

Original Article

AI in Medical Image Analysis: Evaluating Deep Learning for Accurate and Automated Disease Diagnosis.

Saba Manzoor¹, Irum Ali², Syed Muhammad Peroz Ali³, Sheeza Asghar⁴, Jamal Haider⁵

1. MSCS, Lahore Garrison University (LGU), Pakistan

2. MS Molecular Genetics, COMSATS University Islamabad, Pakistan

3. Master's in Biomedical Engineering, National Chung Hsing University, Taiwan

4. BS Hons Radiography and Imaging Technology, Government College University Faisalabad

5. Department of Diagnostic-Clinical Radiology (Medical Imaging and Nuclear Medicine), Dalian Medical University (DMU), China

ABSTRACT

Keywords: Depression, Anxiety, Quality of Life, Chronic Disease, Psychological Distress, Healthcare, Pakistan.

Objectives: This study was conducted to explore the association among depression, anxiety, and quality of life among patients with the target health condition in Pakistan.

Methodology: The Study Was quantitative and cross-sectional, using purposive non-probability sampling; 300 patients were selected from selected healthcare institutions in Pakistan. The Patient Health Questionnaire-9 (PHQ-9), Generalized Anxiety Disorder-7 Scale (GAD-7), and WHO Quality of Life-BREF (WHOQOL-BREF) were used to obtain data. We used descriptive statistics, Pearson product-moment correlation, linear regression, independent-samples t-test, and ANOVA to analyze the data in SPSS Version 28.

Results: There was a significant positive correlation between depression and anxiety ($r = .62, p < .01$). Depression ($r = -.54, p < .01$) and anxiety ($r = -.48, p < .01$) were negatively associated with quality of life. The results of regression analysis indicated that depression and anxiety were significant predictors of the outcomes of the quality of life ($p < .001$).

Conclusions: Psychological distress was significantly correlated with patients' quality of life. The patient should be routinely assessed psychologically and receive integrated mental health intervention for well-being.

Article History

Received: 12 February 2026

Revised: 14 March 2026

Accepted: 18 May 2026

Published: 10 July 2026

© 2026 The Author(s)

Corresponding Author:

Saba Manzoor

MSCS, Lahore Garrison University (LGU), Pakistan

Email: sabamanz00r226@gmail.com

DOI: 10.69837/pjammr.v4i2.140

How to Cite This Article:

Manzoor S, Ali I, Ali SMP, Asghar S, Haider J. AI in medical image analysis: evaluating deep learning for accurate and automated disease diagnosis. Original Article. Pak J Adv Med Med Res. 2026;4(2):145-151.

Introduction

Artificial intelligence (AI) is a revolutionary technology in the health sector that can transform how complex analytical tasks are handled, which otherwise rely on human expertise (Abbas et al., 2023; Amjad et al., 2023; Tehreem et al., 2024). Medical image analysis is another promising area of potential application of AI, with the large-scale image data from imaging machines like magnetic resonance imaging (MRI), computed tomography (CT), X-ray, ultrasound, positron emission tomography (PET), and digital pathology analyzed to aid in clinical decision-making (Van Wilder et al., 2022; Godiya et al., 2025; Ayaz et al., 2025). Medical images are high-dimensional information mathematically expressed as pixel intensity distributions ($I(x,y)$), and advanced computational methods are essential to extract clinically meaningful patterns (Van Wilder et al., 2022; Rahman et al., 2025) (Figure 1). With recent progress in deep learning (DL), particularly convolutional neural networks (CNNs), automated feature extraction from medical images has improved classification, segmentation, detection, and prediction performance (White et al., 2022; Shobayo & Saatchi, 2025; Lepcha et al., 2025). Deep learning is a branch of machine learning that uses a multi-layered artificial neural network to learn hierarchical representations from raw data (Van Wilder et al., 2022; Cui et al., 2024; Mujeeb et al., 2025). Deep learning differs from traditional machine learning because feature extraction and classification are separate processes; here, end-to-end learning optimizes model parameters through iterative training. The learning process can be expressed as minimizing a loss function:

