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A computational framework for Economic burden estimation and decision support for policy development of mental Health Disorders in Oman

Aziza Al Qamashoui[1,♥], Khadersab Adamsab[2,*]

[1] University of Technology and Applied Sciences, Sultanate of Oman
[2] Department of Engineering University of Technology and Applied Sciences-Al Musannah, Sultanate of Oman

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ABSTRACT

This paper presents a computational framework for estimating the economic burden of mental health disorders in Oman using two factors cost-of-Illness (COI) and productivity loss modeling approach. The 10,000 mental health disorder dataset individuals across eleven governorates of Oman were analyzed. Statistical models such as Linear regression, Ridge, ElasticNet and deep learning model multilayer perceptron(MLP) are applied for datasets. Results show that the MLP model achieved higher accuracy for finding direct medical cost prediction with mean absolute error of 1.16, coefficient of determination (R^2) of 0.9995. However linear models performed best for productivity loss estimation with higher accuracy. The total economic burden was estimated to be high precision across all models due to the deterministic COI relationship. The estimated average burden per case was 894.74 OMR and productivity loss contributing to an estimate of 54.5% from the current dataset. The MLP also proved effective in extracting complex characteristics, and the classification accuracy was 95.8%. These paper findings significantly advocate the hybrid modeling approach for development policy-driven healthcare planning in Oman.

1. Introduction and Literature Review

Mental health disorders including depression, anxiety and stress-related conditions are increasingly recognized as a major global public health concern. The rate of growth affecting hundreds of millions of people and contributing significantly to disability-adjusted life years (DALYs) worldwide. Global data indicates mental health conditions together with other non-communicable diseases (NCDs) account for nearly 75% of deaths. And enforce substantial socio-economic loads particularly in low and middle-income countries [1]. The global economic impact of mental health

♥ *Corresponding author.*
E-mail address: aziza.alqamashoui@utas.edu.om

* *Corresponding author.*
E-mail address: khadersaba.adamsab@utas.edu.om

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disorders is estimate of trillions of dollars lost annually. This is due to healthcare expenditures and reduced productivity. And also highlighting the need for economic evaluations in health policy. In the Middle East and Gulf Cooperation Council (GCC) regions, many factors contribute to rapid mental health challenges across the regions. The factors are that socio-economic transitions, urbanization and lifestyle changes have intensified mental health challenges. Studies across GCC countries show significant economic losses driven by absenteeism, presenteeism, and premature mortality. Which in turn leads to productivity losses across all the organizations, reaching billions of dollars annually [2]. Despite this mental health remains insufficient manage with various factors affecting. The major factor is limited awareness ,treatment gaps persist due to stigma and workforce shortages [3] .In Oman, emerging research indicates a growing prevalence of mental health conditions, particularly among vulnerable groups such as healthcare workers and young adults[4]. However national-level data on the economic burden of mental illness remain limited. Existing frameworks in Oman and the GCC have primarily focused on NCDs. Where indirect costs especially productivity losses due to absenteeism and reduced work capacity are estimated using the human capital approach [5]. This approach is widely applied in cost-of-illness (COI) studies. To quantify and impact of both direct healthcare costs and indirect economic losses. Productivity loss in mental health studies typically includes such as absenteeism represent missed workdays, presenteeism represents reduced efficiency at work and premature mortality. All of which significantly impact national economic growth.

