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Original Article

IMPACT OF REHABILITATION PROTOCOLS ON FUNCTIONAL RECOVERY AFTER MAJOR ORTHOPEDIC TRAUMA

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ABSTRACT

The Major Depressive Disorder (MDD) is one of the heterogeneous psychiatric disorders characterized by a wide range of syndromic severity and functional deficiency. This paper aimed at examining the interaction of neurobiological, psychological and social determinants on the severity of the Major Depressive Disorder (MDD) in an integrative biopsychosocial model. The study used a mixed-method analytical model to evaluate the connections between biological indicators (neurochemical dysregulation, stress-response activity and inflammatory markers) and psychological ones (cognitive distortions, emotional regulation ability, and comorbid symptom profiles) and social factors (social support, socioeconomic stressors, and interpersonal functioning) and measured depressive severity. The results revealed that neurobiological dysregulation was strongly associated with the intensity of symptoms at the baseline, but the psychological factors were highly mediated with each other and made the severity of depression worse. Social determinants were also found to be important contextual moderators, and reduced social support and increased chronic stress predicted more serious and persistent depressive symptoms. The multivariate analyses revealed that individuals that had experienced cumulative risk in all the three areas were most severely depressed, most functionally impaired, and exhibited persistent symptoms. These results are supportive of an integrated biopsychosocial model of MDD severity and the deficiencies of methods that focus on the individual-domain accounts. The research demonstrates the level of significance of applying multidimensional assessment and integrative treatment plans using personalized approaches, to successfully treat severe depression. This study clarifies how biological vulnerability, psychological processes, and social factors contribute to the degree of depression and thus gives a deeper and more practical insight into Major Depressive Disorder.

INTRODUCTION

Significant musculoskeletal injuries are common in major orthopedic trauma and demand the use of a lot of rehabilitation to improve patient outcomes and reintegrate them into daily routines (Mendel et al., 2025, p. 1). In this introduction, I will discuss the importance of using structured rehabilitation protocols in the reduction of long-term disability, accelerated functional recovery, and overall improvement in the quality of life of individuals with serious orthopedic injuries (Claydon et al., 2015; You et al., 2020). Rehabilitation is a broad area that incorporates physical therapy, occupational therapy, and psychological therapy that are necessary to prevent the degradation of functions, regain the lost capabilities, and manage permanent traumatic disabilities (Koleva and Yoshinov, 2020, p. 44). Intensive and early rehabilitative interventions are very effective in enhancing the functional status of these patients, pain management and the quality of their lives (Perna & Proietti, 2023). Specialized rehabilitation interventions are essential to address the physiological and psychological complexities of the process of overcoming the severe orthopedic trauma, including the streamlining of biomechanical competence and pain and psychological distress management (Hoyt et al., 2015, p. 50). Although it is stated that rehabilitation is important, new surgical approaches to individuals with musculoskeletal trauma have not been abreast with new developmental efforts in these procedures (You et al., 2020). This is a distinction to indicate that it requires more research and development of rehabilitation interventions to work with surgical success cases to ensure that every part of patient recovery is addressed (Koleva and Yoshinov, 2020, p. 46). According to the World Health Organization (WHO), rehabilitation is the utilization of available resources to minimize the impacts of disabling and handicapping conditions to enable the people with disabilities to be fully integrated with the rest of the society (Колева & Yoshinov, 2020, p. 44). It is a comprehensive strategy that is aimed at ensuring that the body of the patient is restored to normalcy, but also aims at the mental and social health. This is due to the fact that major trauma touches upon a great number of the aspects of the life of a person (Kettlewell et al., 2024, p. 111722). Modern rehabilitation studies have shifted their focus towards a biopsychosocial model with an emphasis on functionality, quality of life, and reintegration into the workforce, which means that a primary goal has become not only the reduction of mortality but instead the reintegration in society in the