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The Construction of Critical Factors for Successfully Introducing Chatbots into Mental Health Services in the Army: Using a Hybrid MCDM Approach

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Abstract: Previous research has shown that although military personnel are at high risk of developing mental disorders because of the excessive stress caused by their work, they also display low levels of intention to seek assistance because of the military culture. This, in turn, creates exorbitant costs for their respective countries. With the rapid development of artificial intelligence (AI)-related digital technologies, chatbots have been successfully applied to mental health services. Although the introduction of chatbots into the military to assist with mental health services is not common, it may become a future trend. This study aims to construct the critical factors for introducing chatbots into mental health services in the military, the relationships between the effects, and a weighting system, to ensure that the introduction of chatbots complies with sustainable practices. This includes four stages. In the initial stage, in accordance with the AI-readiness framework, in combination with the findings of previous research and specialist recommendations, preliminary indicators and items were developed. In the second stage, Fuzzy Delphi was used to confirm each dimension and indicator. In the third stage, using DEMATEL, an influential-network-relation map (INRM) of dimensions and indicators was created. In the fourth stage, using DANP, the relationships between the effects of the indicators and the weighting system were established. The findings of this study indicated that: (1) the key to success includes four dimensions and twenty-one indicators; (2) there is an interdependent relationship between the four dimensions and twenty-one indicators, and they influence each other; and (3) the four dimensions are technologies, goals, boundaries, and activities, in order of importance. Finally, specific suggestions are put forward to provide references for future practical applications and research, drawing on the results of this research.

Keywords: military; mental health; chatbot; DEMATEL; DANP

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1. Introduction

When executing military operations and humanitarian rescue missions, military personnel may constantly experience harsh environments. Prolonged exposure to extreme pressure may cause severe psychological damage [1,2]. A significant amount of research has revealed that military personnel are at a higher risk than civilians of experiencing psychological disorders, including post-traumatic stress disorder (PTSD) [3–6], anxiety [7–9], depression [10–12], suicide and suicidal ideation [13–15], and insomnia and sleep disturbances [15–17]. In turn, this results in immense financial expenditure and social costs [18–21]. However, research has suggested that military personnel exhibit negative intentions to seek help and are reluctant to honestly disclose their actual psychological state because of the stigma attached to mental health problems, as well as fear of the negative impact on their professional careers [22–26]. More in-depth explorations have shown that this situation is associated with military cultures. In the military, the spirit of toughing it out is advocated, and those who seek help are viewed as weaklings [15,27].

However, when contemplating the future of mental health services, many specialists have suggested that artificial intelligence (AI) can be utilized, and have even encouraged human–AI collaboration [28–32]. With the advancement of information technology, chatbots, which have received widespread attention, have been actively applied in the field of mental health and have begun to play an important role [33]. Various studies conducted psychological assessments on active-duty military personnel and veterans by employing chatbots to help identify potential PTSD patients. The findings demonstrated that the participants exhibited a greater willingness to discuss their psychological challenges during the process of chatting with a chatbot [34,35], highlighting the advantage of introducing chatbots into the military to assist with mental health services.

A chatbot is a computer program that uses spoken or written text to simulate human conversations [36]. Eliza, the first known chatbot, was developed in 1966 by Joseph Weizenbaum to simulate and explore communication between humans and machines [37]. As of December 2019, as many as 41 types of chatbot have been applied to the field of mental health, in which they are employed for therapy, training, screening, self-management, counseling, education, and diagnosis. These functions may operate via stand-alone software or the Internet. Chatbots are able to control and guide conversations. Although written text is the most prevalent means of input, the most commonly utilized output method involves a blend of written, spoken, and visual language [38]. A multitude of empirical studies have demonstrated that psychotherapy performed using the intervention of a chatbot can help reduce anxiety and depression in users significantly [39–44].

During the second day of the Russo-Ukrainian War, a self-help chatbot named Friend. First Aid was activated via Telegram to aid Ukraine. This chatbot offered guidance on stress management and relaxation exercises for both adults and children. Within four weeks of its launch, it had already garnered over 40,000 users not only within Ukraine, but also beyond its borders [45]. On 6 May 2022, the Ministry of Health of Ukraine launched its own chatbot, Lisova Poliana Bot, to cater to the needs of veterans and active servicemen. This Telegram-based chatbot is capable of discussing various topics and employs infographics and suggestions developed by the Ministry of Health to address issues such as anxiety, panic attacks, depressive moods, and concerns about family safety. It also provides recommendations from central specialists on how to provide emotional support to fellow servicemen in need and how to maintain a positive and resilient outlook [46]. We predict that the use of chatbots in the military to assist with mental health services will be a future trend.

However, despite the numerous benefits associated with AI technologies, there are multiple obstacles to the introduction of AI technology into organizations' operations [47]. The introduction of AI technologies has an effect on various aspects of organizations, including resource allocation, manpower, culture, and decision-making [48]. However, a literature review on the application of chatbots to the field of mental health revealed that while the majority of research to date has examined the functions [38,49] and practical applications [33,50] of chatbots, topics such as organizations and management have not been explored [51]. Moreover, military organizations are usually more complicated in nature than ordinary civil organizations [52]. Research has demonstrated explicitly that military organizations often confront manifold problems when adopting new technology [53]. From a sustainability perspective, it is important to note that the mental-health-care domain is heavily focused on patients' needs, and the integration of AI technology can introduce several ethical issues that can potentially threaten patient privacy and trust. Recent research highlights the significant consequences that may arise if these issues are not addressed appropriately [54]. Furthermore, the literature does not appear to provide prudent assessments or relevant research outputs in relation to the introduction of chatbots into the military to assist with mental health services. The research shows the construction of key success indicators for the use of chatbots by the army to support mental health services, and related research is still lacking. Therefore, there is a need to develop key success indicators and to conduct further research to ensure that the implementation of chatbots aligns with sustainable practices.

In addition, multiple criteria decision making (MCDM) places an increased emphasis on hybrid applications and interdependencies, while the analytic hierarchy process method, which focuses on hierarchical relationships, is gradually being replaced by DEMATEL-based ANP (DANP) [55]. This study adopted hybrid MCDM, in combination with the Fuzzy Delphi method and DANP, to construct critical success indicators for the military in its introduction of chatbots for mental health services, providing a reference for future decision-making and establishing a foundation for future research.

2. Materials and Methods

2.1. Study Design

The research process adopted in this study was divided into the following four stages: (1) collection of data on dimensions and indicators through a literature review; (2) interviews with specialists and selection of indicators by employing the Fuzzy Delphi method; (3) analysis of the correlations between dimensions and indicators and creation of a cause–effect-relationship diagram for complex relationships observed by adopting DEMATEL and re-inviting experts to administer the questionnaire; and (4) analysis of the weight of DANP among dimensions and indicators using DANP.

2.2. Questionnaire Development

To develop the required questionnaire, the AI-readiness framework developed by Holmstrom (2021) was adopted as the research foundation. The framework proposes that AI-based digital transformation involves four key dimensions: technologies, activities, boundaries, and goals [56]. These dimensions were subsequently established as the research dimensions for this study. Furthermore, the literature review and specialist consultations led to the development of indicators under each dimension. A list of indicator sets with their sources is presented in Table A1. Each item was scored on a 10-point scale. Indicators with high scores were deemed suitable for assessment.