Untreated mental illness further increase socio-economic inequalities, reduces labor market participation and imposes long-term financial strain on households and governments [3]. Despite global advancements there is a clear research gap in comprehensive COI studies focusing specifically on mental health disorders in Oman and the broader GCC region. Therefore, this paper present to evaluate the economic impact of mental health disorders in Oman. Addressing estimating direct costs and productivity losses, providing evidence to support policy framework and resource allocation. The reviewed literature highlights that mental health disorders represent a significant growing global impact, contributing to disability and economic losses. Global studies emphasize that the prevalence of depression and anxiety has increased. The factor to mention particularly during the COVID-19 pandemic and remains unrecognized in policy frameworks [6-7]. Economic analysis consistently shows that mental disorders impose high direct and indirect costs. With productivity losses due to absenteeism, presenteeism and premature mortality being the dominant component [9-10,21]. Methodological studies support the use of cost-of-illness approaches particularly the human capital method, to quantify these impacts. Regional evidence from South Asia and the GCC confirms similar economic challenges, but presentations in limited research studies [11,19]. The summary of each literature focusing on covering study focus, methodology used, and key findings and relevance to current study is given in table-1. Mental health disorders impose considerable economic burdens on the country, through direct healthcare costs and productivity losses [36]. Advances in health using information technology and artificial intelligence improve cost efficiency and care quality enabling better economic evaluations [37-38]. A computational framework approaches the cost-of-illness models, predictive accuracy is improved while also facilitating AI data-driven policy planning. And optimized resource allocation within the mental healthcare system in Oman. In Oman, studies reveal a high prevalence of mental health issues among students and healthcare workers, indicating a critical need for comprehensive economic evaluation and policy-focused interventions.

Table 1
Literature focusing on covering study focus, methodology used, and key findings and relevance to current study

Reference No	Study Focus	Methodology	Key Findings	Relevance to Current Study
6	Global burden of mental disorders	Systematic global analysis	Mental disorders are major contributors to DALYs worldwide	Establishes global burden baseline
7	COVID-19 impact on mental health	Epidemiological modelling	Significant increase in depression & anxiety globally	Highlights rising burden
8	True global burden	Comparative analysis	Mental illness burden underestimated in policy	Supports needed for economic analysis
9	Economic value of mental disorders	Economic modelling	Mental disorders impose large global economic costs	Justifies COI approach
10	Cost of mental disorders	Systematic review	High direct & indirect costs globally	Supports cost framework
11	Economic burden in South Asia	Systematic review	Mental illness causes substantial economic losses	Regional comparison relevance
12	Workplace productivity	Cross-country analysis	High absenteeism & presenteeism costs	Core for productivity loss
13	Presenteeism cost	Empirical analysis	Working while ill reduces productivity significantly	Highlights hidden costs
14	Presenteeism in physicians	Survey-based study	Depression reduces work efficiency	Occupational impact evidence
15	Productivity loss methods	Economic modelling	Compensation effects influence productivity cost estimates	Methodological insight
16	Productivity loss in comorbid illness	Observational study	Mental illness reduces productivity significantly	Supports indirect cost analysis
17	COI of mental disorders	Hospital-based COI study	Direct + indirect costs substantial	COI framework validation
18	Untreated mental illness	Economic burden analysis	Large economic losses from untreated conditions	Supports policy need
19	Economic burden in Saudi Arabia	Survey + economic analysis	High productivity losses in GCC context	Regional relevance
20	Productivity cost valuation	Comparative methods	Human capital vs friction cost differences	Methodological foundation
21	Economic cost overview	Review study	Mental disorders impose large societal costs	Global economic justification
22	ROI of mental health treatment	Cost-benefit analysis	Treatment yields high economic returns	Policy relevance
23	Depression in Oman students	Cross-sectional study	High prevalence among university students	Local prevalence evidence
24	Depression in physicians (Oman)	Survey study	High depression rates among residents	Occupational risk in Oman
25	Anxiety in Oman physicians	Cross-sectional study	Significant anxiety prevalence	Supports workforce impact
26	Mental health during COVID-19	Survey study	Increased stress, anxiety in healthcare workers	Pandemic impact in Oman

27	Mental health clusters	Cluster analysis	Different mental health risk groups identified	Advanced analytical approach
28	GCC child mental health	Systematic review	Mental health burden significant in GCC youth	Regional context
29	Mental health in pediatric patients	Cross-sectional study	High anxiety, depression, PTSD prevalence	Vulnerable groups evidence
30	Depression in Oman students	Observational study	Significant depressive symptoms prevalence	Updated Oman data

