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Accelerating depression intervention: identifying critical psychological factors using MCDM-MOORA technique for early therapy initiation

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Abstract

Background A thorough psychosocial assessment is time-consuming, often requiring multiple sessions to uncover the psychological factors contributing to mental illness, such as depression. The duration varies depending on the severity of the patient's condition and how effectively the psychotherapist can establish rapport. However, prolonged assessment periods pose a significant risk of patient deterioration.

Methods The comprehensive psychosocial intervention, led by the Multi-Criteria Decision-Making (MCDM) approach utilizing the Multi-Objective Optimization by Ratio Analysis (MOORA) method, played a pivotal role in identifying the key psychological factors contributing to the depression of the client among the 21 factors specified by BDI-II analysis.

Results The integration of the MOORA strategy compared to traditional psychotherapy on 254 samples demonstrates a Jaccard similarity coefficient of 0.8, with a minimum error margin of 7% (vulnerability index = 0.57), indicating a significant agreement between the two approaches, both converging towards a similar solution. For patients with extreme depression, the number of sessions reduced from 18 ± 2 to 11 ± 2, showing a 33–35% reduction ($\chi^2 = 6.94$, p = 0.008). Severe depression patients experienced a reduction from 14 ± 2 to 8 ± 1 sessions i.e., 34–39% reduction ($\chi^2 = 8.32$, p = 0.004). Moderate depression patients saw sessions drop from 9 ± 1 to 5 ± 1, i.e., 37–43% reduction ($\chi^2 = 0.29$, p = 0.001). The accuracy for detecting dominant psychological factors improved to 82.88% for extreme, 86.74% for severe, and 90.34% for moderate depression, respectively.

Conclusion The implementation of MOORA facilitated the identification and prioritization of key psychosocial intervention strategies, making the process significantly faster compared to traditional methods. This acceleration greatly enhanced the precision and efficacy of the work. Additionally, critical vulnerable factors were identified through ordered statistics and correlation analysis [Pearson ($\boldsymbol{r}$) = 0.8929 and Spearman's rank ($\boldsymbol{\rho}$) = 0.7551] on the Beck Depression Inventory-II model. These findings were supported by other MCDM schemes such as EDAS and TOPSIS, demonstrating high stability and robustness in dynamic decision-making environments, maintaining consistency

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across scenarios adapted by different psychotherapists. Overall, the combined application of MCDM (MOORA) and targeted psychological interventions yielded substantial positive outcomes in enhancing the well-being of individuals with psychological illnesses, such as depression, cognitive, affective, and somatic syndromes.

Keywords Mental health intervention, Multi-criteria decision-making (MCDM), Dynamic decision-making, Treatment efficacy

Introduction

Depression is a critical concern in the field of psychiatry due to its widespread prevalence and profound impact on individuals globally. Studies have shown that depression affects a significant portion of the population, highlighting its pervasive nature and the extent of its influence on mental well-being Bromet et al. [1]. Moreover, depressive disorders, are recognized as major contributors to the overall burden of disease worldwide, underscoring the substantial public health challenge they present [2]. One of the concerning aspects of depression is the reluctance of many individuals to seek professional help despite experiencing depressive symptoms. This avoidance of treatment can potentially worsen the condition and place additional strain on healthcare systems [3, 4]. Addressing barriers to seeking care and promoting mental health awareness are essential steps in improving outcomes for those affected by depression. Healthcare professionals face significant challenges in managing depression effectively. The complex nature of the disorder, coupled with variations in individual experiences and responses to treatment, often makes diagnosis and treatment challenging [5, 6]. There is an urgent need for enhanced diagnostic tools and therapeutic interventions to better meet the diverse needs of patients with depression. Epidemiological studies reveal a concerning trend. A meta-analysis published in JAMA Psychiatry in 2020 revealed a striking 38% co-occurrence rate between depression and medically unexplained physical symptoms (MUPS), indicating substantial clinical overlap. This overlap not only complicates diagnostic processes but also presents challenges in devising effective treatment strategies. Individuals facing both depression and MUPS frequently experience a cyclic pattern, where physical symptoms worsen emotional distress, and vice versa, leading to a less favorable prognosis [7].

Explorations into the neural underpinnings of depression through recent neuroimaging studies (2022–2024) have revealed potential biological explanations for its co-occurrence with other conditions. Zheng et al. [8] propose the involvement of shared neural circuitry, where depression influences regions associated with pain processing, emotional regulation, and cognitive control. Additionally, the stress response system plays a crucial role, as chronic stress triggered by other conditions can accelerate depressive symptoms. Both depression and MUPS appear to affect regions associated with pain processing, emotional regulation, and cognitive control. Additionally, the stress response system plays a significant role, as chronic stress induced by MUPS can exacerbate depressive symptoms [9, 10].

Detrimental effects of delayed diagnosis in depression

Depression, a prevalent mood disorder impacting millions globally, thrives in the shadows of delayed diagnosis. This delay not only inflicts suffering on individuals but also carries significant societal and economic burdens. Recent research underscores the urgency for streamlined diagnostic approaches to mitigate these consequences. A 2021 meta-analysis published in JAMA Psychiatry revealed a concerning statistic: an average delay of 12 weeks between depressive episode onset and seeking professional help [11]. This delay is further compounded by limitations in the healthcare system. A 2017 survey by the American Psychiatric Association (APA) reported that 41% of patients with depression wait over a month to secure an appointment with a psychotherapist [12]. The typical period without treatment for mental disorders spans from 4 to 23 years [13] and correlates with poorer clinical outcomes [14]. Another study by Ram´ırez et al. [15] conducted a cross-sectional observational study involving 3615 depressed patients in Spain. It revealed that the primary factors contributing to the average diagnosis delay of 9.89 weeks were primarily lower levels of education, experiencing stressful life events prior to the current episode, a history of undiagnosed depressive episodes in the past, and the presence of somatic comorbidities. The patients' demographics indicated a mean age of 50 years (SD = 13.89), with a female-to-male ratio of approximately 67.33:32.63. The researchers approximated that around one-third of women (33%) and one-fifth of men (19%) [16] in the United States experience major depression by the age of 65. Similar estimates have been reported in other high-income countries. For instance, a

2005 study utilizing data from the Netherlands and Australia indicated that approximately 40% of women and 30% of men encounter a major depressive episode by the age of 65, after adjusting for biases [17].

The consequences of delayed diagnosis are far-reaching. Studies published in the Journal of Affective Disorders (2022) demonstrate a significant correlation between diagnostic delay and treatment outcomes. Patients who experience a delay of just four weeks in initiating treatment for major depressive episodes show a 30% decrease in achieving remission [18]. This translates to a prolonged period of suffering, with potential for functional decline, increased medical burden, and even suicidal ideation. The societal impact of delayed depression diagnosis is substantial. A 2021 report by the Organisation for Economic Co-operation and Development (OECD) estimates that depression and anxiety cost the global economy a staggering $1 trillion annually in lost productivity [19]. Delaying diagnosis exacerbates this burden, as individuals remain unable to work effectively while healthcare costs associated with managing untreated depression rise. Beyond the numbers lies a human story of suffering. Delayed diagnosis can lead to a vicious cycle. Unmanaged depression can worsen physical health, increasing the burden of Medically Unexplained Physical Symptoms (MUPS) and further delaying diagnosis as the focus shifts to these unexplained symptoms [20]. This can erode social support networks and deteriorate personal relationships, pushing individuals into deeper isolation.

Delayed diagnosis in depression is a significant public health concern. As we move forward, there is a compelling need for innovative approaches that expedite accurate diagnosis and intervention. Streamlining mental health assessments, leveraging technology-assisted tools, and promoting mental health literacy can all contribute to reducing diagnostic delays and improving patient outcomes. By addressing this issue, we can not only enhance individual well-being but also mitigate the societal and economic burden of depression.

