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Model Group Decision Support System Based on Depression Anxiety Stress Scales Using Ordered Weighted Averaging Aggregation Method

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ABSTRACT Depression, anxiety, and stress are common psychological conditions often triggered by the pressures of daily life. Depression Anxiety Stress Scale (DASS), is a widely used tool for assessing the severity of these disorders, available in different versions such as the DASS-21 and DASS-42. In line with these findings, DASS-21 consists of 21 symptom items, categorized into three types of disorders, with seven items assigned to each. In contrast, the DASS-42 includes 42 symptom items, with 14 items allocated per disorder. Both versions serve as standardized tools for assessing the severity of depression, anxiety, and stress, and the different versions show that one item only affects one disorder. In practice, it can affect several disorders with different priorities. This condition increases the risk of subjective bias in a psychologist's decision-making, as personal experiences and perceptions may influence their assessments. Therefore, this study aims to develop a Group Decision Support System (GDSS) model that considers the preferences of several psychologists in determining the priority of disorders based on the DASS-42 and DASS-21 items. The model has been built using the psychologist's preference method for DASS-42 and DASS-21 in fuzzy form, then combined using the Ordered Weighted Averaging (OWA) method to produce one decision. The alignment of top-priority items between GDSS and DASS was assessed as part of the evaluation. The results show a high degree of similarity, with GDSS matching 16 out of 21 symptom items in DASS-21 and 35 out of 42 items in DASS-42. The GDSS model can accommodate the preferences of decision-makers in providing weighting of the influence on each item in the DASS-21 and DASS-42, thereby providing more objective decisions.

INDEX TERMS Depression Anxiety Stress Scale, Group Decision Support System, Preference, Ordered Weighted Averaging

I. INTRODUCTION

Specific challenges, obstacles, or problems are often triggers for psychological pressure, leading to stress. Subsequently, stress arises from the complex interactions between psychological, physiological, and environmental factors [1]. A study found that 96.4% of 393 respondents reported difficulty managing stress caused by the challenges they faced [2]. Prolonged stress can lead to depression, anxiety, and antisocial behavior [3]. The Indonesia National Adolescent Mental Health Survey (I-NAMHS) reported that the most common disorders experienced by adolescents are anxiety disorders (3.7%) and depression (1%) [4]. Shorey et al. [5], states that approximately 8% of adolescents are suffering from depressive disorders globally, while 34% are experiencing clinically elevated depressive symptoms. Additionally, anxiety disorders affect approximately 10% of the adolescent population, while clinically elevated anxiety symptoms affect approximately 20.5% [5].

Depression Anxiety Stress Scale (DASS) is an assessment tool to measure the levels of depression, anxiety, and stress disorders [6]. DASS-42 consists of 42 question items that include 14 items for each subscale, namely depression, anxiety, and stress [6]. In another version, the DASS-21 consists of 21 items, including seven items for each subscale [7]. The DASS-21, as a shortened version of the DASS-42, has fewer items but can still provide comparable results with the DASS-42. In line with these findings, DASS-21 requires less time, is more practical, less burdensome for respondents, and is more frequently used [8].

Along with technological developments, several studies have used the DASS as the basis for developing systems or applications for detecting psychological disorders. For example, an expert system for early depression detection in adolescents using the DASS-42 [9], predicts Depression, Anxiety, and Stress Levels Using Machine Learning Based on DASS-21 Test Results [10]. The mental health detection models during the COVID-19 pandemic using machine learning based on DASS-42 [11]. The study successfully showed the ability of the DASS-based system to produce a diagnosis of psychological disorders of depression, anxiety, and stress experienced by an individual.

These studies categorize DASS items as affecting only one disorder, as previously mentioned. However, a single item may indicate multiple disorders with varying degrees of priority [12]. Determining the priority of disorders associated with a specific item requires input from multiple psychologists, who collectively provide a reference for weighting DASS items [12]. The involvement of multiple decision-makers enhances decision quality [13, 14], as group decision-making helps mitigate individual biases and errors [15]. By incorporating collective input, group-based decisions become more objective and unbiased [16, 17].

Facilitating group decision-making can be achieved by developing a Group Decision Support System (GDSS) [18]. Several studies show the important role of GDSS in group decision-making. The application of GDSS is used to overcome the subjective judgment of experts in determining distance education software [19]. This application also serves as a tool that facilitates and provides recommendations for planners in reaching mutual agreement in urban spatial planning [20]. It also helps in vendor selection by aggregating the differing preferences of decision-makers [17].

The involvement of multiple decision-makers with varying preferences can however lead to differences in prioritization [17]. Therefore, in developing GDSS, an effective method is required to aggregate the preferences of several decision-makers. One effective aggregation method that performs well is Ordered Weighted Averaging (OWA) [21]. Subsequently, the OWA has been applied in various applications, specifically in decision-making that considers preferences [22, 23], to combine the input data provided by decision-makers [24]. The OWA mechanism uses the linear sorting principle to sort the input data after the input variables are reordered [24]. This approach is commonly used to aggregate opinions [25].

A Previous study using the same method developed a GDSS model based on the DASS-42 for assessing depression, anxiety, and stress disorders. The study showed the suitability of system results to the DASS-42 by 71.43%, with 13 out of 42 items being appropriate because the items of anxiety and stress symptoms overlap by 16.67% while depression and anxiety overlap by 9.54% [12]. The results showed that each item can prioritize more than one disorder, and there are differences with the DASS-42.

Referring to previous results, this study aims to: 1) Develop a GDSS model for prioritizing disorder based on DASS, incorporating the multiple preferences. 2) Applying the OWA method for preference aggregation to combine the preferences of multiple psychologists for prioritizing disorders. 3) Evaluate the model in addressing the prioritization problem, providing valuable information on the flexibility model in the context of psychological disorder assessment based on DASS.

II. METHODS

In this study, DASS-based GDSS model will be developed through several key stages: data collection, model design, implementation, and evaluation. In the data collection stage, expert preferences on DASS items are gathered. Next, during the model design stage, the model's structure is systematically developed, incorporating the OWA integration method to aggregate preference data. The implementation stage involves coding and applying the developed model. Finally, the evaluation stage assesses the model's performance, analyzing the results to identify key insights. The sequence of these stages is illustrated in FIGURE 1, which shows the study process.