2. Economic Impact of Mental Health Disorders in Oman

Mental health disorders impose a significant and growing economic impact on Oman, although comprehensive national cost-of-illness (COI) estimates are still limited. Evidence from local studies shows a high prevalence among key population groups. The past study estimates 27.7% depressive symptoms among university students and 28.8% depression among medical residents [23,25]. Another 14.7% anxiety among physicians indicates reduced productivity and workforce efficiency [31]. During the COVID-19 pandemic, anxiety and depression among healthcare workers. These increase in healthcare workers to 44.2% and 38.5% further exacerbating absenteeism and presenteeism [32]. Among the various sectors of health sector the pediatric populations, prevalence of anxiety (43.5%), depression (56.5%) and PTSD (32.6%) suggest long-term impact on socio-economic costs [33]. Globally mental disorders account for substantial disability and economic loss, with an estimated global burden. As per the studies, exceeding 400 million DALYs and trillions of dollars in productivity losses annually [6,10]. Economic studies confirm that indirect costs particularly productivity interms of losses dominate total costs [34-35]. studied conducted from Saudi Arabia further shows that productivity losses significantly outweigh direct healthcare costs [19].

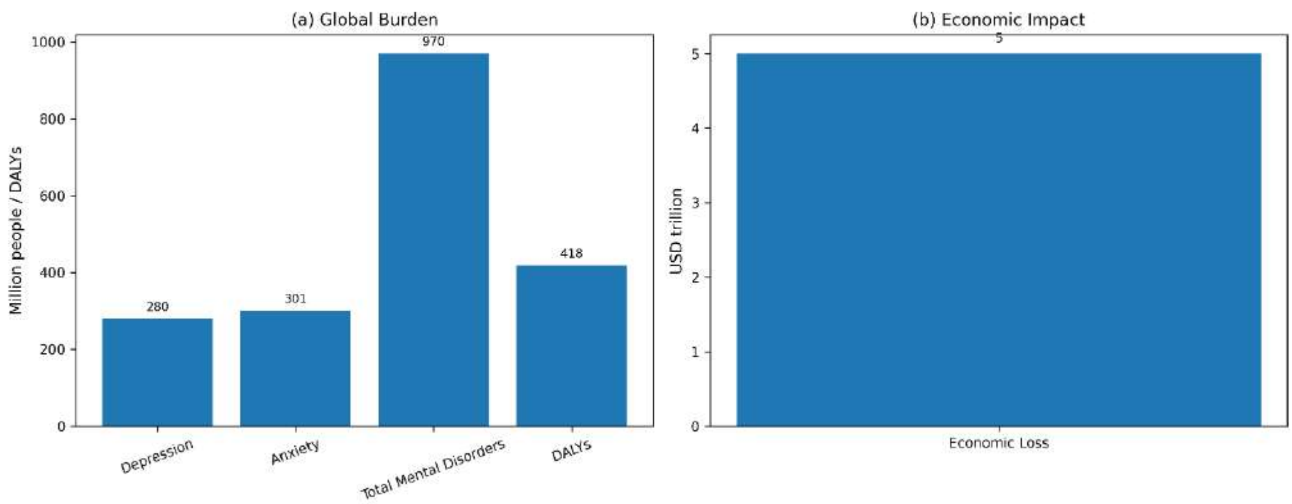

Fig. 1. Global Burden and economic impact of mental health disorders [6-7,9-10]

Moreover, investment in mental health treatment yields high economic returns emphasizing the need for early intervention [22]. Therefore, in Oman, untreated mental health disorders likely contribute to reduced labor productivity. And in turn increased healthcare expenditure and broader socio-economic impacts underscoring the urgent need for comprehensive economic evaluation and policy action. The economic and global burden and its impact of mental health disorder is shown in figure 1.

