A NOVEL TYPE OF FLEXIBLE SOFT ANALYTIC NETWORK PROCESS TO SOLVE THE MULTIPLE-ATTRIBUTE DECISION-MAKING PROBLEM

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Research and development of scientific and technological products have been changing with each passing day in this new millennium. Decisions related to the production of technical products are the key to affecting the sustainable development and market share of enterprises. However, the decision-making related to the production of technology products contains many different evaluation criteria as well as qualitative and quantitative evaluation attributes. Moreover, the correlation between criteria must be considered so it can be treated as a complex multiple-attribute decision-making (MADM) problem. Moreover, performing a multi-attribute decision evaluation often encounters incomplete or missing information provided by experts, which will lead to difficulties in the solution process. In view of the incomplete or missing information of the assessment data, the traditional analytic network process (ANP) method and decision-making trial and evaluation laboratory ANP (DANP) method will delete the incomplete information during the process of assessment and decision-making, and this will bring about non-objective assessment results. In order to solve the above problems, this study proposes a novel type of flexible soft ANP (SANP) method to solve the MADM problems and uses a practical example of smartphone text entry to prove the effectiveness and suitability of the proposed SANP method.

Keywords: Smartphone Text Entry Way; Multiple Attribute Decision-Making; Analytic Network Process; Soft Analytic Network Process; Artificial Intelligence.

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1. INTRODUCTION

How to make the right decisions from complex problems has been an important and complicated issue over the past decade. Because problem evaluation includes many assessment criteria and usually considers both qualitative and quantitative properties, it can be regarded as a multiple-criteria decision-making (MCDM) problem (Wen *et al.*, 2020). A wrong judgment in MCDM problems could have significant influences on individuals or organizations. According to different purposes and different data types, the MCDM problem can be divided into multiple objective decision-making (MODM) and multiple attribute decision-making (MADM). The former is suitable for design/planning, while the latter can be applied in the aspect for evaluation (Tzeng and Huang, 2011). When facing problems that need to be evaluated, through the collection of group opinions, MADM often can understand the interdependence relationship among criteria and help with any analysis. Consequently, MADM can choose the best solution to solve complex problems between criteria that may be full of multiple, disproportionate, or contradictory conditions. To upgrade the quality of decision-making, many scholars have developed various research methodologies and provided more state-of-the-art methods to deal with MADM-related problems. For example, the elimination et choice translating reality (ELECTRE) method was suggested by Roy in 1968 (Roy, 1991), and then Saaty (1980) proposed the analytical hierarchy process (AHP) method. The technique for order preference by similarity to an ideal solution (TOPSIS) was set forth by Hwang and Yoon in 1981 (Tzeng and Huang, 2011), and then Vlsekriterijumska Optimizacija I Kompromisno Resenje (VIKOR) was described by Opricovic in 1998 (Opricovic and Tzeng, 2002).

There are thousands of research studies on practical applications and theoretical findings in the field of MADM. Despite these methodologies' diversity, most research methods have an additive concept and assume the criteria are independent of each other, thus lacking a comprehensive view on the criteria's interactions (Golcuk and Baykasoglu, 2016; Wu, 2008). In order to reflect and solve the correlation between the criteria, the Battelle Memorial Institute of the Geneva Research Center introduced the decision-making trial and evaluation laboratory (DEMATEL) approach (Gabus and Fontela, 1973). In recent years, it has been successfully used in various fields, such as thin film transistor liquid crystal display products (Chang and Cheng, 2011), failure mode and effect analysis (Chang *et al.*, 2014), bibliometric analysis (Koca and Yıldırım, 2021), supplier

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selection (Gergin *et al.*, 2022), while Saaty (1996) proposed the analytic network process (ANP) approach to handle the interactive relationship between the criteria. Many studies have shown that both the DEMATEL and ANP methods can indeed deal with the dependence relationship between criteria systematically for the MADM problem (Kheybari *et al.*, 2020, Buyukozkan and Guleryuz, 2016).

The typical analytic hierarchy process (AHP) method assumes that the evaluation criteria are independent, so it cannot be totally suitable for solving all problems in the real world. Extending the concept of the typical AHP method, the ANP method proposed by Saaty (1996) considers the dependence of feedback between clusters and elements, finds out the influencing factors, and overcomes the disadvantage of the typical AHP method. The ANP method builds a hierarchical structure of all elements (including quality and quantity), shows the relationship between criteria, considers the overall influence of all the elements, provides feedback to the overall structure, forms a network relationship, gives rating priorities among goals, criteria, and alternatives, calculates the relative weighting of each criterion, and determines the most appropriate project alternative (Buyukozkan and Ozturkcan, 2010). The ANP method has been successfully applied in many different fields recently. For example, Chou (2018) utilized the ANP method to identify the influencing factors of registry selection and to adopt correct policies to increase the attractiveness of Taiwan's maritime industry. Findings showed that the operating costs are the most important factor in the case of Taiwan's maritime industry.

Akay and Kocyigit (2020) used the ANP method to determine the criteria's weights for sub-basins with higher flood potential. Their results showed that the ANP method could improve prediction capability, effective management of water resources, and soil protection in the river basin. Zha *et al.* (2020) integrated the Delphi method, Entropy, fuzzy ANP method, and fuzzy PROMETHEE to deal with the equipment layout in a manufacturing system, expecting to select an appropriate equipment layout in the aircraft assembly workshop. The application results reported that this research method can effectively obtain the most suitable alternative for the selection of equipment layout. Relative studies also have covered supply chain risk management (Fazli *et al.*, 2015), tourism (Chen *et al.*, 2012), energy resource selection (Buyukozkan and Guleryuz, 2016), strategy management (Quezada *et al.*, 2018), environmental pollution (Wu *et al*., 2016), supplier selection (Giannakis *et al.*, 2020), and so on.

When dealing with practical MADM problems, because most experts have disparate experience, expertise, and background, their assessment attribute values provided may cover conditions such as definite, uncertainties, vagueness, missing information, etc. The traditional methods for dealing with uncertain information include the fuzzy set theory (Zadeh, 1965), rough set theory (Pawlak, 1982), grey system theory (Deng, 1989), and the concept of the linguistic variable (Zadeh, 1975), which are well-known approaches to handle uncertain situations as well as vague and imprecise information. Recently, many scholars used ANP and DEMATEL methodologies to combine the above methods to be applied in various fields (Mostamand *et al*., 2017; Pamucar *et al*., 2017; Arjomandi *et al*., 2021) and have demonstrated that they can effectively deal with situations that contain uncertainty, imprecision and inaccuracy information, and has been successfully implemented in various fields of human activities. However, when they encounter missing, non-existent, or incomplete information, it is difficult for classical mathematics or algorithms to solve them. To overcome these problems, Molodtsov (1999) proposed the soft set, using the concept of information supplement to deal with missing information.

Consequently, a soft set has been considered to be an effective mathematical tool to handle missing or incomplete information, and many scholars have used it to solve various practical problems. For example, Chang *et al.* (2016) integrated a soft set, AHP, and 2-tuple linguistic representation to evaluate training simulation systems. Their result verified that this integrated solution helps managers allocate limited resources while also improving investment returns and training effects. Alcantud *et al.* (2019) developed an algorithm that combined fuzzy and soft set theories to assess the survival rate in 5 years of lung cancer patients undergoing pneumonectomy. The result shows that it is an effective and precise diagnosis application, and it helps propose a correct survival classification for determining the survival rate. Witarsyah *et al.* (2020) adapted a soft set to group data and classify attribute options for an electronic government system. Their results showed that it can be regarded as a decision-making technology to determine the maturity of using an e-government system and provide useful information for decision-makers to develop and design e-government systems to improve and create more effective public services. On the other hand, many studies in the literature presented that a soft set can be widely applied to deal with decision-making problems, such as investment strategy (Tao *et al.*, 2015), supplier selection (Chang, 2015; Chang, 2019; Wen *et al.*, 2020), pattern recognition, (Selvachandran *et al*., 2018), group decision-making (Liu *et al.*, 2019; Das and Granados, 2022), failure mode and effect analysis (Chang *et al*., 2018), cloud computing (Ezugwu and Adewumi, 2017), and so on.

Ocampo and Seva (2016) applied the typical ANP method to evaluate text entry selection on a touch keyboard smartphone. They showed that speed and accuracy are the main critical factors in the text entry way selection. While the typical ANP method can effectively handle MADM problems in the case of a touch keyboard smartphone, it cannot deal with the condition of incomplete information or missing information, which leads to unobjective solution results. To effectively address the limitations of the typical ANP method, this study proposes a novel flexible evaluation approach that integrates the ANP method and soft set so as to consider all available information fully for solving complex MADM problems.

