 19. DoI values (FF–WNDMTR).

	C1	C2	C3	C4	C5	C6	C7
B1	0.6928	0.7583	0.7952	0.7591	0.7871	0.7702	0.7765
B2	0.6473	0.7404	0.7773	0.7415	0.7746	0.7392	0.7694
B3	0.6996	0.7684	0.7957	0.7653	0.7962	0.7773	0.7879
B4	0.7088	0.7769	0.7924	0.7722	0.7927	0.7774	0.7803
B5	0.6614	0.7451	0.7675	0.7310	0.7691	0.7492	0.7592
B6	0.6622	0.7502	0.7680	0.7262	0.7621	0.7521	0.7609
B7	0.6105	0.7004	0.7193	0.6920	0.7076	0.7042	0.7080
B8	0.6043	0.7001	0.7304	0.6836	0.7215	0.7136	0.7138
B9	0.6190	0.6918	0.7139	0.6766	0.7080	0.6834	0.6901
B10	0.6382	0.6961	0.7305	0.7058	0.7275	0.7329	0.7224
B11	0.6207	0.6907	0.6991	0.6599	0.6949	0.6889	0.7029
B12	0.5609	0.6467	0.6613	0.6436	0.6746	0.6593	0.6574
B13	0.6102	0.6799	0.6988	0.6481	0.7065	0.7189	0.7052
B14	0.6534	0.7502	0.7757	0.7325	0.7756	0.7503	0.7661

Table 20. Calculation of EDs (Ei).

	C1	C2	C3	C4	C5	C6	C7	Ei
B1	0.0503	0.0620	0.0830	0.0614	0.0707	0.0672	0.0761	0.0673
B2	0.0299	0.0470	0.0652	0.0488	0.0614	0.0442	0.0640	0.0515
B3	0.0555	0.0765	0.0915	0.0698	0.0881	0.0811	0.0878	0.0786
B4	0.0693	0.0956	0.1154	0.0836	0.0959	0.0972	0.1037	0.0944
B5	0.0355	0.0511	0.0564	0.0411	0.0567	0.0482	0.0549	0.0491
B6	0.0355	0.0525	0.0563	0.0375	0.0498	0.0502	0.0573	0.0484
B7	0.0153	0.0233	0.0261	0.0191	0.0151	0.0207	0.0227	0.0203
B8	0.0133	0.0233	0.0323	0.0150	0.0227	0.0252	0.0257	0.0225
B9	0.0183	0.0198	0.0232	0.0117	0.0151	0.0102	0.0136	0.0160
B10	0.0258	0.0211	0.0332	0.0255	0.0258	0.0367	0.0303	0.0284
B11	0.0189	0.0191	0.0167	0.0048	0.0088	0.0129	0.0198	0.0144
B12	0.0000	0.0000	0.0000	0.0018	0.0000	0.0000	0.0000	0.0003
B13	0.0153	0.0144	0.0167	0.0000	0.0144	0.0283	0.0213	0.0158
B14	0.0317	0.0525	0.0626	0.0408	0.0575	0.0479	0.0587	0.0503

Table 21. Calculation of TDs (Ti).

	C1	C2	C3	C4	C5	C6	C7	Ti
B1	0.3788	0.3864	0.4817	0.3823	0.4045	0.4007	0.4468	2.8813
B2	0.2495	0.3040	0.3946	0.3164	0.3602	0.2845	0.3888	2.2981
B3	0.4159	0.4560	0.5180	0.4245	0.4798	0.4621	0.4987	3.2549
B4	0.5018	0.5329	0.5947	0.4856	0.5043	0.5182	0.5478	3.6854
B5	0.2834	0.3282	0.3470	0.2720	0.3374	0.3028	0.3406	2.2114
B6	0.2804	0.3324	0.3453	0.2489	0.3009	0.3137	0.3549	2.1765
B7	0.1294	0.1572	0.1679	0.1344	0.0971	0.1413	0.1511	0.9784
B8	0.1153	0.1588	0.2079	0.1059	0.1459	0.1662	0.1698	1.0698
B9	0.1544	0.1407	0.1473	0.0822	0.0955	0.0686	0.0867	0.7754
B10	0.2163	0.1435	0.2177	0.1724	0.1635	0.2375	0.1983	1.3492
B11	0.1569	0.1346	0.1136	0.0359	0.0540	0.0880	0.1294	0.7124
B12	0.0000	0.0000	0.0000	0.0136	0.0000	0.0000	0.0000	0.0136
B13	0.1308	0.1065	0.1153	0.0000	0.0908	0.1869	0.1418	0.7721
B14	0.2549	0.3324	0.3800	0.2672	0.3386	0.2996	0.3594	2.2321

Table 22. Final ranking (FF-CODAS) at τ = 0.02.

Brand	Hi	Rank	Brand	Hi	Rank
B1	14.0783	3	B8	−10.4372	10
B2	8.2351	4	B9	−13.6449	9
B3	21.7585	2	B10	−8.1197	8
B4	27.5187	1	B11	−14.1081	13
B5	7.4218	11	B12	−22.5544	14
B6	7.0981	6	B13	−13.6715	12
B7	−11.1985	7	B14	7.6237	5

5. Validation and Sensitivity Analysis

After we derived the ranking of the alternatives using the hybrid FF–FUCOM–CODAS framework, the test for the validation and stability of the results was performed. The results obtained by using a MCDM algorithm most often suffered from irrationality, less reliability, bias, and variability with respect to any changes in the given conditions [106–108]. The conditions, such as the selection of appropriate criteria for comparing the alternatives; experimental set up; type of information (objective or subjective); variations in the responses; exclusion or inclusion of alternatives; normalization type; and the interplay among the criteria, and the change in their weights are some of the factors influencing the results obtained by using a particular MCDM method [109–111]. Therefore, it is essential to ascertain the effectiveness of the results obtained by using a specific MCDM framework. In our case, we follow a three-stage process.

1. The comparison of the results obtained by using our FF–CODAS method with those derived by applying an established framework using statistical analysis [112,113].
2. The examination of the variations in the original ranking order (using FF–CODAS) if the optimum alternative interchange its value with that of any other sub-optimum one [114–116].
3. Checking the stability in the result through sensitivity analysis [117–119].

For the purpose of comparison, we first applied the following models for ranking the alternatives: the FF—TOPSIS (technique for order of preference by similarity to ideal solution) method [7], for which we used IGSF as a measure (see expression (8)) to calculate the score values [17] and the usual method for deriving the accuracy values (see expression (5)); the classic CODAS method [57], in which we first defuzzified the FF–DMTR (using IGSF) and then used the same for ranking the alternatives, using the conventional steps of the CODAS method; the IGSF score that is founded on a classic evaluation based on distance from average solution (EDAS) [120]; multi-attributive border approximation area comparison (MABAC) [106]; and complex proportional assessment (COPRAS) [121]. Table 23 provides the comparative ranking of the alternatives using all the models mentioned above. We conducted further statistical analysis using the Spearman's rank correlation test (see expression (35)). We observed that all models, including our FF–CODAS, confirmed the same ordering for the top three positions (B4 > B3 > B1). Ranking orders suggested by various models were reasonably consistent and Spearman's rank correlation coefficients (ρ) were all statistically significant (at 0.01 level, two-tailed), and showed very high values. Figure 3 depicts the comparative analysis of ranking orders, which also confirms our findings.

$$\rho = 1 - \frac{6\sum d_i^2}{n\left(n^2 - 1\right)} \tag{35}$$

Here, d_i is the difference between two ranks of each observation and n is the number of observations.