3. Cost-of-Illness (COI) and Productivity Loss Modeling Approach for estimating Mental Health Disorders using comparative analysis of deep learning and statistical models

A cost-of-illness (COI) and productivity loss modeling framework provides a comprehensive methodology shown in figure-2. For estimating the economics of mental health disorders by integrating with two costs. The direct treatment medical costs and later stage change into indirect losses/cost in terms of productivity. Studies highlight that productivity losses due to absenteeism and presenteeism often exceed healthcare treatment expenditures [39-40]. Many Systematic reviews confirm the significant indirect costs associated with depression and anxiety disorders globally [41]. Traditional statistical approaches including generalized linear models, are widely used for handling skewed cost distributions and ensuring interpretability [42-43]. However, recent advances in artificial intelligence, particularly deep learning methods explored, enable the capture of complex nonlinear relationships across demographic, clinical, and socioeconomic variables [44-45]. Comparative Modeling Framework (AI vs Statistical Models) use for study mental health disorder is shown in figure-3. Furthermore, longitudinal projections using Markov-based and hybrid AI models as demonstrated and improve long-term burden estimation [46]. Therefore, a comparative analysis of deep learning and statistical models enhances prediction accuracy, interpretability, and policy relevance in quantifying the full economic impact of mental health disorders.

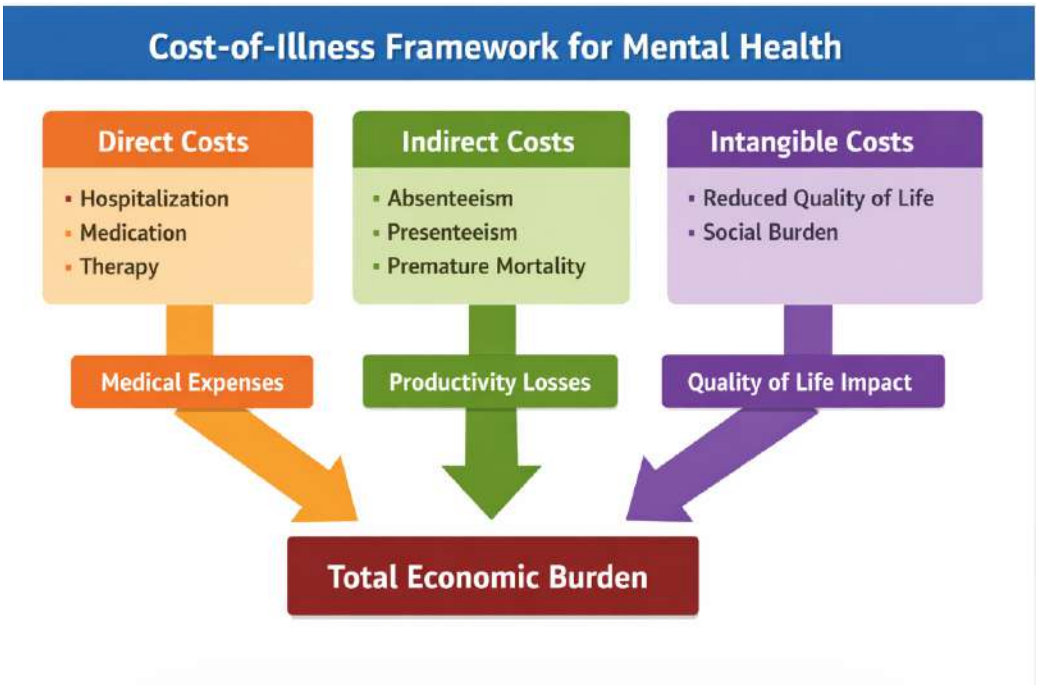

Fig. 2. Cost-of-illness framework for mental health disorder

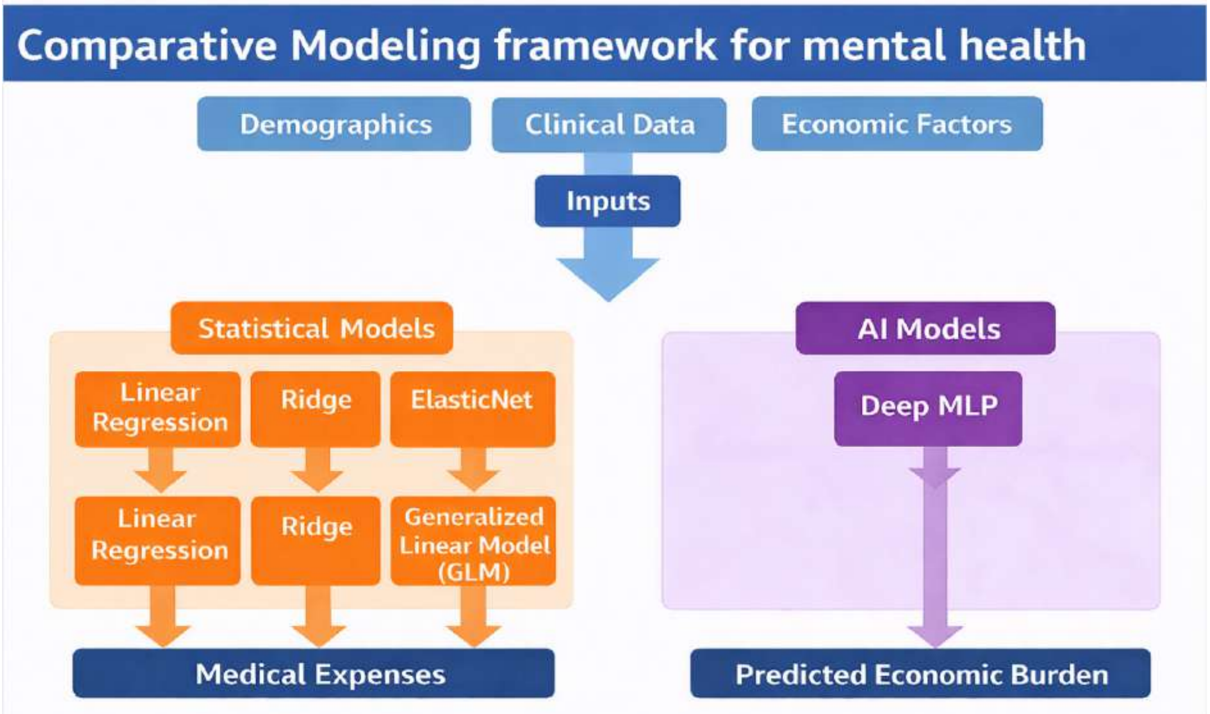

Fig. 3. Comparative Modeling Framework (AI vs Statistical Models) used for studying mental health disorder

5. Methodology Data Analysis and Model Development