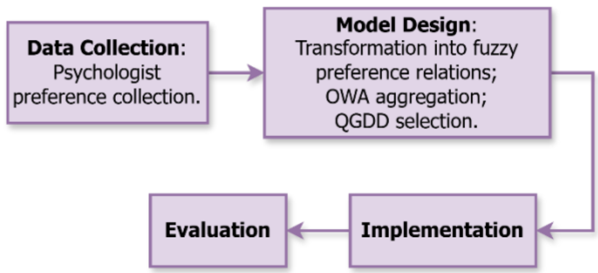

FIGURE 1. Study Proses Diagram

A. DATA COLLECTION

This stage focuses on collecting data and information from sources relevant to the study topic, such as experts, journals, articles, and other sources. Data collection processes are conducted as follows:

1. LITERATURE STUDY

The literature review involves collecting and studying references from relevant articles, journals, and books to this study. At this stage, data was obtained about DASS-21, which consists of 21 symptom items and includes three categories of disorders, and DASS-42, which consists of 42 symptom items. The distribution of DASS-21 [26] and DASS-42 [27] items for each disorder can be seen in TABLE 1 and TABLE 2.

TABLE 1
DASS-21 Item Distribution

Disorder	No Item/Symptom
Depression	3, 5, 10, 13, 16, 17, 21
Anxiety	2, 4, 7, 9, 15, 19, 20
Stress	1, 6, 8, 11, 12, 14, 18

TABLE 2
DASS-42 Item Distribution

Disorder	No Item/ Symptom
Depression	3, 5, 10, 13, 16, 17, 21, 26, 31, 34, 37, 38, 42
Anxiety	2, 4, 7, 9, 15, 19, 20, 23, 25, 28, 30, 36, 40, 41
Stress	1, 6, 8, 11, 12, 14, 18, 22, 27, 29, 32, 33, 35, 39

The assessment is carried out by assigning a score ranging from 0, showing it never occurs, to 3, showing it occurs frequently. The final score is calculated from the total number of scores for each disorder. For the calculation of DASS-21, the total score of the disorder is multiplied by two [28, 29]. The severity of each disorder is divided into five levels [29], as shown in TABLE 3.

TABLE 3
Severity Level

Disorder	Severity Level				
	Normal	Mild	Moderate	Severe	Very Severe
Depression	0 - 9	10 - 13	14 - 20	21 - 27	28+
Anxiety	0 - 7	8 - 9	10 - 14	15 - 19	20+
Stress	0 - 14	15 - 18	19 - 25	26 - 33	34+

2. FIELD STUDY

Field studies were conducted at the Psychology Service Unit of Sebelas Maret University. This included interviews with three psychology experts as well as filling out questionnaires by psychologists for DASS items to give preferences as a reference for finding the priority of disorders (depression, anxiety, or stress). Preferences were provided by the three psychologists using an ordered vector format. This format is $Ok = \left(O^k(1),\ O^k(2), \dots, O^k(m)\right)$ Okm, where $O^k(i)$ is the ranking of decision-makers [30].

In the process of assigning preferences, a ranking system is used, where each DASS symptom item is assigned a number 1, 2, or 3 to show the priority of the disorder associated with the symptom item. The priority order of disorders is sorted based on the preferences of each psychologist, where the smaller the number the higher the priority. At this stage, each psychologist can have different preferences.

B. MODEL DESIGN

An overview of the model design used in this study can be seen in detail in FIGURE 2, which shows the workflow of the developed system. Starting with the input process of preferences obtained from expert psychologists, the preferences are then transformed into a fuzzy preference relation format using the transformation process. In addition, preference aggregation is performed using the OWA operator to form a combined value that shows the combined preferences of the experts involved. Finally, the ranking process is used to determine priorities based on aggregation results.

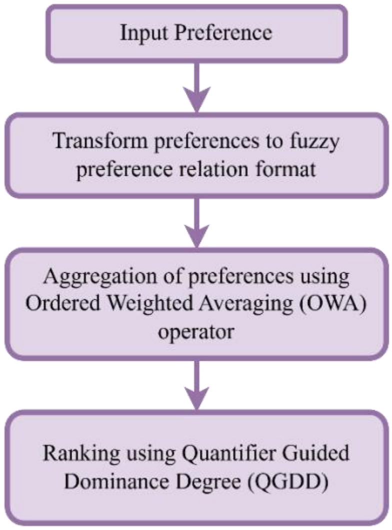

FIGURE 2. Model Design Diagram

1. TRANSFORM PREFERENCE TO FUZZY RELATION PREFERENCE

The preferences provided by each psychologist are consolidated into a single unified preference. Prior to this, the individual preferences, represented in ordered vector format, were converted into a fuzzy preference relation format. According to Chiclana [31], the transformation is shown in Eq. (1) [31]

$$P_{ij}^k = \frac{1}{2}\left(1 + \frac{o^k(j)}{m-1} - \frac{o^k(i)}{m-1}\right); 1 \le i \ne j \le m \tag{1}$$

where $o^k(j)$ represents the ranking position of alternative a_j in o^k, $and\ j = 1,2, \dots, m$. And m is the total number of alternatives available. This ranking shows the relative preference of each alternative according to the k-th decision maker. And P_{ij}^k is the degree of preference that the k-th decision maker assigns to alternative a_i over a_j. Show how preferable a_i is compared to a_j. These values are important for the next process, which is the aggregation of preferences,

2. PREFERENCE AGGREGATION

The fuzzy preference relation matrix that has been obtained will be used to combine the preferences of several decision-makers using the OWA aggregation method. Yager [32] represents the calculation of OWA using Eq. (2) [32]

$$OWA_w\ (a_1, \dots, a_n) = \sum_{i=1}^{n} w_i b_j \tag{2}$$

where b_j denotes the highest value among tin $a_1, \dots,\ a_n$. For the OWA weight, w can be calculated using Eq. (3) [32].

$$w_i = Q\left(\frac{i}{n}\right) - Q\left(\frac{i-1}{n}\right); i = 1, \dots, n. \tag{3}$$

3. ALTERNATIVE RANKING

Alternative selection at this stage aims to produce a ranking of several alternatives. This study will use the Quantifier Guided Dominance Degree (QGDD) method as an alternative selection method. Additionally, QGDD measures the dominance of one alternative over another [33], shown in Eq. (4) [33]

$$QGDD_i = \ F_Q\ (p_{ij}^c, j = 1, \dots, n\ , i \neq j) \tag{4}$$

with

$$F_Q\ (a_1, \dots, a_n) = \sum_{i=1}^{n} w_i b_i \tag{5}$$

The result of this QGDD is a weight that shows the priority ranking of disorders caused by a symptom item and becomes the initial weight that will be multiplied by the questionnaire filled in by the respondent. The ranking is sorted from the largest QGDD value.