Multi-criteria decision making (MCDM) for depression diagnosis: a technical overview

In the field of mental health, particularly in addressing depression [21], the use of multi-criteria decision-making (MCDM) [22] reflects the importance placed on infrastructure development in urban settings. The diagnosis of depression is a multifaceted process [23], much like managing the various elements of city infrastructure. Just as transportation, water management, energy, and communication systems collectively impact urban life, a range of biological, psychological, social, and environmental factors influence an individual's mental health. By employing multi-criteria decision-making in depression diagnosis, we acknowledge the complexity of this condition, considering factors such as symptom severity, duration, impact on daily life, past treatments, and biological influences [24]. This structured approach enables therapists to navigate the complexities effectively, leading to accurate diagnosis, personalized treatment plans, and ongoing monitoring for optimal patient care. Use of multi-criteria decision-making ensures a comprehensive approach to depression diagnosis tailored to each person's unique needs, ultimately contributing to improved mental health outcomes and overall well-being [25, 26].

Several MCDM techniques can be employed to analyze this multi-faceted information and expedite diagnosis. Here are two prominent approaches:

- Analytic Hierarchy Process (AHP): Benfares et al. [27] presented a methodology employing the Analytic Hierarchy Process (AHP), a widely recognized technique in Multi-Criteria Decision Making (MCDM) for diagnosis of metal disorders due to the burden of morbidity, especially in patients with cancer. Their methodology entails organizing diagnostic criteria and patient information into a hierarchical structure, enabling clinicians to assign weights to various factors based on their significance in a particular case. This facilitates a more complex analysis compared to conventional checklist-based approaches.
- Multi-Objective Optimization Analysis: Bellos et al. [28] conducted a survey that underscores the potential of various MCDM techniques in diagnosing mental health conditions. These include the Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE) and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) [29].
- Fuzzy Multi-Criteria Decision Making (MCDM) methods: Ahmad et al. [30] explores the impact of COVID-19 on mental health using Fuzzy Multi-Criteria Decision Making (MCDM) methods. They likely define fuzzy sets to account for the ambiguity inherent in psychological assessments. This allows them to consider factors like social support, anxiety levels, and preexisting conditions in a more nuanced way. However, a potential drawback of this approach is the complexity of assigning fuzzy membership functions and weights to these criteria, requiring significant expert input.

One advantage of Multi-Objective Optimization by Ratio Analysis (MOORA) over AHP, TOPSIS, and PROMETHEE is its capability to handle multi-objective decision-making problems more efficiently. While AHP, TOPSIS, and PROMETHEE are primarily designed for single-objective decision-making or prioritization, MOORA is specifically tailored to address scenarios where there are multiple conflicting objectives to consider simultaneously. This makes MOORA particularly advantageous in situations where decision-makers need to balance and optimize across multiple criteria or objectives concurrently, offering a more comprehensive and versatile approach to decision analysis.

Integrating multi-criteria decision-making in analyzing psychological factors

In many real-world decision-making scenarios, conflicting objectives and criteria must be taken into account simultaneously. For example, the challenge of balancing environmental sustainability with economic growth in urban development projects or reconciling work demands with personal life commitments highlights the presence of conflicting objectives. Similarly, when treating patients suffering from severe depression, there exists a complex interplay between identifying the precise psychological treatment and discerning the dominant psychological factors at play. Among the diverse domains where Multi-Criteria Decision Making (MCDM) [31] finds application, the selection of intervention strategies for patients stands out as pivotal. Traditionally, therapy selection relied on *trial-and-error* methods or depends upon *previous psychological data* and *experiential knowledge*.

While these approaches may yield satisfactory outcomes, they lack a systematic framework to ensure optimal solutions. By contrast, the adoption of MCDM methodologies helps circumvent the use of inappropriate therapeutic strategies and minimizes convergence times toward effective solutions. MCDM offers a structured approach to identify dominant psychological factors, facilitating the selection of optimal therapeutic interventions. This structured framework accelerates the convergence process when compared to conventional methods. This is due to the natural interconnection among these elements, resulting in improved overall evaluation and treatment effectiveness for individuals grappling with depression. One such MCDM technique is adapted in our work is Multi-Objective Optimization by Ratio Analysis (MOORA) [32].

Why is MOORA is relevant for depression analysis

Depression is complex and involve a multitude of interdependent psychological factors, e.g., Sadness, Pessimism, Sense of Failure, Lack of Satisfaction, Guilt Feelings, Sense of Punishment, Self-Dislike, Self-Criticalness, Suicidal Thoughts, Crying, Agitation, Loss of Interest, Indecisiveness, Worthlessness, Loss of Energy, Changes in Sleeping Patterns, Irritability, Changes in Appetite, Concentration Difficulty, Tiredness or Fatigue, and Loss of Interest in Sex, respectively.

Traditional approaches often struggle to effectively analyze and prioritize these factors, leading to interventions that may not address the dominant psychological factors. MOORA, with its structured and data-driven approach, offers several advantages:

- It involves creating a comprehensive list of potential factors contributing to marital discord, drawing on both theoretical and clinical knowledge.
- Using MOORA's structured framework, each factor can be systematically evaluated based on its impact on the conflict. This involves assigning weights to each factor, reflecting their relative importance.
- By identifying the factors with the highest weight, MOORA helps therapists and counselors focus on the most impactful interventions for each couple, leading to more effective conflict resolution.

By integrating MOORA into depression analysis, we can gain a deeper understanding of the complex interplay of psychological factors and develop more targeted and effective interventions for couples experiencing conflict.

A case study analysis

This study employs an elaborate single-case design [33]. Through in-depth face-to-face sessions with the client and her family members, we aim to illustrate the analysis of psychosocial factors contributing to severe depression. Additionally, utilizing a qualitative and concise quantitative exploration across progressive sessions, we assess related depressive states and associated risk factors. The Beck Depression Inventory II (BDI II) [34], a well-organized assessment tool, is utilized to evaluate and illustrate the gradual improvement in recovery within this context. The data used for this assessment was sourced from authentic diagnostic records provided by psychotherapists. Ethical considerations were paramount, and proper consent was obtained from the client and her

Table 1 Session wise BDI-II score analysis for client

Sl. No	Criteria	Session														
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
1	Sadness	3	3	3	2	2	2	2	2	2	2	1	1	1	0	0
2	Pessimism	2	2	2	2	2	2	2	1	1	1	1	1	1	1	1
3	Sense of failure	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
4	Loss of pleasure	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0
5	Guilty feelings	2	2	2	2	1	1	1	1	1	1	1	1	1	0	0
6	Punishment feelings	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
7	Self-dislike	2	2	2	2	2	2	2	2	2	2	2	2	1	1	1
8	Self-criticalness	3	3	3	3	3	3	3	2	2	2	2	2	1	1	1
9	Suicidal thoughts	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0
10	Crying	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0
11	Agitation	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
12	Loss of interest	3	3	3	2	2	2	2	2	2	2	1	1	1	1	1
13	Indecisiveness	2	2	2	2	2	2	2	2	2	2	2	1	1	1	1
14	Worthlessness	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
15	Loss of energy	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0
16	Changes in sleeping	2	2	2	1	1	1	1	1	1	1	1	1	1	1	0
17	Irritability	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0
18	Changes in appetite	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0
19	Concentration difficulty	2	2	1	1	1	1	1	1	1	1	1	1	0	0	0
20	Tiredness or fatigue	2	2	2	2	2	2	2	1	1	1	0	0	0	0	0
21	Loss of interest in sex	3	3	2	2	2	2	2	2	2	2	2	2	2	2	2
	SUM	36	36	34	31	30	30	30	25	22	22	18	17	14	12	11

family members to facilitate reporting for future knowledge enhancement. Brief case details is mentioned below:

- Client information: Index client Mrs. R. S., 34 years, female, Higher Secondary passed, Hindu, hailing from middle socio-economic status, married, belonging from Nuclear family, Howrah, West Bengal, India, staying separately from husband.
- Sources of information: Information was gathered from various sources, including the client's mother, the client herself, the client's daughter, and prescription records.
- Test administer: In this present case, the therapist had undertaken total 15 individual counseling sessions, 5 couples therapy sessions and 1 group therapy session

Test administer: BDI-II score analysis of client

The Beck Depression Inventory-II (BDI-II) score [34] serves as a crucial link between depression and marital conflict, offering profound implications for treatment strategies. Extensive research underscores the utility of BDI-II scores in gauging the emotional well-being of individuals embroiled in marital discord. Elevated BDI-II scores, particularly within the moderate to extreme depression range, have been associated with heightened risks of detrimental behaviors within the marital relationship, similar to its predictive role in non-suicidal self-injury behaviors.