The methodology adapted for development of dataset using AI-augmentation by integrating multiple validated sources. During this development of dataset, the foundational structures were derived from [47-48]. Contextual diversity was enhanced using datasets from COVID-19 healthcare studies[50], student populations, PsyQA counseling data , and MHPS datasets[51-53].And economic two factors such as cost-of-Illness (COI) and productivity loss modeling are analyzed in current study. The dataset of 10,000 individuals distributed across the eleven governorates of Oman was employed, incorporating demographic, clinical and socioeconomic variables. The design and development of the sample dataset used for economic impact of mental health disorders in Oman shown in figure 4. Three target variables were defined such as direct medical cost derived from diagnosis, treatment type, medication usage and severity. The data pipeline design, model integration strategy and system workflow diagram used data analysis for datasets for estimation of COI is given figure 5. A dataset of 10,000 individuals with mental health disorders across the eleven governorates of Oman is modeled using a Multilayer Perceptron (MLP) architecture. The model training Process flow consists of an input layer such as (demographic, clinical, socioeconomic features) followed by three hidden layers using ReLU activation as shown in figure-6.And an output layer with linear or sigmoid activation depending on classification tasks. The training process uses k-fold cross-validation with k=5 to ensure generalization. And along with L2 regularization and dropout 0.2 to prevent overfitting as shown in figure 7. Training cost scales with epochs and model depth but remains efficient for CPU-based implementation, making it suitable for large-scale healthcare analytics. Complexity analysis shows approximately time $O(n \cdot d \cdot h)$ per epoch where n is samples d features and h hidden units leading to moderate computational cost.