C. IMPLEMENTATION

In the implementation process, the ordered vector format is used as the initial method psychologists use to provide a priority order of disorders. After the preferences obtained from the three psychologists are inputted, each preference is converted into a fuzzy preference relation, then the three preferences are combined into one matrix to be aggregated using the OWA method. The results of the aggregation matrix are then processed using the QGDD method to rank alternatives. Additionally, the results obtained from this process are multiplied by the value of the respondent questionnaire, and the model was implemented using Matlab.

D. EVALUATION

The evaluation of the model is conducted in two ways. First, the top priority of disorders generated from the system will be compared with the priority based on DASS. This evaluation aims to examine the difference between the system and DASS. Second, the evaluation is carried out by giving a value of 3 to all symptom items that refer to a particular disorder according to DASS and giving a value of 0 to other items. This second evaluation is used to identify whether one item can refer to more than one disorder, in contrast to the DASS, which only attributes one symptom item to one specific disorder.

III. RESULT

A. PSYCHOLOGIST'S PREFERENCE OF THE DASS ITEMS

Preferences were given by three psychologists using an ordered vector format. At this stage, the preferences given by the three psychologists showed variations or differences in the judgment of the DASS items. This difference is evident in the prioritization of depression, anxiety, and stress disorders based on the symptom items, as the three psychologists assign different priority orders according to their perspectives. These results will serve as input for the data processing stage in the next phase. The preferences provided by the psychologists for DASS items are outlined in APPENDIX I for DASS-21 and APPENDIX II for DASS-42.

B. TRANSFORMATION OF PREFERENCES TO FUZZY PREFERENCE RELATION FORMAT

This stage transforms the preferences of the three expert psychologists into a fuzzy preference relation format. For example, in Appendix 1, row 1, preferences by the first psychologist (P1) are (1, 2, 3), the second psychologist (P2) is (3, 1, 2), the third psychologist (P3) is (1, 2, 3). Furthermore, preferences are converted using Eq. (1) [31] and obtain a fuzzy preference relation matrix as follows:

$P_1 = \begin{bmatrix} 0.5 & 0.75 & 1 \\ 0.25 & 0.5 & 0.75 \\ 0 & 0.25 & 0.5 \end{bmatrix}$, $P_2 = \begin{bmatrix} 0.5 & 0 & 0.25 \\ 1 & 0.5 & 0.75 \\ 0.75 & 0.25 & 0.5 \end{bmatrix}$, and $P_3 = \begin{bmatrix} 0.5 & 0.75 & 1 \\ 0.25 & 0.5 & 0.75 \\ 0 & 0.25 & 0.5 \end{bmatrix}$

C. PREFERENCE AGGREGATION

The fuzzy preference relation matrix of each psychologist will be processed to obtain an aggregation matrix. The aggregation process uses the OWA operator. Based on Eq. (3) [33], the weight vector W is obtained:

W = (0,58;0,24;0,18)

The weight vector W is obtained based on the number of psychologists in this study, which consists of three psychologists. The weight w is used to calculate the aggregation matrix, Pc. Before the aggregation process, the preference matrix elements P1, P2, and P3 need to be sorted from largest to smallest. Then using Eq. (2) [32], the following aggregation matrix is obtained:

$$P_c = \begin{bmatrix} 0.5 & 0.62 & 0.87 \\ 0.69 & 0.5 & 0.75 \\ 0.43 & 0.25 & 0.5 \end{bmatrix}$$

D. ALTERNATIVE RANKING

The ranking of alternatives in this study was carried out using the QGDD method, which aims to determine the priority of existing alternatives, namely depression, anxiety, and stress. Before the QGDD process is carried out, each element in the P_c matrix is sorted first from large to small. Based on Eq. (3) [32], the weight vector W is obtained:

W = (0,58;0,24;0,18).

The weight of W is obtained based on the number of alternatives; in the study, there are three alternatives, namely

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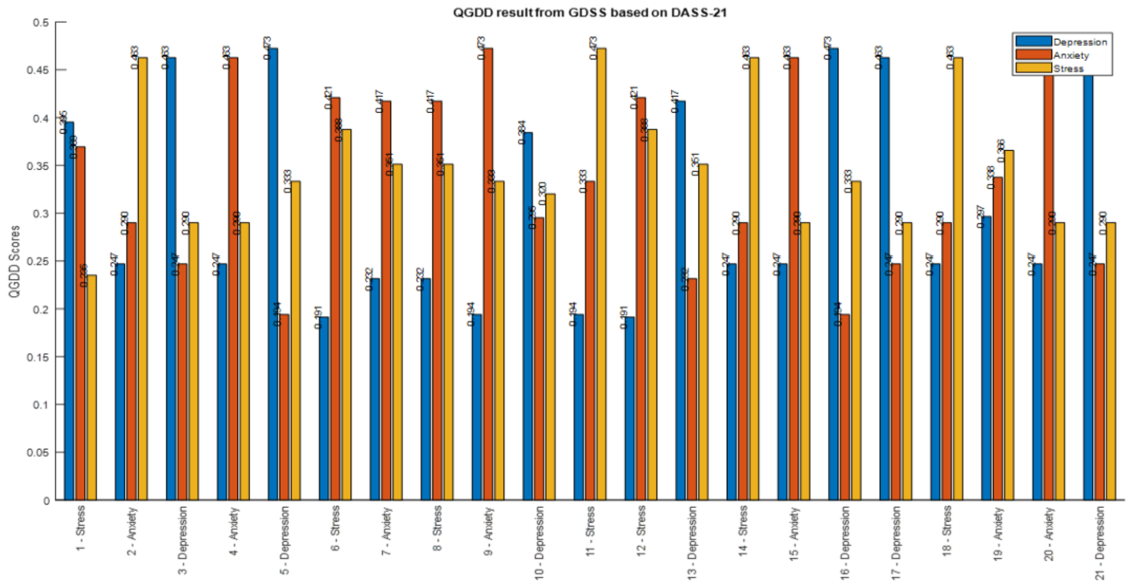