In BDI-II the questionnaire was crafted based on careful clinical observations of attitudes and symptoms prevalent among individuals experiencing depression, contrasting with those less frequently observed in non-depressed psychiatric patients [35]. A total of 21 items were synthesized from these observations, each rated on a severity scale ranging from 0 to 3. The administration of the test typically takes between 5 to 10 min. This method is especially beneficial for evaluating patients experiencing sleep disturbances, as it has been revised to acknowledge that depression can manifest in both increased and decreased sleep patterns [36]. In terms of reliability and validity, Beck and his team conducted a comprehensive study to assess the psychometric properties of the BDI-II. Their findings revealed a high level of internal consistency ($\alpha = 0.91$), indicating strong reliability in measuring depressive symptoms.

The interpretation of BDI-II scores segments depression severity into several categories:

- 1–10: Normal
- 11–16: Mild Mood Disturbance
- 17–20: Borderline Clinical Depression
- 21–30: Moderate Depression
- 31–40: Severe Depression
- 40: Extreme Depression

Recent studies [37–39] and clinical observations highlight the need for comprehensive interventions in marital conflict, addressing both overt manifestations and underlying depression. This underscores the significance of BDI-II as a tool for assessing the severity of emotional distress and its potential ramifications on marital harmony. Recognizing the correlation between BDI-II score and marital conflict can inform targeted interventions aimed at addressing both the emotional distress of individuals and the relational dynamics contributing to marital discord. In a span of 12 months, our client underwent a total 15 psychotherapy sessions and pharmacological treatment, during which their BDI-II scores varied from 36 to 15 is shown in Table 1.

Our contribution

This study employs an elaborate single-case design [33]. Through in-depth face-to-face sessions with the client and her family members, we aim to illustrate the analysis of psychosocial factors contributing to severe depression. Utilizing both qualitative and quantitative explorations across progressive sessions, we assess related depressive states and associated risk factors. The Beck Depression Inventory II (BDI-II) [34], a well-organized assessment tool, is utilized to evaluate and illustrate the gradual improvement in recovery within this context. The data used for this assessment was sourced from authentic diagnostic records provided by psychotherapists.

The process of utilizing the BDI-II framework can be time-consuming as it involves evaluating 21 criteria to identify the dominant psychological factor of depression. This delay in reaching a definitive diagnosis, which involves various psychotherapeutic intervention strategies, can adversely impact the mental and physical well-being of patients. To address this issue, we employ MOORA technique with conventional psychotherapeutic approach. By leveraging MOORA, we aim to expedite the convergence rate in identifying the dominating factors contributing to depression, thus facilitating the selection of appropriate intervention strategies by psychotherapists.

Our study utilizes a comprehensive dataset of 254 samples, divided into extreme (40.15%), severe (34.64%), and moderate (25.19%) depression categories. The results demonstrate that the application of the MOORA method accelerates the convergence process, enabling therapists to identify dominant psychological factors approximately 33–42% faster compared to traditional approaches. Additionally, average accuracy in detecting dominant psychological factors increased to 82.88–90.34%. This advancement has the potential to significantly enhance the efficiency and effectiveness of depression diagnosis and treatment planning in clinical settings.

Verifying the gap: psychological analysis vs. MCDM method

The dominant psychological factors responsible for severe depression problem based on out of 21 factors obtained from BDI-II analysis is solved in this paper following our proposed algorithm (Algo. 1) by employing MOORA method. In the case study the three alternatives psychotherapeutic strategies are addressed e.g., *Individual Counseling*, *Couples Therapy* and *Group Therapy*, respectively with respect to 21 psychological factors associated with depression analysis taken from BDI-II framework. The goal is to use MCDM methods to analyze and rank these alternatives, taking into account various criteria and their respective weights. The term *normalized values* implies that the values for each criterion have been adjusted or scaled to ensure consistency and comparability across the different criteria. For example, if the criteria include factors like Sadness, Guilty Feelings, and Crying, alternatives O1, O2, and O3 might represent different combinations or levels of improvement in these factors described in Table 2. The MCDM process would then involve assigning weights to these criteria and evaluating how well each alternative performs based on these weighted criteria, is shown in Table 3. Assign weights to each criterion based on their relative importance to the decision-making process and these weights can be determined through expert opinion, client discussions, and analytical techniques.

Algorithm 1 Identifying dominant psychological factors for depression analysis using MCDM MOORA method

Input: BDI-II data for depressive symptoms
Output: Dominant psychological factors contributing to depression

Step 1: Select available psychological attributes A_i $(1 \leq i \leq m)$ from the set of attributes and psychotherapeutic intervention strategies i.e., available alternatives O_j $(1 \leq j \leq n)$ from the set of available alternatives $O = \{O_1, O_2, \ldots, O_n\}$.

Step 2: Formulate the decision matrix D of size $m \times n$, where each element d_{ij} $(d_{ij} > 0)$ $(1 \leq i \leq m,\ 1 \leq j \leq n)$ represents the performance of alternative A_i with respect to objective O_j using BDI-II data

$$D = \begin{bmatrix} d_{11} & d_{12} & \cdots & d_{1n} \\ d_{21} & d_{22} & \cdots & d_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ d_{m1} & d_{m2} & \cdots & d_{mn} \end{bmatrix}$$

Step 3: Normalize the decision matrix d_{ij}^{norm} for each alternatives O_j where $d_{ij}^{norm} = \frac{d_{ij}}{\sqrt{\sum_{i=1}^{m} d_{ij}^2}}$.

Step 4: Compute the normalized assessment value (y_{norm}) for each criterion by considering normalized performances of both concerning beneficial attributes and non-beneficial attributes.

$$y_i^{norm} = \sum_{j=1}^{p} d_{ij}^{norm} - \sum_{j=p+1}^{n} d_{ij}^{norm}$$

where p is the number of beneficial attributes and $n - p$ is the number of non-beneficial attributes.

Step 5: Assign weights w_j to each alternative O_j to represent their relative importance, so that $\sum_{j=1}^{n} w_j = 1$.

Step 6: Compute the weighted normalized assessment value (Y_i^{norm}) for each candidate alternative $Y_i^{norm} = \sum_{j=1}^{p} w_j d_{ij}^{norm} - \sum_{j=p+1}^{n} w_j d_{ij}^{norm}$

Step 7: Calculate the normalized weighted (w_{ij}^{norm}) for each psychological factor and objective: $w_{ij}^{norm} = w_j d_{ij}^{norm}$

Step 8: Determine the positive ideal solution (PIS) and negative ideal solution (NIS) for each attribute i.e., maximal objective reference points (P_j^{ref}). PIS for j^{th} beneficial attribute: $P_j^{ref} = max(w_{ij}^{norm})$ and NIS for j^{th} non-beneficial attribute: $P_j^{ref} = min(w_{ij}^{norm})$.

Step 9: Compute the performance scores (PS) for each psychological factor:

$$PS_i = \sum_{j=1}^{n} \frac{P_j^{ref} - w_{ij}^{norm}}{(PIS_j - NIS_j)}$$

Step 10: Rank the psychological factors based on their performance scores to extract key psychological factors (A_i^{key}) $(1 \leq i \leq m)$, with higher scores indicating stronger influence on depression.

Step 11: Identify the critical psychological factors (A^{cr}) to vulnerability, where $A^{cr} \subseteq A^{key} \subseteq A$.