Table 23. Comparative analysis of the rankings.

Brand	Ranking					
	FF–CODAS	FF–TOPSIS	CODAS	COPRAS	EDAS	MABAC
B1	3	3	3	3	3	3
B2	4	4	4	4	4	4
B3	2	2	2	2	2	2
B4	1	1	1	1	1	1
B5	11	6	5	13	12	12
B6	6	7	7	6	6	6
B7	7	10	10	7	7	7
B8	10	9	9	10	10	10
B9	9	11	13	9	9	9
B10	8	8	8	8	8	8
B11	13	13	14	14	13	13
B12	14	14	12	12	14	14
B13	12	12	11	11	11	11
B14	5	5	6	5	5	5
ρ		0.912 **	0.846 **	0.978 **	0.996 **	0.996 **

(** Correlation is significant at the 0.01 level (2-tailed)).

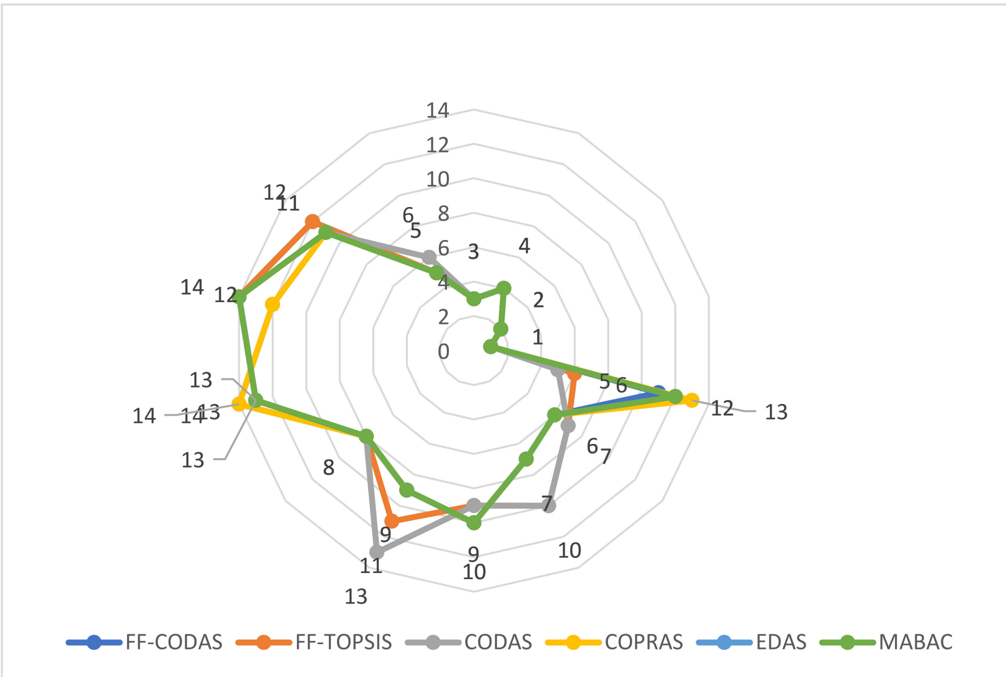


Figure 3. Comparison of ranking results.

Subsequently, we checked the efficacy of the FF–CODAS method by interchanging the values of any optimal solutions (e.g., B3) with some sub-optimal solutionss (e.g., B13). After interchanging the values, we carried out FF–CODAS-based ranking. Table 24 exhibits the comparative analysis.

Table 24. Comparison of ranking with the interchange of values.

Brand	H_i	After Interchange (FF–CODAS)	Original (FF–CODAS)
B1	14.0783	3	3
B2	8.2351	4	4
B3	−13.6715	12	2
B4	27.5187	1	1
B5	7.4218	11	11
B6	7.0981	6	6
B7	−11.1985	7	7
B8	−10.4372	10	10
B9	−13.6449	9	9
B10	−8.1197	8	8
B11	−14.1081	13	13
B12	−22.5544	14	14
B13	21.7585	2	12
B14	7.6237	5	5

We can observe that, after the interchange of values among B3 and B13, their original positions are swapped, while there is no change in the original position of any other alternative. Hence, our FF–CODAS provides a stable result.

For further confirmation, we proceeded to the sensitivity analysis. There are several ways to simulate variations in the given conditions for examining the stability and robustness of the results obtained through a given MCDM framework. In our paper, we followed two schemes, such as:

(i) Variations in the τ value (e.g., [70,71,82]) that were used in the CODAS framework.
(ii) The exchange of criteria weights (e.g., [122]).

Table 25 indicates the experiments carried out for the above-mentioned two schemes of the sensitivity analysis. We varied τ value from 0.02 (original case) to 0.1 and, in another scheme, we exchanged the weights of beneficial and non-beneficial criteria, and those of the most prioritized and other criteria. The results of the sensitivity analysis is shown in Tables 26 and 27, and Figure 4 is a pictorial representation of the outcome of the sensitivity analysis.

Table 25. Sensitivity analysis schemes: (a) scheme (i) and (b) scheme (ii).

Cases (Scheme (i))	τ Value
Original	0.02
Exp 1	0.03
Exp 2	0.04
Exp 3	0.05
Exp 4	0.06
Exp 5	0.07
Exp 6	0.08
Exp 7	0.10

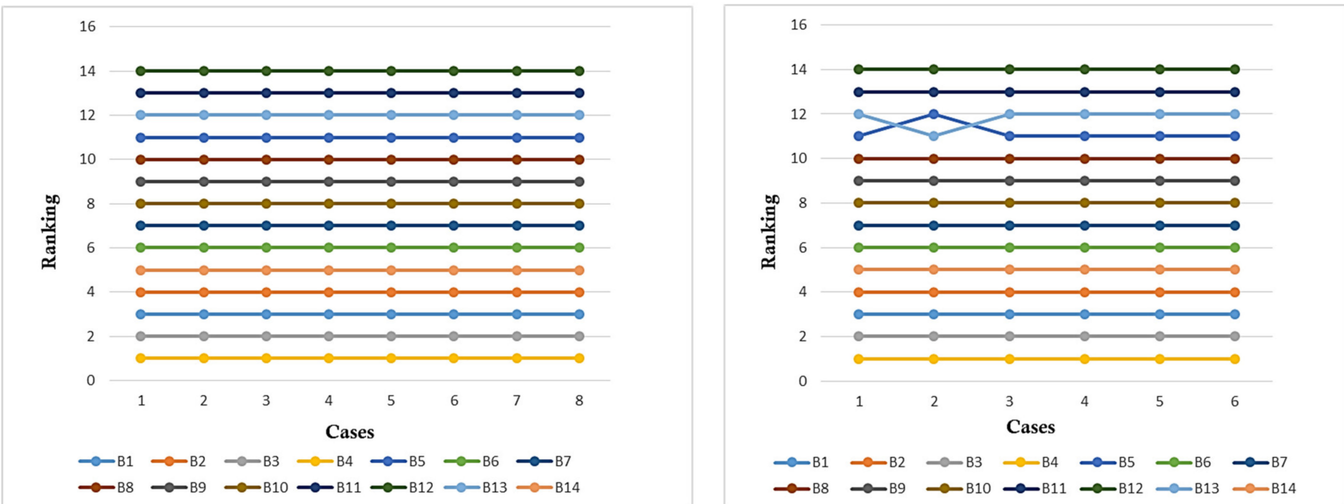
Cases (Scheme (ii))	Criteria Weights						
	C1	C2	C3	C4	C5	C6	C7
Original	0.1039	0.1415	0.1649	0.1386	0.1592	0.1416	0.1503
Exp 1	0.1649	0.1415	0.1039	0.1386	0.1592	0.1416	0.1503
Exp 2	0.1039	0.1415	0.1386	0.1649	0.1592	0.1416	0.1503
Exp 3	0.1039	0.1415	0.1592	0.1386	0.1649	0.1416	0.1503
Exp 4	0.1039	0.1386	0.1649	0.1415	0.1592	0.1416	0.1503
Exp 5	0.1039	0.1415	0.1649	0.1386	0.1503	0.1416	0.1592