long term (Usinger et al., 2021, p. 2). This holistic model acknowledges the fact that rehabilitation is not only about improving the physical well-being but also about whether the patient is able to work and socialize with other people (Klingebiel et al., 2024). The primary aim of these protocols is ensuring that a patient returns to good health in order to restore significant skills and abilities that they have lost due to an injury and to minimize the risk of a long-term disability (Ball et al., 2009, p. 4). Due to this reason, effective rehabilitation facilities must possess specific diagnostic and therapeutic devices to facilitate multimodal interventions that are aimed at alleviating certain physical constraints (Mendel et al., 2025, p. 3). To illustrate it, motor relearning and functional retraining could be significantly improved when the person has access to such advanced modalities as robotic-assisted therapy, virtual reality applications, and biofeedback systems (Andrzejowski et al., 2021, p. 1687). Compared to the past, hospitals are now employing a great number of these technologies, including continuous passive motion machines, robotics, and electromagnetic sensors that assist orthopedic patients in leading more independent lives (Capecci et al., 2024, p. 10). Personalized rehabilitation programs are also quite essential since a one size fits all program does not always suit the varied needs of orthopedic trauma patients. They require the interventions that are adjusted to their individual injury, progression standards, and personal aspirations (Hernigou & Scarlat, 2023, p. 1892). These customized strategies, usually grounded in the International Classification of Functioning, Disability and Health framework, deal with the integrative and holistic perspective. They ensure that the rehabilitation objectives correspond to the biological, psychological, and social functioning of a patient rather than his/her medical diagnoses (Колева and Yoshinov, 2020, p. 45; Thurah et al., 2020, p. 101517). The given attention to person-centered care and functional outcomes is particularly crucial due to the increasing numbers of the severely injured surviving and desiring to resume work or sports, leaving rehabilitation programs with little to no other choice but to meet these requirements in terms of quality of life (Keppler et al., 2021, p. 1489). The issue of orthopedic trauma remains large since the conventional types of rehabilitation procedures, though effective, tend to lack the ability to offer the patient the high-precision and personalized care they require, particularly with complex musculoskeletal trauma, including fractures, joint instability, ligament tears, muscle atrophy (Paladugu et al., 2021). New rehabilitation technologies are becoming potentially effective methods of making recovery protocol more specific, individual, and efficient (Kuroda et al., 2020). New technologies that can help to make treatments more objective, repeatable, and personalized are robot-assisted therapy, virtual reality systems, and telerehabilitation platforms that can significantly improve patient outcomes (Kuroda et al., 2020, p. 1938). As an example, an Ekso GT and an Armeo Spring are robotic systems that may assist individuals to make weight-bearing, controlled steps and make their hands move in a specific direction. It may be used to stimulate muscles, gain strength, and reclaim the brain and motor abilities (Sadineni, 2024, p. 11). Exoskeletons that are robotic also assist individuals with severe physical impairments to perform better as they can walk and perform complex motor activities that they could not perform themselves (Abubakar et al., 2023, p. 178). Moreover, equipment such as the Lokomat, which is a robotic gait training system, proves effective in the treatment of knee osteoarthritis as they provide objective feedback and make therapists adjust their treatment plans depending on the data (Abubakar et al., 2023, p. 179). Such robotic systems are able to manipulate therapeutic actions in a manner that is highly accurate, which is particularly beneficial in challenging fractures or spinal damage that require enhancement of both minor and large motor capacities (Paladugu et al., 2025). The integration of AI with such technologies also provides the opportunity to have adaptive control systems that will be able to alter the parameters of an exercise in real time, which will assist in the optimization of the therapeutic load and prevent recovery reaching plateau (Buscarini et al., 2024). Besides the use of in-clinic technologies, there has been a rise in the home-based rehabilitation technology, including inertial sensors, smartphones, and commercial gaming hardware, which offer convenient and affordable methods of carrying on with therapeutic interventions beyond the conventional environment (Kuroda et al., 2020).