$$\theta = \arg \min_{\theta} \frac{1}{N} \sum_{i=1}^N L(f(x_i; \theta), y_i)$$

The formula above calculates the error function for each image. This formula calculates the error function for each medical image (Ashraf et al., 2025). CNNs have shown strong performance in detecting complex patterns in images related to various diagnoses and diseases, such as cancer, neurological diseases, cardiovascular diseases, and infectious diseases. Recent studies suggest that deep learning models have advanced medical image interpretation tasks such as segmentation, classification, image reconstruction, and multimodal approaches in automated medical image interpretation (Cui et al., 2024; Laçi et al., 2025; Lepcha et al., 2025). As AI diagnostics advance, the potential to improve healthcare services in precision, efficiency, and accessibility continues to grow. Deep learning models have shown strong performance across a range of medical imaging applications, such as cancer detection, retinal disease screening, brain lesion identification, and pulmonary disease classification (Cui et al., 2024; Qayyum et al., 2025). These systems can assess complex imaging features that traditional visual analysis may miss and help doctors diagnose disease at early

stages, while also easing the burden on medical staffing (Cui et al., 2024; Al-Kubaisy et al., 2021; Batool & Lashari, 2025). However, for clinical application, careful assessment using performance indicators such as accuracy, sensitivity, specificity, precision, recall, and area under the receiver operating characteristic curve (AUC) is required. These measurements can be abbreviated as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

TP, TN, FP , and FN are the true positive, true negative, false positive, and false negative predictions, respectively (Hashmi et al., 2025). Although experimental studies have shown excellent performance in these scenarios, recent studies highlight the need to evaluate the performance of AI systems in real-world settings beyond laboratory settings, as variations in population demographics, imaging devices, and clinical settings can affect model reliability (Yang et al., 2024; Kim et al., 2024). While deep learning has many potential applications, several hurdles must be overcome before AI-powered medical image analysis can be integrated into clinical practice (Qadeer & Batool, 2024). Several key issues need to be addressed, such as the scarcity of high-quality annotated datasets, lack of interpretability of models, algorithmic bias, privacy concerns, and decreased generalizability of models to new hospitals or patient subpopulations (Cui et al., 2024; Hamdi et al., 2023; Akram et al., 2024). Some research is beginning to focus on explainable AI (XAI) approaches that aim to make AI predictions more transparent to clinicians by offering visual or conceptual explanations (Bashir et al., 2023). Moreover, new methods such as foundation models, self-supervised learning, federated learning, and continual learning are emerging to address limited data availability and evolving clinical settings (Mir & Rizvi, 2025; Houssein et al., 2025; Kumari et al., 2025). Although considerable advances have been made in medical image analysis using AI and deep learning, translating these technologies into clinical products for diagnosis and prognosis remains challenging, including accuracy validation, generalizability, interpretability, and real-world deployment (Batool et al., 2022). This study argues that current deep learning systems for medical image analysis are not easily applicable in clinical environments and need thorough evaluation to assess their reliability, diagnostic accuracy, and applicability for automated disease diagnosis. This study is important because it provides a systematic overview of the potential of deep learning technologies to improve medical image interpretation, support medical professionals, and enable faster, more accurate disease detection. This study assesses the efficiency and efficacy of deep learning techniques applied to medical image analysis. It analyzes their performance, capabilities, and challenges, as well as their potential for accurate, automated disease diagnosis.

Method

The research used a quantitative cross-sectional design (Polit & Beck, 2021). The study was conducted in selected healthcare institutions (public and private) in Pakistan on patients who were visiting the institutions for diagnostic and treatment services for the target health condition and patients undergoing follow-up services