Table 26. Ranking (Sensitivity Analysis Scheme (i)).

Brand	Original	Exp 1	Exp 2	Exp 3	Exp 4	Exp 5	Exp 6	Exp 7
	τ = 0.02	τ = 0.03	τ = 0.04	τ = 0.05	τ = 0.06	τ = 0.07	τ = 0.08	τ = 0.10
B1	3	3	3	3	3	3	3	3
B2	4	4	4	4	4	4	4	4
B3	2	2	2	2	2	2	2	2
B4	1	1	1	1	1	1	1	1
B5	11	11	11	11	11	11	11	11
B6	6	6	6	6	6	6	6	6
B7	7	7	7	7	7	7	7	7
B8	10	10	10	10	10	10	10	10
B9	9	9	9	9	9	9	9	9
B10	8	8	8	8	8	8	8	8
B11	13	13	13	13	13	13	13	13
B12	14	14	14	14	14	14	14	14
B13	12	12	12	12	12	12	12	12
B14	5	5	5	5	5	5	5	5

Table 27. Ranking (Sensitivity Analysis Scheme (ii)).

Brand	Original	Exp 1	Exp 2	Exp 3	Exp 4	Exp 5
B1	3	3	3	3	3	3
B2	4	4	4	4	4	4
B3	2	2	2	2	2	2
B4	1	1	1	1	1	1
B5	11	12	11	11	11	11
B6	6	6	6	6	6	6
B7	7	7	7	7	7	7
B8	10	10	10	10	10	10
B9	9	9	9	9	9	9
B10	8	8	8	8	8	8
B11	13	13	13	13	13	13
B12	14	14	14	14	14	14
B13	12	11	12	12	12	12
B14	5	5	5	5	5	5



(**a**) (**b**)

Figure 4. Presentation of the results of the sensitivity analysis: (**a**) scheme (i) and (**b**) scheme (ii).

From Table 24 and Figure 4, we can observe that the original ranking order remains unchanged for the scheme (i) of the sensitivity analysis, while, in scheme (ii), other than the minor variations in B5 and B13, all other alternatives hold their relative positions and remain unchanged. Therefore, we concluded that our FF–CODAS framework provided a stable and robust solution.

6. Research Implications

Understanding consumer behavior to decide on an effective marketing mix, in terms of product design; formulating appropriate segmentation; targeting and positioning (STP) strategies; setting up competitive prices; reaching the target consumers and engaging with them; and, finally, to reap the competitive advantages, is of paramount importance to the decision makers in industries. The extensive developments in the technology industries now witness fleeting product life cycles and rapid changes in the consumers' choices and preferences, especially for high-tech products, such as smartphones. In this regard, this paper sheds light on consumers' selection parameters in the pre-buying stage, while they decide on purchasing a specific brand. The present study unearths a new dimension for explaining the basis for consumers' decision-making, based on the UTAUT2 theory and, thereby, comparing leading smartphone brands holistically in a comprehensive MCDM framework with imprecise information. It also provides a reference model for the consumers who wish to compare the brands in an unbiased way before finalizing their decisions.

Furthermore, this paper proposes a novel FUCOM–CODAS framework, under the FF environment, which showcases a new manner of uncertain decision-making. The model used in this paper can be applied to solve various other real-life issues in group decision-making scenarios; for instance, supplier selection based on the sustainability criteria [76], the management of solid waste for better municipality service [123], construction management [124], and the identification of challenges in the presence of COVID-19 for designing social enterprise systems [125]. The framework used in this paper is a rare combination of multi-objective optimization-based preferential weighting of the criteria and the distance-based ranking of the available choices, with respect to the anti-ideal solution with imprecise information, combining both subjective and objective categories.

7. Conclusions and Future Scope

In this paper, we addressed the real-life problem of interest, such as understanding the priority motives of the consumers, while selecting a specific smartphone brand for finalizing a purchase decision. We applied a MAGDM framework to first prioritize the criteria identified (7 in our case) on the basis of the UTAUT2 model and, thereafter, we carried out a comparative analysis of 14 leading brands in India. Consumers' decisions are subjective in nature, with lot of imprecision. A total of 15 DMs participated in our study. This group of DMs was considerably heterogeneous in nature as it consisted of both the users and dealers who interacted with the buyers, and all the DMs have substantial experience. Considering the analysis, with the uncertainty of imprecise information, we extended the extant MAGDM models and proposed a novel integrated framework of FUCOM–CODAS methods using FFN-based linguistic scales. We observed that C3 (product quality and reliability), C5 (features and functionalities), and C7 (social image) are given more preference by the DMs. In other words, HM, PE, and SI are found to be dominant constructs. Our analysis reveals that the alternatives are ordered as B4 > B3 > B1 > B2 > B14 > ... > B13 > B11 > B12 as per the opinions of the DMs. We observed that the brands with a supreme quality, innovative applications, and a brand image with affordable price ranges were given more significance by the users or DMs. The results obtained by using our FF–FUCOM–CODAS framework shows notable consistency with extant MCDM models (both with FFNs and crisp values). Using extensive experimentation during the sensitivity analysis, we concluded that our method is capable of providing a stable and robust solution. Some of the advantages of our proposed model are lesser complexity and ability to withstand subjective bias, reasonably accurate and stable solutions, and flexibility on the part of the decision makers. However, the disadvantage is that FFS is a special case of q-ROFS, not a generalized one. Furthermore, for a large-scale-group decision-making scenario, the proposed model should be tested to examine its efficacy. An overall limitation of our research design is that we can consider the opinions of a number of experts to compare the smartphone brands, which may not be a good idea to posit a definitive statement against the brands.