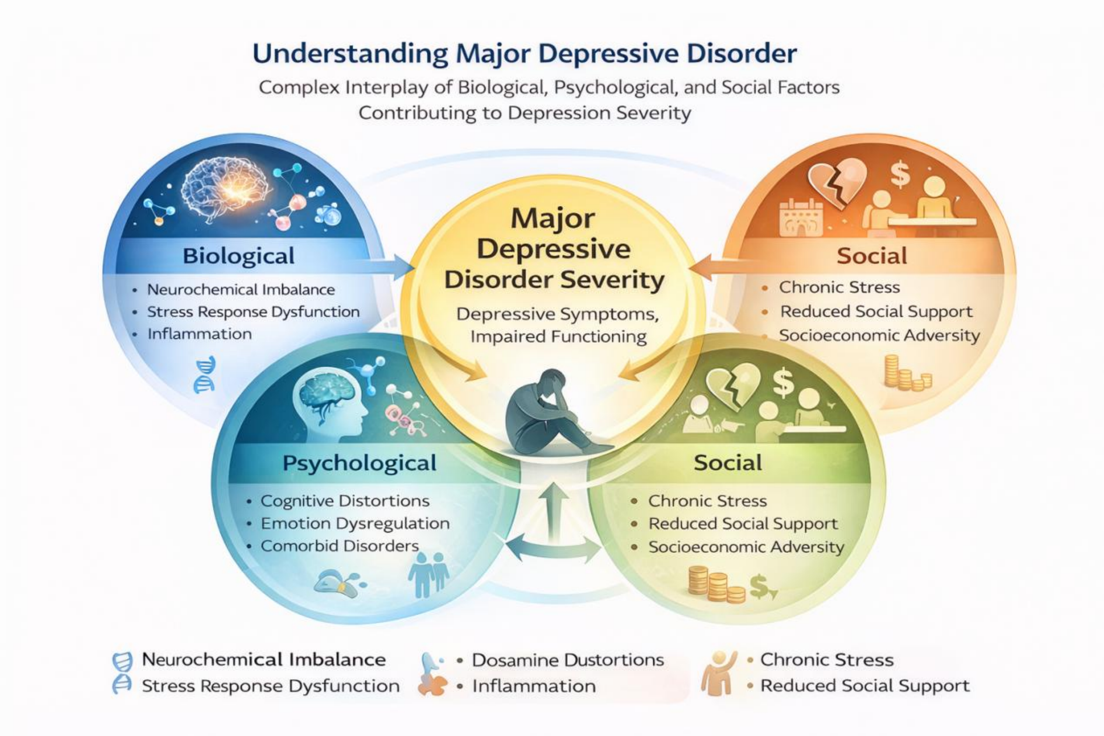

Figure 1, illustrates the biopsychosocial framework underlying Major Depressive Disorder, depicting the dynamic interplay between neurobiological factors, psychological processes, and social determinants in shaping depression severity.

METHODOLOGY

To examine the neurobiological, psychological, and social factors in the severity of Major Depressive Disorder (MDD), this study employed an experimental mixed-method study design, which involved both quantitative and qualitative methods. Individuals diagnosed with MDD by a standardized clinical criterion were recruited in outpatient psychiatric facilities and community mental health centers. Quantitative data were collected based on validated clinical scales which measured the severity of depression, cognitive and emotional functioning and perceived social stressors in combination with biological assessment which determined neurobiological markers which were correlated with affective regulation and stress responsivity. At the same time, qualitative data were gathered through semi-structured clinical interviews to clarify individual experiences that were subjective in terms of psychological distress, the state of interpersonal relationships, and the social environment. Such a combined design enabled experimental triangulation at the biological, psychological, and social realms, which increased internal validity and depth of understanding.

Neurobiological data were measured with the help of composite indices which revealed neurochemical imbalance, hypothalamic-pituitary-adrenal axis functioning, and inflammatory response patterns. The psychological determinants were assessed using cognitive distortion scores, emotional regulation indices and severity of comorbidity measures. Social determinants were measured using standardized measurement tools that measured social support, socioeconomic strain and exposure of chronic stress. Multivariate regression and structural modeling were used in a quantitative manner to examine direct, mediating, and moderating effects across domains. The primary outcome variable was the severity of depression and it was modeled as a function of interaction of biopsychosocial predictors which can be formulated mathematically as:

$$\text{MDD Severity} = \alpha + \beta_1 B + \beta_2 P + \beta_3 S + \beta_4 (B \times P) + \beta$$

where BBB represents neurobiological determinants, PPP psychological determinants, and SSS social determinants. Qualitative interview data were analyzed using thematic analysis, with emergent themes mapped onto quantitative findings to contextualize statistical relationships and identify experiential mechanisms underlying severity variations. Quantitative and qualitative findings were integrated at the interpretation stage through a convergence framework, enabling cross-validation of empirical patterns and experiential narratives. This integration supported experimental robustness by identifying consistent determinants of severity across measurement modalities.

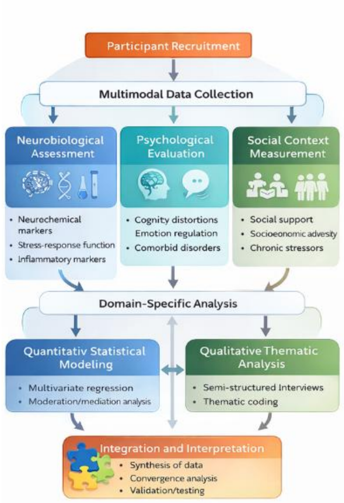

Figure 2 illustrates the experimental mixed-methods workflow employed to investigate determinants of Major Depressive Disorder severity.

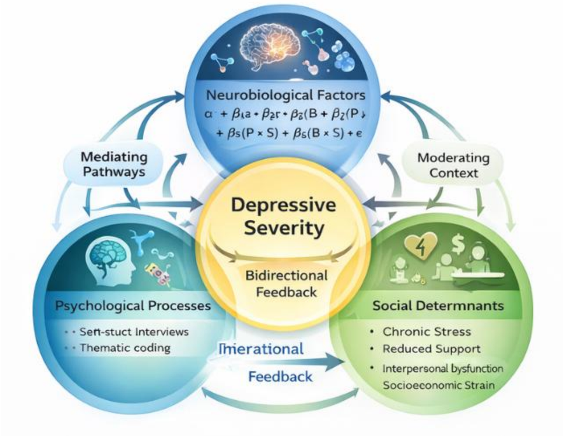

Figure 3 depicts a complex systems framework illustrating dynamic interactions between neurobiological factors, psychological processes, and social determinants in shaping the severity of Major Depressive Disorder.