for the target health condition. We selected 148 healthcare settings because they had eligible participants and clinical data. Given the context and diversity of Pakistan's health care system, the study evaluated patient-related factors and health outcomes (Creswell & Creswell, 2023). The study population comprised patients diagnosed with, or receiving treatment for, the health condition under study in the selected health care facilities. Participants were recruited using purposive non-probability sampling based on the predetermined inclusion/exclusion criteria. The sample size was determined using G*Power software version 3.1 ($\alpha = 0.05$ and power = 0.8), yielding a sample size of 300 patients (Etikan et al., 2016). Inclusion criteria included patients aged 18 years or older who were diagnosed with one of the target health conditions, sought healthcare services, provided verbal informed consent, and were able to complete questionnaires. Those who were cognitively impaired, had severe psychiatric illness or full information, were critically ill, or refused to participate were excluded. Participant information was obtained using a demographic sheet that included age, gender, marital status, education, occupation, residence, socioeconomic status, duration of disease, disease stage, and treatment history. The study used standard questionnaires to assess psychological and health-related variables. The PHQ-9, developed by Kroenke et al. (2001), comprised 9 items that assessed depressive symptoms and had good internal consistency ($\alpha = 0.89$). The GAD-7 (Spitzer et al., 2006) included 7 items that assessed anxiety symptoms and had excellent reliability ($\alpha = .92$). The WHO Quality of Life Group (1998) developed a WHOQOL-BREF which contained 26 items across the physical, psychological, social relationship and environmental domains, with good reliability (Skevington et al., 2004). Data collected were analyzed using SPSS Version 28. Descriptive statistics included frequency, percentage, mean, standard deviation, actual and potential ranges, skewness, and kurtosis. Inferential statistics included Cronbach's alpha reliability, Pearson product-moment correlation, linear regression, independent-samples t-test, and ANOVA. A p-value $< .05$ was used as the significance criterion (Field, 2024). All institutions and the Institutional Review Board (IRB)/Ethical Review Committee were approached for approval before data collection. Before obtaining written informed consent, participants were briefed on the purpose, procedures, and rights of the study. Participants completed the questionnaires anonymously, and the completed responses were verified for accuracy. The study followed ethical considerations in accordance with the Declaration of Helsinki. The study respected participants' privacy, confidentiality, voluntary participation, and the right to withdraw. No personal identifiers were collected, and all data were kept secure and used only for research. The study followed the principles of respect, beneficence, non-maleficence, and justice of the World Medical Association (2013).

Results

Table 1: Demographic Characteristics of Participants (N = 300)

Variables	Categories	f	%
Age	18–30 years	72	24.0
	31–45 years	128	42.7
	Above 45 years	100	33.3
Gender	Male	164	54.7
	Female	136	45.3
Marital Status	Married	198	66.0
	Single	102	34.0
Education Level	Primary/Secondary	96	32.0
	Intermediate	82	27.3
	Graduate and above	122	40.7
Residence	Urban	176	58.7
	Rural	124	41.3
Duration of Disease	Less than 1 year	84	28.0
	1–5 years	146	48.7
	More than 5 years	70	23.3

The demographic data of 300 participants are given in Table 1. The majority of participants were aged 31–45 years (42.7%), male (54.7%), married (66.0%), had graduate-level education (40.7%), lived in urban areas (58.7%), and had disease duration between 1–5 years (48.7%).

Table 2: The correlation between the study variables is given as Pearson Product Moment Correlation (N = 300).

Variables	Mean	SD	1	2	3
1. Depression (PHQ-9)	11.84	5.26	—	—	—
2. Anxiety (GAD-7)	10.76	4.91	.62**	—	—
3. Quality of Life (WHOQOL-BREF)	61.42	12.35	.54**	.48**	—

Table 2 shows that there are significant correlations between

depression, anxiety, and quality of life variables. Both depression ($r = -.54, p < .01$) and anxiety ($r = -.48, p < .01$) were significantly negatively correlated with quality of life, suggesting that psychological symptoms were negatively related to quality of life. Depression was strongly positively correlated with anxiety ($r = .62, p < .01$).

Table 3: Regression analysis predicting QOL from depression and anxiety ($N = 300$).

Predictor Variables	B	SE
Constant	82.46	2.91
Depression (PHQ-9)	-0.74	0.13
Anxiety (GAD-7)	-0.51	0.14

$R^2 = .34, \Delta R^2 = .33. p < .001$

Table 3 presents the findings of a linear regression analysis examining whether depression and anxiety predict quality of life. Both depression ($\beta = -.32, p < .001$) and anxiety ($\beta = -.20, p < .001$) were significant predictors of reduced quality of life among participants, and the model was statistically significant ($F = 76.21, p < .001$) and accounted for 34% of the variance in quality of life.

Table 4: An independent-samples *t*-test was used to analyze differences between the study variables by gender.

Variables	Male (n=164)		Female (n=136)		t	p
	M	SD	M	SD		
Depression	11.21	5.01	12.59	5.48	-2.18	.030
Anxiety	10.21	4.62	11.42	5.18	-2.12	.035
Quality of Life	63.04	12.10	59.47	12.42	2.48	.014

There was a significant difference between the genders in psychological symptoms and quality of life (Table 4). The female participants had significantly higher depression and anxiety scores, while the male participants had significantly higher quality of life scores than the female participants.