FIGURE 3. QGDD result from GDSS based on DASS-21

depression, anxiety, and stress. Furthermore, the results of QGDD using Eq. (4) [33] are obtained:

$QGDD_1 = 0.743$
$QGDD_2 = 0.691$
$QGDD_3 = 0.439$

Calculate the proportion of values with Eq. (6) [33] to get a distribution with a total value equal to 1.

$$prop = \frac{QGDD_{ij}}{\sum_{j=1}^{n} QGDD_j} \tag{6}$$

To get the following results:

$prop_1 = 0{,}397$
$prop_2 = 0{,}369$
$prop_3 = 0{,}234$

The value obtained shows the priority ranking of the existing disorders. QGDD_1 yields the largest value, showing that, based on this value, the order of priorities is as follows: depression is the top priority, followed by anxiety and then stress.

E. EVALUATION

Model evaluation was conducted in two ways. First, comparing the top priority disorders generated from the decision support system with DASS. Second, the evaluation was conducted by assigning a value of 3 to all symptom items that refer to a particular disorder according to DASS and assigning a value of 0 to the other items. FIGURE 3 and 4 present the comparison of the top priority according to GDSS with DASS. The top priority is shown by the disorder with the highest score. FIGURE 3 shows that for depressive disorders, 7 symptoms were identified as the same as DASS-21. In anxiety disorders, 6 symptoms corresponded to DASS-21, while 1 showed stress disorder. While in stress disorder, only 3 corresponded to DASS-21, 3 showed anxiety disorder, and 1 showed depressive disorder. Overall, the system shows that 80.95% (17 out of 21 items) of the symptoms have the same top priority as DASS-21. FIGURE 4 of the system shows that in depressive disorder, 14 symptoms were identified as the same as DASS-42. In anxiety disorders, 10 correspond to DASS-42, 2 show depressive disorders, and the other 2 show stress disorders. While in stress disorders, only 11 correspond to DASS-42, 3 show anxiety disorders in general, the system shows 83.33% (35 out of 42 items) of the symptoms that have the same top priority as DASS-42.

For the second evaluation, three scenarios were experimented with. First, assign a value of 3 to all items referring to depression according to DASS and a value of 0 to the other items. Second, assign a value of 3 to all items referring to anxiety according to DASS and a value of 0 to the other items. Third, score three on all items referring to stress according to DASS and zero on the other items. Each scenario was given a total score of 4.

TABLE 4
Trial for GDSS Based on DASS-21

Disorders	Depression	Anxiety	Stress
Scenario -1	**18.8108**	9.9364	13.2528
Scenario -2	10.2613	**17.4360**	14.3027
Scenario -3	10.1868	15.2533	**16.5598**

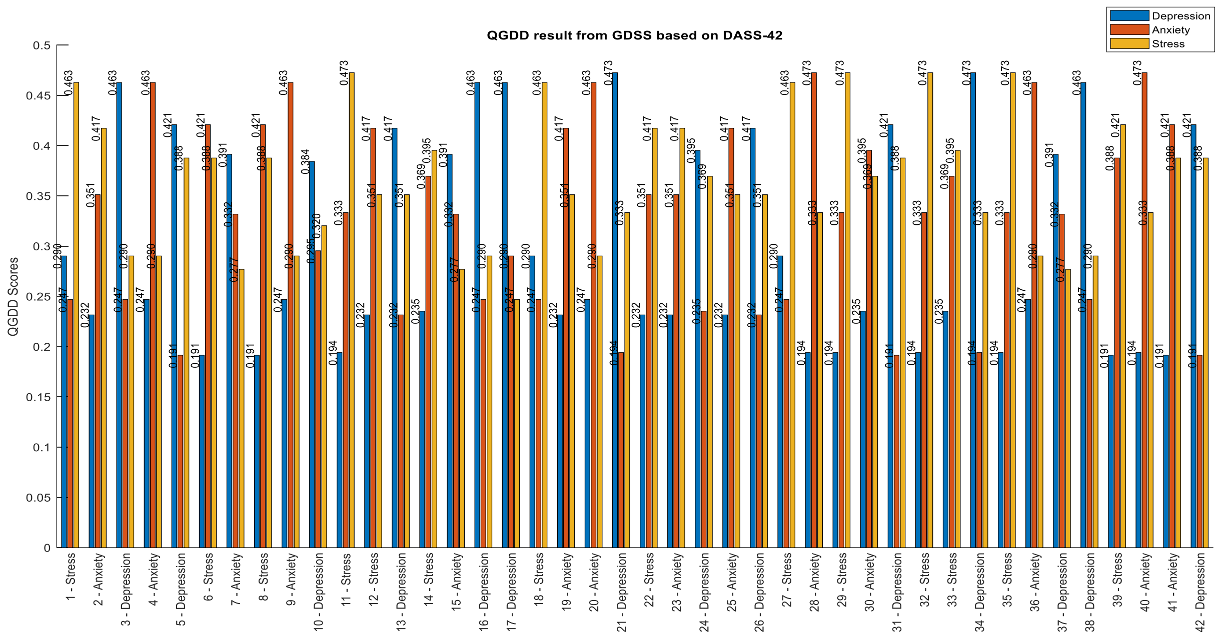

FIGURE 4. QGDD result from GDSS based on DASS-42

For example, the second evaluation calculation for scenario one on DASS-21-based GDSS. For items that refer to depressive disorders according to DASS-21, the values in Appendix 1, namely items no. 3, 5, 10, 13, 16, 17, and 21, are multiplied by 3, while other items are multiplied by 0. In DASS-21, the total value is multiplied by 2. Each scenario is given a total value of 42. The experimental results of the three scenarios are described in TABLE 4 and TABLE 5:

TABLE 5
Trial for GDSS Based on DASS-42

Disorders	Depression	Anxiety	Stress
Scenario -1	**18.1930**	9.9578	13.8492
Scenario -2	10.5347	**17.4389**	14.0263
Scenario -3	9.4650	14.4333	**18.1017**

TABLE 4 shows the results of the GDSS experiment based on DASS-21. In scenario 1, the highest preference is for depressive disorder, with a value of 18.8108; in scenario 2, the highest preference is for anxiety disorder, with a value of 17.4360; and in scenario 3, the highest preference is for stress disorder, with a value of 16.5598. TABLE 5 shows the results of the GDSS experiment based on DASS-42. In scenario-1, the highest preference is for depressive disorder with a value of 18.1930; in scenario-2, the highest preference is for anxiety disorder with a value of 17.4389; and in scenario-3, the highest preference is for stress disorder with a value of 18.1017. Each scenario shows that there is a likelihood value for all disorders with different priorities, even though the DASS only refers to one particular disorder.