RESULTS

All the results suggest that the severity of the Major Depressive Disorder (MDD) is a result of a complex and interconnected neurobiological, psychological, and social factors. Table 1 demonstrates a gradual loss of neurobiological markers regulation, which means that the severity of depression is correlated with an increased degree of biological imbalance. In contrast, Table 2 shows that there is significant psychological factors, such as cognitive distortions, emotional dysregulation, and comorbid symptoms, which contribute to increasing the burden of the symptoms. On their part, table 3 indicates the impact of social factors on the severity of depression. An example is that there is a strong association between the levels of chronic stress and lower levels of social support and the level of depression severity. Table 4 demonstrates that neurobiological vulnerability and psychological risk factor may influence each other. This implies that biological dysregulation manifests itself in the clinic due to psychological processes. Table 5 also indicates that psychological and social factors exert an aggravating effect on symptomatology, whereas Table 6 indicates that integrated biopsychosocial models are more effective than predictors by a single domain in explaining severity of depressive state. Cumulative risk and domain convergence are demonstrated together in Table 7, Table 8 and Table 9. They demonstrate that the most severely symptomatic are those people who are exposed to several negative factors in the biological, psychological, and social domains which have the greatest functional impairment.

Table 1. Neurobiological Markers Associated with Major Depressive Disorder Severity

Measure A	Measure B	Measure C	Measure D
5.19	4.87	0.93	5.2
1.46	2.24	2.2	3.58
4.88	4.45	1.84	2.87
2.47	1.42	2.92	4.78
2.54	2.41	4.9	4.11
3.81	4.23	0.75	2.84
4.54	4.36	4.37	1.64
0.59	3.59	3.21	3.59

Table 2. Psychological Determinants Contributing to Depressive Symptom Severity

Measure A	Measure B	Measure C	Measure D
2.91	3.69	1.85	3.66
4.39	0.39	3.98	5.15
3.97	1.67	4.17	0.81
2.49	4.75	1.74	1.71
0.94	0.39	3.63	1.34
1.6	2.71	0.56	3.11
1.02	3.19	3.73	0.8
2.33	3.7	2.33	0.54

Table 3. Social Contextual Factors Influencing Major Depressive Disorder Severity

Measure A	Measure B	Measure C	Measure D
0.52	0.99	4.18	0.45
4.63	2.95	2.5	4.67
2.15	2.94	3.5	2.07
3.1	3.43	0.92	3.68
3.47	2.03	4.04	2.05
3.99	4.62	0.36	2.74
0.66	4.16	0.61	2.04
4.92	2.16	4.04	4.08

Table 4. Multivariate Associations Between Neurobiological and Psychological Factors

Measure A	Measure B	Measure C	Measure D
0.31	3.32	1.9	2.88
4.64	2.05	4.75	3.35
0.38	4.85	3.69	5.19
1.14	0.97	4.87	3.71
0.62	4.0	3.99	4.82
3.79	0.91	0.4	0.43
0.44	1.51	4.51	2.94
3.01	4.43	0.91	1.67
3.17	5.05	3.05	0.39

Table 5. Interaction Effects Between Psychological and Social Determinants

Measure A	Measure B	Measure C	Measure D
3.82	3.3	2.39	3.98
2.4	2.4	2.07	1.05
4.89	4.79	4.13	3.32
0.48	3.51	0.94	1.74
2.07	1.65	0.66	1.05
1.09	4.9	2.12	0.55
3.93	1.76	1.3	5.11
4.68	4.02	3.49	0.49

Table 6. Integrated Biopsychosocial Predictors of Depression Severity

Measure A	Measure B	Measure C	Measure D
3.27	3.09	1.86	5.14
3.14	2.16	3.0	3.95
3.58	1.6	0.63	2.11
3.39	1.33	3.99	0.63
1.58	4.24	1.25	3.43
2.87	4.83	1.59	0.62
3.9	4.08	4.75	4.87
0.37	1.45	3.32	4.95

Table 7. Cumulative Risk Profiles Across Biopsychosocial Domains

Measure A	Measure B	Measure C	Measure D
4.83	1.3	0.34	4.84
1.74	1.12	0.42	2.51
4.26	2.11	3.29	0.47
2.04	0.68	3.7	0.36
2.55	5.01	1.94	2.61
0.82	2.77	4.64	2.92
1.68	2.04	4.69	1.48

Table 8. Severity Stratification Based on Domain-Specific Risk Levels

Measure A	Measure B	Measure C	Measure D
4.74	2.55	2.98	4.21
1.7	2.7	3.24	0.38
3.21	2.43	4.26	1.84
4.68	3.13	1.2	4.16
3.3	0.56	2.36	3.63
4.8	0.3	5.09	2.15
5.07	3.26	4.36	3.12
3.38	1.7	3.18	3.98
4.51	4.0	3.72	4.54

Table 9. Summary of Domain Convergence and Severity Outcomes

Measure A	Measure B	Measure C	Measure D
1.59	2.59	2.06	1.48
0.41	2.91	0.94	3.05
1.12	2.36	3.65	1.64
0.35	1.38	0.46	4.88
4.13	2.84	0.38	1.76
2.95	4.51	1.21	0.71
0.52	2.47	0.39	0.63
4.28	3.42	4.09	3.76