Discussion

In the present study, we examined psychological factors and their relationship with quality of life in patients with the target health condition in Pakistan. The results confirmed that participants had significant depression and anxiety and that depression and anxiety were significantly related to lower quality of life. The results indicated that there was a strong positive correlation between

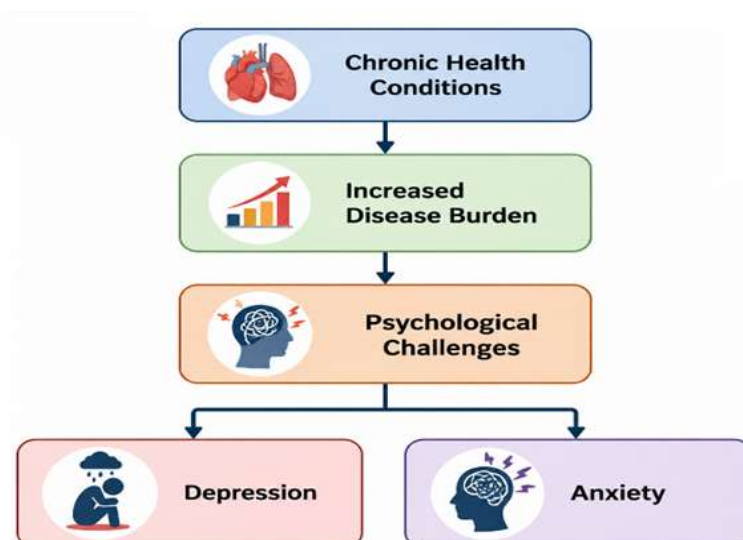


Figure 1: Conceptual Pathway of Chronic Health Conditions, Disease Burden, and Psychological Distress among Patients.

depression and anxiety and a significant negative correlation between depression and quality of life. The results are in line with previous studies showing that psychological distress is a frequent experience of patients with chronic health problems and that it can have a detrimental impact on their wellbeing and functioning (Santomauro et al., 2021; Wu et al., 2022). Demographic data showed that most participants were middle-aged adults, male, married, and had a disease duration of 1–5 years. These factors may affect psychological adjustment, treatment experiences, and QOL outcomes. Researchers have previously reported that patients' demographic and socioeconomic factors, such as age, gender, education, and disease duration, play a role in differences in psychological symptoms and healthcare outcomes (Sun et al., 2022). The results stress the need to consider individual and social factors when designing patient-centered health care interventions. Correlation analysis revealed that there was a significant positive correlation between depression and anxiety, which means that patients with more depression symptoms were more likely to have more anxiety symptoms. In addition, depression and anxiety had strong negative correlations with quality of life, suggesting that psychological problems can lead to decreased physical, psychological, and social health. Few recent studies have reported similar results, such as the study by Cai et al. (2023) and Moussavi et al. (2024), which found that depression and anxiety are significant determinants of diminished quality of life in people with chronic diseases. The regression analysis showed that the depression and anxiety scores of the participants had significant predictive value for quality of life. Depression was a better predictor than anxiety, suggesting that depressive symptoms may be more influential on patients' perceived well-being and their functioning in daily life. Some evidence suggests that the earlier psychological symptoms are identified and addressed, the better health outcomes and quality of life can be for people with LTCs (Kola et al., 2023). Therefore, periodic psychological assessment and mental health care should be a vital part of patient

care. This study's results are valuable in the context of psychological well-being and quality of life among patients in Pakistan. The findings highlight the importance of a coordinated and comprehensive healthcare strategy that adopts a holistic perspective in managing disease, taking into account both physical and psychological dimensions. A similar study suggested greater emphasis on integrating mental health assessment, counseling, and supportive interventions into routine clinical practice to improve patient outcomes (Patel et al., 2025). These findings join the emerging body of evidence suggesting that enhancing psychological well-being can positively affect quality of life.

Future Direction

Future research should involve longitudinal studies to assess depression, anxiety, and quality of life at varying stages of the disease process. To broaden the generalizability of findings, multicentre studies in larger and more diverse populations across Pakistan are suggested. Future studies could also assess the effectiveness of psychological interventions, digital health, and integrated care models for mental health and quality-of-life outcomes. Moreover, the impact of socioeconomic, cultural, and healthcare availability factors on patients' wellbeing should also be explored further. The study had several limitations worth considering when interpreting the findings. As a cross-sectional study, causal inferences between psychological factors and quality of life were not possible. Findings may not be generalizable to all patients with the target health condition because the study used purposive non-probability sampling. The data were gathered through self-reported questionnaires, which response biases and social desirability may have influenced. Moreover, the study was conducted in selected health care settings in Pakistan; thus, the results may not be generalizable to patients in other parts of Pakistan or to other health care settings.