To continue the above discussion, the present study has some scope for further applications. Firstly, the FF domain, for example, is relatively new and steadily growing. Future studies can attempt to address some real-life problems by the extended applications of extant MCDM methods using FFNs. Within our limited search, we observed that few methods, such as TOPSIS, EDAS, WASPAS, CRITIC, TODIM, and WPM, have been applied in the FF environment. Secondly, we applied FF–FUCOM–CODAS to the smartphone brand selection problem. Our model can also be applied and tested in various other complex and dynamic real-life situations, with subjective and objective information and different assumptions. Thirdly, we used the UTAUT2 model in conjunction with the findings of past research to select the criteria for comparing the brands. One future study can derive the selection criteria through a large scale of exploratory research, using a combination of advanced text mining based on reviews and opinions mostly posted on social media, and opinion-based surveys to finalize the criteria and revisiting the existing models, such as TRA, TPB, TAM, UTAUT, and UTAUT2. In this regard, the frameworks of some advanced theories of consumer behavior can also be considered for developing a new comprehensive model, on the basis of which a holistic analysis can be carried out using MCDM methods.

Nevertheless, we believe that the above-mentioned future scopes would not undermine the usefulness of our work. We intend that the framework developed in this paper can be helpful to solve many complex real-life problems. We trust that our approach to compare smartphone brands extends the growing literature and provides a new perspective to both strategic decision makers from the industry and common users.

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Declaration: This research adheres to all ethical and confidentiality requirements.

Appendix A

Rating of the 14 DMUs (B1, B2, . . . , B14) by 15 DMs (DM1, DM2, ..., DM15)

Table A1. Rating of DMUs for criterion 1.

Decision Maker	C1																											
	B1		**B2**		**B3**		**B4**		**B5**		**B6**		**B7**		**B8**		**B9**		**B10**		**B11**		**B12**		**B13**		**B14**	
DM1	0.6	0.3	0.5	0.4	0.8	0.1	0.9	0.1	0.6	0.3	0.6	0.3	0.6	0.3	0.5	0.4	0.5	0.4	0.5	0.4	0.6	0.3	0.5	0.4	0.5	0.4	0.6	0.3
DM2	0.3	0.6	0.5	0.4	0.9	0.1	0.9	0.1	0.1	0.8	0.1	0.8	0.1	0.8	0.4	0.5	0.7	0.2	0.7	0.2	0.7	0.2	0.1	0.8	0.5	0.4	0.7	0.2
DM3	0.8	0.1	0.7	0.2	0.7	0.2	0.9	0.1	0.8	0.1	0.7	0.2	0.6	0.3	0.6	0.3	0.8	0.1	0.9	0.1	0.6	0.3	0.8	0.1	0.8	0.1	0.8	0.1
DM4	0.7	0.2	0.5	0.4	0.8	0.1	0.9	0.1	0.7	0.2	0.6	0.3	0.3	0.6	0.1	0.8	0.3	0.6	0.1	0.8	0.1	0.8	0.4	0.5	0.4	0.5	0.7	0.2
DM5	0.7	0.2	0.7	0.2	0.8	0.1	0.9	0.1	0.6	0.3	0.7	0.2	0.6	0.3	0.6	0.3	0.5	0.4	0.6	0.3	0.7	0.2	0.4	0.5	0.7	0.2	0.6	0.3
DM6	0.8	0.1	0.1	0.9	0.9	0.1	0.9	0.1	0.9	0.1	0.7	0.2	0.5	0.4	0.5	0.4	0.4	0.5	0.4	0.5	0.4	0.5	0.1	0.8	0.1	0.8	0.6	0.3
DM7	0.7	0.2	0.7	0.2	0.6	0.3	0.6	0.3	0.4	0.5	0.4	0.5	0.3	0.6	0.3	0.6	0.1	0.8	0.5	0.4	0.1	0.8	0.1	0.8	0.1	0.8	0.7	0.2
DM8	0.7	0.2	0.6	0.3	0.8	0.1	0.9	0.1	0.6	0.3	0.7	0.2	0.6	0.3	0.5	0.4	0.6	0.3	0.6	0.3	0.7	0.2	0.4	0.5	0.7	0.2	0.5	0.4
DM9	0.8	0.1	0.9	0.1	0.9	0.1	0.9	0.1	0.7	0.2	0.7	0.2	0.6	0.3	0.8	0.1	0.7	0.2	0.6	0.3	0.5	0.4	0.3	0.6	0.1	0.8	0.1	0.8
DM10	0.9	0.1	0.8	0.1	0.4	0.5	0.6	0.3	0.8	0.1	0.8	0.1	0.3	0.6	0.3	0.6	0.4	0.5	0.8	0.1	0.3	0.6	0.1	0.8	0.4	0.5	0.6	0.3
DM11	0.8	0.1	0.7	0.2	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.5	0.4	0.4	0.5	0.3	0.6	0.5	0.4	0.3	0.6	0.3	0.6	0.4	0.5	0.6	0.3
DM12	0.6	0.3	0.6	0.3	0.6	0.3	0.8	0.1	0.7	0.2	0.7	0.2	0.7	0.2	0.6	0.3	0.7	0.2	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3
DM13	0.4	0.5	0.4	0.5	0.4	0.5	0.4	0.5	0.4	0.5	0.4	0.5	0.4	0.5	0.4	0.5	0.4	0.5	0.4	0.5	0.4	0.5	0.4	0.5	0.4	0.5	0.4	0.5
DM14	0.6	0.3	0.5	0.4	0.8	0.1	0.9	0.1	0.5	0.4	0.6	0.3	0.5	0.4	0.5	0.4	0.4	0.5	0.4	0.5	0.7	0.2	0.4	0.5	0.7	0.2	0.7	0.2
DM15	0.8	0.1	0.6	0.3	0.7	0.2	0.9	0.1	0.7	0.2	0.7	0.2	0.6	0.3	0.5	0.4	0.7	0.2	0.7	0.2	0.8	0.1	0.5	0.4	0.7	0.2	0.5	0.4

Table A2. Rating of DMUs for criterion 2.