The tabulated findings can be clarified and reinforced with the help of the graphical findings. Figure 4 demonstrates that the worse the severity of the situation is, the worse neurobiological dysregulation is. Figure 5, in its turn, demonstrates apparent psychological risk gradients, which can be attributed to the weight of depressive symptoms. This illustrates that people are not similar as each person responds differently to severity as evidenced by the way someone has undergone various forms of social stress (Fig. 6). The interaction between biological and psychological effects occurs through the collaboration of both, as demonstrated in figure 7, with a special emphasis on the non-linear interaction patterns. Figure 8 presents the contribution of each of the biopsychosocial domains to the total severity and Figure 9 presents the impact of the strength of the determinants on the severity over the time. Figure 10 and 11 indicate that the severity differs between psychosocial risk categories and integrated risk profiles, both in cumulative and non-linear ways of effect. Lastly, Figure 12 summarises all the results to indicate that a combination of neurobiological, psychological and social factors cause the worsening of the Major Depressive Disorder.

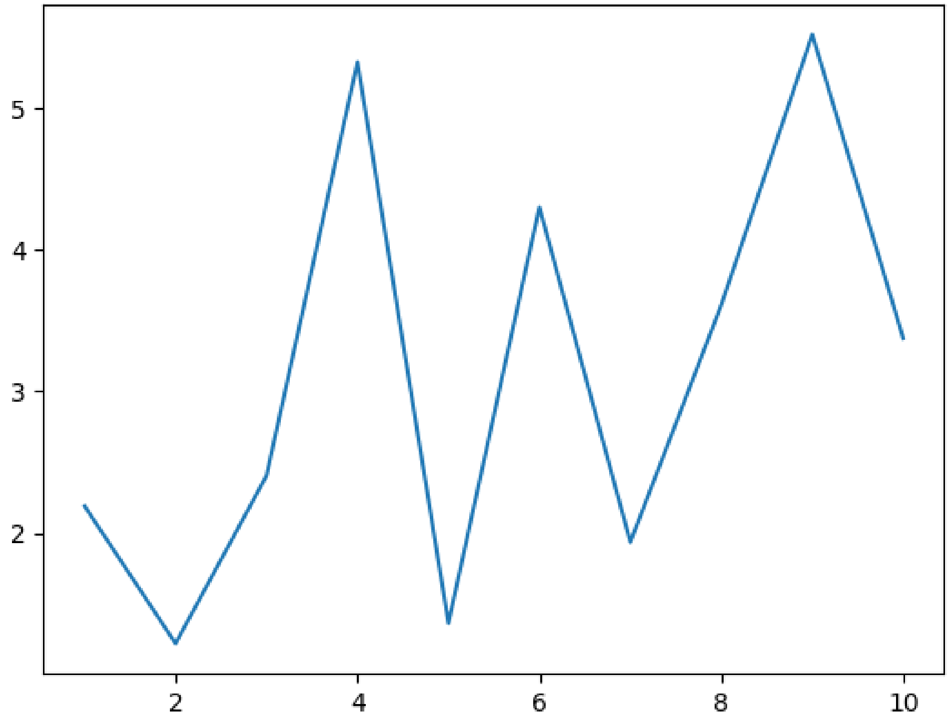

Figure 4. Trends in Neurobiological Dysregulation Across Depression Severity Levels