2.2.1. Technologies

While the dimension of technologies was originally defined as “changes in digital technology [56]”, it was subsequently revised to “changes in acceptance of introducing chatbots into the military to assist with mental health services” in this study. The United Arab Emirates, while introducing AI technologies into the healthcare sector to assist in management of chronically ill patients, discovered that the success of this policy was dependent on policymakers, doctors, nurses, and patients’ level of perceived ease of use and usefulness of new technologies [57]. Chatterjee et al. identified the importance of perceived ease of use and perceived usefulness of Indian-based small- and medium-sized enterprises’ AI digital transformation [58]. In accordance with these findings, two indicators were developed: A1—enhancement of the ease of system operations; and A2—focus on a case’s perceptions toward user experience.

2.2.2. Activities

The dimension of activities, which was previously defined as “changes in activities, triggered by changes in digital technology [56]”, was redefined as “fundamental changes in military mental health services after the introduction of chatbots” to fit with the purpose of this study. Research on AI-based digital transformation in enterprises has examined human-resource management and recruitment [59], digital learning [60], and business-process management [61,62]. In the field of healthcare, data security and privacy issues have received considerable attention [63]. Moreover, research has suggested that enterprises equip employees with AI-related knowledge by offering training sessions, seminars, and workshops to reduce employee resistance to the adoption of AI [64].

Accordingly, the following indicators were developed: B1—revising guidelines for military mental health services; B2—adjusting the content of mental health advocacy and education activities; B3—adjusting the content of the mental-health-service website; B4—adjusting selection criteria for military-mental-health-management trainees; B5—adjusting the content of programs for mental-health-management trainees; B6—adjusting the content of and hours spent in on-the-job education and training; B7—examining and modifying psychological testing and assessment tools; B8—adjusting the currently practiced three-tier prevention-and-referral mechanism, namely, primary detection and prevention, secondary profession counseling, and tertiary medical interventions; B9—adjusting the current practice of professional supervision for mental health services; and B10—improving privacy and data-security issues.

2.2.3. Boundaries

The dimension of boundaries, which was formerly defined as "changes that occur in digital transformation and may involve expansion, contraction or even the disappearance of boundaries [56]", was redefined as "expansion, contraction, or even disappearance of organization, staffing, and power of the unit responsible for policy implementation after the introduction of chatbots into the military to assist with mental health services". Research on AI digital transformation has explored empowering leadership [64] and firm reorganization [65]. Lucija et al. identified organizational change and operational capabilities as crucial elements in the process of digital transformation in enterprises [66]. Furthermore, research on influential factors in the introduction of electronic records and information management into the Malaysian military found that the leadership and governance structures were latent factors in the success of the policy [53]. This indicates that restructuring the current organizational framework plays a highly critical role in system implementation.

Accordingly, the following indicators were developed: C1—adjusting the organizational structure of the responsible department; C2—adjusting the rank of the manager responsible for relevant affairs; C3—adding operating mechanisms for communication and coordination with other departments; C4—endowing practitioners with responsibilities and powers; C5—enhancing recognition and support from the commander; and C6—reviewing the budget.

2.2.4. Goals

The dimension of goals were originally defined as "profound effects on organizations' deep structure [56]" and redefined as "effects generated on the work performance and project inspection of the unit responsible for policy implementation after chatbots are introduced into the military" to better serve the purpose of this study. Ahmad et al. argued that development of appropriate performance indicators currently plays an essential role in the digital transformation of enterprises [67]. Accordingly, the following indicators were developed in this study: D1—adjusting how work performance is presented; D2—adjusting administrative supervision items; and D3—adjusting selection criteria for personnel with outstanding performance.

2.3. Evaluation Criteria

The Fuzzy Delphi method, an evaluation-index system, was employed in this study. The Delphi method, initially developed by Rand Corporation in the 1950s, was designed to solicit specialist opinions through a questionnaire to afford groups the opportunity to arrive at a consensus [68]. Murray et al. designed the Fuzzy Delphi method to integrate the Delphi method and the Fuzzy Theory in an effort to improve the multi-person decision-making model adopted by the traditional Delphi method, as well as to construct fuzzy preference relations among all specialists and further obtain groups' collective preference relations as the best alternative [69]. Jeng continued to improve the Fuzzy Delphi method by applying double triangular fuzzy numbers to integrate specialist opinions and, thus, reduce the number of repeated surveys in 2001 [70,71]. In addition, the gray-zone test is employed to more effectively determine whether specialist cognition demonstrates a consistent convergence; that is, whether a consensus is reached. In this study, the improved Fuzzy Delphi method proposed by Jeng was employed for indicator selection. The application of and steps in the testing method were as follows:

Step 1: A fuzzy expert survey on all the assessment items considered herein was designed and an appropriate specialist group was formed. All the specialists were requested to provide a possible interval value for each assessment item. While the lower bound of an interval value represents a specialist's most conservative perception of the value of the quantitative score for an assessment item, the upper bound represents the specialist's most optimistic perception of the value of the quantitative score for the item.

Step 2: For each assessment item i, all the specialists' most conservative perceptions of values and their most optimistic perceptions of the values were calculated. Extreme values beyond two standard deviations were subsequently excluded. While the lower bound C_L^i, mean C_M^i, and upper bound C_U^i of the remaining most-conservatively-perceived values that were not excluded were subsequently calculated, the lower bound O_L^i, mean O_M^i, and upper bound O_U^i of the remaining most-optimistically-perceived values were calculated.

Step 3: We created the triangular fuzzy numbers for the most conservative perceived value $C^i = (C_L^i, C_M^i, C_U^i)$ and the most optimistic perceived value $O^i = (O_L^i, O_M^i, O_U^i)$ for each assessment item i, using the information gathered in Step 2. This process is illustrated in Figure 1.

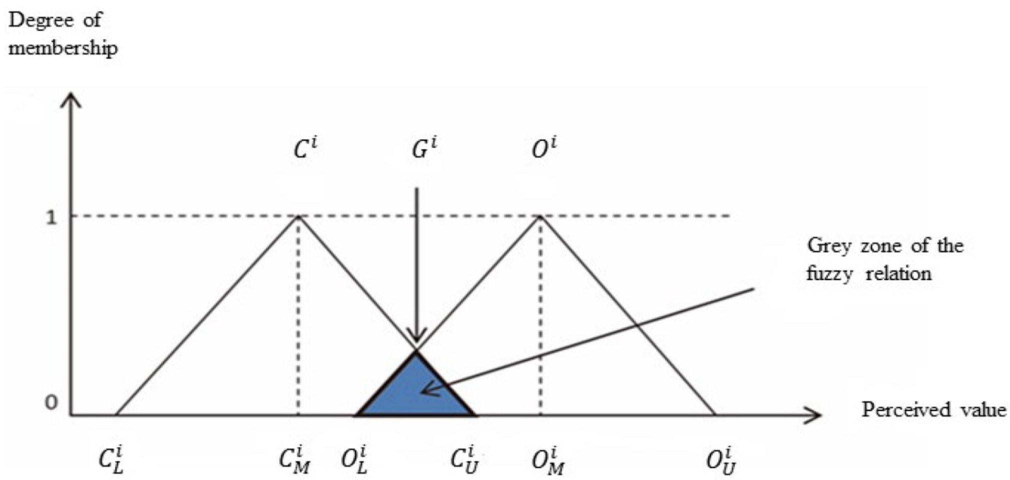

Figure 1. Double triangular fuzzy technique.