Decision Maker	C2																											
	B1		**B2**		**B3**		**B4**		**B5**		**B6**		**B7**		**B8**		**B9**		**B10**		**B11**		**B12**		**B13**		**B14**	
DM1	0.6	0.3	0.6	0.3	0.8	0.1	0.8	0.1	0.8	0.1	0.8	0.1	0.6	0.3	0.6	0.3	0.6	0.3	0.5	0.4	0.6	0.3	0.4	0.5	0.5	0.4	0.6	0.3
DM2	0.5	0.4	0.5	0.4	0.9	0.1	0.9	0.1	0.4	0.5	0.4	0.5	0.4	0.5	0.4	0.5	0.7	0.2	0.7	0.2	0.7	0.2	0.4	0.5	0.7	0.2	0.7	0.2
DM3	0.7	0.2	0.7	0.2	0.7	0.2	0.9	0.1	0.8	0.1	0.7	0.2	0.7	0.2	0.7	0.2	0.8	0.1	0.8	0.1	0.7	0.2	0.7	0.2	0.7	0.2	0.8	0.1
DM4	0.7	0.2	0.7	0.2	0.9	0.1	0.9	0.1	0.7	0.2	0.8	0.1	0.7	0.2	0.5	0.4	0.5	0.4	0.5	0.4	0.5	0.4	0.5	0.4	0.5	0.4	0.5	0.4
DM5	0.6	0.3	0.7	0.2	0.8	0.1	0.9	0.1	0.7	0.2	0.7	0.2	0.6	0.3	0.6	0.3	0.5	0.4	0.7	0.2	0.7	0.2	0.5	0.4	0.8	0.1	0.7	0.2
DM6	0.8	0.1	0.4	0.5	0.9	0.1	0.9	0.1	0.9	0.1	0.7	0.2	0.1	0.8	0.1	0.8	0.1	0.9	0.1	0.8	0.1	0.8	0.1	0.8	0.1	0.9	0.5	0.4
DM7	0.8	0.1	0.7	0.2	0.7	0.2	0.7	0.2	0.4	0.5	0.4	0.5	0.4	0.5	0.4	0.5	0.4	0.5	0.4	0.5	0.4	0.5	0.4	0.5	0.5	0.4	0.7	0.2
DM8	0.8	0.1	0.7	0.2	0.8	0.1	0.9	0.1	0.7	0.2	0.8	0.1	0.6	0.3	0.6	0.3	0.7	0.2	0.7	0.2	0.7	0.2	0.4	0.5	0.8	0.1	0.8	0.1
DM9	0.8	0.1	0.9	0.1	0.9	0.1	0.9	0.1	0.7	0.2	0.7	0.2	0.6	0.3	0.8	0.1	0.5	0.4	0.1	0.8	0.1	0.9	0.1	0.9	0.1	0.9	0.8	0.1
DM10	0.9	0.1	0.8	0.1	0.5	0.4	0.8	0.1	0.8	0.1	0.8	0.1	0.3	0.6	0.5	0.4	0.4	0.5	0.7	0.2	0.7	0.2	0.3	0.6	0.4	0.5	0.8	0.1
DM11	0.9	0.1	0.7	0.2	0.9	0.1	0.9	0.1	0.6	0.3	0.6	0.3	0.6	0.3	0.7	0.2	0.5	0.4	0.7	0.2	0.5	0.4	0.3	0.6	0.3	0.6	0.5	0.4
DM12	0.7	0.2	0.6	0.3	0.6	0.3	0.8	0.1	0.7	0.2	0.7	0.2	0.7	0.2	0.6	0.3	0.7	0.2	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.7	0.2
DM13	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3
DM14	0.6	0.3	0.6	0.3	0.9	0.1	0.7	0.2	0.6	0.3	0.7	0.2	0.8	0.1	0.6	0.3	0.5	0.4	0.4	0.5	0.7	0.2	0.8	0.1	0.7	0.2	0.8	0.1
DM15	0.9	0.1	0.8	0.1	0.8	0.1	0.9	0.1	0.9	0.1	0.8	0.1	0.7	0.2	0.7	0.2	0.8	0.1	0.7	0.2	0.6	0.3	0.6	0.3	0.7	0.2	0.7	0.2

Table A3. Rating of DMUs for criterion 3.

Decision Maker	C3																											
	B1		**B2**		**B3**		**B4**		**B5**		**B6**		**B7**		**B8**		**B9**		**B10**		**B11**		**B12**		**B13**		**B14**	
DM1	0.7	0.2	0.6	0.3	0.7	0.2	0.7	0.2	0.8	0.1	0.8	0.1	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.7	0.2	0.7	0.2
DM2	0.7	0.2	0.7	0.2	0.9	0.1	0.9	0.1	0.6	0.3	0.6	0.3	0.5	0.4	0.6	0.3	0.8	0.1	0.7	0.2	0.8	0.1	0.5	0.4	0.7	0.2	0.8	0.1
DM3	0.7	0.2	0.7	0.2	0.7	0.2	0.9	0.1	0.7	0.2	0.7	0.2	0.7	0.2	0.7	0.2	0.8	0.1	0.8	0.1	0.7	0.2	0.7	0.2	0.7	0.2	0.7	0.2
DM4	0.6	0.3	0.5	0.4	0.8	0.1	0.9	0.1	0.8	0.1	0.8	0.1	0.6	0.3	0.6	0.3	0.4	0.5	0.4	0.5	0.3	0.6	0.5	0.4	0.4	0.5	0.6	0.3
DM5	0.7	0.2	0.7	0.2	0.8	0.1	0.9	0.1	0.7	0.2	0.7	0.2	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.7	0.2	0.5	0.4	0.8	0.1	0.7	0.2
DM6	0.8	0.1	0.6	0.3	0.9	0.1	0.9	0.1	0.8	0.1	0.8	0.1	0.1	0.8	0.1	0.8	0.1	0.8	0.1	0.9	0.1	0.9	0.1	0.9	0.1	0.9	0.7	0.2
DM7	0.8	0.1	0.8	0.1	0.8	0.1	0.8	0.1	0.6	0.3	0.5	0.4	0.4	0.5	0.4	0.5	0.4	0.5	0.4	0.5	0.4	0.5	0.4	0.5	0.4	0.5	0.6	0.3
DM8	0.8	0.1	0.7	0.2	0.8	0.1	0.9	0.1	0.7	0.2	0.8	0.1	0.7	0.2	0.7	0.2	0.6	0.3	0.6	0.3	0.7	0.2	0.5	0.4	0.7	0.2	0.7	0.2
DM9	0.8	0.1	0.9	0.1	0.9	0.1	0.9	0.1	0.4	0.5	0.3	0.6	0.6	0.3	0.8	0.1	0.6	0.3	0.6	0.3	0.1	0.9	0.1	0.9	0.1	0.9	0.8	0.1
DM10	0.8	0.1	0.8	0.1	0.6	0.3	0.9	0.1	0.8	0.1	0.8	0.1	0.3	0.6	0.5	0.4	0.3	0.6	0.7	0.2	0.3	0.6	0.1	0.8	0.4	0.5	0.8	0.1
DM11	0.9	0.1	0.7	0.2	0.9	0.1	0.9	0.1	0.5	0.4	0.5	0.4	0.5	0.4	0.6	0.3	0.4	0.5	0.7	0.2	0.6	0.3	0.3	0.6	0.3	0.6	0.5	0.4
DM12	0.7	0.2	0.6	0.3	0.6	0.3	0.7	0.2	0.7	0.2	0.7	0.2	0.6	0.3	0.6	0.3	0.7	0.2	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.7	0.2
DM13	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3
DM14	0.7	0.2	0.7	0.2	0.9	0.1	0.9	0.1	0.5	0.4	0.6	0.3	0.7	0.2	0.5	0.4	0.3	0.6	0.6	0.3	0.6	0.3	0.4	0.5	0.5	0.4	0.6	0.3
DM15	0.9	0.1	0.8	0.1	0.8	0.1	0.9	0.1	0.7	0.2	0.7	0.2	0.6	0.3	0.6	0.3	0.7	0.2	0.7	0.2	0.6	0.3	0.5	0.4	0.7	0.2	0.7	0.2

Table A4. Rating of DMUs for criterion 4.