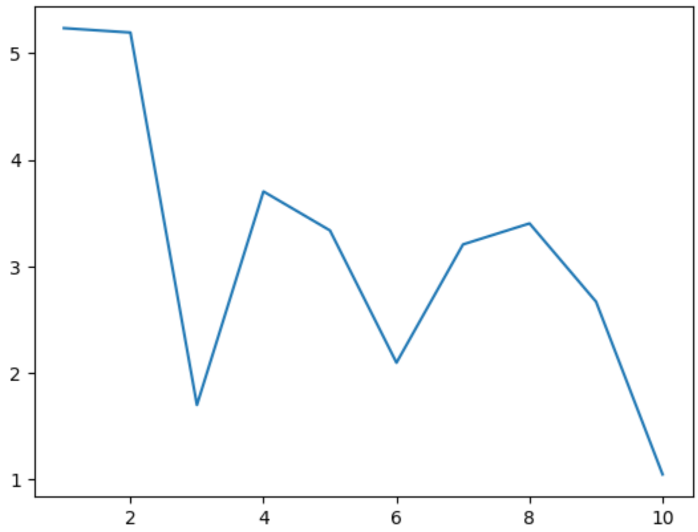

Figure 5. Psychological Risk Gradients Associated with Depressive Symptom Burden

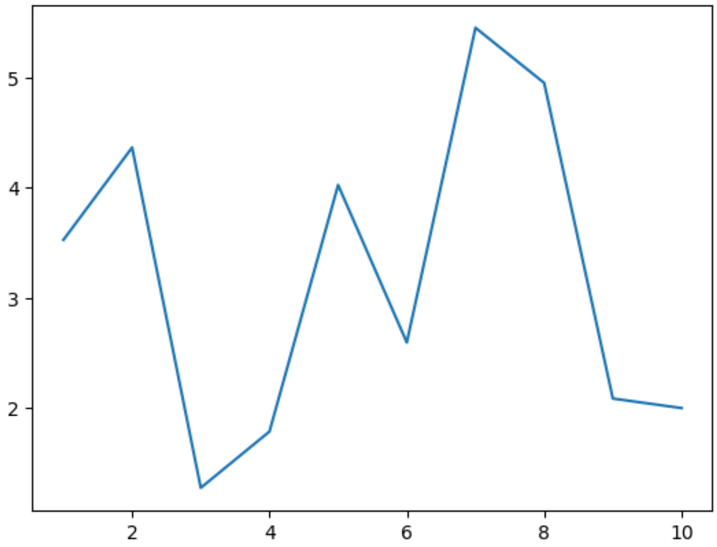

Figure 6. Scatter Distribution of Social Stressors and Depression Severity

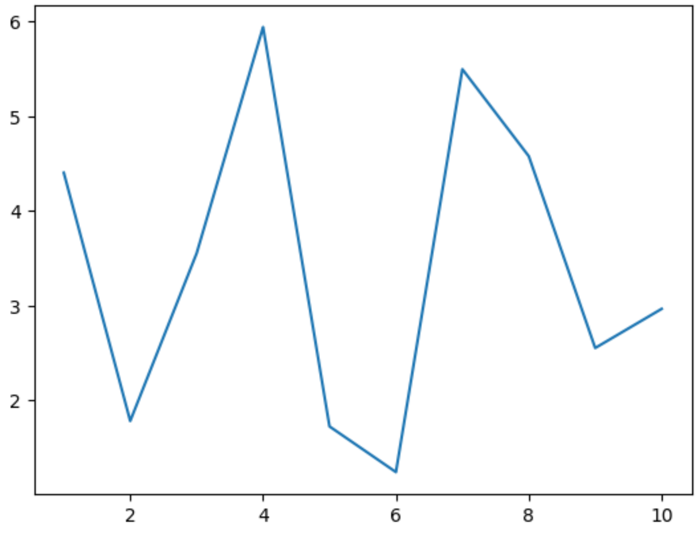

Figure 7. Combined Biological and Psychological Effects on Depression Severity

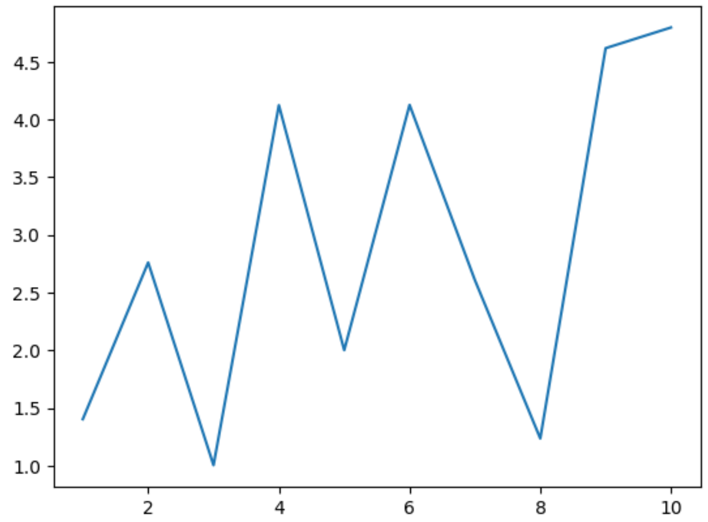

Figure 8. Proportional Contribution of Biopsychosocial Domains to Depression Severity