Step 4: The following methods were used to determine whether there was a consensus among the specialist opinions:

(1) If two triangular fuzzy numbers did not overlap, that is, $C_U^i \le O_L^i$, this indicated the presence of a consensus zone among the interval values of all the specialist opinions, which tended to fall within the scope of the consensus zone. Therefore, let the expert consensus value G^i for an assessment item i be equal to the arithmetic mean of C_M^i and O_M^i. Then, $G^i = (C_M^i + O_M^i)/2$.

(2) If two triangular fuzzy numbers overlapped, that is, $C_U^i > O_L^i$, and the gray zone of the fuzzy relation ($Z^i = C_U^i - O_L^i$) was smaller than the interval range between the geometric mean of the optimistically perceived value and the geometric mean of conservatively perceived value for an assessment item rated by specialists ($M^i = O_M^i - C_M^i$), this indicated that although there was no consensus zone among the interval values of specialist opinions, the two specialists giving extreme values, that is, the divergence between the most conservative and optimistic perceptions of an assessment item i, compared to other specialists' opinions, was not sufficiently significant to create a difference in opinion. Thus, we determined the consensus importance value G_i of

assessment item i by taking the fuzzy relation of the two triangular fuzzy numbers and performing an intersection (min) operation. Next, we found the quantitative score of the fuzzy set with the maximum membership value.

(3) If two triangular fuzzy numbers overlapped, that is, $C_U^i > O_L^i$, and the gray zone of the fuzzy relation ($Z^i = C_U^i - O_L^i$) was greater than the interval range between the geometric mean of the optimistically perceived value and the geometric mean of conservatively perceived value for an assessment item rated by specialists ($M^i = O_M^i - C_M^i$), this indicated that there was no consensus zone among the interval values of specialist opinions, and that the two specialists who gave extreme values, that is, when the specialists' opinions showed significant divergence due to extreme values given by the most conservative and optimistic specialists, the assessment items were considered unresolved. These unresolved items were then provided to the specialists for their reference, and Steps 1 to 4 were repeated to conduct another survey until a consensus was reached on all assessment items. The objective was to obtain the consensus-importance value G_i.

2.4. Decision-Making Trial and Evaluation Laboratory (DEMATEL): Constructing Influential Network Relation Map (INRM)

Using the results shown in the Evaluation Criteria section, the dimensions and indicators for the introduction of chatbots into mental health services in the military were constructed. Here, the correlations between problems and the cause–effect relationships among dimensions and indicators were analyzed through DEMATEL. The steps adopted were as follows [54]:

Step 1: Calculating the direct-influence matrix using scores

We assume that H experts compare pairwise n indicators, measuring the degree of influence using a 0–4 rating scale, where 0–4 points represent no influence (0), minimum influence (1), low influence (2), moderate influence of index i on index j (3), and high influence (4). The results of the scores given by each expert form the non-negative matrix $X^h = \left[X_{ij}^h\right]_{n\times n}$, where $h = 1, 2, \ldots, H$, and $X^1, \ldots, X^h, \ldots, X^H$, represent the matrix of scores awarded by H experts based on their experience. The mean value for H experts is $g_{ij} = \frac{1}{H}\sum_{h=1}^{H} x_{ij}^h$, and the mean matrix is denoted as the direct-influence matrix G, represented by Formula (1), which indicates the degree to which a given indicator influences and is influenced by another.

$$G = \begin{bmatrix} g_{11} & \cdots & g_{1j} & \cdots & g_{1n} \\ \vdots & & \vdots & & \vdots \\ g_{i1} & \cdots & g_{ij} & \cdots & g_{in} \\ \vdots & & \vdots & & \vdots \\ g_{n1} & \cdots & g_{nj} & \cdots & g_{nm} \end{bmatrix} \quad (1)$$

Step 2: Normalizing the direct-influence matrix.

The normalized direct-influence matrix, which is represented by matrix D, is obtained by normalizing the mean matrix G. This is performed using Formulas (2) and (3), and the indicators on the main diagonals are set to zero.

$$D = s \times G \quad (2)$$

$$s = \min\left\{ 1/\max_i \sum_{j=1}^{n} b_{ij}\ ,\ 1/\max_j \sum_{i=1}^{n} b_{ij} \right\} \quad (3)$$

Step 3: Attaining the total-influence matrix T

The total-influence matrix T is obtained using Formula (4), where I represents the $n \times n$ matrix.

$$\begin{aligned} T &= \left[t_{ij}\right]_{n\times n}, i, j = 1,\ 2, \cdots, n \\ T &= D + D^2 + \cdots + D^q \\ &= D\left(I + D + D^2 + \cdots + D^{q-1}\right) \\ &= D\left(I + D + D^2 + \cdots + D^{q-1}\right)(\mathrm{I} - \mathrm{D})(\mathrm{I} - \mathrm{D})^{-1} \\ &= D(\mathrm{I} - \mathrm{D})^{-1},\ \lim_{q\to\infty} D^q = [0]_{n\times n} \end{aligned} \tag{4}$$

Step 4: Analyzing the results

The values in each row and column in the total-influence matrix are summed using Formulas (5) and (6). When $i = j$ and $i,\ j \in \{1,\ 2, \cdots, n\}$, the vector of the horizontal axis is $(d_i + r_i)$, which represents the total influence among factors. The total degree to which a given factor influences and is influenced by other factors shows the magnitude of its influence within the set of issues; greater values indicate that the factor is closer to the center of an event, which is a feature known as prominence. When the prominence $(d_i + r_i)$ is greater than 0, the greater the value, the more important the given factor with respect to all evaluation factors, and the greater the magnitude of the relationship. The vector of the vertical axis is $(d_i - r_i)$, defined as the degree to which a factor influences or is influenced by other factors. This represents the degree of cause–effect relationship among factors, known as their relation. When relation $(d_i - r_i)$ is positive, a greater positive value indicates a given factor exerts a higher degree of direct influence on other factors, leading the factor to be classified into the cause group. When relation $(d_i - r_i)$ is negative, a greater negative value indicates that a given factor is influenced by other factors to a higher degree, leading the factor to be classified into the effect group. Accordingly, a factor is shown in the form of a point $(d_i + r_i, d_i - r_i)$ in the two-dimensional Cartesian coordinate system to indicate its influence and role in cause–effect relationships.

$$d = (d_i)_{n\times 1} = \left[\sum_{j=1}^{n} t_{ij}\right]_{n\times 1} = (d_1,\ \cdots,\ d_i, \cdots,\ d_n)' \tag{5}$$

$$r = \left(r_j\right)_{n\times 1} = \left(r_j\right)'_{1\times n} = \left[\sum_{i=1}^{n} t_{ij}\right]'_{1\times n} = \left(r_1,\ \cdots,\ r_j, \cdots,\ r_n\right)' \tag{6}$$

2.5. DEMATEL-Based Analytic Network Process (DANP): Constructing Influential Weights

This study analyzed the correlations and weights among dimensions and indicators for the introduction of chatbots into mental health services in the military using DANP. The following steps were taken [55,71–73].