The rest of this paper runs as follows. Section 2 reviews related works on the ANP method, soft set, and DEMATEL method. Section 3 proposes a flexible soft analytic network process method. Section 4 applies an illustrative example of the evaluation methodology for text entry to demonstrate its effectiveness. Finally, Section 5 offers conclusions and future works.

2. LITERATURE REVIEW

This section introduces some basic concepts and procedures related to the ANP method, soft sets, and the DEMATEL method.

2.1 ANP Method

Extending the concept of the AHP method, Saaty first proposed the ANP method (Saaty, 1996) to solve complex network problems with dependence between the criteria and feedback elements. The AHP and ANP methods' solution processes are both the same. They use a pairwise comparison matrix to compute eigenvalues and eigenvectors and determine the priority of criteria. The solution steps of the ANP approach are introduced as below.

Step 1: Define attributes of the problem and establish a networking architecture

This step analyzes the attributes of the decision-making problem, identifies the elements that affect the decision-making (including goals, evaluation criteria, and alternatives), and develops the problem structuring. Each element of the cluster may have a relationship, and there may be feedback between clusters, from top to bottom, that form a network structure. A questionnaire design is then completed.

Step 2: Complete the questionnaire survey and conduct pairwise comparisons

Professionals are asked to answer a series of questions and to provide the necessary relationships of each decision component. Based on Saaty's 9-point priority measurement scale (Table 1), this step conducts pairwise comparisons of the criteria on the clusters, then offers a questionnaire survey, integrates expert preferences, and establishes comparison matrix A.

Table 1. The scales of pairwise comparison (Saaty, 1980)

Definition	Intensity of relative importance
Equal importance	1
Moderately importance	3
Strongly importance	5
Very strongly importance	7
Extremely importance	9
The intensity value of intermediate judgment	2, 4, 6, 8

Step 3: Consistency testing and building a supermatrix

After establishing comparison matrices A, where each matrix segment expresses the relationship between two nodes (clusters), this step then conducts a pairwise comparison and computes the maximal eigenvalues and eigenvector λ_{max} using Equation (1). Saaty used the consistency index (CI) and consistency ratio (CR) to confirm the consistency of the comparison matrix, as in Equations (2) and (3). If CR < 0.1, then the pairwise comparison shows consistency (Saaty, 1990). The random index (RI) is seen in Table 2 (n: number of criteria). Finally, each submatrix (goals, criteria, and elements) is integrated into the same matrix to form a supermatrix.

$$AW = \lambda_{max} W \quad (1)$$

$$CI = \frac{\lambda_{max} - n}{n-1} \quad (2)$$

$$CR = \frac{CI}{RI} \quad (3)$$

Table 2. Random index table (Saaty, 1980)

N	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
RI	0.00	0.00	0.52	0.89	1.11	1.25	1.35	1.40	1.45	1.49	1.52	1.54	1.56	1.58	1.59

Step 4: Calculate the priority and select the best alternative

The unweighted supermatrix must be normalized, and each matrix column sum is transformed to unity, called the weighted supermatrix. The weight of each element is calculated until the weights have to remain in a long-term stable condition, as in Equation (4). The results from weight are calculated from the priority of the alternative.

$$\lim_{k\to\infty} W^k . \tag{4}$$

2.2 Soft Set

When dealing with practical issues related to decision-making, because most experts have disparate expertise, experience, and backgrounds, evaluating attribute values may produce vague and imprecise information, and there may even be situations where information is missing or does not exist, causing MADM problems to become more complicated. To overcome these hurdles, Molodtsov (1999) proposed the concept of a soft set. It not only can resolve problems of associated data that are incomplete, uncertain, or ambiguous but also can circumvent assessment attribute information that is missing or non-existent during linguistic information aggregation. A soft set is defined as follows.

Let *U* be the initial universal set, and *E* is a set of parameters, where *P*(*U*) is the power set of *U*. A pair (*F, A*) is called a soft set over *U*, and $A \subset E$ and *F* is a mapping given by $F: A \to P(U)$.

Definition 1 (Ali *et al.*, 2009; Maji *et al.*, 2003). For two soft sets (*F, A*) and (*G, B*) on the common universal set *U*, the union of (*F, A*) and (*G, B*) is represented by (*H, C*), and these conditions should be satisfied:

(i) $C = A \cup B$

(ii) $\forall e \in C$

$$H(e) = \begin{cases} F(e) & if\ e \in A - B \\ G(e) & if\ e \in B - A \\ F(e) \cup G(e) & if\ e \in A \cap B \end{cases} . \tag{5}$$

Definition 2 (Maji *et al.*, 2003; Ali *et al.*, 2009). For two soft sets (*F, A*) and (*G, B*) on the common universal set *U*, the intersection set of (*F, A*) and (*G, B*) is represented by (*H, C*), and these conditions should be satisfied:

$C = A \cap B$

$\forall e \in C, H(e) = F(e)\ or\ G(e)$ (as both are the same set)

Definition 3 (Maji *et al.*, 2003; Ali *et al.*, 2009). For two soft sets (*F, A*) and (*G, B*) on the common universal set *U*, if they meet the following conditions, then (*F, A*) is the subset of (*G, B*), denoted as $(F, A) \tilde{\subset} (G, B)$.

$A \subseteq B$

$\forall e \in A, F(e) \subseteq G(e)$

Definition 4 (Maji *et al.*, 2003; Ali *et al.*, 2009). For two soft sets (*F, A*) and (*G, B*) on the common universal set *U*; if (*F, A*) is the subset of (*G, B*) and (*G, B*) is the subset of (*F, A*), then (*F, A*) and (*G, B*) are expressed as a soft equilibrium.

2.3 DEMATEL Method

For solving scientific projects about human affairs, the Battelle Memorial Institute at the Geneva Research Center in 1973 adopted the DEMATEL method to handle complex problems. It is a mathematical calculation method for analyzing causality, effectively finding out the core criteria between elements or facets (Tzeng *et al.*, 2007). Decision-makers can divide multiple measurement criteria into a causal group to understand causality more easily and to improve the understanding of decision-making issues. The DEMATEL method produces a causal diagram through the visualization of the structure using matrices (Chang *et al.*, 2013). The method-solving steps are described below.

Step 1. Produce the initial average matrix

Experts are asked, using a scale set of 0 to 4, to rate the influence of each relationship among the dimensions or criteria (where 0 is "no influence", 1 is "low influence", 3 is "high influence", and 4 is "very high influence"), then integrates the influence results that pairwise comparison that was consulted by experts, and generating an *n*×*n* direct-relation matrix *A*.

$$A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{bmatrix}. \quad (6)$$

Step 2. Normalizing the direct-relation matrix *S*

Based on the direct-relation matrix *A*, Equations (7) and (8) are used to obtain the normalized direct relationship matrix *S*.

$$S = k.A \quad (7)$$

$$k = min\left[\frac{1}{\max\limits_{i}\sum_{j=1}^{n}|a_{ij}|}, \frac{1}{\max\limits_{j}\sum_{i=1}^{n}|a_{ij}|}\right]. \quad (8)$$

Step 3. Derive the total direct-relation matrix *T*

Based on the normalized direct relationship matrix *S*, Equation (9) is used to calculate the total relation matrix *T*, where *I* is denoted as the identity matrix.

$$T = S + S^2 + S^3 + \cdots = \sum_{k=1}^{\infty} S^k = S(I - S)^{-1}. \quad (9)$$

Step 4. Compute cause group and effect group

The sums of the rows and columns in matrix *T* are separately denoted as *D* and *R* values through Equations (10), (11), and (12); $(D + R)$ and $(D - R)$ are then calculated, where $(D + R)$ is called prominence and indicates the strength of influences between each criterion, and $(D - R)$ is used for dividing criteria into two groups. A positive $(D - R)$ indicates the criteria belong to the cause group, and if $(D - R)$ is negative, then the criteria belong to the effect group.

$$T = [t_{ij}]_{n\times n}, i, j = 1,2, \ldots, n \quad (10)$$

$$D = [t_i]_{n\times 1} = \left[\sum_{j}^{n} t_{ij}\right]_{n\times 1} \quad (11)$$

$$R = [t_j]_{1\times n} = \left[\sum_{i}^{n} t_{ij}\right]_{1\times n}. \quad (12)$$

3. THE PROPOSED NEW APPROACH

3.1 The Reason for Using the ANP Method and Soft Set

Due to actual situations in the real world, the evaluation criteria or options used to deal with decision-making problems are not completely independent, but there is usually an interactive relationship. The typical ANP method is the most widely used research method for the above issue. The advantage of the typical ANP method is that it can solve complex network problems with dependence between criteria and feedback elements so as to determine the priority of criteria.