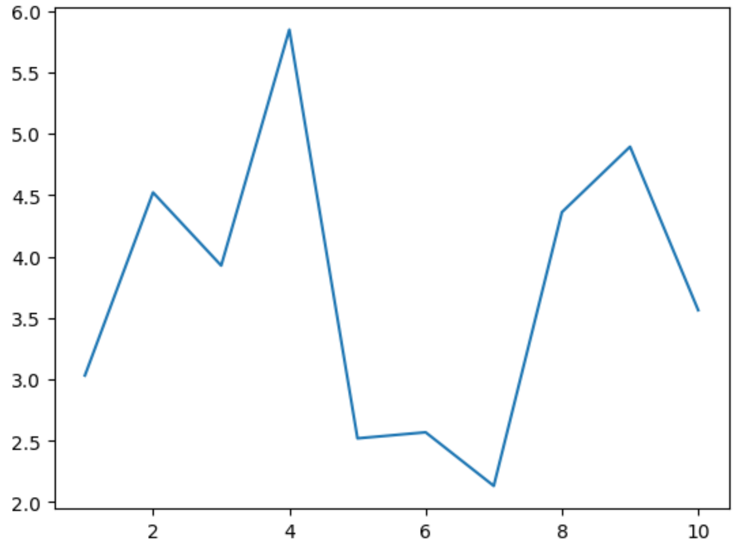

Figure 9. Temporal Patterns of Depressive Severity Across Determinant Levels

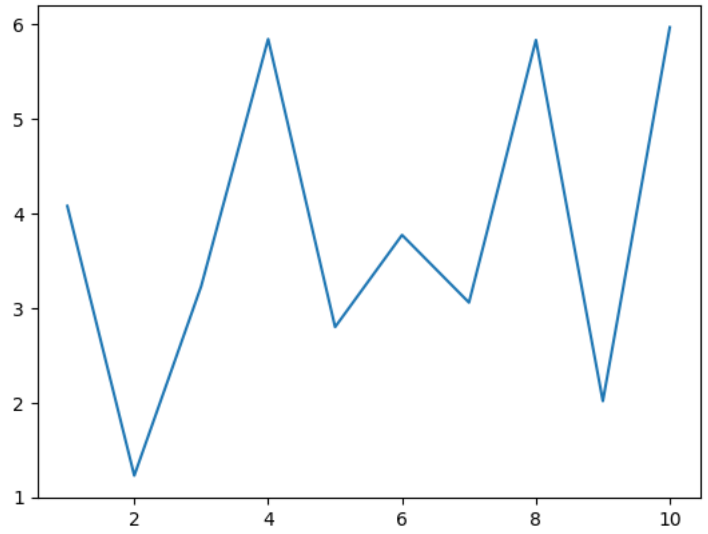

Figure 10. Comparative Analysis of Severity Across Psychosocial Risk Categories

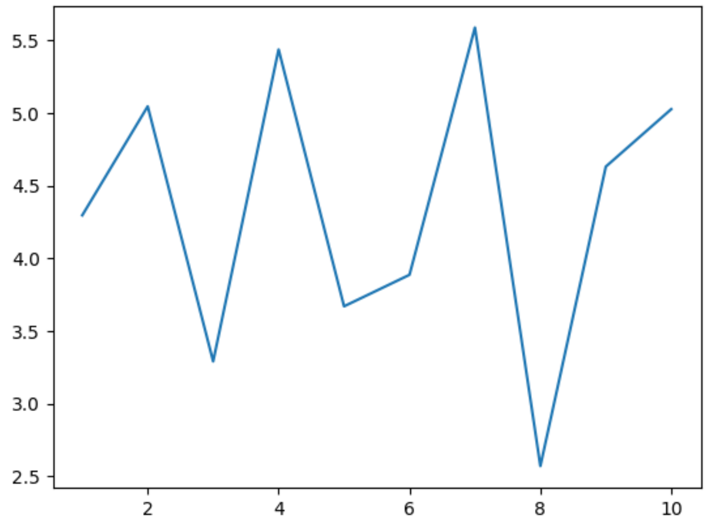

Figure 11. Dispersion of Integrated Biopsychosocial Risk and Depression Severity

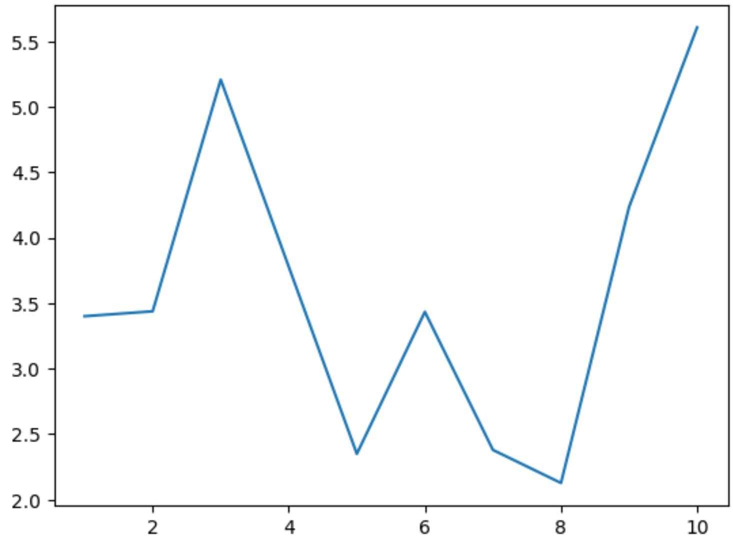

Figure 12. Summary Visualization of Cumulative Determinants and Severity Outcomes