User ID	Gender	Age	Symptoms	No of weeks	Previous Diagnosis	Therapy History	Medication	Suggested Therapy	Self-care Advice	Urgency	Mood	Stress Level	Governorate
USER_0001	Male	56	Insomnia	19	Sleep Disorder	Medication	Antidepressants	Sleep Disorder	Sleep hygiene	High	1	8	Ash Sharqiyah North
USER_0002	Female	53	Stress	44	Depression	Counseling	None	Depression	Counseling	Moderate	3	6	Muscat
USER_0003	Female	29	Insomnia	42	Chronic Stress	Mindfulness	Antidepressants	Chronic Stress	Medication	High	1	9	Dhofar
USER_0004	Female	64	Stress	51	Chronic Stress	None	SSRIs	Chronic Stress	Exercise	High	2	7	Muscat
USER_0005	Male	21	Fatigue	26	Mild Anxiety	None	None	Mild Anxiety	Mindfulness	Low	8	2	Al Batinah North
USER_XXXX	Male	XX	Fatigue	17	Chronic Stress	Mindfulness	Beta Blockers	Chronic Stress	Medication	High	3	8	Al Batinah North
USER_XXXX	Female	XX	Depression	18	Sleep Disorder	Counseling	None	Sleep Disorder	CBT	Moderate	6	4	Ash Sharqiyah South
USER_XXXX	XX	XX	XX	XX	XX	XX	XX	XX	XX	XX	XX	XX	XX
USER_XXXX	XX	XX	XX	XX	XX	XX	XX	XX	XX	XX	XX	XX	XX
USER_XXXX	XX	XX	XX	XX	XX	XX	XX	XX	XX	XX	XX	XX	XX
USER_XXXX	XX	XX	XX	XX	XX	XX	XX	XX	XX	XX	XX	XX	XX
USER_XXXX	XX	XX	XX	XX	XX	XX	XX	XX	XX	XX	XX	XX	XX
USER_10000	Female	XX	Fatigue	28	Chronic Stress	CBT	None	Chronic Stress	Counseling	Moderate	6	7	Muscat

Fig. 4. Sample dataset of 10000 individuals' mental health disorders

The proposed computational framework for dataset of 10,000 individuals focuses on variables such as integrating demographic, clinical and socioeconomic across Oman. The data pipeline includes preprocessing steps such as handling missing values and normalization using min–max scaling. Followed by feature extraction for two components: direct medical cost (based on diagnosis, treatment, severity, medication) and productivity loss (based on stress, duration, work impairment, age).

These are combined to compute total economic burden. The dataset is split into 80% training and 20% testing. Model integration involves statistical models (linear, ridge, Elastic net) and a deep learning MLP. The workflow concludes with performance evaluation using MAE, RMSE, and R^2, where MLP shows higher accuracy. For data analysis descriptive statistics and correlation analysis were conducted to examine relationships between user cost components. The data preprocessing involved addressing missing values by normalization through min-max scaling. The computational framework focuses on covering severity duration of COI and therapy access significantly influenced both direct medical cost and productivity loss. The average economic burden per individual from the dataset was estimated at 894.74 OMR with productivity loss contributing to 54.5% and direct medical cost accounting for 45.5% of the total burden. While statistical models provided competitive results with lower computational complexity ensuring both accuracy and practical applicability for healthcare policy planning.