When solving MADM issues, because experts have different experiences and backgrounds in their professional fields, the information they provide often includes complete, incomplete, and non-existent information at the same time. These reasons will cause biased and non-objective assessment results. To address the MADM issues, this study integrates the ANP method and the soft set technique (called SANP method) to handle flexible information MADM issues. The proposed SANP method uses the concept of supplement information by a soft set to effectively deal with complete, incomplete, and non-existent information during the solution process and makes the solution results correspond more to real-world conditions.

3.2 The Procedure of the Proposed SANP Method

The procedure of the proposed SANP method is as follows.

Step 1. Analyze decision-making problems and establish network structures

An assessment team of cross-domain experts is constructed based on the decision-making problem. The team members define the problem, analyze the attributes of the problem and the characteristics of interdependence and self-feedback, and establish a problem hierarchy network structure (including goals, criteria, and alternatives).

Step 2. Confirm the evaluation criteria and complete the questionnaire design

The hierarchy of decision-making problems identifies the relation of dependencies between the selected metrics to construct the network model in a logical way and establishes appropriate and parsimonious evaluation indicators. Finally, the questionnaire design is completed.

Step 3. Implement assessment of the expert questionnaire

The team of experts used pairwise comparisons of Saaty's 9-point scale (Table 1) for goals, criteria, and alternatives to build a pairwise comparison matrix.

Step 4. Information supplement

For incomplete information, an information supplement uses the concept of a soft set to supplement the data of the questionnaire.

Step 5. Apply the ANP method to confirm the relationships of clusters and dependencies

Based on the results of step 4, the ANP method is applied to calculate the local weight of these criteria, and the consistency index (CI) and consistency ratio (CR) are used to confirm the consistency of the comparison matrix. If CR < 0.1, then the assessment results are acceptable. The initial unweighted supermatrix is finished after pairwise comparison of elements. The initial unweighted supermatrix can understand the dependencies and feedback relationships among each element (including goals, criteria, and alternatives).

Step 6. Apply the ANP method to prioritize the alternatives

After normalizing the unweighted supermatrix, the weighted supermatrix is calculated. The results of the weighted supermatrix use Equation (4) to reach a steady-state condition, and then long-term, stable sets of weights are obtained. Each row represents the weight of each criterion. These outcomes include the rankings of goals, evaluation criteria, and alternatives, as well as the global priority for each element.

4. ILLUSTRATIVE EXAMPLE

4.1 Overview

The widespread use of smartphones has rapidly increased the amount of information gathered by individuals. The smartphone must have a simple interface and convenient text entry method in order to speed up information transmission. This study uses the text entry way of smartphone evaluation to illustrate the reasonableness and correctness of the proposed method (adapted from Ocampo and Seva, 2016). The composition of the text entry way for a touch keyboard smartphone contains 3 levels of hierarchical structure: goals, criteria, and alternatives.

Goal (G) is the first component of a hierarchical structure, representing the most suitable text entry way for touch keyboard smartphone selection. Criteria denote the second composition of hierarchical structure, including the distance between buttons (DB), button arrangement (BA), number of buttons (NB), size of buttons (SB), familiarity (FA), and popularity (PO). Alternatives are the third composition of hierarchical structure, including 5 text entry way: clustered handwriting style (CHS), free handwriting style (FHS), multitap (M), multitap with T9 (MT9), and QWERTY (Q). Table 3 shows the decision element description of the text entry way (Ocampo and Seva, 2016).

The ANP network hierarchy structure of the most suitable text entry way for touch keyboard smartphone selection is shown in Figure 1. The assessment team of text entry way includes different backgrounds of 5 experts. Because they have disparate experience, expertise, and background, their assessment attribute values provided may cover conditions such as uncertainties and vagueness of information. In order to be objective, they will not score in unfamiliar criteria and avoid affecting the assessment results, so it will use * to indicate missing/non-existent data. According to Tables 1 and 3, each expert determines the importance score of pairwise comparisons between the 6 evaluation criteria (DB, BA, NB, SB, FA, and PO), respectively. The results are shown in Table 4. According to Table 1, each expert determines the importance score of pairwise comparisons between the 5 different alternatives (CHS, FHS, M, SB, MT9, and Q) under the criteria of DB, respectively. The results are shown in Table 5. Based on Table 1, each expert determines the importance score of pairwise comparisons between the 6 evaluation criteria (DB, BA, NB, SB, FA, and PO) regarding the M text entry way, respectively, and the results are shown in Table 6. Based on Table 1, each expert determines the importance score of pairwise comparisons between the 4 evaluation criteria (DB, BA, NB, and SB) under the criteria of DB, respectively. The results are shown in Table 7.

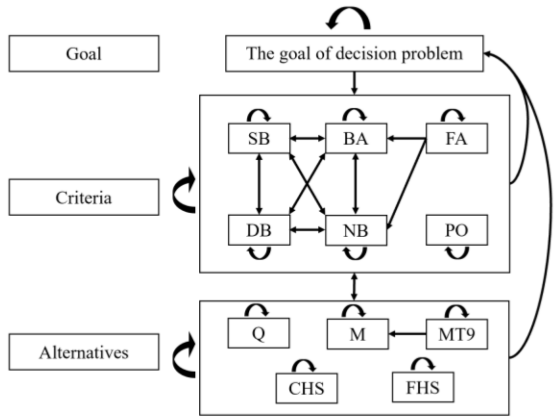

Figure 1. Interrelations between elements of the ANP network hierarchy model

Table 3. The structure of the evaluation components

Hierarchical structure	Decision elements	Description
Goal	G	Goal of decision problem
Criteria	DB	The distance of the text entry way from one button to another
	BA	Arrangement of buttons thought to affect the text entry way
	NB	Button population of a text entry way
	SB	Button size for text input way
	FA	Users are familiar with the perceived time range of text entry way
	PO	Popularity of the method regarding users' knowledge about their surroundings environment
Alternatives (Text entry way)	CHS	The keyboard is divided into 4 boxes; users can keystroke letters, numbers, and symbols in different areas, respectively
	FHS	The user enters a letter by handwriting and then hits an icon next to the input box to select the writing mode (alpha, numeric, and symbolic)
	M	Multiple keystrokes are required to enter characters, and there is no prediction function
	MT9	Entering characters requires multiple keystrokes with a predictive function
	Q	Standard typewriter and computer keyboard layout based on the Latin alphabet

Table 4. Pairwise comparisons of different criteria

Dimension	Experts	DB	BA	NB	SB	FA	PO
DB	Experts 1	1	1/2	1/5	2	1	3
	Experts 2	1	*	1/4	1/2	*	2
	Experts 3	1	1/4	1/6	1/2	1/2	2
	Experts 4	1	1/3	1/5	1	1/2	5
	Experts 5	1	1/4	1/5	1/2	1/2	2
BA	Experts 1	2	1	3	6	4	8
	Experts 2	*	1	2	4	2	4
	Experts 3	4	1	*	3	2	*
	Experts 4	3	1	3	6	3	7
	Experts 5	4	1	2	3	3	5
NB	Experts 1	5	1/3	1	2	4	4
	Experts 2	4	1/2	1	6	3	6
	Experts 3	6	*	1	6	4	6
	Experts 4	5	1/3	1	4	4	5
	Experts 5	5	1/2	1	*	2	4
SB	Experts 1	1/2	1/6	1/2	1	1/2	5
	Experts 2	2	1/4	1/6	1	1	2
	Experts 3	2	1/3	1/6	1	2	3

Dimension	Experts	DB	BA	NB	SB	FA	PO
	Experts 4	1	1/6	1/4	1	1/3	3
	Experts 5	2	1/3	*	1	1	2
FA	Experts 1	1	1/4	1/4	2	1	3
	Experts 2	*	1/2	1/3	1	1	5
	Experts 3	2	1/2	1/4	1/2	1	6
	Experts 4	2	1/3	1/4	3	1	4
	Experts 5	2	1/3	1/2	1	1	7
PO	Experts 1	1/3	1/8	1/4	1/5	1/3	1
	Experts 2	1/2	1/4	1/6	1/2	1/5	1
	Experts 3	1/2	*	1/6	1/3	1/6	1
	Experts 4	1/5	1/7	1/5	1/3	1/4	1
	Experts 5	1/2	1/5	1/4	1/2	1/7	1