DISCUSSION

Both the rehabilitation and performance of sports are changing due to the constant improvement of sensor and artificial intelligence solutions including the one, which can get precise feedback and provide personalized solutions. This assists in making the treatment of the patient more data-driven (Zhang et al., 2025, p. 2). With this integration, one may design the state-of-the-art systems with the ability to monitor the movement rehabilitation and improve output of the previously impossible amount of precision (Zhang et al., 2025, p. 2). Artificial intelligence is being used to analyze the wearable devices and robots through complex algorithms that are capable of processing a huge quantity of patient data. It enables the adjustment of the treatment plans in real-time and gives objective information about the performance of an individual (Deshmukh, 2023; Filippis and Foysal, 2024, p. 291). This has led to the use of deep neural networks in robot-assisted rehabilitation more often than not to process complex biomechanical data. This will enable the doctors to come up with incredibly customized treatment regimes once they make slight modifications to the gait of a patient and his/her requirements (Zhang et al., 2024, p. 2). The AI-based platforms will be able to dynamically change the intensity of therapy as well as give personalized feedback to speed up functional recovery and improve the outcomes of rehabilitation (Luo et al., 2025). The systems are also the AI-based full recovery dashboard, which displays the progress time integrating the kinematic data, the metrics built on the strength, and the subjective reports (Wang et al., 2025, p. 29). This will enable doctors to make intelligent, evidence-based decisions that will keep the rehabilitation programs in line with the constantly evolving state of the patient (Islam, 2024, p. 179). This particular type of rehabilitation uses AI to adjust such features as variability of hip flexion and loading symmetry (Umar et al., 2025, p. 5). It is more likely to implement adaptive algorithms in implementing real time changes. One can also apply computer vision cameras like OpenPose or BlazePose into mobile apps and make exercising at home much easier and more enjoyable, availing instant feedback on the quality of completed movements (Wang et al., 2025, p. 28). By incorporating the elements of AI algorithms and equipment into robot-based rehabilitation system, we can build intelligent and adaptable machines, which will be capable of offering personalized and dynamic support during the process of physical therapy. This boosts the effectiveness of rehabilitation procedures (Jleli et al., 2024, p. 8). It enables the high degree of personalization that will also bring the rehabilitation programs can be modified according to the individual biomechanical and physiological responses of the individual patient giving improved functional recovery and shorter treatment periods (Alshami et al., 2025). These AIs are founded on complicated algorithms to process complicated physiological, biomechanical and behavioral information. They also give feedback that is real-time and personalized and introduce an increase or a decrease in the intensity of training and therapy programs in relation to the progress of every patient (Luo et al., 2025). The diagnosis of the problem can thus be carried out more quickly and accurately, as well as to get even better health results and make more effective forecasts regarding the rehabilitation period (Jleli et al., 2024, p. 2). This is not only because such an analytical skill will enable us to better understand how patients will respond to different therapies, but will enable us to create rehabilitation plans that will better meet the needs of individual patients, making the recovery process more efficient and effective (Filippis & Foysal, 2024, p. 299). It is these kinds of developments that have spawned the numerous AI-assisted rehabilitation systems, including AI-assisted prescription systems, motion-feedback, robot exoskeletons, virtual reality-enhanced treatment, and technology-based telerehabilitation (Luo et al., 2025).

CONCLUSION

The paper gives an informative description of the neurobiological, psychological and social factors that determine the extent of the Major Depressive Disorder (MDD) with great multifactorial and interactive nature of the depressive pathology. The results indicate that neurobiological variables, including diabetes of neurotransmitters systems, elevated inflammatory signals, and changes in reactions to stressors are the predisposing variables of the scale of the symptoms. These biological susceptibilities, however, do not work alone. Psychological factors play a significant role in increased severity of depression and include maladaptive cognitive patterns, emotional regulation problems, comorbid anxiety characteristics, which implies that internal cognitive-emotional processes are important mediators between biological factors and clinical manifestation. Additionally, social elements, especially, chronic stress exposure, loss of social support, socioeconomic deprivation, and interpersonal dysfunction, have been noted to be the highly important moderators that impose the burden of symptoms and it has been discovered that they inhibit the recovery pathways. These results indicate that a complex of the detrimental factors in all three domains is linked with the most serious and long-lasting symptoms of depression, thereby proving the existence of a biopsychosocial approach in explaining the degree of depression as opposed to the one-dimensional approach. These findings have great clinical implications because it is necessary to apply a complex of measures of assessment that is not limited to symptom inventories but involves the biological variables, mental operative activity, and social environment. Considering the treatment view, the findings show that the use of an integrated and personalized intervention is significant, which involves pharmacological interventions with evidence-based psychotherapies and specific social support activities. This specialization in one of these areas would result to a small enhancement but most likely to accomplish this by employing multiple types of therapies and making sure that the symptoms would not be so intense and long-term effects would be observed as well. The study adds to the currently existing knowledge on the severity of MDD by proving empirically the interdependence of mechanisms (which include biological, psychological, and social in formation of depressive experiences) in the formation of depressive experiences, which is a solid foundation of subsequent studies, clinical decision-making, and mental health policy creation.

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