Decision Maker	C4																											
	B1		**B2**		**B3**		**B4**		**B5**		**B6**		**B7**		**B8**		**B9**		**B10**		**B11**		**B12**		**B13**		**B14**	
DM1	0.6	0.3	0.5	0.4	0.6	0.3	0.7	0.2	0.7	0.2	0.7	0.2	0.5	0.4	0.5	0.4	0.5	0.4	0.8	0.1	0.7	0.2	0.5	0.4	0.5	0.4	0.6	0.3
DM2	0.7	0.2	0.7	0.2	0.9	0.1	0.9	0.1	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.7	0.2	0.5	0.4	0.6	0.3	0.8	0.1
DM3	0.7	0.2	0.7	0.2	0.7	0.2	0.9	0.1	0.7	0.2	0.7	0.2	0.7	0.2	0.7	0.2	0.7	0.2	0.8	0.1	0.7	0.2	0.7	0.2	0.7	0.2	0.7	0.2
DM4	0.5	0.4	0.5	0.4	0.7	0.2	0.8	0.1	0.7	0.2	0.6	0.3	0.5	0.4	0.4	0.5	0.4	0.5	0.3	0.6	0.1	0.8	0.5	0.4	0.3	0.6	0.7	0.2
DM5	0.6	0.3	0.6	0.3	0.8	0.1	0.9	0.1	0.6	0.3	0.7	0.2	0.6	0.3	0.6	0.3	0.6	0.3	0.7	0.2	0.7	0.2	0.5	0.4	0.7	0.2	0.7	0.2
DM6	0.9	0.1	0.5	0.4	0.9	0.1	0.9	0.1	0.9	0.1	0.7	0.2	0.8	0.1	0.6	0.3	0.5	0.4	0.7	0.2	0.4	0.5	0.5	0.4	0.1	0.8	0.6	0.3
DM7	0.8	0.1	0.8	0.1	0.8	0.1	0.7	0.2	0.5	0.4	0.5	0.4	0.4	0.5	0.3	0.6	0.6	0.3	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.6
DM8	0.7	0.2	0.6	0.3	0.8	0.1	0.8	0.1	0.7	0.2	0.7	0.2	0.7	0.2	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.7	0.2	0.7	0.2
DM9	0.8	0.1	0.9	0.1	0.9	0.1	0.9	0.1	0.7	0.2	0.5	0.4	0.4	0.5	0.7	0.2	0.1	0.8	0.1	0.8	0.1	0.9	0.1	0.9	0.1	0.9	0.8	0.1
DM10	0.8	0.1	0.8	0.1	0.7	0.2	0.9	0.1	0.8	0.1	0.8	0.1	0.3	0.6	0.4	0.5	0.3	0.6	0.7	0.2	0.1	0.8	0.1	0.9	0.3	0.6	0.8	0.1
DM11	0.8	0.1	0.7	0.2	0.8	0.1	0.9	0.1	0.5	0.4	0.5	0.4	0.5	0.4	0.5	0.4	0.5	0.4	0.6	0.3	0.6	0.3	0.5	0.4	0.5	0.4	0.5	0.4
DM12	0.7	0.2	0.7	0.2	0.6	0.3	0.7	0.2	0.7	0.2	0.7	0.2	0.6	0.3	0.6	0.3	0.7	0.2	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.7	0.2
DM13	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3
DM14	0.9	0.1	0.8	0.1	0.7	0.2	0.7	0.2	0.4	0.5	0.5	0.4	0.5	0.4	0.3	0.6	0.3	0.6	0.5	0.4	0.3	0.6	0.4	0.5	0.1	0.8	0.5	0.4
DM15	0.8	0.1	0.9	0.1	0.9	0.1	0.8	0.1	0.7	0.2	0.7	0.2	0.6	0.3	0.6	0.3	0.7	0.2	0.8	0.1	0.7	0.2	0.5	0.4	0.7	0.2	0.7	0.2

Table A5. Rating of DMUs for criterion 5.

Decision Maker	C5																											
	B1		**B2**		**B3**		**B4**		**B5**		**B6**		**B7**		**B8**		**B9**		**B10**		**B11**		**B12**		**B13**		**B14**	
DM1	0.7	0.2	0.5	0.4	0.7	0.2	0.7	0.2	0.8	0.1	0.8	0.1	0.6	0.3	0.6	0.3	0.6	0.3	0.8	0.1	0.7	0.2	0.6	0.3	0.7	0.2	0.7	0.2
DM2	0.7	0.2	0.7	0.2	0.9	0.1	0.9	0.1	0.6	0.3	0.7	0.2	0.6	0.3	0.6	0.3	0.8	0.1	0.8	0.1	0.8	0.1	0.6	0.3	0.8	0.1	0.8	0.1
DM3	0.7	0.2	0.7	0.2	0.7	0.2	0.9	0.1	0.7	0.2	0.7	0.2	0.7	0.2	0.7	0.2	0.7	0.2	0.7	0.2	0.7	0.2	0.7	0.2	0.7	0.2	0.7	0.2
DM4	0.7	0.2	0.7	0.2	0.8	0.1	0.8	0.1	0.8	0.1	0.6	0.3	0.5	0.4	0.4	0.5	0.5	0.4	0.5	0.4	0.5	0.4	0.6	0.3	0.4	0.5	0.7	0.2
DM5	0.6	0.3	0.6	0.3	0.8	0.1	0.9	0.1	0.7	0.2	0.7	0.2	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.7	0.2	0.5	0.4	0.8	0.1	0.7	0.2
DM6	0.8	0.1	0.7	0.2	0.9	0.1	0.9	0.1	0.9	0.1	0.9	0.1	0.1	0.9	0.1	0.9	0.1	0.9	0.1	0.9	0.1	0.9	0.1	0.9	0.1	0.9	0.6	0.3
DM7	0.8	0.1	0.8	0.1	0.8	0.1	0.7	0.2	0.5	0.4	0.4	0.5	0.4	0.5	0.4	0.5	0.4	0.5	0.4	0.5	0.4	0.5	0.4	0.5	0.4	0.5	0.4	0.5
DM8	0.8	0.1	0.8	0.1	0.9	0.1	0.9	0.1	0.8	0.1	0.8	0.1	0.8	0.1	0.8	0.1	0.7	0.2	0.8	0.1	0.7	0.2	0.7	0.2	0.8	0.1	0.8	0.1
DM9	0.8	0.1	0.9	0.1	0.9	0.1	0.9	0.1	0.6	0.3	0.6	0.3	0.6	0.3	0.8	0.1	0.7	0.2	0.7	0.2	0.3	0.6	0.3	0.6	0.3	0.6	0.8	0.1
DM10	0.9	0.1	0.9	0.1	0.8	0.1	0.8	0.1	0.9	0.1	0.9	0.1	0.3	0.6	0.6	0.3	0.3	0.6	0.7	0.2	0.1	0.8	0.1	0.9	0.5	0.4	0.8	0.1
DM11	0.7	0.2	0.6	0.3	0.8	0.1	0.8	0.1	0.4	0.5	0.4	0.5	0.4	0.5	0.5	0.4	0.5	0.4	0.5	0.4	0.4	0.5	0.4	0.5	0.4	0.5	0.6	0.3
DM12	0.7	0.2	0.6	0.3	0.6	0.3	0.7	0.2	0.7	0.2	0.7	0.2	0.6	0.3	0.6	0.3	0.7	0.2	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.7	0.2
DM13	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3
DM14	0.7	0.2	0.8	0.1	0.9	0.1	0.9	0.1	0.7	0.2	0.6	0.3	0.6	0.3	0.6	0.3	0.3	0.6	0.3	0.6	0.4	0.5	0.4	0.5	0.1	0.8	0.7	0.2
DM15	0.9	0.1	0.9	0.1	0.8	0.1	0.9	0.1	0.9	0.1	0.8	0.1	0.7	0.2	0.7	0.2	0.6	0.3	0.7	0.2	0.6	0.3	0.5	0.4	0.8	0.1	0.8	0.1

Table A6. Rating of DMUs for criterion 6.