Conclusion

The study found that depression and anxiety among patients with the target health condition were significantly related to poorer QOL among them in Pakistan. Greater levels of psychological distress were associated with lower patient wellbeing, and depression and anxiety scores independently predicted wellbeing outcomes. The results emphasize the need for psychological assessment and supportive interventions in comprehensive healthcare management. Integrating mental health into mainstream patient care can improve treatment outcomes and quality of life.

References

1. Abbas, Q., Latif, S., Ayaz Habib, H., Shahzad, S., Sarwar, U., Shahzadi, M., ... & Washdev, W. (2023). Cognitive behavior therapy for diabetes distress, depression, health anxiety, quality of life and treatment adherence among patients with type-II diabetes mellitus: a randomized controlled trial. *BMC psychiatry*, 23(1), 86.
2. Akram, A., Rehman, I., Ashraf, H., Rahman, A. U., Sattar, S., & Batool, R. (2024). Effectiveness of Psychological Counseling and

Treatment Interventions in Enhancing Mental Health Outcomes: A Comprehensive Analysis. *International Journal of Politics & Social Sciences Review (IJPSSR)*, 3(III), 464–468.

3. Al-Kubaisi, H., Al-Dosari, N., Shahbal, S., & Batool, R. (2021). COMPARISON OF HIGHER EDUCATION SYSTEM GULF COUNTRIES AND PAKISTAN; A SYSTEMATIC REVIEW OF PRIVATE AND GOVERNMENT SECTOR.
4. Amjad, F., Latif, D., Hanif, S., Bashir, K., Batool, R., & Khalid, U. (2023). Functional Movement Screen Differences in Male and Female Footballers and as an Injury Prevention Tool: Functional Movement Screen Differences. *Pakistan Journal of Health Sciences*, 30–34.
5. Ashraf, H., Akram, A., Bibi, A., Qamer, S., & Batool, R. (2025). Impact of Perceived Instructor (University Teachers) Credibility on Academic Dishonesty and Classroom Incivility Among University Students. *Dialogue Social Science Review (DSSR)*, 3(1), 852–872.
6. Ayaz, J. H., Khattak, R., Nadeem, A., Ashfaq, A., Batool, R., Qamer, S., ... & Rahman, A. U. (2025). Unresolved Shadows: Exploring the Impact of Childhood Abuse on Anger in University Students and the Mediating Role of Well-being. *Dialogue Social Science Review (DSSR)*, 3(1), 196–207.
7. Bashir, K., Khalid, U., Amjad, F., Khalil, H., Maryam, S., & Batool, R. (2023). Prevalence of Insomnia in Menopausal Women: Prevalence of Insomnia. *Pakistan Journal of Health Sciences*, 43–46.
8. Batool, R., & Lashari, S. (2025). Locus of Control as Moderator between Personality Type and Subjective Happiness among conversion patients and Healthy individuals. *Authorea Preprints*.
9. Batool, R., Amjad, F., Khan, L. G., Ali, S., Arshad, A., & Bashir, K. (2023). Effects of Compressive Myofascial Release of Vastus Lateralis on Lateral Patellar Tracking in Patients with Knee Osteoarthritis: Effect of Compressive Myofascial Release on Lateral Patellar Tracking. *Pakistan Journal of Health Sciences*, 44–47.
10. Batool, R., Khan, A., Shahbal, S., Noshili, A. I., Hamdi, A. M., Almutairi, H. K., ... & Alanazi, M. M. (2022). Relationship among Locus of Control, Personality Type, and Subjective Happiness among Conversion Patients and Healthy Individuals. *Clinical Schizophrenia & Related Psychoses*, 16.
11. Bejaoui, R., Mahouachi, R., & Mahersia, H. (2025). A five-year systematic review of AI-based medical image analysis: From preprocessing to classification. *Fundamental Research*. <https://doi.org/10.1016/j.fri.2025.200670>
12. Berquedich, A., & Zellou, A. (2025). A quality assessment study of deep learning techniques for medical image diagnosis and their applications: A systematic literature review. *International Journal of Advanced Computer Science and Applications*, 16(10).