[* indicates missing/non-existent data]

Table 5. Pairwise comparison of alternatives regarding DB

DB	Experts	CHS	FHS	M	MT9	Q
CHS	Expert 1	1	1	8	7	5
	Expert 2	1	1	7	5	*
	Expert 3	1	1	6	6	7
	Expert 4	1	2	8	8	4
	Expert 5	1	1	5	5	6
FHS	Expert 1	1	1	8	6	4
	Expert 2	1	1	5	5	4
	Expert 3	1	1	6	4	3
	Expert 4	1/2	1	7	7	4
	Expert 5	1	1	*	4	5
M	Expert 1	1/8	1/8	1	1/4	1/3
	Expert 2	1/7	1/5	1	1	1
	Expert 3	1/6	1/6	1	*	1
	Expert 4	1/8	1/7	1	1/4	1/3
	Expert 5	1/5	*	1	2	1
MT9	Expert 1	1/7	1/6	4	1	1
	Expert 2	1/5	1/5	1	1	2
	Expert 3	1/6	1/4	*	1	1/2
	Expert 4	1/8	1/7	4	1	2
	Expert 5	1/5	1/4	1/2	1	1/2
Q	Expert 1	1/5	1/4	3	1	1
	Expert 2	*	1/4	1	1/2	1
	Expert 3	1/7	1/3	1	2	1
	Expert 4	1/4	1/4	3	1/2	1
	Expert 5	1/6	1/5	1	2	1

[* indicates missing/non-existent data]

Table 6. Pairwise comparison of criteria regarding the M text entry way

M	Experts	DB	BA	NB	SB	FA	PO
DB	Experts 1	1	1/3	1/5	1/5	1/2	1/2
	Experts 2	1	1/5	1/7	1/6	1/3	1/3
	Experts 3	1	1/4	1/6	1/8	1/5	1/5
	Experts 4	1	1/3	1/5	1/5	1/2	1/2
	Experts 5	1	1/6	1/8	1/7	1/4	1/4
BA	Experts 1	3	1	1	1/2	3	2
	Experts 2	5	1	1/4	1/5	5	3
	Experts 3	4	1	1/3	1/3	2	1
	Experts 4	3	1	1	1/2	3	2

M	Experts	DB	BA	NB	SB	FA	PO
	Experts 5	6	1	1/2	1/4	4	1
NB	Experts 1	5	1	1	1/2	4	3
	Experts 2	7	4	1	1/4	6	5
	Experts 3	6	3	1	1/4	5	4
	Experts 4	5	1	1	1/2	4	3
	Experts 5	8	2	1	1/2	3	3
SB	Experts 1	5	2	2	1	4	3
	Experts 2	6	5	4	1	5	5
	Experts 3	8	3	4	1	6	6
	Experts 4	5	2	2	1	4	3
	Experts 5	7	4	2	1	7	4
FA	Experts 1	2	1/3	1/4	1/4	1	1
	Experts 2	3	1/5	1/6	1/5	1	1
	Experts 3	5	1/2	1/5	1/6	1	1/2
	Experts 4	2	1/3	1/4	1/4	1	1
	Experts 5	4	1/4	1/3	1/7	1	1/3
PO	Experts 1	2	1/2	1/3	1/3	1	1
	Experts 2	3	1/3	1/5	1/5	1	1
	Experts 3	5	1	1/4	1/6	2	1
	Experts 4	2	1/2	1/3	1/3	1	1
	Experts 5	4	1	1/3	1/4	3	1

Table 7. Pairwise comparison of criteria regarding DB

DB	Experts	DB	BA	NB	SB
DB	Experts 1	1	5	3	5
	Experts 2	1	2	3	5
	Experts 3	1	3	3	4
	Experts 4	1	4	2	4
	Experts 5	1	3	2	4
BA	Experts 1	1/5	1	1/2	1
	Experts 2	1/2	1	1/3	4
	Experts 3	1/3	1	1	3
	Experts 4	1/4	1	1/3	2
	Experts 5	1/3	1	1/4	2
NB	Experts 1	1/3	2	1	4
	Experts 2	1/2	3	1	3
	Experts 3	1/3	3	1	5
	Experts 4	1/2	3	1	3
	Experts 5	1/2	4	1	3
SB	Experts 1	1/5	1	1/4	1
	Experts 2	1/5	1/4	1/3	1
	Experts 3	1/4	1/3	1/5	1
	Experts 4	1/4	1/2	1/3	1
	Experts 5	1/4	1/2	1/3	1

4.2 Application of the ANP Method (Giannakis *et al.*, 2020)

The advantages of the typical ANP method are that it can overcome the limitations of the AHP method and can effectively handle the dependence and feedback relationship of the assessment indicator. The typical ANP method can only deal with complete information. In Tables 4-7, experts 2, 3, and 5 lack partial professional knowledge of the criteria and cannot give the appropriate ratings of the criteria. Only experts 1 and 4 provide complete information of the appropriate ratings for the criteria. Therefore, the data of Tables 4-7 (experts 1 and 4 provided complete information) show the unweighted supermatrix, weighted supermatrix, and limited supermatrix of text entry way for touch keyboard smartphone selection, which is shown in Table 8.

Due to the conditions and limitations of a valid questionnaire, only the rating results of experts 1 and 4 can perform arithmetic average calculations (rounded to the nearest ten) for the calculation weight. For instance, in Table 4, the priority vector results of BA show that the most important weight value is 0.3971, followed by the weights of NB, FA, DB, SB, and PO at 0.2703, 0.1176, 0.1017, 0.078, and 0.0353, respectively. In order to check for consistency of the matrix, this section employs Equations (1), (2), and (3) to calculate λ_{max}=6.5637 and then shows the calculation for the CI value. The calculation results show that the CR value is 0.09, which meets the consistency standard (CR <0.1).

$$CI = \frac{\lambda_{max} - n}{n-1} = \frac{6.5637-6}{6-1} = 0.1127$$
$$CR = \frac{CI}{RI} = \frac{0.1127}{1.25} = 0.09$$

Tables 5-7 also list results completed in reference to the above approach. The eigenvector of alternatives with respect to DB is $[0.4366, 0.3540, 0.0357, 0.0894, 0.0843]^T$, the CR value is 0.06, the weights of the criteria with respect to the M text entry way are $[0.0529, 0.1980, 0.2573, 0.3171, 0.0807, 0.0940]^T$, the CR value is 0.01, the weights of the criteria with respect to DB are $[0.5261, 0.1188, 0.2657, 0.0894]^T$, and the CR value is 0.02, which all conform to the standard of consistency. After reorganizing the data of the evaluation criteria from experts 1 and 4 and completing the weight calculation from Tables 4-7, this study converts the solution result into an unweighted supermatrix of the solution procedure of ANP in Table 8.

In order to achieve meaningful limiting priorities, according to step 5 in Section 2.1, the unweighted super matrix needs to be normalized to a stochastic and converted into a weighted super matrix. Based on Equation (4), the long-term stability weight of the limit supermatrix is obtained through the weight matrix calculated by 5 rounds. These weights are the global priority vector of each element. Finally, the unweighted, weighted, and limit supermatrices are all presented in Table 8.