Step 1: Establishing the total-influence matrix

Based on the views of experts, the total-influence matrix, $\boldsymbol{T}$, for the indicators are obtained through DEMATEL. In DANP, the total-influence matrix for indicators is $T = \left[t_{ij}\right]_{n\times n}$, when $\sum_{j=1}^{m} m_j = n,\ m < n$, and T_c^{ij} are $m_i \times m_j$ matrix, as indicated by Formula (7). The $\boldsymbol{D}_m$ represents the m-th cluster, $\boldsymbol{C}_{mm}$ signifies the m-th indicator in the m-th dimension, and $\boldsymbol{T}_c^{ij}$ denotes the sub-matrix for a comparison of indicators in the i-th and j-th dimensions.

$$T_c = \begin{bmatrix} T_c^{11} & \cdots & T_c^{1j} & \cdots & T_c^{1n} \\ \vdots & & \vdots & & \vdots \\ T_c^{i1} & \cdots & T_c^{ij} & \cdots & T_c^{in} \\ \vdots & & \vdots & & \vdots \\ T_c^{n1} & \cdots & T_c^{nj} & \cdots & T_c^{nn} \end{bmatrix} \tag{7}$$

Step 2: Building an unweighted super-matrix W

The normalized total-influence matrix for indicators $\boldsymbol{T}_C$ was obtained with $\boldsymbol{T}_C$ divided by the sum of the columns of factors in a given dimension $d_i = \sum_{j=1}^{m} t_{ij},\ i = 1, 1, \ldots, m$, $\boldsymbol{T}_c^{\alpha}$ as indicated in Formula (8):

$$T_c^{\alpha} = \begin{bmatrix} T_c^{\alpha 11} & \cdots & T_c^{\alpha 1j} & \cdots & T_c^{\alpha 1n} \\ \vdots & & \vdots & & \vdots \\ T_c^{\alpha i1} & \cdots & T_c^{\alpha ij} & \cdots & T_c^{\alpha in} \\ \vdots & & \vdots & & \vdots \\ T_c^{\alpha n1} & \cdots & T_c^{\alpha nj} & \cdots & T_c^{\alpha nn} \end{bmatrix} \tag{8}$$

Based on the pairwise comparison of indicators, the unweighted super-matrix $\boldsymbol{W}$ was obtained by transposing $\boldsymbol{T}_c^{\alpha}$, as indicated in Formula (9):

$$\boldsymbol{W} = (T_c^{\alpha})' = \begin{bmatrix} \boldsymbol{w}^{11} & \cdots & \boldsymbol{w}^{i1} & \cdots & \boldsymbol{w}^{n1} \\ \vdots & & \vdots & & \vdots \\ \boldsymbol{w}^{1j} & \cdots & \boldsymbol{w}^{ij} & \cdots & \boldsymbol{w}^{nj} \\ \vdots & & \vdots & & \vdots \\ \boldsymbol{w}^{1n} & \cdots & \boldsymbol{w}^{in} & \cdots & \boldsymbol{w}^{nn} \end{bmatrix} \tag{9}$$

Step 3: Attaining a weighted super-matrix $\boldsymbol{W}^{\alpha}$

The total-influence matrix for dimensions $\boldsymbol{T}_D = \left[\boldsymbol{t}_{ij}^{D}\right]_{m\times n}$ was obtained through DEMATEL using Formula (10).

$$T_D = \begin{bmatrix} t_D^{11} & \cdots & t_D^{1j} & \cdots & t_D^{1n} \\ \vdots & & \vdots & & \vdots \\ t_D^{i1} & \cdots & t_D^{ij} & \cdots & t_D^{in} \\ \vdots & & \vdots & & \vdots \\ t_D^{n1} & \cdots & t_D^{nj} & \cdots & t_D^{nn} \end{bmatrix} \tag{10}$$

To standardize the matrix, each level and dimension were normalized by the total degree of effect, as demonstrated in Equation (11).

$$\begin{aligned} T_D^{\alpha} &= \begin{bmatrix} t_D^{11}/d_1 & \cdots & t_D^{1j}/d_1 & \cdots & t_D^{1n}/d_1 \\ \vdots & & \vdots & & \vdots \\ t_D^{i1}/d_i & \cdots & t_D^{ij}/d_i & \cdots & t_D^{in}/d_i \\ \vdots & & \vdots & & \vdots \\ t_D^{n1}/d_n & \cdots & t_D^{nj}/d_n & \cdots & t_D^{nn}/d_n \end{bmatrix} \\ &= \begin{bmatrix} t_D^{\alpha 11} & \cdots & t_D^{\alpha 1j} & \cdots & t_D^{\alpha 1n} \\ \vdots & & \vdots & & \vdots \\ t_D^{\alpha i1} & \cdots & t_D^{\alpha ij} & \cdots & t_D^{\alpha in} \\ \vdots & & \vdots & & \vdots \\ t_D^{\alpha n1} & \cdots & t_D^{\alpha nj} & \cdots & t_D^{\alpha nn} \end{bmatrix} \end{aligned} \tag{11}$$

In order to obtain the weighted super-matrix, the unweighted super-matrix T_D^{α} was normalized. This process involved dividing each element of T_D^{α} by the sum of its corresponding column to reflect the relative importance of each criterion in the decision-making process, as demonstrated in Equation (12).

$$\boldsymbol{W}^{\alpha} = \boldsymbol{T}_D^{\alpha}\boldsymbol{W} = \begin{bmatrix} t_D^{\alpha 11} \times \boldsymbol{W}^{11} & \cdots & t_D^{\alpha i1} \times \boldsymbol{W}^{i1} & \cdots & t_D^{\alpha n1} \times \boldsymbol{W}^{n1} \\ \vdots & & \vdots & & \vdots \\ t_D^{\alpha 1j} \times \boldsymbol{W}^{1j} & \cdots & t_D^{\alpha ij} \times \boldsymbol{W}^{ij} & \cdots & t_D^{\alpha nj} \times \boldsymbol{W}^{nj} \\ \vdots & & \vdots & & \vdots \\ t_D^{\alpha 1n} \times \boldsymbol{W}^{1n} & \cdots & t_D^{\alpha in} \times \boldsymbol{W}^{in} & \cdots & t_D^{\alpha nn} \times \boldsymbol{W}^{nn} \end{bmatrix} \quad (12)$$

Step 4: Limiting the weighted super-matrix $\boldsymbol{W}^{\alpha}$

In the weighted super-matrix, the sum of the values in each column is 1; however, given that the values do not converge, the weights of the received influence for indicators remain unknown. By multiplying the weighted super-matrix $\boldsymbol{W}^{\alpha}$ by itself z times until its values converge, that is, $\lim_{z\to\infty} (W^{\alpha})^z$, the weights of received influence for each indicator are finally obtained and used to establish the importance for each indicator. These weights are termed global weights, also known as DANP weights. Furthermore, the global weights of all indicators in a given dimension are summed to yield the local weight of the dimension, and then the local weight of a given indicator is obtained by dividing the global weight of the indicator by the local weight of the related dimension.