IV. DISCUSSION

Based on the results of this study, the GDSS model developed using the preferences of three psychologists showed the priority of impairment of a particular item with different levels. The first evaluation results show that there are differences in the main priorities between the GDSS model and DASS. For example, in the case of stress and anxiety disorders, as shown in FIGURE 3, 3 out of the 7 items specifically items 6, 8, and 12 have the highest priority for anxiety in the GDSS model. However, according to DASS-21, these items are categorized under stress. This difference occurs due to the influence of preferences by psychologists, where two of the three psychologists in APPENDIX I give the first priority to anxiety, thereby the GDSS model accumulates these preference values, resulting in the highest priority for anxiety. A similar situation occurs in DASS-42. For example, in the case of anxiety and stress disorders, as shown in FIGURE 4, 3 out of the 11 items specifically items 6, 8, and 12 have the highest priority for anxiety in the GDSS model. However, according to DASS-42, these items are categorized under stress.

The second evaluation conducted with three scenarios shows that the GDSS model can represent the top priority with the same disturbances as DASS, both on DASS-21 and DASS-42. However, the total score is not only focused on one disturbance but the total score is also distributed across other disturbances. This shows the flexibility of the model to accommodate the collective preferences of psychologists.

This study also tried to implement it with a combination of two psychologists. The results show that the main priorities generated differ from those produced by the combination of the three psychologists' preferences. This discrepancy arises from the variations in the preferences that psychologists assign to DASS items. The results of the experiment with a combination of two psychologists can be seen in TABLE 6 and TABLE 7.

TABLES 6 and TABLE 7 show that the top priority of disorders given in a particular scenario differs for each combination of psychologists. This difference shows that the variation in preferences affects the results, as the model will calculate based on the given preferences. These results show that the GDSS model can generate varying priorities based on the preference inputs from the psychologists, which provides a more flexible picture of the priority of disorders based on diverse professional views. This variation in prioritization suggests that the model is sensitive to changes in psychologists' preferences, which impacts the results.

disorders. DASS-21-based GDSS can provide relevant disorder prioritization with less data. The use of DASS-21 and DASS-42 as a basis for preferences provides a flexible approach to adapting to patient needs. An investigation shows that the involvement of more than two psychologists can improve decision quality in this GDSS model.

The results of this evaluation suggest that GDSS models can provide prioritization by aggregating psychologists' preferences. The differences in top priorities between the GDSS and DASS models highlight the model's ability to adjust its priorities based on each psychologist's interpretation and individual preferences. The model's flexibility in accommodating these preferences can be an alternative tool that can support group decisions based on DASS. The GDSS model represents the collective view of psychologists better than individual preferences.

TABLE 6

Trial for GDSS based on DASS-21 with a combination of 2 psychologists

Disorder	P1_P2			P1_P3			P2_P3		
	Depression	Anxiety	Stress	Depression	Anxiety	Stress	Depression	Anxiety	Stress
Scenario-1	18.8282	10.4284	12.7434	19.3580	8.5904	14.0516	18.3176	10.7834	12.8990
Scenario-2	8.5700	17.8215	15.6085	10.8876	17.9099	13.2025	11.3343	16.5614	14.1042
Scenario-3	9.0815	15.6087	17.3097	11.0550	14.4281	16.6158	10.5202	15.9958	15.4839

TABLE 7

Trial for GDSS based on DASS-42 with a combination of 2 psychologists

Disorder	P1_P2			P1_P3			P2_P3		
	Depression	Anxiety	Stress	Depression	Anxiety	Stress	Depression	Anxiety	Stress
Scenario-1	17.3309	9.1472	12.5218	17.4085	8.6764	12.9151	16.4587	10.0300	12.5112
Scenario-2	9.6468	17.8389	14.5144	10.6354	18.2471	13.1175	11.4099	16.2462	14.3439
Scenario-3	8.7996	14.2914	18.9090	10.1362	13.6879	18.1759	9.5922	15.2640	17.1438

In comparison, a previous study by Kusumadewi (2020) with the same method using DASS-42 and the number of psychologists, as many as two people showed similar results, namely that there were differences in the determination of the main priorities between GDSS and DASS-42, specifically in anxiety and stress disorders. However, the evaluation with the same three scenarios showed different results where the condition with the main priority of stress was identified as anxiety, according to the GDSS. Comparison with some other previous studies can be seen in TABLE 8.

Compared to the investigation by Kusumadewi [12], this study expands by involving more than two psychologists and implementing DASS-21. In contrast to the results by Hidayatullah [36] and Rahmatullah [37], who used Twitter data, this study is based on DASS instrument, which has stronger validation. While Sun [34] and Yesudas [40] used historical data, this study's approach focuses on the psychologist's preferences directly, increasing interactivity.

The evaluation results of DASS-21-based GDSS and DASS-42-based GDSS models did not show significant differences, both can produce similar prioritization of

V. CONCLUSION

In conclusion, this study aimed to develop a DASS-based GDSS model for the prioritization of mental disorders. The model is designed to consider multiple psychologists' preferences in determining the prioritization of disorders. Using DASS and the OWA aggregation operator, this study evaluated the adaptability of the GDSS model. Based on the evaluation, the GDSS model is relevant in supporting group decision-making. The model can accommodate psychologists' preferences in prioritizing disorders. In DASS-21-based GDSS, 16 out of 21 symptom items showed the same major disorder prioritization as in the original DASS-21, reflecting a high degree of agreement. Similarly, on the DASS-42-based GDSS, 35 out of 42 symptom items corresponded to the top priority.