Table 8. The unweighted, weighted, and limited supermatrices of the ANP method

		Goal	Criteria						Alternative				
Unweighted supermatrix		G	DB	BA	NB	SB	FA	PO	CHS	FHS	M	MT9	Q
Goal	G	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Criteria	DB	0.1017	0.5261	0.1681	0.1196	0.2866	0.0000	0.0000	0.0673	0.0656	0.0529	0.3280	0.0842
	BA	0.3971	0.1188	0.5453	0.2083	0.0000	0.1116	0.0000	0.1822	0.1503	0.1980	0.1192	0.2241
	NB	0.2703	0.2657	0.2866	0.5755	0.1681	0.3003	0.0000	0.1822	0.1503	0.2573	0.3280	0.0842
	SB	0.0780	0.0894	0.0000	0.0966	0.5453	0.0000	0.0000	0.1822	0.1503	0.3171	0.0612	0.0842
	FA	0.1176	0.0000	0.0000	0.0000	0.0000	0.5881	0.0000	0.3545	0.4180	0.0807	0.1192	0.1351
	PO	0.0353	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000	0.0317	0.0656	0.0940	0.4450	0.3881
Alternative	CHS	0.0000	0.4366	0.1620	0.1133	0.1127	0.2568	0.0549	1.0000	0.0000	0.0000	0.0000	0.0000
	FHS	0.0000	0.3540	0.2116	0.0813	0.1361	0.4857	0.1459	0.0000	1.0000	0.0000	0.0000	0.0000
	M	0.0000	0.0357	0.2701	0.1336	0.3582	0.1143	0.2234	0.0000	0.0000	1.0000	0.3333	0.0000
	MT9	0.0000	0.0894	0.2701	0.1336	0.3582	0.0567	0.0738	0.0000	0.0000	0.0000	0.6667	0.0000
	Q	0.0000	0.0843	0.0863	0.5382	0.0348	0.0866	0.5020	0.0000	0.0000	0.0000	0.0000	1.0000
Weighted supermatrix		G	DB	BA	NB	SB	FA	PO	CHS	FHS	M	MT9	Q
Goal	G	0.5000	0.3333	0.3333	0.3333	0.3333	0.3333	0.3333	0.3333	0.3333	0.3333	0.2941	0.3333
Criteria	DB	0.0509	0.1754	0.0560	0.0399	0.0955	0.0000	0.0000	0.0224	0.0219	0.0176	0.0965	0.0281
	BA	0.1986	0.0396	0.1818	0.0694	0.0000	0.0372	0.0000	0.0607	0.0501	0.0660	0.0351	0.0747
	NB	0.1352	0.0886	0.0955	0.1918	0.0560	0.1001	0.0000	0.0607	0.0501	0.0858	0.0965	0.0281
	SB	0.0390	0.0298	0.0000	0.0322	0.1818	0.0000	0.0000	0.0607	0.0501	0.1057	0.0180	0.0281
	FA	0.0588	0.0000	0.0000	0.0000	0.0000	0.1960	0.0000	0.1182	0.1393	0.0269	0.0351	0.0450
	PO	0.0177	0.0000	0.0000	0.0000	0.0000	0.0000	0.3333	0.0106	0.0219	0.0313	0.1309	0.1294
Alternative	CHS	0.0000	0.1455	0.0540	0.0378	0.0376	0.0856	0.0183	0.3333	0.0000	0.0000	0.0000	0.0000
	FHS	0.0000	0.1180	0.0705	0.0271	0.0454	0.1619	0.0486	0.0000	0.3333	0.0000	0.0000	0.0000
	M	0.0000	0.0119	0.0900	0.0445	0.1194	0.0381	0.0745	0.0000	0.0000	0.3333	0.0980	0.0000
	MT9	0.0000	0.0298	0.0900	0.0445	0.1194	0.0189	0.0246	0.0000	0.0000	0.0000	0.1961	0.0000
	Q	0.0000	0.0281	0.0288	0.1794	0.0116	0.0289	0.1673	0.0000	0.0000	0.0000	0.0000	0.3333
Limited supermatrix		G	DB	BA	NB	SB	FA	PO	CHS	FHS	M	MT9	Q
Goal	G	0.3986	0.3986	0.3986	0.3986	0.3986	0.3986	0.3986	0.3986	0.3986	0.3986	0.3986	0.3986
Criteria	DB	0.0510	0.0510	0.0510	0.0510	0.0510	0.0510	0.0510	0.0510	0.0510	0.0510	0.0510	0.0510
	BA	0.1251	0.1251	0.1251	0.1251	0.1251	0.1251	0.1251	0.1251	0.1251	0.1251	0.1251	0.1251
	NB	0.1107	0.1107	0.1107	0.1107	0.1107	0.1107	0.1107	0.1107	0.1107	0.1107	0.1107	0.1107
	SB	0.0383	0.0383	0.0383	0.0383	0.0383	0.0383	0.0383	0.0383	0.0383	0.0383	0.0383	0.0383
	FA	0.0474	0.0474	0.0474	0.0474	0.0474	0.0474	0.0474	0.0474	0.0474	0.0474	0.0474	0.0474
	PO	0.0296	0.0296	0.0296	0.0296	0.0296	0.0296	0.0296	0.0296	0.0296	0.0296	0.0296	0.0296
Alternative	CHS	0.0366	0.0366	0.0366	0.0366	0.0366	0.0366	0.0366	0.0366	0.0366	0.0366	0.0366	0.0366
	FHS	0.0430	0.0430	0.0430	0.0430	0.0430	0.0430	0.0430	0.0430	0.0430	0.0430	0.0430	0.0430
	M	0.0425	0.0425	0.0425	0.0425	0.0425	0.0425	0.0425	0.0425	0.0425	0.0425	0.0425	0.0425
	MT9	0.0297	0.0297	0.0297	0.0297	0.0297	0.0297	0.0297	0.0297	0.0297	0.0297	0.0297	0.0297
	Q	0.0475	0.0475	0.0475	0.0475	0.0475	0.0475	0.0475	0.0475	0.0475	0.0475	0.0475	0.0475

4.3 Application of the DANP Method (Chen *et al.*, 2012)

The DANP method combines the calculation rules of the DEMATEL and typical ANP methods, distinguishing two phases to calculate the weights of alternatives. Phase 1 uses the DEMATEL method to analyze the relationship between each criterion to find out the critical criterion. Phase 2 uses the typical ANP method to determine the priority and weights of alternatives. The DANP method can only deal with complete information and cannot handle incomplete information provided by the experts. Because the standard evaluation scale of the DEMATEL method is 0-4, it is different from the 1-9 scale of the AHP method, and so 5 experts were asked to point out the influence of each relationship among the 6 evaluation criteria presented in Table 8.

Table 9. The original average matrix

Dimension	Experts	DB	BA	NB	SB	FA	PO
DB	Experts 1	0	2	1	2	3	2
	Experts 2	0	3	2	1	3	2
	Experts 3	0	4	1	1	4	1
	Experts 4	0	3	1	2	4	2
	Experts 5	0	2	2	1	3	2
BA	Experts 1	1	0	2	3	2	4
	Experts 2	3	0	1	3	2	4
	Experts 3	3	0	2	4	2	4
	Experts 4	1	0	3	3	2	4
	Experts 5	2	0	3	4	1	4
NB	Experts 1	4	3	0	2	1	2
	Experts 2	3	1	0	2	1	3
	Experts 3	4	3	0	2	2	2
	Experts 4	3	2	0	2	2	1
	Experts 5	3	2	0	1	2	2
SB	Experts 1	4	1	4	0	3	2
	Experts 2	4	2	3	0	2	2
	Experts 3	4	1	4	0	2	2
	Experts 4	4	1	4	0	2	2
	Experts 5	4	2	4	0	3	2
FA	Experts 1	2	2	1	1	0	2
	Experts 2	1	3	1	2	0	3
	Experts 3	2	1	1	1	0	2
	Experts 4	1	2	1	2	0	1
	Experts 5	2	2	1	2	0	3
PO	Experts 1	1	1	2	2	1	0
	Experts 2	1	1	3	1	2	0
	Experts 3	2	2	2	2	1	0
	Experts 4	2	1	2	1	1	0
	Experts 5	2	1	3	2	2	0

The DANP method only handles complete information issues in the MADM problems. In terms of criteria evaluation, this section is similar to the traditional ANP method in section 4.2. When encountering the problem of incomplete expert rating information, it can only be evaluated based on experts 1 and 4 expert ratings in Tables 4-7. Therefore, Table 9 can also only consider complete information by experts 1 and 4.

After normalizing in Table 9, one can obtain the original influence matrix, as shown in Table 10. One can next use Equations (7), (8), and (9) to calculate the original influence matrix, obtaining the total relation matrix T, which is presented in Table 11.

Table 10. The original influence matrix

	DB	BA	NB	SB	FA	PO
DB	0.0000	0.1852	0.0741	0.1481	0.2593	0.1481
BA	0.0741	0.0000	0.1852	0.2222	0.1481	0.2963
NB	0.2593	0.1852	0.0000	0.1481	0.1111	0.1111
SB	0.2963	0.0741	0.2963	0.0000	0.1852	0.1481
FA	0.1111	0.1481	0.0741	0.1111	0.0000	0.1111
PO	0.1111	0.0741	0.1481	0.1111	0.0741	0.0000

Table 11. The total relation matrix

	DB	BA	NB	SB	FA	PO
DB	0.4612	0.5481	0.5103	0.5531	0.6630	0.5911
BA	0.6091	0.4328	0.6640	0.6599	0.6221	0.7554
NB	0.7064	0.5735	0.4598	0.5780	0.5808	0.5868
SB	0.7938	0.5515	0.7569	0.5039	0.6994	0.6655
FA	0.4412	0.4151	0.3957	0.4128	0.3290	0.4411
PO	0.4330	0.3440	0.4355	0.3936	0.3820	0.3152

After completing the total relation matrix, Equations (10), (11), and (12) are used to get the D and R values and then to calculate the prominence (D+R) and relation (D-R), respectively. In terms of (D+R), the value of SB is 7.0723, which means this criterion is the most important and has a closer relationship with each other, while the value of PO (5.6584) is the lowest, which means that the relationship is less closely linked. In terms of (D-R), the values of BA, SB, and NB are 0.8783, 0.8697, and 0.2631, respectively. It indicates that they have stronger relations with other criteria and belong to cause factors, followed by DB (-0.1179), FA (-0.8414), and PO (-1.0518), which are negative and which indicate they belong to the effect factors. The calculation results are shown in Table 12.