2.6. Participants

The study was conducted in Taiwan. The Ministry of National Defense (MND) granted permission for professionals with over two years of experience in military mental health services and adeptness in operating the MND Mental Health Inspection and Analysis Information Platform System to be invited to participate in the survey. First, specialists were emailed an invitation, which included a letter that explained the study and a written consent form. The participants were requested to submit the written informed consent form via email, which entailed ticking a box indicating consent on the first page of the questionnaire. They were further informed that they could withdraw from the survey at any stage. Prior to the formal survey, a series of briefings were arranged to introduce the robots, which were trained by AI to be empathic and capable of understanding human conversations effectively, including Woebot, Wysa, X2, and Youper. During the briefings, the current status and results of related research on the application of chatbots to military mental health services were elucidated. Finally, all the participants were notified that they would receive a gift worth approximately USD 10 after completing the survey in compensation for their time.

2.7. Ethical Considerations

The study followed ethical guidelines. The participants were informed that their participation was voluntary and that their data would be used only for research purposes and processed anonymously. Consent was assumed upon the return of completed questionnaires. Since the participants were not subjected to physical or psychological procedures, no approval was required from the Ministry of Health and Welfare, Taiwan. The study adhered to the principles outlined in the Declaration of Helsinki and complied with the General Data Protection Regulation when data were handled.

3. Results

3.1. Characteristics of Expert Panel

As shown in Table 1, the participants included 22 specialists, all of whom possessed the required qualifications. Of the participants, 12 were male and 10 were female. Furthermore, there were four lieutenant colonels, 18 majors, three captains, one sergeant, and one civil servant. Four served as mental health officers in high-level staff units, including the MND, command headquarters, and theater of operations, and were responsible for the planning and supervision of mental health services. Fifteen were psychological counselors in grassroots military units, and one served as a counseling psychologist in a military hospital. They were all responsible for performing practical work in mental health services. Furthermore, two of the participants served as instructors at military training units at the time at which the survey was conducted. In addition to teaching and conducting research on related programs, they were responsible for complying with guidelines. Eleven of the participants took part in the Military Mental Health Inspection and Analysis Information Platform System Pilot Project from January 2021 to July 2021 and provided suggestions for the testing and assessment of this information system after it was introduced to some units, as well as for its integration with the existing platform. Furthermore, the participants had a range of relevant service years, with an average of 6.95 years. The participants' backgrounds are displayed in Table A2.

Table 1. Demographic characteristics.

Demographic	Description	*N*	%	Cumulative Percentage
Gender	Male	12	54.55	54.55
	Female	10	45.45	100.00
Education	Bachelor	7	31.82	31.82
	Master	15	68.18	100.00
Service	Army	7	31.82	31.82
	NAVY	2	9.09	40.91
	Air Force	11	50.00	90.91
	Military Police	1	4.55	95.46
	Civilian	1	4.55	100.00
Job Type	Practical	16	72.73	72.73
	Education Training	2	9.09	81.82
	Planning and Supervision	4	18.18	100.00
Working Years	1–5	4	18.18	18.18
	6–10	17	77.27	95.45
	11–15	1	4.55	100.00

3.2. Results of the Fuzzy-Delphi-Specialist Survey

The participants were forbidden from discussing their specialist opinions with each other or establishing any horizontal connections, and were requested to engage in the survey only through the researcher. After two rounds of surveys were conducted, all the specialists' most conservative perceived values and their most optimistically perceived values fell within two standard deviations. No overlap occurred in the double triangular fuzzy numbers of the indicators B10 and D2, indicating a high degree of consensus among the specialists. Despite the observation of overlaps in the double triangular fuzzy numbers of the remaining 19 indicators, the gray zones of the fuzzy relationships were found to be less than the interval ranges between the geometric mean of the optimistic perceptions and the geometric mean of the conservative perceptions for the evaluation items assessed by the experts. In other words, $M_i > Z_i$, which indicated that there was no excessive divergence of opinion among the specialists.

Subsequently, the indicators were selected. Wu and Huang proposed that the threshold value of specialist consensus should be set between 5 and 7 [74]. Had the threshold value been set too low, the effects of the indicator selection would not have been determined adequately. Consequently, the threshold value in this study was set at 7. The specialist-consensus values obtained in this study fell between 7.42 and 9.15, so the entire range was greater than 7. Ultimately, all the 21 indicators in this study were included (Table A3).

3.3. Constructing Cause–Effect Relationships among Dimensions and Indicators

As shown in Formula (1), the direct-influence matrix for the dimensions and indicators was established based on the results of the influences among the 21 indicators. The direct-influence matrix was normalized following Formulas (2) and (3), and the total-influence matrix T was obtained using Formula (4), as shown in Table A4. The total-influence matrix obtained through the normalization reached a stable state. This provided information on how one indicator influenced another and served as a basis for the creation of a cause–effect relationship diagram.

Furthermore, the values in each row and column of the total-influence matrix were summed using Formulas (5) and (6) to obtain the sums of the exerted and received influences for the dimensions and indicators, as shown in Table A5. The vector on the horizontal axis, (d + r), represents the magnitude of the total influences among the factors, with greater values indicating that a given factor was closer to the center of an event, denoted as prominence. The vector on the vertical axis is (d − r) was defined as the degree to which a factor influences or is influenced by other factors. This represents the degree of the cause–effect relationship among the factors, denoted as the *relation*. When the relation ($d_i - r_i$) is positive, greater positive values indicate that the given factor exerts a higher degree of direct influence on other factors, leading the factor to be classified into the cause group. When relation (d − r) is negative, a greater negative value indicates that a given factor is influenced by other factors to a higher degree, leading the factor to be classified into the effect group.

Based on the results presented in Table A5, a factor was developed in the form of a point (d + r, d − r) in the two-dimensional Cartesian coordinate system. The cause–effect relationships between the dimensions are detailed in Figure 2. The total-influence degree was in the following order: A. Technologies and D. Goals, followed by B. Activities and C. Boundaries. In this study, the A. Technologies and D. Goals were greater than the threshold.

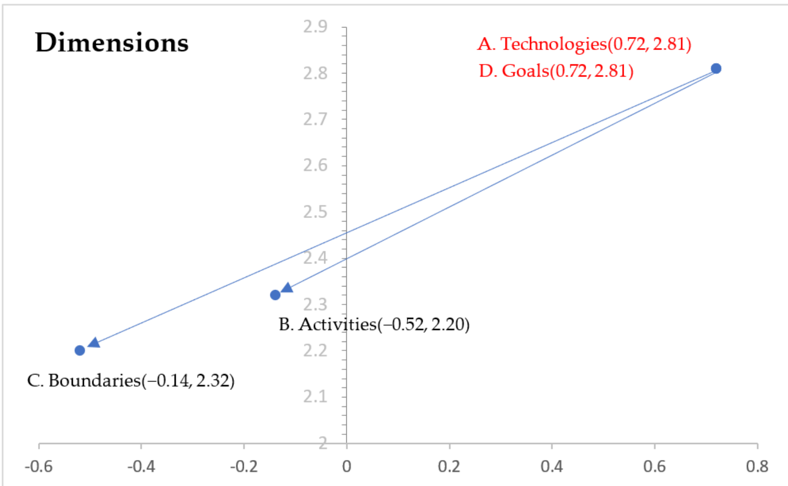

Figure 2. Cause–effect relationships between dimensions. Note: The red font means cause.