Decision Maker	C6																											
	B1		**B2**		**B3**		**B4**		**B5**		**B6**		**B7**		**B8**		**B9**		**B10**		**B11**		**B12**		**B13**		**B14**	
DM1	0.6	0.3	0.6	0.3	0.7	0.2	0.8	0.1	0.8	0.1	0.8	0.1	0.6	0.3	0.6	0.3	0.6	0.3	0.8	0.1	0.6	0.3	0.6	0.3	0.6	0.3	0.8	0.1
DM2	0.8	0.1	0.7	0.2	0.9	0.1	0.9	0.1	0.6	0.3	0.6	0.3	0.5	0.4	0.7	0.2	0.8	0.1	0.8	0.1	0.8	0.1	0.6	0.3	0.8	0.1	0.8	0.1
DM3	0.8	0.1	0.6	0.3	0.7	0.2	0.9	0.1	0.7	0.2	0.8	0.1	0.8	0.1	0.8	0.1	0.8	0.1	0.8	0.1	0.7	0.2	0.8	0.1	0.8	0.1	0.8	0.1
DM4	0.7	0.2	0.7	0.2	0.8	0.1	0.8	0.1	0.6	0.3	0.5	0.4	0.4	0.5	0.3	0.6	0.3	0.6	0.7	0.2	0.1	0.8	0.5	0.4	0.7	0.2	0.7	0.2
DM5	0.5	0.4	0.5	0.4	0.8	0.1	0.9	0.1	0.7	0.2	0.7	0.2	0.6	0.3	0.6	0.3	0.5	0.4	0.5	0.4	0.6	0.3	0.4	0.5	0.7	0.2	0.5	0.4
DM6	0.9	0.1	0.1	0.8	0.9	0.1	0.9	0.1	0.8	0.1	0.8	0.1	0.7	0.2	0.7	0.2	0.4	0.5	0.7	0.2	0.6	0.3	0.4	0.5	0.7	0.2	0.5	0.4
DM7	0.8	0.1	0.8	0.1	0.8	0.1	0.7	0.2	0.5	0.4	0.5	0.4	0.5	0.4	0.5	0.4	0.5	0.4	0.4	0.5	0.4	0.5	0.4	0.5	0.4	0.5	0.5	0.4
DM8	0.8	0.1	0.7	0.2	0.9	0.1	0.9	0.1	0.7	0.2	0.7	0.2	0.6	0.3	0.6	0.3	0.5	0.4	0.6	0.3	0.6	0.3	0.5	0.4	0.7	0.2	0.7	0.2
DM9	0.6	0.3	0.9	0.1	0.9	0.1	0.9	0.1	0.7	0.2	0.7	0.2	0.6	0.3	0.8	0.1	0.6	0.3	0.7	0.2	0.5	0.4	0.3	0.6	0.3	0.6	0.7	0.2
DM10	0.9	0.1	0.9	0.1	0.7	0.2	0.9	0.1	0.9	0.1	0.9	0.1	0.5	0.4	0.6	0.3	0.3	0.6	0.7	0.2	0.4	0.5	0.1	0.8	0.6	0.3	0.8	0.1
DM11	0.9	0.1	0.8	0.1	0.9	0.1	0.9	0.1	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.4	0.5	0.6	0.3	0.6	0.3	0.4	0.5	0.4	0.5	0.6	0.3
DM12	0.8	0.1	0.6	0.3	0.7	0.2	0.8	0.1	0.8	0.1	0.8	0.1	0.6	0.3	0.6	0.3	0.7	0.2	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.7	0.2
DM13	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3
DM14	0.8	0.1	0.9	0.1	0.9	0.1	0.9	0.1	0.5	0.4	0.6	0.3	0.4	0.5	0.3	0.6	0.1	0.8	0.5	0.4	0.3	0.6	0.4	0.5	0.5	0.4	0.7	0.2
DM15	0.8	0.1	0.9	0.1	0.8	0.1	0.9	0.1	0.8	0.1	0.8	0.1	0.6	0.3	0.6	0.3	0.7	0.2	0.6	0.3	0.6	0.3	0.4	0.5	0.7	0.2	0.8	0.1

Table A7. Rating of DMUs for criterion 7.

Decision Maker	C7																											
	B1		**B2**		**B3**		**B4**		**B5**		**B6**		**B7**		**B8**		**B9**		**B10**		**B11**		**B12**		**B13**		**B14**	
DM1	0.7	0.2	0.6	0.3	0.7	0.2	0.9	0.1	0.8	0.1	0.8	0.1	0.6	0.3	0.6	0.3	0.6	0.3	0.7	0.2	0.7	0.2	0.6	0.3	0.6	0.3	0.8	0.1
DM2	0.9	0.1	0.8	0.1	0.9	0.1	0.9	0.1	0.7	0.2	0.7	0.2	0.1	0.8	0.1	0.8	0.1	0.8	0.1	0.8	0.1	0.8	0.1	0.8	0.1	0.8	0.8	0.1
DM3	0.8	0.1	0.8	0.1	0.7	0.2	0.9	0.1	0.8	0.1	0.9	0.1	0.8	0.1	0.8	0.1	0.8	0.1	0.8	0.1	0.8	0.1	0.8	0.1	0.8	0.1	0.8	0.1
DM4	0.7	0.2	0.7	0.2	0.7	0.2	0.8	0.1	0.7	0.2	0.6	0.3	0.6	0.3	0.4	0.5	0.3	0.6	0.5	0.4	0.3	0.6	0.4	0.5	0.4	0.5	0.5	0.4
DM5	0.6	0.3	0.7	0.2	0.8	0.1	0.9	0.1	0.7	0.2	0.7	0.2	0.6	0.3	0.6	0.3	0.5	0.4	0.6	0.3	0.7	0.2	0.4	0.5	0.7	0.2	0.6	0.3
DM6	0.9	0.1	0.5	0.4	0.9	0.1	0.9	0.1	0.8	0.1	0.8	0.1	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.7	0.2
DM7	0.8	0.1	0.8	0.1	0.8	0.1	0.7	0.2	0.4	0.5	0.4	0.5	0.4	0.5	0.4	0.5	0.4	0.5	0.4	0.5	0.4	0.5	0.4	0.5	0.4	0.5	0.6	0.3
DM8	0.6	0.3	0.7	0.2	0.8	0.1	0.9	0.1	0.7	0.2	0.7	0.2	0.7	0.2	0.7	0.2	0.6	0.3	0.7	0.2	0.7	0.2	0.5	0.4	0.7	0.2	0.7	0.2
DM9	0.7	0.2	0.7	0.2	0.9	0.1	0.9	0.1	0.7	0.2	0.7	0.2	0.6	0.3	0.8	0.1	0.7	0.2	0.7	0.2	0.6	0.3	0.4	0.5	0.4	0.5	0.8	0.1
DM10	0.9	0.1	0.9	0.1	0.8	0.1	0.9	0.1	0.9	0.1	0.9	0.1	0.4	0.5	0.5	0.4	0.1	0.8	0.6	0.3	0.3	0.6	0.1	0.9	0.6	0.3	0.8	0.1
DM11	0.8	0.1	0.7	0.2	0.9	0.1	0.9	0.1	0.5	0.4	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.7	0.2	0.6	0.3	0.4	0.5	0.4	0.5	0.5	0.4
DM12	0.7	0.2	0.6	0.3	0.7	0.2	0.7	0.2	0.7	0.2	0.7	0.2	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.7	0.2
DM13	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3	0.6	0.3
DM14	0.9	0.1	0.9	0.1	0.8	0.1	0.9	0.1	0.5	0.4	0.6	0.3	0.5	0.4	0.5	0.4	0.3	0.6	0.5	0.4	0.4	0.5	0.3	0.6	0.6	0.3	0.7	0.2
DM15	0.9	0.1	0.8	0.1	0.9	0.1	0.9	0.1	0.8	0.1	0.8	0.1	0.6	0.3	0.7	0.2	0.8	0.1	0.7	0.2	0.7	0.2	0.5	0.4	0.7	0.2	0.8	0.1