Table 12. Criteria summarized table of the level of causal influence

Criteria	D	R	D+R	D-R
DB	3.3268	3.4447	6.7715	-0.1179
BA	3.7433	2.8650	6.6083	0.8783
NB	3.4853	3.2222	6.7075	0.2631
SB	3.9710	3.1013	7.0723	0.8697
FA	2.4349	3.2763	5.7112	-0.8414
PO	2.3033	3.3551	5.6584	-1.0518

Since the DANP method distinguishes between two phases of operation, after determining the relationship structure between criteria by DEMATEL, phase 2 uses the ANP approach to obtain the criteria weight and alternatives' weight. The solution procedure of Tables 5-7 was also completed in reference to section 4.2, and the weights of alternatives with respect to DB are $[0.4366, 0.3540, 0.0357, 0.0894, 0.0843]^T$, the CR value is 0.06, the weights of the criteria with respect to M text entry way are $[0.0529, 0.1980, 0.2573, 0.3171, 0.0807, 0.0940]^T$, the CR value is 0.01, the weights of the criteria with respect to DB are $[0.5261, 0.1188, 0.2657, 0.0894]^T$, and the CR value is 0.02, all conforming to the standard of consistency.

After reorganizing the data of the evaluation criteria of experts 1 and 4 and completing the weight calculation from Tables 5-7, this study converts the solution result into an unweighted supermatrix for the solution procedure of ANP in Table 13. In order to achieve meaningful limiting priorities, according to step 5 in Section 2.1, the unweighted supermatrix needs to be normalized to be transformed into a weighted supermatrix. Based on Equation (4), the long-term stability weight of the limit supermatrix is obtained through the weight matrix calculated by 6 rounds. These weights are the global priority vector of each element. Finally, the unweighted, weighted, and limit supermatrices are presented in Table 13.

Table 13. The solution procedure of DANP

		Criteria						Alternative				
Unweighted supermatrix		DB	BA	NB	SB	FA	PO	CHS	FHS	M	MT9	Q
Criteria	DB	0.5261	0.1681	0.1196	0.2866	0.0000	0.0000	0.0673	0.0656	0.0529	0.3280	0.0842
	BA	0.1188	0.5453	0.2083	0.0000	0.1116	0.0000	0.1822	0.1503	0.1980	0.1192	0.2241
	NB	0.2657	0.2866	0.5755	0.1681	0.3003	0.0000	0.1822	0.1503	0.2573	0.3280	0.0842
	SB	0.0894	0.0000	0.0966	0.5453	0.0000	0.0000	0.1822	0.1503	0.3171	0.0612	0.0842
	FA	0.0000	0.0000	0.0000	0.0000	0.5881	0.0000	0.3545	0.4180	0.0807	0.1192	0.1351
	PO	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000	0.0317	0.0656	0.0940	0.4450	0.3881
Alternative	CHS	0.4366	0.1620	0.1133	0.1127	0.2568	0.0549	1.0000	0.0000	0.0000	0.0000	0.0000
	FHS	0.3540	0.2116	0.0813	0.1361	0.4857	0.1459	0.0000	1.0000	0.0000	0.0000	0.0000
	M	0.0357	0.2701	0.1336	0.3582	0.1143	0.2234	0.0000	0.0000	1.0000	0.3333	0.0000
	MT9	0.0894	0.2701	0.1336	0.3582	0.0567	0.0738	0.0000	0.0000	0.0000	0.6667	0.0000
	Q	0.0843	0.0863	0.5382	0.0348	0.0866	0.5020	0.0000	0.0000	0.0000	0.0000	1.0000
Weighted supermatrix		DB	BA	NB	SB	FA	PO	CHS	FHS	M	MT9	Q
Criteria	DB	0.2631	0.0840	0.0598	0.1433	0.0000	0.0000	0.0336	0.0328	0.0265	0.1366	0.0421
	BA	0.0594	0.2726	0.1042	0.0000	0.0558	0.0000	0.0911	0.0751	0.0990	0.0497	0.1121
	NB	0.1329	0.1433	0.2878	0.0841	0.1501	0.0000	0.0911	0.0751	0.1287	0.1366	0.0421
	SB	0.0447	0.0000	0.0483	0.2727	0.0000	0.0000	0.0911	0.0751	0.1586	0.0255	0.0421
	FA	0.0000	0.0000	0.0000	0.0000	0.2940	0.0000	0.1772	0.2090	0.0404	0.0497	0.0676
	PO	0.0000	0.0000	0.0000	0.0000	0.0000	0.5000	0.0158	0.0328	0.0470	0.1854	0.1941
Alternative	CHS	0.2183	0.0810	0.0567	0.0564	0.1284	0.0275	0.5000	0.0000	0.0000	0.0000	0.0000
	FHS	0.1770	0.1058	0.0407	0.0681	0.2428	0.0730	0.0000	0.5000	0.0000	0.0000	0.0000
	M	0.0179	0.1350	0.0668	0.1791	0.0571	0.1117	0.0000	0.0000	0.5000	0.1388	0.0000
	MT9	0.0447	0.1350	0.0668	0.1791	0.0283	0.0369	0.0000	0.0000	0.0000	0.2777	0.0000
	Q	0.0422	0.0431	0.2691	0.0174	0.0433	0.2510	0.0000	0.0000	0.0000	0.0000	0.5000
Limited supermatrix		DB	BA	NB	SB	FA	PO	CHS	FHS	M	MT9	Q
Criteria	DB	0.0634	0.0634	0.0634	0.0634	0.0634	0.0634	0.0634	0.0634	0.0634	0.0634	0.0634
	BA	0.0890	0.0890	0.0890	0.0890	0.0890	0.0890	0.0890	0.0890	0.0890	0.0890	0.0890
	NB	0.1154	0.1154	0.1154	0.1154	0.1154	0.1154	0.1154	0.1154	0.1154	0.1154	0.1154
	SB	0.0676	0.0676	0.0676	0.0676	0.0676	0.0676	0.0676	0.0676	0.0676	0.0676	0.0676
	FA	0.0776	0.0776	0.0776	0.0776	0.0776	0.0776	0.0776	0.0776	0.0776	0.0776	0.0776
	PO	0.0917	0.0917	0.0917	0.0917	0.0917	0.0917	0.0917	0.0917	0.0917	0.0917	0.0917
Alternative	CHS	0.0877	0.0877	0.0877	0.0877	0.0877	0.0877	0.0877	0.0877	0.0877	0.0877	0.0877
	FHS	0.1109	0.1109	0.1109	0.1109	0.1109	0.1109	0.1109	0.1109	0.1109	0.1109	0.1109
	M	0.1107	0.1107	0.1107	0.1107	0.1107	0.1107	0.1107	0.1107	0.1107	0.1107	0.1107
	MT9	0.0557	0.0557	0.0557	0.0557	0.0557	0.0557	0.0557	0.0557	0.0557	0.0557	0.0557
	Q	0.1302	0.1302	0.1302	0.1302	0.1302	0.1302	0.1302	0.1302	0.1302	0.1302	0.1302

4.4 Application of the Proposed Method

The typical ANP method and the DANP method cannot handle restrictions that include complete, incomplete, and non-existent information simultaneously. In order to deal with these conditions, this study integrates the typical ANP method and soft set (called SANP method) to overcome the above-mentioned problems for the smartphone text entry way. The solution procedure runs as follows.

Step 1. Analyze decision-making problems and establish network structures

The expert assessment team clearly defined the attributes of the decision-making problem, analyzed the characteristics of interdependence and self-feedback, and established a hierarchical structure. The structure is then decomposed into a network rational system.