These results show no significant difference in prioritization results between the two scales, showing the flexibility of the GDSS model to work across different versions of DASS. However, the few differences in prioritization between the GDSS and DASS models show that the model can effectively adapt to the input preferences of psychologists. This shows the

TABLE 8

Comparison with previous studies

Authors	Method	Concept	Advantages	Weakness
Kusumadewi et al. [12]	GDSS with OWA	Using the preferences of 2 experts to rate the DASS using the DASS-42 instrument	Involves two perspectives and experiences from different individuals, resulting in more diverse and comprehensive decisions.	The use of the DASS-42 instrument will lead to a large number of questions, which can be tiring for respondents.
Sun et al. [34]	Machine Learning: Naïve Bayesian, Support Vector Machine (SVM), MLP, Random Forest, XGBoost	Using historical data of assessment using DASS-42	Automatic decision-making based on model output.	Relies entirely on historical data and existing patterns. Cannot inherently understand values in Social or cultural context decision-making without being automatically generated from explicit coding outputs. And the best machine learning model algorithms generated are black box, making it difficult to understand the decision-making flow.
Sastypratiwi [35]	GDSS with OWA	using several experts to build a fuzzy-based knowledge model specifically for mental disorders in children	Has the flexibility of determining knowledge based that is free from experts and literature.	The knowledge-based collection does not use the DASS-42 or DASS-21 standards, which can lead to a large number of items being asked of the assessee.
Hidayatullah et al. [36]	Machine learning: ID3, C4.5, CART	using Twitter social media expressions for depression detection, while the data labeling process uses DASS-42	Decision-making is generated automatically from model output. Model used is already a glass box.	Relies entirely on historical data related to social activities. Data labeling is from one point of view only. In addition, this model only focuses on detection using the DASS-42 Depression, where each question in the DASS-42 intersects depression, anxiety, and stress.
Ramadhani et al. [37]	Machine learning: XLNet's Pretained	using Twitter social media expressions for depression detection, while the data labeling process uses DASS-42	Automatic decision-making based on model output.	Relies entirely on historical data and existing patterns. Cannot inherently understand social values or cultural context without explicit coding. And the machine learning algorithms used are black box, making it difficult to understand the decision-making flow.
Ghorpade-Aher et al. [39]	Machine learning: SVM, Neural Network	Using DASS-21 examination result data as data to build machine learning models.	Automatic decision-making based on model output.	Relies entirely on historical data and existing patterns. Cannot inherently understand social values or cultural context without explicit coding. And the machine learning algorithms used are black box, making the decision-making process difficult to explain.
Anthony Yesudas [40]	Machine learning: Random Forest, Neural Network, Naïve Bayesian	using DASS-42 examination result data as data to build machine learning models.	Automatic decision-making based on model output.	Relies entirely on historical data and existing patterns. Cannot inherently understand social values or cultural context without explicit coding. And the machine learning algorithms used are black box, making the decision-making process difficult to explain.
Proposed	GDSS with OWA	using the preferences of more than 2 experts to provide DASS-21 and DASS-42 ratings	involves more than two different perspectives and experiences of psychologists so that the decisions made are more diverse and comprehensive. The assessment can also be customized, either using DASS-42 or DASS-21, depending on the circumstances.	Model has not considered the level of influence of each psychologist.

model's ability to incorporate the expert opinions of different psychologists while maintaining reliability. Furthermore, involving more than two psychologists in the decision-making process is essential, as the variation in preferences can lead to more objective and balanced results. Future investigation can explore the use of other methods and approaches to perform aggregation processes other than OWA to improve the flexibility of the GDSS model, and should also consider other preference formats. This approach can take into account the subjective nature of psychologist preferences. Further results can be compared with this study to identify opportunities for improving group decision-making processes to be more accurate and reliable.

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REFERENCE

[1] S. Muhammad Khir et al., "Efficacy of progressive muscle relaxation in adults for stress, anxiety, and depression: A systematic review," *Psychol. Res. Behav. Manag.*, pp. 345-365, 2024, doi: 10.2147/PRBM.S437277.

[2] F. Kaligis et al., "Mental health problems and needs among transitional-age youth in Indonesia," *Int. J. Environ. Res. Public Health*, Vol. 18, No. 8, pp. 1-14, 2021, doi: 10.3390/ijerph18084046.

[3] A. Anjum, S. Hossain, M. T. Hasan, E. Christopher, Md. E. Uddin, and Md. T. Sikder, "Stress symptoms and associated factors among adolescents in Dhaka, Bangladesh: Findings from a cross-sectional study," *BMC Psychiatry*, Vol. 22, No. 1, pp. 1-11, 2022, doi: 10.1186/s12888-022-04340-0.

[4] A. E. Wahdi, S. A. Wilopo, and H. E. Erskine, "The Prevalence of Adolescent Mental Disorders in Indonesia: An Analysis of Indonesia – National Mental Health Survey (I-NAMHS)," *J. Adolesc. Heal.*, vol. 72, no. 3, p. S70, 2023, doi: 10.1016/j.jadohealth.2022.11.143.

[5] S. Shorey, E.D.Ng, C.H.J. Wong, "Global prevalence of depression and elevated depressive symptoms among adolescents: A systematic review and meta-analysis," *Br. J. Clin. Psychol.*, Vol. 61, No. 2, pp. 287–305, June. 2022, doi:10.1111/bjc.12333.

[6] H. S. Lovibond and P. F. Lovibond, "The structure of negative emotional states: Comparison of the Depression Anxiety Stress Scales (DASS) with the Beck Depression and Anxiety Inventories," *Behav. Res. Ther.*, Vol. 33, No. 3, pp. 335-343, 1995, doi: 10.1016/0005-7967(94)00075-U

[7] J. D. Henry, and J. R. Crawford, "The short-form version of the Depression Anxiety Stress Scales (DASS-21): Construct validity and normative data in a large non-clinical sample," *Br. J. Clin. Psychol*, Vo. 44, No. 2, pp. 227-239, 2005, doi: 10.1348/014466505X29657.

[8] M. Makara-Studzińska, E. Tyburski, M. Załuski, K. Adamczyk, J. Mesterhazy, and A. Mesterhazy, "Confirmatory Factor Analysis of Three Versions of the Depression Anxiety Stress Scale (DASS-42, DASS-21, and DASS-12) in Polish Adults," *Front. Psychiatry*, vol. 12, pp. 1-9, January 2022, doi: 10.3389/fpsyt.2021.770532.