By examining the influence of the relationships between the dimensions, we determined the priority of influences to be A = D > B > C. This result indicated that Technologies and Goals were the most fundamental influencing factors.

Similarly, based on the results presented in Table A5, for the dimension of A. Technologies, the INRM was used to reveal the following order of influences: A1 > A2. For the dimension of B. Activities, the order of influences was as follows: B10 > B9 > B6 > B8 > B5 > B2 > B1 > B3 > B4 > B7. For the dimension of C. Boundaries, the order of influences was as follows: C2 > C1 > C3 > C4 > C5 > C6. For the dimension of D. Goals, the order of influences was as follows: D1 > D2 > D3. These results also showed that the economic scales A1, enhancing the ease of system operations, B10, improving privacy and data-security issues, C2, adjusting the rank of the manager responsible for relevant affairs, and D1, adjusting how work performance is presented, were the most fundamental influencing factors in their respective dimensions.

3.4. DANP Influencial Weights of Dimensions and Indicators

The DEMATEL method was used to yield the total-influence matrix T, presenting the DANP total-influence matrix for the indicators $\boldsymbol{T}_C$, as shown in Formula (7). Subsequently, the total-influence matrix was normalized, as in Formula (8), and the normalized total-influence matrix was $\boldsymbol{T}_C^{\alpha}$. From the pairwise comparison of the indicators and the fundamental concept of ANP, the unweighted super-matrix W was obtained by transposing the normalized total-influence matrix ($\boldsymbol{T}_C^{\alpha}$), using Formula (9). The unweighted super-matrix is shown in Table A6. The total-influence matrix for the dimensions ($\boldsymbol{T}_D$) was obtained using Formula (10), and the normalized total-influence matrix for the dimensions ($\boldsymbol{T}_D^{\alpha}$) was obtained using Formula (11). The normalized weighted super-matrix was obtained using the normalized total-influence matrix for the dimensions and unweighted super-matrix W, as shown in Formula (12). In the weighted super-matrix, the sum of values in each column was 1. By multiplying the weighted super-matrix by itself multiple times until its values converged, the limit weighted super-matrix was obtained, as shown in Table A6.

Finally, after obtaining the global weights of all the indicators in a given dimension, the local weights of the individual dimensions were determined by summing these global weights. Next, to obtain the local weight of a specific indicator, the global weight of the indicator was divided by the local weight of its related dimension, as demonstrated in Table A7. The four dimensions, listed in descending order of weight, were: A—Technologies (0.390); D—Goals (0.368); C—Boundaries (0.171); and B—Activities (0.072). The 21 indicators, arranged in descending order of global weight, were: A1 (0.507), A2 (0.493), D1 (0.416), D2 (0.339), D3 (0.245), C5 (0.246), C6 (0.216), C4 (0.208), C3 (0.145), C1 (0.097), B2 (0.135), C2 (0.088), B5 (0.123), B6 (0.122), B1 (0.101), B3 (0.098), B7 (0.093), B8 (0.088), B9 (0.086), B10 (0.078), and B4 (0.077). The influential weight of a given indicator was used to establish the importance of its indicator. These weights were termed global weights, or DANP weights.

4. Discussion

4.1. Principal Findings

The purpose of this study was to evaluate the critical success factors for introducing chatbots into the military to assist with mental health services. In accordance with the AI-readiness framework, preliminary indicators were established after considering the influences of the introduction of chatbots in four dimensions, that is, technologies, activities, boundaries, and goals, as well as after conducting a literature review and specialist consultations. Furthermore, the Fuzzy Delphi method was employed to select the indicators. Ultimately, 21 key indicators were determined.

This study further adopted the DEMATEL technique to investigate the influences among the dimensions and indicators. First, for the influences among the four dimensions, A—Technologies and D—Goals were the influencing dimensions, while C—Boundaries and B—Activities were the influenced dimensions. This indicates that, for the successful introduction of chatbots into mental health services in the military, it is advisable to give precedence to improvements in technologies and goals before exploring other dimensions. This will help to ensure that chatbots are implemented in line with sustainable practices.

In terms of technologies, A1 and A2 were the influencing and influenced indicators, respectively, indicating that a special focus should be placed on enhancing the ease of system operations to improve perceptions of user experience. In terms of activities, B10, B9, B6, B8, B5, and B2 were the influencing indicators, signifying the importance of privacy and data security issues, the professional supervision of mental health services, and on-the-job education and training.

Among the boundaries, C1, C2, and C3 were the influencing indicators, indicating that the experts attached greater importance to adjusting the rank of the manager responsible for relevant affairs, adjusting the organizational structure of the responsible department, and adding operating mechanisms for communication and coordination with other departments. Among the goals, D2 was an influencing indicator, revealing the importance of adjusting how work performance is presented. Finally, DANP was applied to obtain the weights of the dimensions and indicators.

The dimension of Technologies, which was the first to be developed in this study, focuses on users' acceptance of a new technology when it is introduced into their organization. Past research showed that the perceived ease of system's operation among users is of great importance and is the key factor in AI-based digital transformation in organizations, which is in line with the results of this study [57,58]. Activities and Boundaries, the second and third dimensions developed in this study, respectively focus on fundamental changes and changes in organizational boundaries, respectively, which occur after a technology is adopted. This study revealed a high degree of consensus among the specialists in relation to privacy and data-security issues and administrative supervision. Privacy and confidentiality are widely perceived as top priorities in mental health services because their absence may lead to failed treatments [75]. A research report published by the U.S. Army War College in 2002 recommended that the military, in the face of digitization, should consider personnel training and how to operate in a bureaucratic system to improve management efficiency and other critical factors [76]. This is further supported by the results of this study. Moreover, the military is characterized by a hierarchical structure of command, with an additional emphasis on honor. This may also serve as a reason why the indicator of adjusting how work performance is presented is of critical importance.

4.2. Implications of This Study for Sustainability in Healthcare

The integration of chatbots into military mental health services can offer significant benefits to both patients and the institution. However, sustainability concerns must be taken into consideration, and key success indicators should be established to ensure that the implementation of chatbots aligns with sustainable-healthcare=development goals. The unique aspect of this study is the use of DEMATEL and DANP techniques to establish the causal relationship between dimensions and indicators, as well as to determine the weightings of each dimension and indicator. This will aid in the development of a more sustainable military-mental-health system.

4.3. Strengths and Limitations

In this study, we presented a hybrid decision-making approach. However, this research method is yet to be commonly applied in the field of mental health. Therefore, this study may serve as a reference for future research in related fields. Moreover, due to insufficient human resources and other objective factors, there may be some degree of bias in the results. However, we are of the view that these biases would have had negligible effects on the results, and that they can be disregarded. Therefore, the findings show positive feasibility and practicality; hence, they can be used in policy formulation by executive departments.

5. Conclusions

As AI-technology-based products have become indispensable aspects of people's lives, military mental-health services should be developed accordingly, and they should embrace transformation. This prospective study developed key indicators for the introduction of chatbots into mental health services in the military and obtained the influences and weights of the indicators. These findings could be applied to future discussions on schools, other government departments, and enterprises with organizational structures. Moreover, in the future, a questionnaire survey may be conducted during the testing–evaluation or application stage, when chatbots are formally implemented to provide a reference for the effective evaluation of their implementation.