Table 2 Normalized values for each criterion

Criteria	O1	O2	O3
Sadness	0.8	0.6	0.9
Pessimism	0.7	0.5	0.8
Sense of failure	0.6	0.4	0.7
Loss of pleasure	0.9	0.7	0.8
Guilty feelings	0.7	0.5	0.6
Punishment feelings	0.6	0.4	0.7
Self-dislike	0.8	0.7	0.9
Self-criticalness	0.6	0.8	0.7
Suicidal thoughts	0.7	0.6	0.8
Crying	0.5	0.6	0.4
Agitation	0.8	0.7	0.9
Loss of interest	0.7	0.9	0.8
Indecisiveness	0.6	0.7	0.5
Worthlessness	0.9	0.8	0.7
Loss of energy	0.8	0.7	0.9
Changes in sleeping	0.6	0.5	0.7
Irritability	0.7	0.8	0.6
Changes in appetite	0.4	0.3	0.5
Concentration difficulty	0.8	0.9	0.7
Tiredness or fatigue	0.7	0.6	0.8
Loss of interest in sex	0.9	0.8	0.7

Table 3 Assigned weights for each criterion

Criteria	Weight
Sadness	0.04
Pessimism	0.04
Sense of failure	0.04
Loss of pleasure	0.04
Guilty feelings	0.08
Punishment feelings	0.08
Self-dislike	0.08
Self-criticalness	0.064
Suicidal thoughts	0.064
Crying	0.048
Agitation	0.048
Loss of interest	0.096
Indecisiveness	0.096
Worthlessness	0.096
Loss of energy	0.064
Changes in sleeping	0.064
Irritability	0.064
Changes in appetite	0.08
Concentration difficulty	0.08
Tiredness or fatigue	0.08
Loss of interest in sex	0.08
Total	1.0

For each alternative, the weighted normalized scores for each criterion is shown in Table 4.

Identify the best (maximum for benefit criteria) and worst (minimum for cost criteria) values for each criterion across all alternatives. Mathematically, let us denote the positive ideal solution for criterion i as PIS_i and the negative ideal solution as NIS_i. For a maximization criterion, the positive ideal solution is the maximum value across all alternatives for that criterion, and for a minimization criterion, it is the minimum value across all alternatives which is shown in Table 5.

The positive and negative ideal solutions are determined as follows:

For a maximization criterion i: $PIS_j = \max(O1_j, O2_j, O3_j),\ NIS_j = \min(Oj_i, O2_j, O3_j)$

For a minimization criterion i: $PIS_j = \min\left(O1_j, O2_j, O3_j\right), NIS_j = \max\left(O1_j, O2_j, O3_j\right)$

The performance scores (PS) help quantify the distance between each alternative's performance and the best and worst solutions across all criteria, aiding in evaluating

Table 4 Weighted normalized scores for each criterion and alternative

Criteria	Weight	O1	O2	O3
Sadness	0.05	0.03584	0.02688	0.04032
Pessimism	0.05	0.03136	0.0224	0.03584
Sense of failure	0.05	0.06588	0.06792	0.05136
Loss of pleasure	0.05	0.04032	0.03136	0.03584
Guilty feelings	0.1	0.05936	0.0424	0.05088
Punishment feelings	0.1	0.05088	0.03392	0.05936
Self-dislike	0.1	0.06784	0.05936	0.07632
Self-Criticalness	0.08	0.04128	0.05504	0.04816
Suicidal thoughts	0.08	0.04816	0.04128	0.05504
Crying	0.06	0.0264	0.03168	0.02112
Agitation	0.06	0.04224	0.03696	0.04752
Loss of interest	0.12	0.07056	0.09072	0.08064
Indecisiveness	0.12	0.06048	0.07056	0.0504
Worthlessness	0.12	0.0141	0.0163	0.0148
Loss of energy	0.08	0.05504	0.04816	0.06272
Changes in sleeping	0.08	0.04128	0.0344	0.04816
Irritability	0.08	0.04816	0.05504	0.04128
Changes in appetite	0.1	0.03392	0.02544	0.0424
Concentration difficulty	0.1	0.06784	0.07632	0.05936
Tiredness or fatigue	0.1	0.05936	0.05088	0.06784
Loss of interest in sex	0.1	0.07632	0.06784	0.05936

Table 5 Positive and negative ideal solutions

Criteria	Positive Ideal Solution	Negative Ideal Solution
Sadness	0.04032	0.02688
Pessimism	0.03584	0.02204
Sense of failure	0.06136	0.06792
Loss of pleasure	0.04032	0.03136
Guilty feelings	0.05936	0.04245
Punishment feelings	0.05936	0.03392
Self-dislike	0.07632	0.05936
Self-criticalness	0.05504	0.04128
Suicidal thoughts	0.05504	0.04128
Crying	0.03168	0.02112
Agitation	0.04752	0.03696
Loss of interest	0.09072	0.07056
Indecisiveness	0.07056	0.05041
Worthlessness	0.01429	0.03812
Loss of energy	0.06272	0.04816
Changes in sleeping	0.04816	0.03448
Irritability	0.05504	0.04128
Changes in appetite	0.04242	0.02544
Concentration difficulty	0.07632	0.05936
Tiredness or fatigue	0.06784	0.05088
Loss of interest in sex	0.07632	0.05936

Table 6 Performance scores for each attributes and alternative

Criteria	Alternative O1	Alternative O2	Alternative O3
Sadness	0.003792	0.003344	0.003016
Pessimism	0.001968	0.00182	0.001792
Sense of failure	0.005294	0.007396	0.006568
Loss of pleasure	0.002016	0.001968	0.001792
Guilty feelings	0.003936	0.00424	0.004088
Punishment feelings	0.003088	0.003392	0.003936
Self-dislike	0.004784	0.005936	0.007632
Self-criticalness	0.0033024	0.0034032	0.0038528
Suicidal thoughts	0.0017528	0.0018224	0.0014032
Crying	0.001884	0.0021008	0.0012672
Agitation	0.0025344	0.0022176	0.0028512
Loss of interest	0.0044672	0.0068864	0.005706
Indecisiveness	0.0032576	0.0044672	0.005248
Worthlessness	0.001692	0.001506	0.001776
Loss of energy	0.0034032	0.0038528	0.0034176
Changes in sleeping	0.0033024	0.002752	0.0038528
Irritability	0.0038528	0.0024032	0.0033024
Changes in appetite	0.003392	0.002544	0.00124
Concentration difficulty	0.003784	0.003632	0.003536
Tiredness or fatigue	0.002136	0.002588	0.003784
Loss of interest in sex	0.007632	0.006784	0.005085

their relative performances is shown in Table 6. Rank the attributes based on their performance scores.

Inference of MOORA

To infer the most effective criteria for each alternative, we can examine the performance scores for each criterion and alternative combination. The performance scores indicate the contribution of each criterion to the effectiveness or preference of an alternative. The analysis is based on the computed data shown in Table 6.

For Alternative O1

- Most Effective Criteria: Loss of Interest in Sex (0.007632), Sense of Failure (0.005294), Self-Dislike (0.004784), Loss of Interest (0.0044672).
- Least Effective Criteria: Worthlessness (0.001692), Suicidal Thoughts (0.0017528), Crying (0.001884), Pessimism (0.001968).

For Alternative O2

- Most Effective Criteria: Sense of Failure (0.007396), Loss of Interest (0.0068864), Loss of Interest in Sex (0.006784), Self-Dislike (0.005936), Indecisiveness (0.0044672), Guilty Feelings (0.00424).
- Least Effective Criteria: Worthlessness (0.001506), Pessimism (0.00182), Suicidal Thoughts (0.0018224), Loss of Pleasure (0.001968).

For Alternative O3

- Most Effective Criteria: Self-Dislike (0.007632), Sense of Failure (0.006568), Indecisiveness (0.005248), Loss of Interest in Sex (0.005085), Guilty Feelings (0.004088).
- Least Effective Criteria: Changes in Appetite (0.00124), Worthlessness (0.001776), Crying (0.0012672).