[9] N. Syafitri, Y. Arta, A. Siswanto, and S. P. Rizki, "Expert System to Detect Early Depression in Adolescents using DASS 42," *Proceedings of the Second International Conference on Science, Engineering, and Technology*, 2019, pp. 211–218, doi: 10.5220/0009158202110218.

[10] A. Singh and D. Kumar, "Identification of Anxiety and Depression Using DASS-21 Questionnaire and Machine Learning," in First International Conference on Advances in Computing and Future Communication Technologies (ICACFCT), Meerut, India, 2021, pp. 69-74.

[11] S. Singh et al., "Comparative Analysis of Machine Learning Models to Predict Depression, Anxiety and Stress," in 11th International Conference on System Modeling & Advancement in Research Trends (SMART), Moradabad, India, 2022, pp. 1-5.

[12] S. Kusumadewi, and H. Wahyuningsih, "Group Decision Support System Model For Assessment Of Depression, Anxiety And Stress Disorders Based On DASS-42," *Jurnal Teknologi Informasi dan Ilmu Komputer*, Vol. 7, No. 2, pp. 219-228, 2020, doi: 10.25126/jtiik.202071052.

[13] S. Wan, J. Dong, and S. Chen, "An integrated method for shared power bank supplier selection based on linguistic hesitant fuzzy multi-criteria group decision making," *Knowledge-Based Syst.*, vol. 301 pp.1-25, 2024, doi: 10.1016/j.knosys.2024.112300.

[14] P. Sugiartawan, I. M. Yudiana, and P. I. Prakoso, "Group Decision Support System Fuzzy Profile Matching Method With Organizational Citizenship Behaviour," *IJCCS (Indonesian J. Comput. Cybern. Syst.)*, Vol. 15, No. 4, 2021, doi: 10.22146/ijccs.70047.

[15] P. Liu, R. Dang, P. Wang, and X. Wu, "Unit consensus cost-based approach for group decision-making with incomplete probabilistic linguistic preference relations," *Inf. Sci. (Ny).*, vol. 624, pp. 849–880, 2023, doi: 10.1016/j.ins.2022.12.114.

[16] S. M. Ghavami, J. Maleki, and T. Arentze, "A multi-agent assisted approach for spatial Group Decision Support Systems: A case study of disaster management practice," *Int. J. Disaster Risk Reduct.*, vol. 38, June, p. 101223, 2019, doi: 10.1016/j.ijdrr.2019.101223..

[17] A. P. Sahida, B. Surarso, and R. Gernowo, "The combination of the MOORA method and the Copeland Score method as a Group Decision Support System (GDSS) Vendor Selection," *International Seminar on Research of Information Technology and Intelligent Systems (ISRITI)*, 2019, pp. 340–345, doi: 10.1109/ISRITI48646.2019.9034579.

[18] M. Rabiee, B. Aslani, and J. Rezaei, "A decision support system for detecting and handling biased decision-makers in multi-criteria group decision-making problems," *Expert Syst. Appl.*, Vol. 171, p. 114597, 2021, doi:10.1016/j.eswa.2021.114597.

[19] P. Ziemba, M. Piwowarski, and K. Nermend," Software systems supporting remote education – Fuzzy assessment using a multi-criteria group decision-making method," *Appl. Soft Comput.* Vol. 149, p. 110971, 2023, doi: 10.1016/j.asoc.2023.110971.

[20] S. M. Ghavami, M. Taleai, and T. Arentze, "An intelligent web-based spatial group decision support system to investigate the role of the opponents' modeling in urban land use planning," *Land Use Policy*, Vol. 120, p. 106256, 2022, doi: 10.1016/j.landusepol.2022.106256.

[21] J. Xie, B. Wu, and W. Zou, "Ordered Weighted Utility Distance Operators and Their Applications in Group Decision-Making," *Appl. Soft Comput*, Vol. 150, p. 111016, 2024, doi: 10.1016/j.asoc.2023.111016.

[22] L. Jin, Z. Chen, R. R. Yager, T. Senapati, R. Mesiar, D. G. Zamora, B. Dutta, and L. Martínez, "Ordered weighted averaging operators for basic uncertain information granules," *Inf. Sci*, Vol. 645, p. 119357, 2023, doi: 10.1016/j.ins.2023.119357.

[23] R. Cheng, R. Zhu, Y. Tian, B. Kang, and J. Zhang, "A multi-criteria group decision-making method based on OWA aggregation operator and Z-numbers," *Soft Comput*, Vol. 27, No. 3, pp. 1439–1455, 2023, doi: 10.1007/s00500-022-07667-8.

[24] L. Jin, R. Mesiar, and R.R. Yager, "Ordered Weighted Averaging Aggregation on Convex Poset," *EEE Trans. Fuzzy Syst.*, Vol. 27. No. 3. pp. 612-617, 2019, doi:10.1109/tfuzz.2019.2893371.

[25] I. Bueno, R. A. Carrasco, R. Ureña, and E. Herrera-Viedma, "Application of an opinion consensus aggregation model based on OWA operators to the recommendation of tourist sites," *Procedia Computer Science*, 162, pp. 539–546, 2019 doi: 10.1016/j.procs.2019.12.021.

[26] A. Thiyagarajan, T. G. James, and R. R. Marzo, "Psychometric properties of the 21-item Depression, Anxiety, and Stress Scale (DASS-21) among Malaysians during COVID-19: a methodological study," *Humanit. Soc. Sci. Commun.*, Vol. 9, p. 220, 2022, doi: 10.1057/s41599-022-01229-x.

[27] S. R. Marsidi, "Identification Of Stress, Anxiety, And Depression Levels Of Students In Preparation For The Exit Exam Competency Test," *J. Vocat. Health Stud.*, Vol. 5, No. 2, pp. 87-93, 2021, doi: 10.20473/jvhs.V5.I2.2021.87-93.

[28] S. H. Park et al., "Validation of the 21-item Depression, Anxiety, and Stress Scales (DASS-21) in individuals with autism spectrum disorder," *Psychiatry Res.*, Vol. 291, p. 113300, 2020, doi: 10.1016/j.psychres.2020.113300.

[29] A. O. Coker, O. O. Coker, and D. Sanni, "Psychometric properties of the 21-item Depression Anxiety Stress Scale (DASS-21)," *Afr. Res. Rev.*, Vol. 12, No. 2, pp. 135-142, April, 2018. doi: 10.4314/afrrev.v12i2.13.