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Institutional Review Board Statement: This study was conducted in accordance with the principles of the Declaration of Helsinki, and data were handled according to the General Data Protection Regulation.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: Not applicable.

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Conflicts of Interest: The author declares no conflict of interest.

Appendix A

Table A1. List of Indicator Sets with Their Sources.

Dimension	Assessment Criteria	Indicator	References
A. Technologies	Changes in the acceptance of introduction of chatbots into the military to assist with mental health services	A1—enhancing the ease of system operations	[55,57]
		A2—focus on a case's perceptions toward user experience	[55,57]
B. Activities	Fundamental changes in military mental-health services after the introduction of chatbots	B1—revising guidelines for military mental health services	[61,62]
		B2—adjusting the content of mental health advocacy and education activities	[64]
		B3—adjusting the content of the mental-health-service website	[64]
		B4—adjusting selection criteria for military-mental-health-management trainees	[59]
		B5—adjusting the content of programs for mental-health-management trainees	[60]
		B6—adjusting the content of and hours spent in on-the-job education and training	[60,64]
		B7—examining and modifying psychological testing and assessment tools	Expert interview
		B8—adjusting the currently practiced three-tier-prevention and referral mechanism, namely, primary detection and prevention, secondary profession counseling, and tertiary medical interventions	Expert interview
		B9—adjusting the current practice of professional supervision for mentalhealth services	Expert interview
		B10—improving privacy and data security issues	[63,67]
C. Boundaries	Expansion, contraction, or even disappearance of organization, staffing, and the power of the unit responsible for policy implementation after the introduction of chatbots into the military to assist with mental health services	C1—adjusting the organizational structure of the responsible department	[64–66]
		C2—adjusting the rank of the manager responsible for relevant affairs	[64–66]
		C3—adding operating mechanisms for communication and coordination with other departments	[66]
		C4—endowing practitioners with responsibilities and powers	[53,64]
		C5—enhancing recognition and support from the commander	[53]
		C6—reviewing the budget	Expert interview
D. Goals	Effects on the work performance and project inspection of the unit responsible for policy implementation after chatbots are introduced into the military	D1—adjusting how work performance is presented	[53]
		D2—adjusting administrative supervision items	[53]
		D3—adjusting selection criteria for personnel with outstanding performance	Expert interview

Table A2. List of Members.

Num.	Gender	Class	Education	Services	Unit Type	Job Type	Years
P1	female	CPT	Master’s	Army	Logistics	Practical	6
P2	female	LCDR	Master’s	NAVY	Collection	Practical	7
P3	female	MAJ	Bachelor’s	Air Force	Air wing	Practical	9
P4	male	MAJ	Master’s	Air Force	Logistics	Practical	6
P5	male	MAJ	Machelor’s	Air Force	Logistics	Practical	14
P6	female	MAJ	Master’s	Air Force	Training	Education training	9
P7	female	MAJ	Master’s	Army	Field	Practical	8
P8	male	MAJ	Bachelor’s	Air Force	Air wing	Practical	7
P9	male	MAJ	Master’s	Army	Reserve	Practical	7
P10	male	MAJ	Bachelor’s	Air Force	Air wing	Practical	10
P11	female	CPT	Bachelor’s	Air Force	Training	Practical	6
P12	male	LCDR	Master’s	NAVY	Senior staff	planning and supervision	7
P13	male	LTC	Master’s	Military Police	Senior staff	planning and supervision	10
P14	male	MAJ	Bachelor’s	Air Force	Senior staff	planning and supervision	7
P15	male	CPT	Master’s	Air Force	Antiaircraft missile	Practical	4
P16	female	MAJ	Master’s	Army	Field	Practical	9
P17	male	LTC	Master’s	Army	Training	education training	6
P18	male	LTC	Master’s	Army	Senior staff	planning and supervision	5
P19	male	SSG	Bachelor’s	Army	Special operations	Practical	2
P20	female	MAJ	Master’s	Air Force	Antiaircraft missile	Practical	6
P21	female	MAJ	Master’s	Air Force	Training	Practical	6
P22	female	civilian	Master’s	None	Hospital	Practical	2

Table A3. Triangular Fuzzy Numbers and Final Weight Values of Each Indicator.

Indicators	C_L^i	C_U^i	O_L^i	O_U^i	C_M^i SD	O_M^i SD	C^i	O^i	$M^i - Z^i$	G^i	$G^i > 7$
A1	7	9	8	10	8.12 0.86	9.24 0.83	8.00	9.09	0.12	8.58	Yes
A2	7	9	8	10	8.29 0.85	9.41 0.87	8.28	9.37	0.12	8.67	Yes
B1	6	9	8	10	7.82 1.01	9.06 0.90	7.65	8.95	0.24	8.47	Yes
B2	6	9	8	10	7.82 1.13	9.12 0.93	7.55	8.91	0.30	8.49	Yes
B3	6	9	8	10	7.53 1.12	9.00 0.94	7.47	8.91	0.47	8.40	Yes
B4	6	9	8	10	7.59 1.12	8.76 0.90	7.34	8.55	0.17	8.35	Yes
B5	6	9	8	10	7.53 0.94	8.76 0.83	7.34	8.64	0.23	8.34	Yes
B6	6	9	8	10	7.82 0.95	9.12 0.86	7.76	9.00	0.30	8.49	Yes
B7	5	8	7	9	6.88 1.05	8.06 0.83	6.74	7.91	0.18	7.49	Yes
B8	5	8	7	9	6.76 0.90	7.88 0.78	6.51	7.78	0.12	7.42	Yes
B9	5	8	7	9	6.82 1.13	8.12 0.78	6.67	8.05	0.30	7.49	Yes
B10	8	9	9	10	8.59 0.51	9.71 0.47	8.67	9.76	1.12 *	9.15	Yes
C1	6	9	8	10	8.00 1.00	9.29 0.85	8.07	9.33	0.29	8.56	Yes
C2	6	9	8	10	8.35 1.06	9.53 0.80	8.20	9.42	0.18	8.70	Yes
C3	7	9	8	10	8.47 0.72	9.59 0.71	8.42	9.52	0.12	8.75	Yes
C4	7	9	8	10	8.59 0.71	9.71 0.69	8.51	9.61	0.12	8.81	Yes
C5	7	9	8	10	8.47 0.80	9.59 0.80	8.47	9.56	0.12	8.75	Yes
C6	6	9	8	10	8.29 0.92	9.47 0.80	8.22	9.37	0.18	8.68	Yes
D1	6	9	8	10	7.82 1.01	8.94 0.83	7.89	9.01	0.12	8.44	Yes
D2	7	9	9	10	8.41 0.62	9.47 0.51	8.38	9.49	1.11 *	8.94	Yes
D3	7	9	8	10	8.18 0.73	9.24 0.75	8.06	9.10	0.06	8.60	Yes

* $C_U^i \leq O_L^i$.

Table A4. Total-Influence Matrix for Indicators *T*: Indicators.