Overall Inference

- Sense of Failure, Loss of Interest in Sex, Self-Dislike, and Loss of Interest are consistently among the most effective criteria across all alternatives. This suggests that addressing issues related to failure, sexual interest, and self-perception is crucial for all considered alternatives.
- Worthlessness, Suicidal Thoughts and Crying are among the least effective criteria across all alternatives, suggesting that they have a smaller impact compared to other criteria.

Step 10 of Algo. 1 identifies the specific BDI-II parameters potentially contributing to the client's vulnerability to relapse employing ordered statistics for all alternatives. Considering the parametric score range of 0 to 4, a mean value of approximately 1.5 can be estimated. We determined that parameters with average scores exceeding 1.5 after the final assessment are indicative of sustained vulnerabilities. Table 7 lists these *seven vulnerable parameters i.e., key psychological factors* (A^{key}), $\forall i \in m$.

It is important to note that not all vulnerable parameters i.e., key psychological factors (A^{key}) necessarily translate to key drivers of depression. Vulnerable parameters are empirically observed based on their individual mean scores. However within this group, critical parameters i.e., critical psychological factors (A^{cr}) emerge as those exhibiting consistently high scores (≤ 2) throughout all 15 assessments. Table 7 shows *three critical parameters* (marked in bold) for our client, causing most vulnerability towards relapse, and those are not suppressed by the series of different intervention strategies.

Lemma 1 *For any given critical parameter x and vulnerable parameter y, the relationship holds:* $x \subseteq y$. *The reverse implication (y ct x) is not universally true.*

Table 7 Critical psychological factors

No	Parameters	Max mean	Min Std. Dev
1	Sense of failure	2.0	0
2	Loss of interest in sex	2.4	0.5477
3	Self-dislike	2.0	0.8366
4	Loss of interest	1.8	0.5477
5	Self-criticalness	1.8	0.8366
6	Pessimism	1.6	0.5477
7	Indecision	1.6	0.5477

Proof Let $X = \{2, 2, 2, 1, 1\}$ and $Y = \{3, 3, 2, 2, 2\}$ represent the BDI-II scores for parameters x and y over five assessments, respectively. The parametric means ($\bar{X}$ and $\bar{Y}$) for x and y are calculated as 1.6 and 2.4, respectively. Thus, $\bar{X} > 1.5$ and $\bar{Y} > 1.5$, classifying both x and y as vulnerable parameters. However, upon closer inspection of the BDI-II score patterns, it is evident that parameter x is suppressed in the final assessment, $Xpost = \{3\}$, despite $\bar{X} > 1.5$. In contrast, parameter y remains unaltered in the post-assessment, $Ypost = \{2\}$, with $\bar{Y} > 1.5$. Hence, x fails to be a subset of y in the post-assessment, highlighting the asymmetry in vulnerability. Consequently, the proof establishes the lemma. □

Validation of ranking performance

Comparison with other methods

In our analysis, we evaluated the performance of the MOORA method in analyzing critical psychological factors underlying severe depression of our client, comparing it with other existing methods such as EDAS [40] and TOPSIS [41]. To assess the ranking performance of the MOORA method, we conducted Spearman's rank correlation analysis [42] presented in Table 8. The analysis was conducted across 21 components of psychological factors for all three alternatives. The result indicates that Spearman's rank correlation coefficient (ρ) which is > 0.8, signifies a very strong statistical dependency between the results obtained from all three methods.

Analyzing sensitivity with variable attributes weights

The outcomes of MCDM methods are significantly influenced by the assigned weight to criteria attributes. Minor adjustments in these weight coefficients can sometimes lead to alterations in final decisions. Consequently, sensitivity analysis is conducted to assess the responsiveness of MCDM results to such changes in weight criteria coefficients. The objective of sensitivity analysis in MDM is to understand how changes in weight criteria coefficients impact the decision-making process.

In our study, the assignment of weights to each psychological criterion is derived from the collective

Table 8 Comparative study of spearman's rank correlation analysis

Method	Spearman's rank correlation
MOORA vs. EDAS	0.856
MOORA vs. TOPSIS	0.9108

Table 9 Assigned weights for each criterion in three different sets (*S*)

Criteria	Weights of criteria		
	S1	**S2**	**S3**
Sadness	0.04	0.05	0.03
Pessimism	0.04	0.03	0.05
Sense of failure	0.04	0.04	0.04
Loss of pleasure	0.04	0.03	0.05
Guilty feelings	0.08	0.07	0.09
Punishment feelings	0.08	0.09	0.07
Self-dislike	0.08	0.09	0.07
Self-criticalness	0.064	0.065	0.063
Suicidal thoughts	0.064	0.063	0.065
Crying	0.048	0.05	0.046
Agitation	0.048	0.046	0.05
Loss of interest	0.096	0.095	0.097
Indecisiveness	0.096	0.097	0.095
Worthlessness	0.096	0.097	0.095
Loss of energy	0.064	0.065	0.063
Changes in sleeping	0.064	0.065	0.063
Irritability	0.064	0.063	0.065
Changes in appetite	0.08	0.079	0.081
Concentration difficulty	0.08	0.081	0.079
Tiredness or fatigue	0.08	0.079	0.081
Loss of interest in sex	0.08	0.081	0.079

Table 10 Ranking result of criteria for three different sets (*S*) with MOORA approach

Criterion	S_1	S_2	S_3
Sense of Failure	1	2	1
Loss of Interest in Sex	2	1	2
Self-Dislike	3	3	3
Loss of Interest	4	5	6
Indecisiveness	5	7	5
Guilty Feelings	6	9	9
Self-Criticalness	7	6	11

insights of three psychotherapists. These weights are established subsequent to the examination of the client's initial five BDI-II scores. Table 9 refers to the weight sets $S=\{S_1, S_2, S_3\}$ patterns for sensitivity analysis. The MOORA approach is then executed in this newly proposed conditions. Table 10 represents the first seven lowest ranked (i.e., best choice) psychological factors out of 21 factors. Based on the analysis presented in Table 10, the ranking order of the client's crucial psychological factors associated with depression (with weight distribution by psychotherapist 1 is as follows: Self-Criticalness > Guilty Feelings > Indecisiveness > Loss of Interest > Self-Dislike > Loss of Interest in Sex > Sense of Failure. This implies that *Self-Criticalness* ranks highest as the worst favorable choice (out of 7 key psychological factors), while Sense of Failure ranks lowest as the most favorable choice for determining psychotherapeutic intervention strategy. Despite variations in weighting conditions for the last two sets, resulting in a 4.5% change in key psychological factors, the top three critical psychological factors i.e., *Sense of Failure*, *Loss of Interest in Sex* and *Self-Dislike*, respectively, remain consistent, indicating the robustness and stability of the analysis.

It is also observed that the computed values are as follows: Spearman's rank correlation [42] coefficient $(\rho)=0.7802$, and Pearson correlation [43] coefficient $(r)=0.8951$. These correlation coefficients indicate a statistically strong positive relationship between the ranks assigned to the criteria across the three sets, highlighting the effectiveness of our analysis in adapting to dynamic decision-making scenarios.

Ultimately, there is no evidence of rank reversal occurring whatsoever, regardless of adjustments made to the number of elements within the decision matrix. This reinforces the stability of the MOORA approach within a dynamic environment.