Step 2. Confirm the evaluation criteria and complete the questionnaire design

According to the network rational system of step 1, the relation of dependencies is identified between the selected metrics that construct the network model. The evaluation indicators of the research problem (involved goals, evaluation criteria, and alternatives) are confirmed, and then the questionnaire design is completed.

Step 3. Implement expert questionnaire assessment

According to Saaty's 9-point scale (Table 1) of the typical ANP method, the SANP method consults the experts to respond to a series of questions and provides questionnaire information for the necessary relationship of each decision component (involved goals, evaluation criteria, and alternatives) to build a pairwise comparison matrix.

Step 4. Information supplement

In order to fully consider the experts' ratings, the proposed SANP method uses the soft set concept to supplement incomplete information, according to the data from experts in Table 4. For example, Expert 2 provides information that is incomplete in dimension DB. We use the information provided by Experts 1, 3, 4, and 5 to supplement the incomplete information provided by Expert 2. In dimension DB, Experts 1, 3, 4, and 5 rated BA as 1/2, 1/4, 1/3, and 1/4, respectively. The arithmetic average of these four ratings is computed to get 1/3 and filled it into the rating column of Expert 2 to calculate the arithmetic average. The process of dealing with the other missing information also follows the DB method to complete the entire questionnaire information in sequence so that the originally invalid questionnaire can be transformed into a valid questionnaire. Table 5 is also completed in reference to the above approach. Finally, the incomplete information of Tables 4-5 is processed by the soft set and presented in Table 14 and Table 15, respectively.

Table 14. Pairwise comparisons of criteria

	DB	BA	NB	SB	FA	PO
DB	1.0000	0.3333	0.2033	0.9000	0.6250	2.8000
BA	3.2500	1.0000	2.5000	4.4000	2.8000	6.0000
NB	5.0000	0.4167	1.0000	4.5000	3.4000	5.0000
SB	1.5000	0.2500	0.2708	1.0000	0.9667	3.0000
FA	1.7500	0.3833	0.3167	1.5000	1.0000	5.0000
PO	0.4067	0.1795	0.2067	0.3733	0.2186	1.0000

Table 15. Pairwise comparisons of criteria

	CHS	FHS	M	MT9	Q
CHS	1.0000	1.2000	6.8000	6.2000	5.5000
FHS	0.8333	1.0000	6.5000	5.2000	4.0000
M	0.1471	0.1538	1.0000	0.8750	0.7333
MT9	0.1613	0.1923	1.1429	1.0000	1.2000
Q	0.1818	0.2500	1.3636	0.8333	1.0000

Step 5. Apply the ANP method to confirm the relationships of clusters and dependencies

To determine the weight of each criterion, this study calculates the data from Tables 14-15 that can be supplemented by the soft set. The weights of Table 14 are $[0.0821, 0.3615, 0.2919, 0.0960, 0.1286, 0.0399]^T$, the CR value is 0.09, the weights of Table 15 are $[0.4292, 0.3591, 0.0598, 0.0745, 0.0774]^T$, and the CR value is 0.005, all conforming to the standard of consistency (CR<0.1).

Because Tables 6-7 have complete rating information of experts, this study can calculate the arithmetic mean first and then implement the weight calculation. The CR value should be calculated to check the consistency of the matrix. The solution procedure is also completed in reference to section 4.2. The weights of Table 6 are $[0.0396, 0.1624, 0.2471, 0.3940, 0.0692, 0.0877]^T$, the CR value is 0.03, the weights of Table 7 are $[0.5051, 0.1526, 0.2608, 0.0815]^T$, and the CR value is 0.03, conforming to the standard of consistency (CR<0.1).

After finishing the weight calculation of the criteria and alternative, this study converts the solution result into an unweighted supermatrix from the solution procedure of ANP in Table 16. According to Table 16, this study can understand each cluster and element dependence relation. For example, W_{ij} is zero between the cluster and within the elements of the first column, meaning no relationship.

Step 6. Apply the ANP method to prioritize the alternatives

In this step, according to step 5 in Section 2.1, the unweighted super matrix needs to be normalized and converted into a weighted supermatrix. Based on Equation (4), the long-term stability weight of the limit supermatrix is obtained through the weight matrix calculated by 5 rounds. These weights are the global priority vector of each element. Finally, the weighted and limit supermatrices are presented in Table 16.

Table 16. The solution procedure of ANP

		Goal	Criteria						Alternative				
Unweighted supermatrix		G	DB	BA	NB	SB	FA	PO	CHS	FHS	M	MT9	Q
Goal	G	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Criteria	DB	0.0821	0.5051	0.1681	0.1196	0.2866	0.0000	0.0000	0.0673	0.0656	0.0396	0.3280	0.0842
	BA	0.3615	0.1526	0.5453	0.2083	0.0000	0.1116	0.0000	0.1822	0.1503	0.1624	0.1192	0.2241
	NB	0.2919	0.2608	0.2866	0.5755	0.1681	0.3003	0.0000	0.1822	0.1503	0.2471	0.3280	0.0842
	SB	0.0960	0.0815	0.0000	0.0966	0.5453	0.0000	0.0000	0.1822	0.1503	0.3940	0.0612	0.0842
	FA	0.1286	0.0000	0.0000	0.0000	0.0000	0.5881	0.0000	0.3545	0.4180	0.0692	0.1192	0.1351
	PO	0.0399	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000	0.0317	0.0656	0.0877	0.4450	0.3881
Alternative	CHS	0.0000	0.4292	0.1620	0.1133	0.1127	0.2568	0.0549	1.0000	0.0000	0.0000	0.0000	0.0000
	FHS	0.0000	0.3591	0.2116	0.0813	0.1361	0.4857	0.1459	0.0000	1.0000	0.0000	0.0000	0.0000
	M	0.0000	0.0598	0.2701	0.1336	0.3582	0.1143	0.2234	0.0000	0.0000	1.0000	0.3333	0.0000
	MT9	0.0000	0.0745	0.2701	0.1336	0.3582	0.0567	0.0738	0.0000	0.0000	0.0000	0.6667	0.0000
	Q	0.0000	0.0774	0.0863	0.5382	0.0348	0.0866	0.5020	0.0000	0.0000	0.0000	0.0000	1.0000
Weighted supermatrix		G	DB	BA	NB	SB	FA	PO	CHS	FHS	M	MT9	Q
Goal	G	0.5000	0.3333	0.3333	0.3333	0.3333	0.3333	0.3333	0.3333	0.3333	0.3333	0.2941	0.3333
Criteria	DB	0.0411	0.1684	0.0560	0.0399	0.0955	0.0000	0.0000	0.0224	0.0219	0.0083	0.0965	0.0281
	BA	0.1808	0.0509	0.1818	0.0694	0.0000	0.0372	0.0000	0.0607	0.0501	0.0471	0.0351	0.0747
	NB	0.1460	0.0869	0.0955	0.1918	0.0560	0.1001	0.0000	0.0607	0.0501	0.0859	0.0965	0.0281
	SB	0.0480	0.0272	0.0000	0.0322	0.1818	0.0000	0.0000	0.0607	0.0501	0.1414	0.0180	0.0281
	FA	0.0643	0.0000	0.0000	0.0000	0.0000	0.1960	0.0000	0.1182	0.1393	0.0204	0.0351	0.0450
	PO	0.0200	0.0000	0.0000	0.0000	0.0000	0.0000	0.3333	0.0106	0.0219	0.0303	0.1309	0.1294
Alternative	CHS	0.0000	0.1431	0.0540	0.0378	0.0376	0.0856	0.0183	0.3333	0.0000	0.0000	0.0000	0.0000
	FHS	0.0000	0.1197	0.0705	0.0271	0.0454	0.1619	0.0486	0.0000	0.3333	0.0000	0.0000	0.0000
	M	0.0000	0.0199	0.0900	0.0445	0.1194	0.0381	0.0745	0.0000	0.0000	0.3333	0.0980	0.0000
	MT9	0.0000	0.0248	0.0900	0.0445	0.1194	0.0189	0.0246	0.0000	0.0000	0.0000	0.1961	0.0000
	Q	0.0000	0.0258	0.0288	0.1794	0.0116	0.0289	0.1673	0.0000	0.0000	0.0000	0.0000	0.3333
Limited supermatrix		G	DB	BA	NB	SB	FA	PO	CHS	FHS	M	MT9	Q
Goal	G	0.3986	0.3986	0.3986	0.3986	0.3986	0.3986	0.3986	0.3986	0.3986	0.3986	0.3986	0.3986
Criteria	DB	0.0459	0.0459	0.0459	0.0459	0.0459	0.0459	0.0459	0.0459	0.0459	0.0459	0.0459	0.0459
	BA	0.1167	0.1167	0.1167	0.1167	0.1167	0.1167	0.1167	0.1167	0.1167	0.1167	0.1167	0.1167
	NB	0.1148	0.1148	0.1148	0.1148	0.1148	0.1148	0.1148	0.1148	0.1148	0.1148	0.1148	0.1148
	SB	0.0439	0.0439	0.0439	0.0439	0.0439	0.0439	0.0439	0.0439	0.0439	0.0439	0.0439	0.0439
	FA	0.0497	0.0497	0.0497	0.0497	0.0497	0.0497	0.0497	0.0497	0.0497	0.0497	0.0497	0.0497
	PO	0.0310	0.0310	0.0310	0.0310	0.0310	0.0310	0.0310	0.0310	0.0310	0.0310	0.0310	0.0310
Alternative	CHS	0.0355	0.0355	0.0355	0.0355	0.0355	0.0355	0.0355	0.0355	0.0355	0.0355	0.0355	0.0355
	FHS	0.0426	0.0426	0.0426	0.0426	0.0426	0.0426	0.0426	0.0426	0.0426	0.0426	0.0426	0.0426
	M	0.0433	0.0433	0.0433	0.0433	0.0433	0.0433	0.0433	0.0433	0.0433	0.0433	0.0433	0.0433
	MT9	0.0295	0.0295	0.0295	0.0295	0.0295	0.0295	0.0295	0.0295	0.0295	0.0295	0.0295	0.0295
	Q	0.0484	0.0484	0.0484	0.0484	0.0484	0.0484	0.0484	0.0484	0.0484	0.0484	0.0484	0.0484