Indicators	A1	A2	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10	C1	C2	C3	C4	C5	C6	D1	D2	D3
A1	0.05	0.13	0.06	0.10	0.08	0.05	0.10	0.10	0.09	0.06	0.04	0.06	0.03	0.03	0.07	0.13	0.15	0.14	0.14	0.09	0.05
A2	0.11	0.03	0.05	0.07	0.06	0.03	0.06	0.06	0.05	0.04	0.05	0.04	0.03	0.02	0.05	0.10	0.11	0.10	0.07	0.05	0.04
B1	0.03	0.04	0.02	0.06	0.04	0.03	0.05	0.04	0.04	0.05	0.04	0.02	0.02	0.01	0.04	0.07	0.05	0.04	0.09	0.11	0.05
B2	0.03	0.07	0.04	0.03	0.07	0.02	0.05	0.04	0.04	0.04	0.03	0.02	0.01	0.01	0.04	0.05	0.08	0.05	0.05	0.05	0.03
B3	0.03	0.04	0.02	0.06	0.01	0.01	0.03	0.02	0.01	0.02	0.02	0.02	0.01	0.01	0.02	0.04	0.04	0.04	0.03	0.03	0.02
B4	0.03	0.03	0.03	0.03	0.02	0.02	0.05	0.04	0.03	0.02	0.03	0.03	0.03	0.03	0.04	0.07	0.07	0.05	0.05	0.04	0.07
B5	0.03	0.03	0.03	0.04	0.03	0.04	0.03	0.07	0.03	0.03	0.04	0.03	0.02	0.02	0.03	0.07	0.07	0.06	0.05	0.04	0.04
B6	0.03	0.03	0.02	0.05	0.02	0.03	0.04	0.02	0.02	0.02	0.03	0.03	0.01	0.01	0.02	0.04	0.04	0.06	0.03	0.03	0.02
B7	0.04	0.04	0.08	0.07	0.04	0.02	0.06	0.06	0.02	0.03	0.04	0.03	0.02	0.02	0.03	0.05	0.06	0.06	0.06	0.08	0.04
B8	0.04	0.04	0.11	0.10	0.08	0.04	0.12	0.09	0.05	0.03	0.05	0.03	0.04	0.03	0.06	0.08	0.10	0.07	0.08	0.08	0.05
B9	0.02	0.02	0.02	0.03	0.02	0.02	0.03	0.03	0.01	0.02	0.01	0.02	0.01	0.01	0.01	0.03	0.03	0.04	0.03	0.03	0.02
B10	0.09	0.12	0.07	0.06	0.05	0.03	0.08	0.06	0.05	0.04	0.04	0.03	0.02	0.02	0.05	0.10	0.10	0.10	0.09	0.08	0.04
C1	0.08	0.05	0.09	0.08	0.07	0.06	0.07	0.07	0.05	0.06	0.05	0.04	0.04	0.09	0.13	0.13	0.15	0.14	0.13	0.11	0.06
C2	0.05	0.05	0.09	0.09	0.06	0.06	0.07	0.07	0.04	0.05	0.05	0.05	0.11	0.04	0.14	0.15	0.16	0.15	0.13	0.11	0.07
C3	0.04	0.04	0.05	0.05	0.04	0.03	0.05	0.05	0.03	0.05	0.03	0.03	0.07	0.06	0.04	0.09	0.10	0.10	0.07	0.06	0.03
C4	0.08	0.07	0.11	0.11	0.08	0.09	0.11	0.11	0.08	0.10	0.08	0.09	0.10	0.10	0.13	0.08	0.16	0.13	0.13	0.12	0.10
C5	0.09	0.08	0.08	0.10	0.09	0.07	0.10	0.10	0.07	0.07	0.05	0.06	0.11	0.10	0.15	0.16	0.09	0.17	0.15	0.12	0.09
C6	0.11	0.07	0.06	0.10	0.07	0.06	0.11	0.13	0.10	0.07	0.09	0.08	0.05	0.04	0.07	0.09	0.12	0.07	0.10	0.09	0.07
D1	0.03	0.03	0.03	0.05	0.03	0.03	0.04	0.04	0.04	0.03	0.02	0.02	0.03	0.03	0.04	0.06	0.09	0.06	0.04	0.08	0.05
D2	0.02	0.02	0.04	0.05	0.03	0.02	0.04	0.04	0.03	0.03	0.04	0.03	0.03	0.02	0.04	0.05	0.06	0.05	0.09	0.03	0.05
D3	0.02	0.03	0.03	0.04	0.02	0.03	0.03	0.04	0.02	0.03	0.03	0.02	0.02	0.02	0.03	0.05	0.05	0.04	0.10	0.05	0.02

Table A5. Sum of Influencing and Influenced Factors among Dimensions and Indicators.

Dimensions/Indicators	d	r	d + r	d − r	Cause/ Effect
A	**1.76**	**1.05**	**2.81**	**0.72**	**cause**
A1	1.20	1.06	2.26	0.15	cause
A2	0.95	1.13	2.08	−0.18	effect
B	**0.84**	**1.36**	**2.20**	**−0.52**	**effect**
B1	0.54	1.03	1.57	−0.48	effect
B2	0.83	0.78	1.62	0.05	cause
B3	0.83	1.31	2.14	−0.47	effect
B4	0.61	1.28	1.89	−0.67	effect
B5	0.93	0.91	1.84	0.01	cause
B6	1.37	0.89	2.26	0.48	cause
B7	0.45	0.87	1.32	−0.43	effect
B8	1.31	0.77	2.08	0.54	cause
B9	1.73	0.81	2.53	0.92	cause
B10	1.81	0.73	2.54	1.08	cause
C	**1.09**	**1.23**	**2.32**	**−0.14**	**effect**
C1	2.16	1.66	3.82	0.50	cause
C2	2.09	1.88	3.97	0.21	cause
C3	1.75	1.72	3.47	0.04	cause
C4	0.86	1.70	2.56	−0.84	effect
C5	0.81	1.47	2.28	−0.66	effect
C6	0.71	1.02	1.72	−0.31	effect
D	**1.76**	**1.05**	**2.81**	**0.72**	**cause**
D1	1.20	1.06	2.26	0.15	cause
D2	0.95	1.13	2.08	−0.18	effect
D3	0.84	1.36	2.20	−0.52	effect

Table A6. Limit Weighted Super-Matrix T.

Indicators	A1	A2	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10	C1	C2	C3	C4	C5	C6	D1	D2	D3
A1	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11
A2	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11
B1	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
B2	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03
B3	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
B4	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
B5	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
B6	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
B7	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
B8	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
B9	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
B10	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
C1	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03
C2	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
C3	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04
C4	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06
C5	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07
C6	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06
D1	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13
D2	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10
D3	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07

Table A7. DANP Influential Weights of Dimensions and Indicators.

Dimensions/Indicators	Local Weight	Overall Weight	Ranking
A	0.390		**1**
A1	0.507	0.109	2
A2	0.493	0.106	3
B	0.072		**4**
B1	0.101	0.020	15
B2	0.135	0.027	11
B3	0.098	0.019	16
B4	0.077	0.015	21
B5	0.123	0.024	13
B6	0.122	0.024	14
B7	0.093	0.018	17
B8	0.088	0.018	18
B9	0.086	0.017	19
B10	0.078	0.015	20
C	0.171		**3**
C1	0.097	0.028	10
C2	0.088	0.025	12
C3	0.145	0.041	9
C4	0.208	0.059	8
C5	0.246	0.069	6
C6	0.216	0.061	7
D	0.368		**2**
D1	0.416	0.127	1
D2	0.339	0.103	4
D3	0.245	0.075	5

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