Statistical analysis on large scale samples

Materials and methods

Data were collected between August 2017 and June 2020 at the Institute of Post-Graduate Medical Education and Research (IPGMER), Kolkata, India. The institute provides long-term residential treatment programs exceeding 30 days. Participants were adult residents of West Bengal, India, aged 18 years or older, residing in rural, urban, or metropolitan cities, primarily Siliguri, Durgapur, Kolkata. The majority presented with depressive symptoms. Exclusion criteria encompassed severe somatic illness, psychosis, or cognitive impairment that could compromise informed consent or study participation. A total of 254 individuals (92 males (36.2%), 162 females (63.8%)) were enrolled, with median ages of 34 (± 4.2) and 31 (± 3.7) years for males and females, respectively. Demographic analysis revealed that 38 (15%) were college students (22 (58%) male, 16 (42%) female), 68 (27%) were homemakers (55 (82%) female, 13 (8%) male), and 148 (58%) were employed in the private, government, or semi-government sectors. Educational attainment varied, with 30 (12%) possessing a primary education or less, 59 (23%) completing secondary school, 101 (40%) holding an undergraduate degree, and 46 (18%) a postgraduate degree, 18 (7%) did not specify their educational level. Similar to occupation, educational attainment differed significantly between genders ($p < 0.05$). Sample belongs to mainly three

Table 11 Depression categorization based on gender distribution

Gender	Depression category Extreme	Severe	Moderate
Male	38 (37.25%)	30 (34.09%)	19 (29.68%)
Female	64 (62.75%)	58 (65.91%)	45 (70.3%)
Total	102 (40.15%)	88 (34.64%)	64 (25.19%)

different categories of family types i.e., nuclear (190, 75%), joint (46, 18%) and others (18, 7%) with family monthly income ranges: 8% < 10 K, 19% 10 K − 20 K, 28% 20 K − 35 K, 35% 35 K − 50 K, 10% 50 K< and belong to 28% from rural, 35% urban and 37% cities.

Patients were followed up for an average of 12–16 weeks, receiving a comprehensive treatment regimen addressing addiction, mental health, and somatic health concerns. The intervention encompassed a multimodal approach, including individual and group psychotherapy sessions. Psychometric assessments were administered at baseline, during treatment, and at follow-up to monitor symptom severity, treatment efficacy, and overall clinical improvement. Additionally, patients received adjunctive therapies as indicated, such as pharmacotherapy, case management, and family involvement, to enhance treatment outcomes and support long-term recovery.

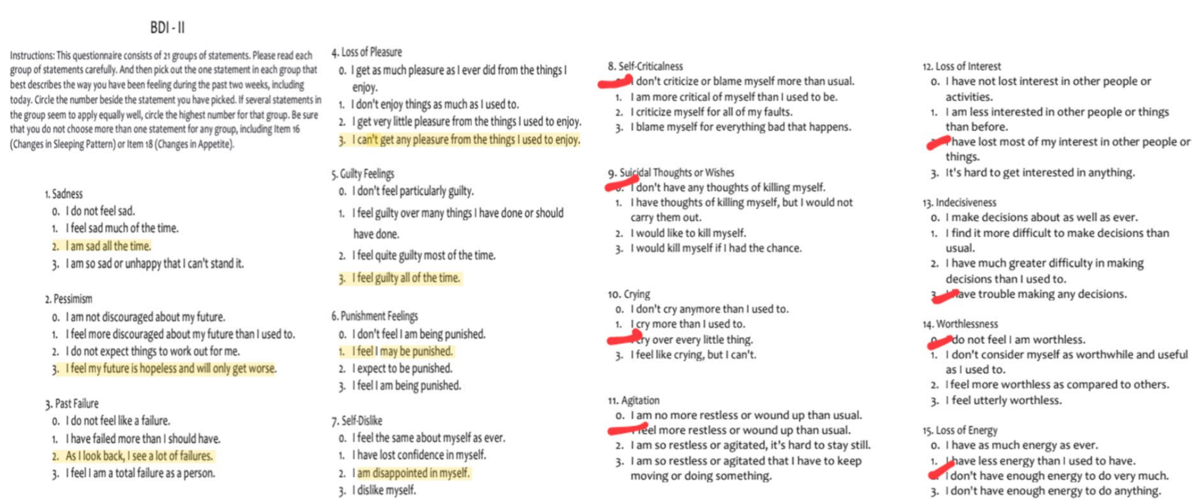
Table 11 represents gender distribution of samples for different categories of depression. It has been observed that, extreme depression among the female population is nearly 1.68 times higher than male population. Similarly, for severe and moderate depression, the female population is dominated by 1.93 and 2.36 times, respectively.

Table 12 presents a statistical comparison between the MCDM-MOORA technique and conventional methods for detecting critical psychological parameters in different depression categories. e.g., Extreme Depression (40%), Severe Depression (35%), and Moderate Depression (25%) among the entire sample space. Figure 1 represents BDI-II response of two random clients suffering from severe depression which was collected online during the Covid-19 pandemic (Figs. 2, 3).

Based on the data presented in Table 12, it is evident that the integration of MCDM-MOORA with conventional psychotherapeutic methods significantly reduces the number of sessions required for treating different categories of depression. For patients with extreme depression, the number of sessions reduced from 18 ± 2 to

Table 12 Comparison of psychotherapy sessions between conventional and MCDM-MOORA techniques across depression categories

Depression category	Sample size (n)	Number of Psychotherapeutic Sessions		Session Number	χ^2	df	P
		Conventional	Conventional + MOORA	Reduction (%)			
Extreme	102 (40.15%)	18 ± 2	11 ± 2	33–35	6.94	1	0.008
Severe	88 (34.64%)	14 ± 2	8 ± 1	34–39	8.32	1	0.004
Moderate	64 (25.19%)	9 ± 1	5 ± 1	37–43	10.29	1	0.001


BDI - II

Instructions: This questionnaire consists of 21 groups of statements. Please read each group of statements carefully. And then pick out the one statement in each group that best describes the way you have been feeling during the past two weeks, including today. Circle the number beside the statement you have picked. If several statements in the group seem to apply equally well, circle the highest number for that group. Be sure that you do not choose more than one statement for any group, including Item 16 (Changes in Sleeping Pattern) or Item 18 (Changes in Appetite).

1. Sadness
0. I do not feel sad.
1. I feel sad much of the time.
2. I am sad all the time.
3. I am so sad or unhappy that I can't stand it.

2. Pessimism
0. I am not discouraged about my future.
1. I feel more discouraged about my future than I used to.
2. I do not expect things to work out for me.
3. I feel my future is hopeless and will only get worse.

3. Past Failure
0. I do not feel like a failure.
1. I have failed more than I should have.
2. As I look back, I see a lot of failures.
3. I feel I am a total failure as a person.

4. Loss of Pleasure
0. I get as much pleasure as I ever did from the things I enjoy.
1. I don't enjoy things as much as I used to.
2. I get very little pleasure from the things I used to enjoy.
3. I can't get any pleasure from the things I used to enjoy.

5. Guilty Feelings
0. I don't feel particularly guilty.
1. I feel guilty over many things I have done or should have done.
2. I feel quite guilty most of the time.
3. I feel guilty all of the time.

6. Punishment Feelings
0. I don't feel I am being punished.
1. I feel I may be punished.
2. I expect to be punished.
3. I feel I am being punished.

7. Self-Dislike
0. I feel the same about myself as ever.
1. I have lost confidence in myself.
2. I am disappointed in myself.
3. I dislike myself.

8. Self-Criticalness
don't criticize or blame myself more than usual.
1. I am more critical of myself than I used to be.
2. I criticize myself for all of my faults.
3. I blame myself for everything bad that happens.

9. Suicidal Thoughts or Wishes
I don't have any thoughts of killing myself.
1. I have thoughts of killing myself, but I would not carry them out.
2. I would like to kill myself.
3. I would kill myself if I had the chance.

10. Crying
0. I don't cry anymore than I used to.
1. I cry more than I used to.
ry over every little thing.
3. I feel like crying, but I can't.

11. Agitation
0. I am no more restless or wound up than usual.
eel more restless or wound up than usual.
2. I am so restless or agitated, it's hard to stay still.
3. I am so restless or agitated that I have to keep moving or doing something.

12. Loss of Interest
0. I have not lost interest in other people or activities.
1. I am less interested in other people or things than before.
have lost most of my interest in other people or things.
3. It's hard to get interested in anything.

13. Indecisiveness
0. I make decisions about as well as ever.
1. I find it more difficult to make decisions than usual.
2. I have much greater difficulty in making decisions than I used to.
ave trouble making any decisions.