[30] S. Kusumadewi et al., "Fuzzy Multiattribute Decision Making (FMDAM)," Yogyakarta: Graha Ilmu, 2006.

[31] F. Chiclana, E. Herrera-Viedma, F. Herrera, "Integrating Three Representation Models in Fuzzy Multipurpose Decision Making Based on Preference Relations," *University of Granada*, 1998.

[32] R.R. Yager, "Quantifier Guided Aggregation Using OWA Operators," *Int. J. Intell. Syst.*, Vol. 11, pp. 49-73, 1996, doi: 10.1002/(SICI)1098-111X(199601)11:1%3C49::AID-INT3%3E3.0.CO;2-Z

[33] F. Herrera and E. Herrera-Viedma, "Linguistic Decision Analysis: Steps for Solving Decision Problems under Linguistic Information," *Fuzzy Sets Syst.*, Vol. 115, pp, 67-82, 2000, doi: 10.1016/S0165-0114(99)00024-X.

[34] Y. H. Sun, Q. Liu, N. Y. Lee, X. Li, and K. Lee, "A novel machine learning approach to shorten depression risk assessment for

convenient uses," *J. Affect. Disord.*, vol. 312, pp. 275–291, Sep. 2022, doi: 10.1016/j.jad.2022.06.035.
[35] H. Sastypratiwi, "Knowledge Base Development Framework with Fuzzy Preference Based on Group Decision Maker ." J. Comput. Soc., vol. 5, No. 1, pp. 15-26. 2024.
[36] M. R. Hidayatullah and Warih Maharani, "Depression Detection on Twitter Social Media Using Decision Tree," *J. RESTI (Rekayasa Sist. Teknol. Inf.)*, vol. 6, no. 4, pp. 677–683, Aug. 2022, doi: 10.29207/resti.v6i4.4275.
[37] I. Ramadhani and W. Maharani, "Predicting Depressive Disorder Based on DASS-42 on Twitter Using XLNet's Pretrained Model Classification Text," *JoSYC*, vol. 3, no. 4, pp. 379–385, Sep. 2022, doi: 10.47065/josyc.v3i4.2157.
[38] J. Ghorpade-Aher, A. Memon, S. Chugh, A. Chebolu, P. Chaudhari, and J. Chavan, "DASS-21 Based Psychometric Prediction Using Advanced Machine Learning Techniques," *JAIT*, vol. 14, no. 3, pp. 571–580, 2023, doi: 10.12720/jait.14.3.571-580.
[39] A. Yesudas, "A Machine Learning Framework to Predict Depression, Anxiety and Stress." M.Sc. Research Project, Sch. Comput., Nat. Coll. of Ireland, Ireland. 2022.

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APPENDIX

APPENDIX I

Psychologists' Preferences for DASS-21

No	Psychologist 1			Psychologist 2			Psychologist 3		
	D	A	S	D	A	S	D	A	S
1	1	2	3	3	1	2	1	2	3
2	3	2	1	2	3	1	3	2	1
3	1	3	2	1	3	2	1	2	3
4	3	1	2	3	1	2	2	1	3
5	1	3	2	1	3	2	1	3	2
6	3	2	1	3	1	2	3	1	2
7	3	1	2	3	2	1	2	1	3
8	3	2	1	3	1	2	2	1	3
9	3	1	2	3	1	2	3	1	2
10	1	3	2	3	1	2	1	3	2
11	3	2	1	3	2	1	3	2	1
12	3	2	1	3	1	2	3	1	2
13	1	3	2	1	2	3	2	3	1
14	3	2	1	3	2	1	2	3	1
15	3	1	2	3	1	2	2	1	3
16	1	3	2	1	3	2	1	3	2
17	1	3	2	1	2	3	1	3	2
18	3	2	1	3	2	1	2	3	1
19	3	1	2	3	2	1	1	3	2
20	3	1	2	3	1	2	2	1	3
21	1	3	2	1	2	3	1	3	2

APPENDIX II

Psychologists' Preferences for DASS-42

No	Psychologist 1			Psychologist 2			Psychologist 3		
	D	A	S	D	A	S	D	A	S
1	2	3	1	3	2	1	2	3	1
2	3	1	2	2	3	1	3	2	1
3	1	3	2	1	3	2	1	2	3
4	3	1	2	3	1	2	2	1	3
5	1	3	2	1	3	2	1	3	2
6	3	2	1	3	1	2	3	1	2
7	3	1	2	1	3	2	1	2	3
8	3	2	1	3	1	2	3	1	2
9	3	1	2	3	1	2	2	1	3
10	1	3	2	3	1	2	1	3	2
11	3	2	1	3	2	1	3	2	1
12	3	2	1	3	1	2	2	1	3
13	1	3	2	1	2	3	2	3	1
14	3	2	1	3	2	1	2	1	3
15	3	1	2	1	3	2	1	2	3
16	1	3	2	1	3	2	1	2	3
17	1	3	2	1	2	3	1	2	3
18	2	3	1	3	2	1	2	3	1
19	3	1	2	3	2	1	2	1	3
20	2	1	3	3	1	2	3	1	2
21	1	3	2	1	3	2	1	3	2
22	1	3	2	3	1	2	2	3	1
23	3	1	2	3	2	1	2	3	1
24	1	3	2	1	3	2	3	2	1
25	3	1	2	3	2	1	2	1	3
26	1	3	2	1	2	3	2	3	1
27	2	3	1	1	2	3	2	3	1
28	3	1	2	3	1	2	3	1	2
29	3	2	1	3	2	1	3	2	1
30	3	1	2	3	1	2	2	3	1
31	1	3	2	1	3	2	2	3	1
32	3	2	1	3	2	1	3	2	1
33	3	2	1	3	2	1	2	1	3
34	1	3	2	1	3	2	1	3	2
35	3	2	1	3	2	1	3	2	1
36	3	1	2	2	1	3	3	1	2
37	2	3	1	3	2	1	2	3	1
38	3	1	2	2	3	1	3	2	1
39	1	3	2	1	3	2	1	2	3
40	3	1	2	3	1	2	2	1	3
41	3	1	2	3	2	1	3	1	2
42	1	3	2	1	3	2	2	3	1