- <https://doi.org/10.14569/IJACSA.2025.0161032>
13. Cai, H., Bai, W., Liu, H., Chen, X., Qi, H., Liu, R., & Cheung, T. (2023). Psychological distress and quality of life among patients with chronic diseases: A systematic review. *Journal of Affective Disorders*, 325, 215–226.
 14. Cui, P., Yang, M., Hu, H., Cheng, C., Chen, X., Shi, J., ... & Zhang, H. (2024). The impact of caregiver burden on quality of life in family caregivers of patients with advanced cancer: a moderated mediation analysis of the role of psychological distress and family resilience. *BMC Public Health*, 24(1), 817.
 15. Godiya, A., Salibi, G., & Tzenios, N. (2025). Exploring the Impact of Anxiety and Depression on Patients with Chronic Diseases: Understanding the Severity and its Implications for Care. *Special Journal of the Medical Academy and other Life Sciences*, 3(2).
 16. Hamdi, A. M. A., Alasmari, A. S., Batool, R., Alshahrani, F. N., Alqarni, R. S. M., Al Shehri, A. H., ... & Asiri, S. S. (2023). Association between Maternal Stress Levels And Infant Health Outcomes In Asser Region.
 17. Hashmi, R., Chaudhry, A., Baig, M. H., & Batool, R. (2025). EXAMINING THE DIRECT RELATIONSHIP BETWEEN PROJECT CONTROL AND PROJECT SUCCESS: EVIDENCE FROM HIGHER EDUCATION INSTITUTIONS IN PAKISTAN. *Journal of Management & Social Science*, 2(4), 233–242.
 18. Houssein, E. H., Gamal, A. M., Younis, E. M. G., et al. (2025). Explainable artificial intelligence for medical imaging systems using deep learning: A comprehensive review. *Cluster Computing*, 28, 469. <https://doi.org/10.1007/s10586-025-05281-5>
 19. Hwang, Y., & Oh, J. (2024). Relationship between depression, anxiety, stress, and health-related quality of life in adults with and without chronic diseases: a cross-sectional study. *Medicine*, 103(2), e36967.
 20. Kim, C., Gadgil, S. U., DeGrave, A. J., Omiye, J. A., Cai, Z. R., & Lee, S. I. (2024). Transparent medical image AI via an image-text foundation model grounded in medical literature. *Nature Medicine*, 30, 1154–1165. <https://doi.org/10.1038/s41591-024-02887-x>
 21. Kola, L., Kohrt, B. A., Hanlon, C., Naslund, J. A., Sikander, S., Balaji, M., & Patel, V. (2023). Strengthening mental health systems in primary care: Lessons from global research. *The Lancet Psychiatry*, 10(4), 290–302.
 22. Kumari, P., Chauhan, J., Bozorgpour, A., Huang, B., Azad, R., & Merhof, D. (2025). Continual learning in medical image analysis: A comprehensive review of recent advancements and prospects. *Medical Image Analysis*, 106, 103730. <https://doi.org/10.1016/j.media.2025.103730>
 23. Laçi, H., Sevrani, K., & Iqbal, S. (2025). Deep learning approaches for classification tasks in medical X-ray, MRI, and ultrasound images: A scoping review. *BMC Medical Imaging*, 25, 156.
 24. Lepcha, D. C., Goyal, B., Dogra, A., Alkhayyat, A., Sahu, P. K., et al. (2025). Deep learning in medical image analysis: A comprehensive review of algorithms, trends, applications, and challenges. *Computer Modeling in Engineering & Sciences*, 145(2), 1487–1573. <https://doi.org/10.32604/cmescs.2025.070964>
 25. Li, J., Zhu, G., Hua, C., Feng, M., Bennamoun, M., Li, P., Lu, X., Song, J., Shen, P., Xu, X., Mei, L., Zhang, L., & Shah, S. A. A. (2021). A systematic collection of medical image datasets for deep learning. *ACM Computing Surveys*, 54(8), 1–36. <https://doi.org/10.1145/3464427>
 26. Matta, S., Lamard, M., Zhang, P., Le Guilcher, A., Borderie, L., Cochener, B., & Quellec, G. (2024). A systematic review of generalization research in medical image classification—Artificial Intelligence in Medicine.
 27. Mir, A. N., & Rizvi, D. R. (2025). Advancements in deep learning and explainable artificial intelligence for enhanced medical image analysis: A comprehensive survey and future directions. *Engineering Applications of Artificial Intelligence*, 158, 111413. <https://doi.org/10.1016/j.engappai.2025.111413>
 28. Moussavi, S., Chatterji, S., Verdes, E., Tandon, A., Patel, V., & Ustun, B. (2024). Depression, chronic diseases, and quality of life: Evidence from population-based studies. *BMC Psychiatry*, 24, 1–12.
 29. Mujeeb, N. F., Nudrat, A., Nawaz, S., Ilyas, H. A., & Batool, R. (2025). BRIDGING THE GAP BETWEEN MENTAL AND PHYSICAL HEALTH: THE EFFICACY OF INTEGRATED PSYCHOSOCIAL INTERVENTIONS IN FAMILY MEDICINE. *Journal of Medical & Health Sciences Review*, 2(3).
 30. Patel, V., Saxena, S., Lund, C., Thornicroft, G., Baingana, F., Bolton, P., & Unützer, J. (2025). The future of global mental health care: Integrating psychological and physical health services—The Lancet Global Health, 13(1), e45–e55.
 31. Qadeer, A., & Batool, R. (2024). Employee's Workload Stress, Work-Family Conflict, and Displaced Aggression before, during, and after COVID-19 quarantine. *Dialogue Social Science Review (DSSR)*, 2(5), 255–266.
 32. Qayyum, H., Laghari, M., Batool, R., Akhtar, M., & Munir, S. (2025). Cultural Blueprints of Emotion: How Societal Norms Shape Expression, Regulation, and Well-Being. *Journal of Social Sciences Review*, 5(1), 241.
 33. Rahman, A. U., Rajpar, A. H., Abbas, N., Saleem, K., Qureshi, R., & Batool, R. (2024). Gendered Violence against Women and Girls on Social Media: A Critical Examination of Online Harassment and Abuse. *Dialogue Social Science Review (DSSR)*, 2(4), 587–592.