14. Worthlessness
do not feel I am worthless.
1. I don't consider myself as worthwhile and useful as I used to.
2. I feel more worthless as compared to others.
3. I feel utterly worthless.

15. Loss of Energy
0. I have as much energy as ever.
1. I have less energy than I used to have.
I don't have enough energy to do very much.
3. I don't have enough energy to do anything.

Fig. 1 Sample BDI-II response of two random patients collected online

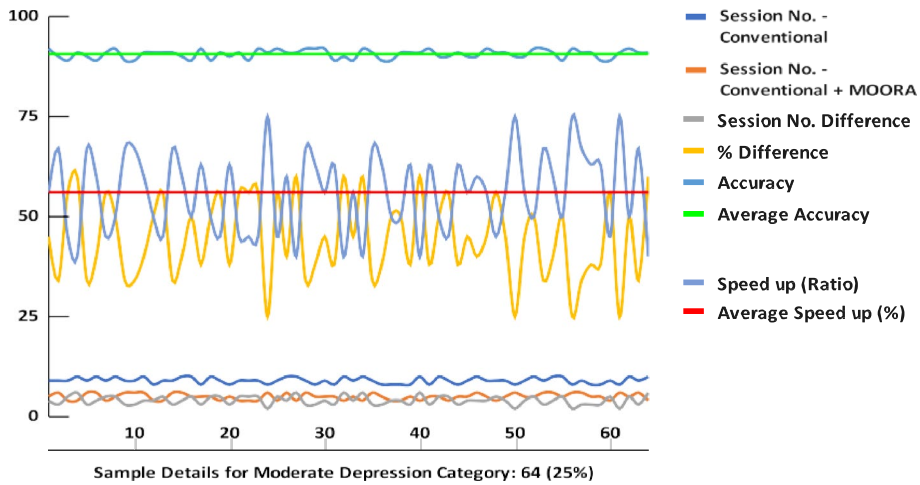


Fig. 2 Effectiveness of MCDM-MOORA over conventional method for samples with moderate depression

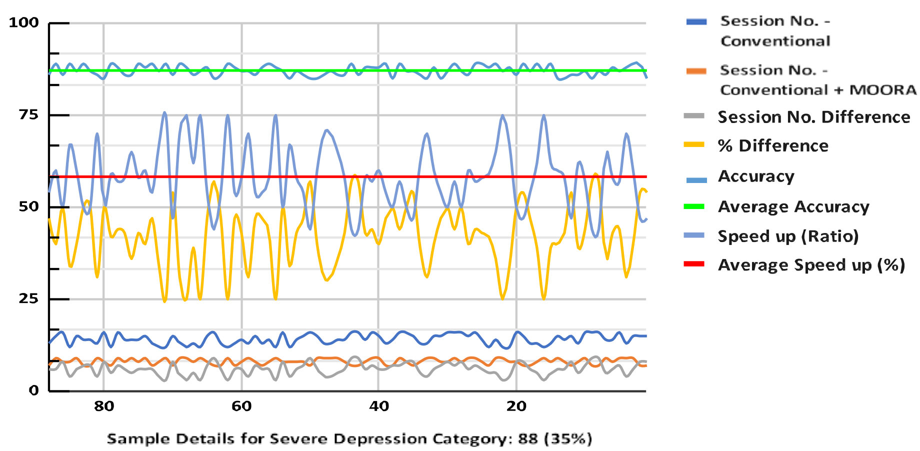


Fig. 3 Effectiveness of MCDM-MOORA over conventional method for samples with severe depression

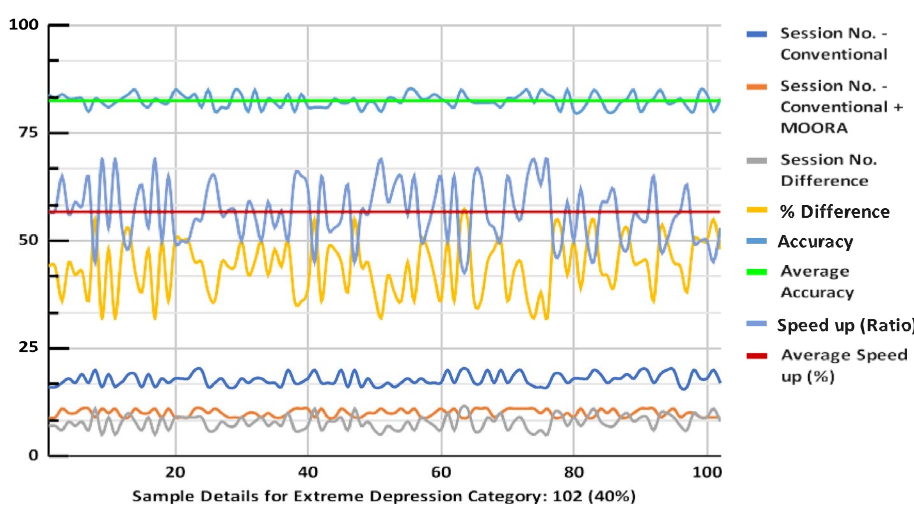


Fig. 4 Effectiveness of MCDM-MOORA over conventional method for samples with extreme depression