4.5 Comparison and Discussion

In order to handle complete, incomplete, and non-existent information during the solution process, this study proposes the SANP method, which integrates the soft set and ANP method, in order to effectively handle the MADM problems. To prove the effectiveness and correctness of the proposed SANP method, this section compares the difference in solution results between the typical ANP, DANP, and SANP methods. The computation results are obtained in Tables 8, 13, and 16, respectively and summarized in Table 17. According to the comparison results in Table 17, this study is able to realize several advantages of the proposed SANP method, as shown in Table 18.

Table 17. Comparison results between the ANP, DANP, and proposed SANP methods

	Typical ANP method (Giannakis *et al.*, 2020)	DANP method (Chen *et al.*, 2012)	SANP method	Ranking by using ANP method (Giannakis *et al.*, 2020)	Ranking by using DANP method (Chen *et al.*, 2012)	Ranking by using SANP method
DB	0.0510	0.0634	0.0459	3	6	4
BA	0.1251	0.0890	0.1167	1	3	1
NB	0.1107	0.1154	0.1148	2	1	2
SB	0.0383	0.0676	0.0439	5	5	5
FA	0.0474	0.0776	0.0497	4	4	3
PO	0.0296	0.0917	0.0310	6	2	6
CHS	0.0366	0.0877	0.0355	4	4	4
FHS	0.0430	0.1109	0.0426	2	2	3
M	0.0425	0.1107	0.0433	3	3	2
MT9	0.0297	0.0557	0.0295	5	5	5
Q	0.0475	0.1302	0.0484	1	1	1

The main advantages of the proposed SANP method are as follows.

(1) The consistency of the evaluation scale

Chen *et al*. (2012) used the DANP method, which combined DEMATEL and ANP methods to solve the MADM problem. Due to the comparison scale of the DEMATEL method is designed with five levels (0-4) representing “no influence”, “low influence”, “medium influence”, “high influence”, and “very high influence”, respectively. And the comparison scale of the ANP method is designed with nine levels (1-9). Therefore, during the solution procedure, DANP needs to conduct two kinds of scale to deal with the decision problem, which will incur situation that the scales are confused when the experts score. However, the typical ANP method (Giannakis *et al*., 2020) and the proposed SANP method use the same scales of nine levels (1-9) in the whole solution procedure, so they can reduce the measurement error for scale conversions.

(2) Simplified solution procedure.

During the solution of the MADM problem, Chen *et al*. (2012) used the DANP method, that needs to be divided into two phases in the calculation process, where phase 1 needs to use the DEMATEL method to calculate the relative relationship between the criteria. Phase 2 needs to use the ANP method to calculate the relative relationship between the alternatives, which will become more complicated. However, the ANP method not only can consider multiple criteria, including both quantitative and qualitative as the same as the AHP method (Saaty, 1996), but also can show the direct and indirect relationship of all the elements (goals, criteria, and alternatives), calculates the relative weighting of each criteria, as well as determine the most appropriate alternative, and solve complex network problems (Buyukozkan and Ozturkcan, 2010). Therefore, the calculations of the typical ANP method (Giannakis *et al*., 2020) and the proposed SANP method both use the ANP method and are able to determine the relative weighting of each criteria and alternative. Both methods are relatively simple than the DANP method.

(3) Dealing with information of assessment attributes that have missing or nonexistent information.

During information processing in MADM problems, because most experts have disparate experience and background, their assessment attribute values provided may cover conditions such as definite, uncertainties, vagueness, missing information, etc. Fuzzy set theory (Zadeh, 1965), rough set theory (Pawlak, 1982), and gray system theory (Deng, 1989) have demonstrated that they are well-known approaches to handle uncertain situations as well as vague and imprecise information. However, when they encounter missing, non-existent, or incomplete information, it is difficult for classical mathematics or algorithms to solve them. When dealing with questionnaire information, if the questionnaire contains incomplete information, then it will always be regarded as an invalid questionnaire. However, this kind of practice often eliminates the questionnaire where experts provide information, and thus, it cannot reflect real information. According to the traditional questionnaire analysis method, the typical ANP method (Giannakis *et al*., 2020) and DANP method (Chen *et al*., 2012) process data that make them easily ignore some important information provided by experts so that they will obtain different results from the actual situation. The proposed SANP method adopts the soft set concept to supplement missing, non-existent, or incomplete information, with the aim to keep important questionnaire information. Therefore, it can handle missing or incomplete information effectively, and all the questionnaire information can be fully considered and truly presented.

Table 18. Differences between the three calculation methods

Method selection	Solving characteristic		
	Consistency of the evaluation scale	Simplify solution procedure	Missing or nonexistence information
Typical ANP method (Giannakis *et al.*, 2020)	○	○	X
DANP method (Chen *et al.*, 2012)	X	X	X
SANP method	○	○	○

5. CONCLUSION AND FUTURE WORK

In response to today's rapid development of science and technology, technological products' life cycles have become shorter and change more rapidly. Thus, decisions related to the production of technology products are the key for affecting the sustainable development and market share of enterprises. However, the evaluation of decision-making related to the production of technology products is a complex MADM problem. It contains many different evaluation criteria as well as qualitative and quantitative evaluation attributes, and a correlation between the criteria must be considered.

The traditional ANP and DANP methods are both used to solve these issues of the MADM problem concerning qualitative and quantitative evaluation attributes. Although these two methods have the advantage of considering the correlation between different criteria, the traditional ANP and DANP methods still have some limitations. For example, when managers encounter incomplete or missing information, they will not fully consider all available information to objectively solve the MADM problems, causing increased complexity to the solution process. In order to solve these issues, this study proposes a novel SANP approach that integrates the soft set and ANP method through the existing data sets of experts to supplement the missing/non-existent data of other experts and will consider the available information fully and let experts in various fields exerting their due experience, professional knowledge, and ability in the specialized part to effectively handle different MADM problems. The proposed SANP method has some advantages, such as (1) the traditional ANP method (Ocampo and Seva, 2016) is a special case of the proposed SANP method, (2) the proposed SANP method adopts consistency of the evaluation scale, (3) the proposed SANP method can deal with information of assessment attributes that are missing or non-existent, (4) the proposed SANP method can simultaneously handle information on qualitative and quantitative evaluation attributes, (5) the solution steps of the proposed SANP method are simpler than the DANP method.

Even the proposed method can deal with information of assessment attributes that are missing or non-existent and also can simultaneously handle information on qualitative and quantitative evaluation attributes. However, it lacks in considering about hesitate and ambiguous information. In the future, about the section on information consideration, follow-up studies can add some research methods, such as intuitionistic fuzzy set, picture fuzzy set, and Fermatean fuzzy set. Additionally, in the weighting considerations section, follow-up studies can probe different weight calculation methods, such as the full consistency method (FUCOM), best-worst method (BWM) or level-based weight assessment (LBWA) method.

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