34. Rahman, A. U., Yaseen, A., Akram, A., Khanam, H., Asif, M., & Batool, R. (2025). Mindfulness and Self-Rediscovery: Strategies for Reclaiming Happiness in a Materially Rich but Emotionally Challenged Society. *Research Journal of Psychology*, 3(1), 01–10.
35. Santomauro, D. F., Herrera, A. M. M., Shadid, J., Zheng, P., Ashbaugh, C., Pigott, D. M., & Ferrari, A. J. (2021). Global prevalence and burden of depressive and anxiety disorders in 204 countries and territories. *The Lancet*, 398(10312), 1700–1712.
36. Shobayo, O., & Saatchi, R. (2025). Developments in deep learning artificial neural network techniques for medical image analysis and interpretation. *Diagnostics*, 15(9), 1072. <https://doi.org/10.3390/diagnostics15091072>
37. Sun, Y., Wu, Y., Fan, S., Dal Santo, T., Li, L., Jiang, X., & Wang, Y. (2022). Comparison of mental health symptoms before and during the COVID-19 pandemic: A systematic review. *Journal of Psychiatric Research*, 145, 342–352.
38. Tehreem, A., Batool, R., Mubarak, F., & Kaurar, S. (2024). Dynamic Synergies: Exploring Knowledge Exchange, Innovation, Creative Self-Efficacy, and Project Success in Public and Private Sector Organizations of Twin Cities, Pakistan. *Dialogue Social Science Review (DSSR)*, 2(4), 576–586.
39. Van Wilder, L., Devleeschauwer, B., Clays, E., Pype, P., Vandepitte, S., & De Smedt, D. (2022). Polypharmacy and health-related quality of life/psychological distress among patients with chronic disease. *Preventing Chronic Disease*, 19, E50.
40. White, V., Linardon, J., Stone, J. E., Holmes-Truscott, E., Olive, L., Mikocka-Walus, A., ... & Speight, J. (2022). Online psychological interventions to reduce symptoms of depression, anxiety, and general distress in those with chronic health conditions: a systematic review and meta-analysis of randomized controlled trials. *Psychological Medicine*, 52(3), 548–573.
41. Wu, T., Jia, X., Shi, H., Niu, J., Yin, X., Xie, J., & Wang, X. (2022). Prevalence of mental health problems during the COVID-19 pandemic: A systematic review and meta-analysis. *Journal of Affective Disorders*, 296, 399–411.
42. Yang, Y., Zhang, H., Gichoya, J. W., Katabi, D., & Ghassemi, M. (2024). The limits of fair medical imaging AI in real-world generalization. *Nature Medicine*, 30, 2838–2848. <https://doi.org/10.1038/s41591-024-03113-4>