Appendix B

Table A8. Normalized Matrix (FF–NDMTR).

	C1		C2		C3		C4		C5		C6		C7	
B1	0.2267	0.6767	0.7267	0.1933	0.7467	0.1667	0.7267	0.1867	0.7400	0.1733	0.7533	0.1667	0.7667	0.1667
B2	0.3267	0.5867	0.6667	0.2400	0.6933	0.2133	0.6867	0.2267	0.7200	0.2000	0.6867	0.2367	0.7200	0.1933
B3	0.2067	0.7133	0.7800	0.1600	0.7800	0.1533	0.7600	0.1667	0.7933	0.1400	0.8000	0.1400	0.7933	0.1400
B4	0.1667	0.8000	0.8333	0.1267	0.8467	0.1267	0.8067	0.1400	0.8200	0.1333	0.8467	0.1200	0.8467	0.1267
B5	0.2967	0.6067	0.6867	0.2267	0.6600	0.2400	0.6533	0.2533	0.7067	0.2133	0.6867	0.2200	0.6867	0.2200
B6	0.2967	0.6000	0.6800	0.2200	0.6567	0.2400	0.6333	0.2667	0.6800	0.2333	0.6933	0.2133	0.7000	0.2133
B7	0.4167	0.4700	0.5567	0.3367	0.5367	0.3567	0.5500	0.3467	0.5367	0.3667	0.5733	0.3267	0.5533	0.3433
B8	0.4300	0.4600	0.5600	0.3367	0.5667	0.3300	0.5267	0.3667	0.5733	0.3333	0.5867	0.3067	0.5667	0.3300
B9	0.3967	0.4933	0.5533	0.3533	0.5200	0.3700	0.5067	0.3833	0.5333	0.3667	0.5133	0.3767	0.5000	0.3867
B10	0.3500	0.5533	0.5467	0.3467	0.5800	0.3267	0.5733	0.3167	0.5833	0.3200	0.6400	0.2600	0.5867	0.3100
B11	0.3933	0.4933	0.5467	0.3567	0.5067	0.4000	0.4733	0.4200	0.5033	0.3967	0.5300	0.3633	0.5333	0.3567
B12	0.5267	0.3533	0.4400	0.4567	0.4233	0.4833	0.4567	0.4533	0.4700	0.4400	0.4633	0.4300	0.4433	0.4567
B13	0.4167	0.4733	0.5300	0.3800	0.5100	0.4000	0.4433	0.4467	0.5300	0.3700	0.6033	0.2933	0.5467	0.3500
B14	0.3167	0.5800	0.6800	0.2200	0.6800	0.2200	0.6433	0.2533	0.6933	0.2067	0.6800	0.2200	0.6933	0.2067

Appendix C

Table A9. Weighted Normalized Matrix (FF–WNDMTR).

	C1		C2		C3		C4		C5		C6		C7	
B1	0.3356	0.8571	0.4045	0.7925	0.4396	0.7442	0.4018	0.7924	0.4298	0.7565	0.4235	0.7759	0.4416	0.7639
B2	0.2851	0.8903	0.3647	0.8171	0.4014	0.7751	0.3751	0.8141	0.4154	0.7740	0.3777	0.8154	0.4078	0.7811
B3	0.3577	0.8489	0.4432	0.7716	0.4652	0.7340	0.4254	0.7801	0.4707	0.7312	0.4588	0.7570	0.4622	0.7442
B4	0.4157	0.8301	0.4865	0.7465	0.5226	0.7113	0.4611	0.7615	0.4930	0.7256	0.4985	0.7406	0.5078	0.7330
B5	0.2959	0.8814	0.3776	0.8106	0.3788	0.7903	0.3538	0.8267	0.4060	0.7820	0.3777	0.8070	0.3851	0.7965
B6	0.2923	0.8814	0.3733	0.8071	0.3766	0.7903	0.3414	0.8326	0.3878	0.7932	0.3821	0.8035	0.3940	0.7928
B7	0.2246	0.9131	0.2979	0.8572	0.3011	0.8437	0.2920	0.8634	0.2977	0.8524	0.3077	0.8535	0.3019	0.8516
B8	0.2196	0.9160	0.2998	0.8572	0.3194	0.8329	0.2787	0.8702	0.3198	0.8395	0.3156	0.8459	0.3098	0.8465
B9	0.2363	0.9084	0.2960	0.8631	0.2911	0.8488	0.2674	0.8756	0.2957	0.8524	0.2731	0.8709	0.2709	0.8669
B10	0.2673	0.8967	0.2921	0.8608	0.3276	0.8315	0.3056	0.8527	0.3259	0.8341	0.3480	0.8263	0.3218	0.8386
B11	0.2363	0.9076	0.2921	0.8643	0.2832	0.8598	0.2489	0.8867	0.2780	0.8631	0.2826	0.8664	0.2901	0.8565
B12	0.1672	0.9356	0.2322	0.8950	0.2347	0.8870	0.2397	0.8961	0.2586	0.8775	0.2451	0.8874	0.2387	0.8889
B13	0.2262	0.9131	0.2825	0.8720	0.2852	0.8598	0.2324	0.8943	0.2937	0.8536	0.3256	0.8406	0.2980	0.8540
B14	0.2815	0.8874	0.3733	0.8071	0.3923	0.7791	0.3476	0.8267	0.3969	0.7780	0.3734	0.8070	0.3895	0.7890

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