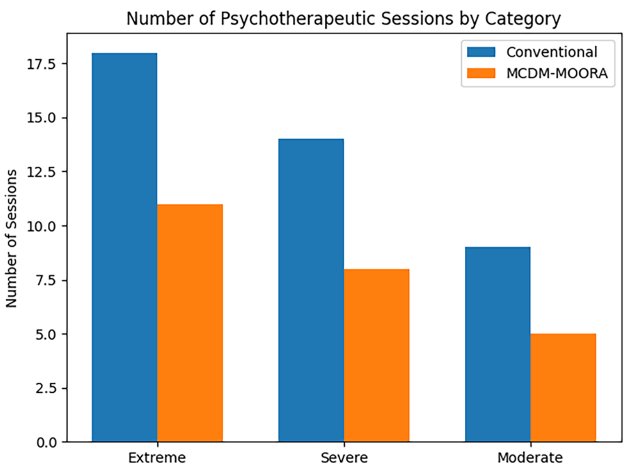


Fig. 5 Average number of psychotherapeutic sessions by category

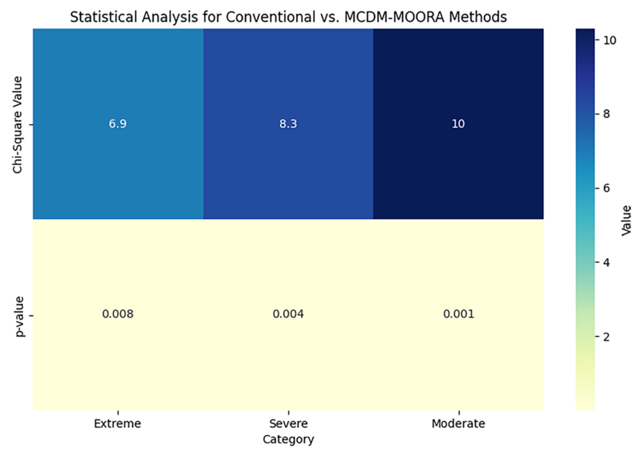


Fig. 7 Statistical analysis for conventional vs. MCDM-MOORA methods

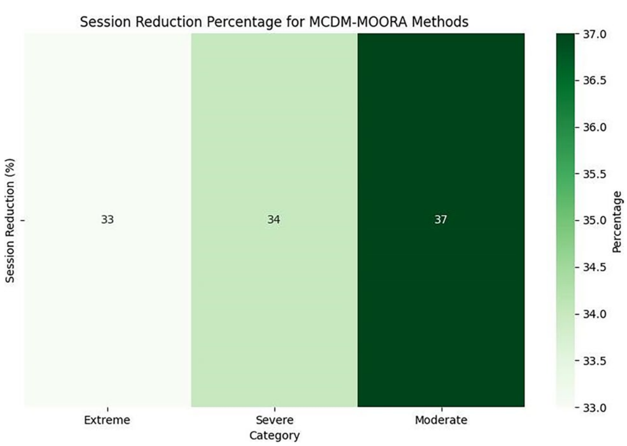


Fig. 6 Average session reduction percentage for MCDM-MOORA methods

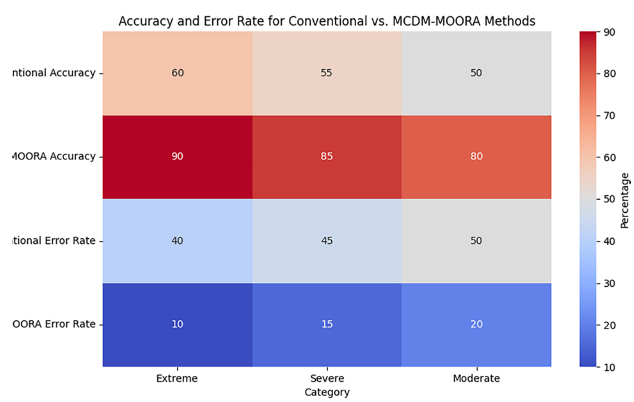


Fig. 8 Accuracy and error rate for conventional vs. MCDM-MOORA methods

11 ± 2, showing a 33–35% reduction ($\chi^2 = 6.94$, $p = 0.008$) and also depicted in Figs. 4, 5. The heatmap representation of our findings is depicted in Fig. 6. Severe depression patients experienced a reduction from 14 ± 2 to 8 ± 1 sessions i.e., 34–39% reduction ($\chi^2 = 8.32$, $p = 0.004$) also presented in Fig. 3. Moderate depression patients saw sessions drop from 9 ± 1 to 5 ± 1, i.e., 37–43% reduction ($\chi^2 = 0.29$, $p = 0.001$) shown in Fig. 2.

The accuracy rates for detecting critical psychological factors using the MCDM-MOORA method were 82.88% for extreme depression, 86.74% for severe depression, and 90.34% for moderate depression, significantly higher than conventional methods. Moreover, the speed of session completion improved notably, with speed-ups of 33.03–35.74%, 34.62–38.93%, and 36.88–42.93% for extreme, severe, and moderate depression, respectively, shown in Figs. 7, 8.

In conclusion, the integration of MCDM-MOORA with conventional psychotherapeutic sessions is highly beneficial from a psychotherapist's perspective. This approach not only enhances the accuracy in identifying dominant psychological factors but also significantly accelerates the therapeutic process. By converging faster, it allows for more efficient and effective treatment planning, ultimately improving patient outcomes.

Impact of work

In general, psychosocial intervention entails a comprehensive psychosocial assessment, which consumes a considerable amount of time. In this present case study, commencing with the establishment of a therapeutic alliance and then detailed assessment reporting to significant psychological factors like pessimism, guilty feelings, self-dislike, Loss of Interest in Sex etc., demanded an extensive timeframe of 11 sessions which is around 8 h and 25 min.

To minimize advanced treatment approaches, exploitation of MOORA technique with traditional psychotherapy can be an effective combination as it streamlines decision making processes by executing quantitative assessment of multiple criteria, thereby reducing the assessment timeline.

Our study reveals the *Jaccard similarity coefficient* [44] for specific alternatives e.g., O1, O2, O3 are 0.2, 0.4, 0.4, respectively computed with first five session data values. Whereas, the overall *Jaccard similarity coefficient* considering all alternatives i.e., ($O1 \cup O2 \cup O3$) is 0.8 with a minimum error margin of 7% (vulnerability index = 0.57). This indicates that the true value of the overall *Jaccard similarity coefficient* could range from approximately 0.744 to 0.856 due to statistical variability.

Additionally, therapists can evaluate different possible treatments, prioritize intervention on the basis of individual needs, and emphasize therapy and intervention across several dimensions. Similar to our findings, the amalgamation of MOORA and traditional individual psychotherapy can maximize the therapeutic outcome within a limited timeframe along with enhancing the efficiency and efficacy of the therapeutic intervention. In this case study, the integration of the MOORA strategy enables therapists to identify dominant psychological factors an average 39.34% faster compared to traditional processes.

Potential limitation of the work

Despite the promising results of integrating the MOORA technique with traditional psychotherapeutic approaches, there are several potential limitations to consider.

Firstly, the application of MCDM techniques to complex psychological phenomena may oversimplify the intricate and multifaceted nature of mental health conditions. While MCDM provides a structured framework for decision-making, it may not fully capture the subjective experiences and individual differences that are critical in psychological assessments.

Secondly, the assignment of weights to the psychological criteria, although based on expert consultation, could introduce biases and may not accurately reflect the relative importance of each factor for all patients. This could affect the reliability and validity of the results.

Furthermore, the data used in our study, while comprehensive, is limited to a specific demographic and geographic population, potentially limiting the generalizability of our findings.

Additionally, the dynamic nature of mental health requires continuous validation and adjustment of the MCDM models to ensure they remain relevant and effective over time.

Lastly, while the MOORA technique demonstrated a significant reduction in the number of sessions required to identify dominant psychological factors, it is essential to balance this efficiency with the need for thorough and individualized patient care.

These limitations highlight the need for a balanced and holistic approach to mental health assessments, combining innovative quantitative methods with comprehensive clinical expertise.

Conclusion

Based on the data presented in Table 12, integrating MOORA techniques with conventional psychotherapeutic sessions significantly enhances the efficiency of treatment for patients with different categories of depression. The number of sessions required for extreme depression was reduced by 33–35%, for severe depression by 34–39%, and for moderate depression by 37–43%, with corresponding chi-square values of 6.94, 8.32, and 10.29, all statistically significant ($p < 0.01$). The accuracy of detecting dominant psychological factors increased to 82.88% for extreme depression, 86.74% for severe depression, and 90.34% for moderate depression.

Additionally, the process speed-up for the number of sessions required using the combined approach are 33.03–35.74%, 34.62–38.93%, and 36–88-42.93% for extreme, severe, and moderate depression cases, respectively. These findings indicate that adopting the MOORA technique alongside conventional psychotherapeutic sessions significantly improves the speed and accuracy of identifying critical psychological factors, thereby enabling more effective and timely interventions, and ultimately enhancing patient outcomes.

The study further highlights critical vulnerable factors identified through ordered statistics and correlation [Pearson (r) = 0.8929 and Spearman's rank (ρ) = 0.7551] analysis on the Beck Depression Inventory-II model, and the results are also supported by other existing MCDM schemes e.g., EDAS and TOPSIS. Additionally, proposed method also delivers high stability and robustness in the dynamic decision making environment where the critical psychological factors are remain same for multiple scenarios adapted by different psychotherapists. Overall, the combined application of MOORA and targeted psychological interventions has demonstrated substantial positive outcomes in enhancing the well-being of patients.

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Author contributions

Concept and design: PM, AP, and DRD Analysis: PM, AP, DRD and BG. Interpretation of analysis: AP and PM. Drafting of the manuscript: PM, DRD, BG. Critical revision of the manuscript for important intellectual content: PM, SM, AP, NA, ASB and SBC. Supervision: PM, AP, SM and NA. All authors have read and agreed to the published version of the manuscript.

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Data availability

The datasets presented in this article are not readily available due to ethical restrictions; we cannot publish the data currently. The data is controlled by Centre of Excellence, Institute of Psychiatry (IOP), Kolkata, West Bengal 700046, India.

Declarations

Ethics approval and consent to participate

The study was approved by Institute of Post-Graduate Medical Education and Research (IPGMER), Kolkata, India Ethics committee/Institutional review board (ECR/35/Inst/WB/2013/RR-16 on 21 March 2017). Written informed consent was obtained from the participant and her family.

Consent for publication

Written informed consent from the participant and her family was obtained to contribute to the research and subsequent publication.

Competing interests

The authors declare no competing interests.

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