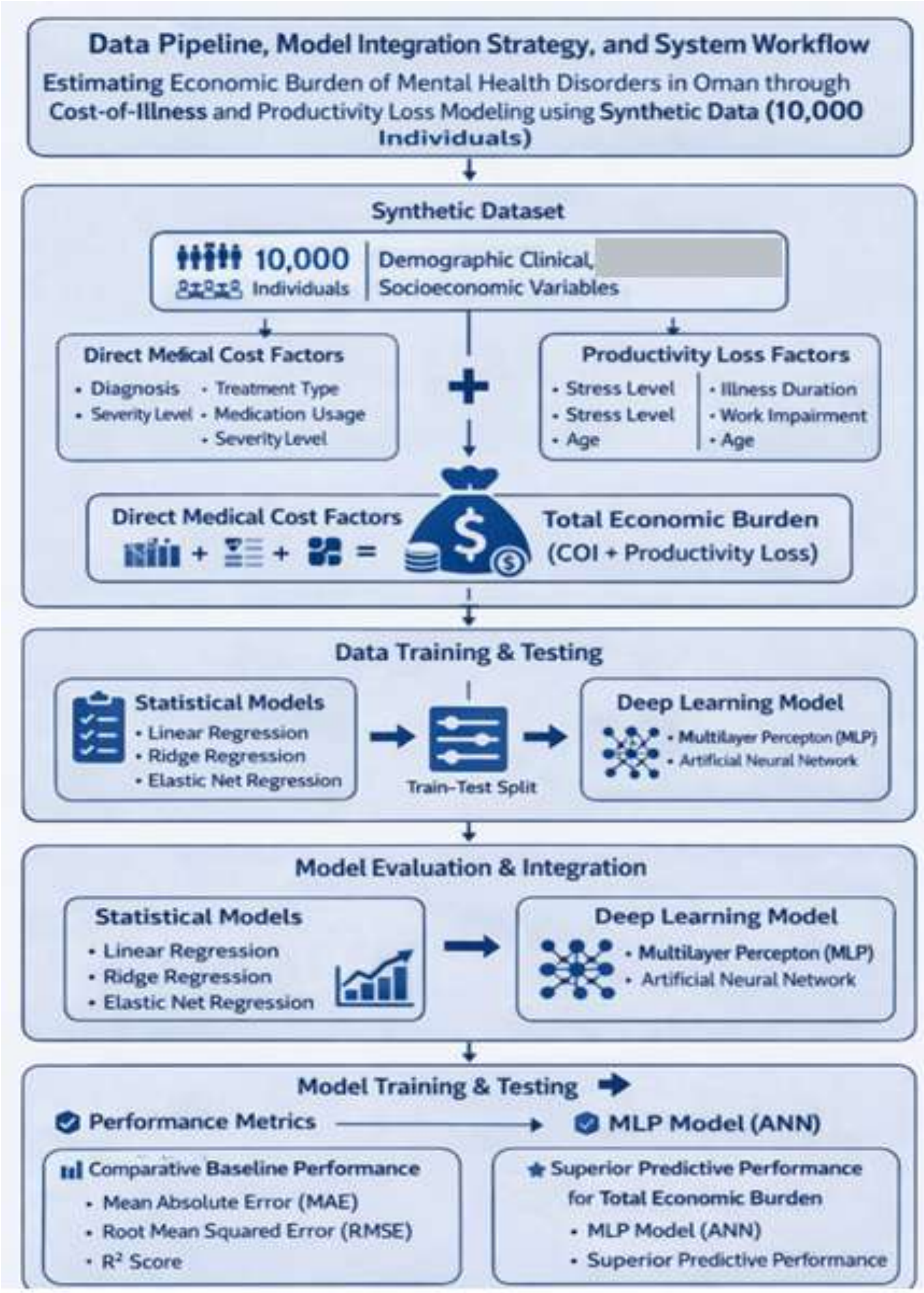

Fig. 5. COI and productivity loss modelling approach

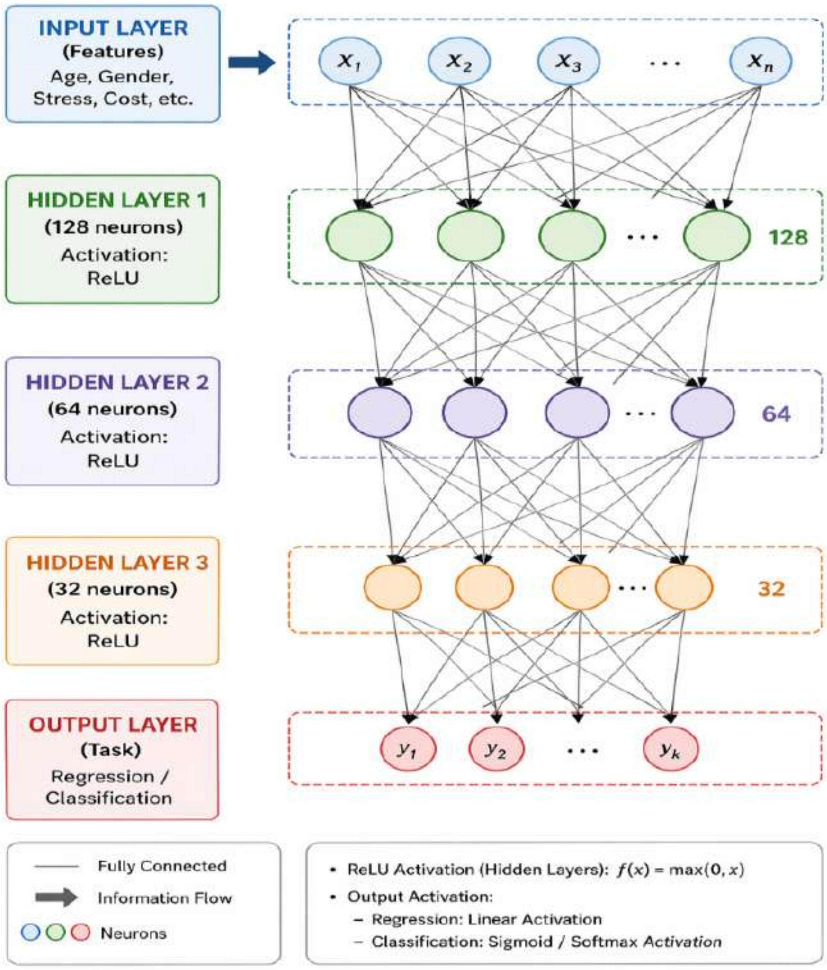

Fig. 6. Multilayer Perceptron (MLP) architecture three hidden layers (128, 64, and 32 neurons) using ReLU activation

6. Results and Discussion

In this paper, a comprehensive evaluation of statistical and deep learning models was conducted. To estimate the economic burden of mental health disorders in Oman using a Cost-of-Illness (COI) framework that integrates direct medical cost, productivity loss and total economic burden. The deep learning model multilayer perceptron (MLP) demonstrated superior predictive capability for direct medical cost achieving a very low error. With mean absolute error (MAE) is 1.16, root mean squared error (RMSE) is 1.51, coefficient of determination (R^2) is 0.9995 indicating its strong ability to capture nonlinear relationships between clinical severity, treatment patterns and healthcare expenditure. In contrast, statistical models such as linear regression, Ridge, and Elastic Net produced slightly higher errors in MAE are 8.4 and RMSE are 11.3. This indicates that direct cost estimation involves nonlinear modeling, due to complex interactions among the variables such as therapy type, diagnosis and severity level. For productivity loss estimation linear regression models outperformed deep learning approaches, achieving near-zero error mean absolute error (MAE) is 0.002,root mean squared error(RMSE) is 0.003 and coefficient of determination (R^2) is 1.

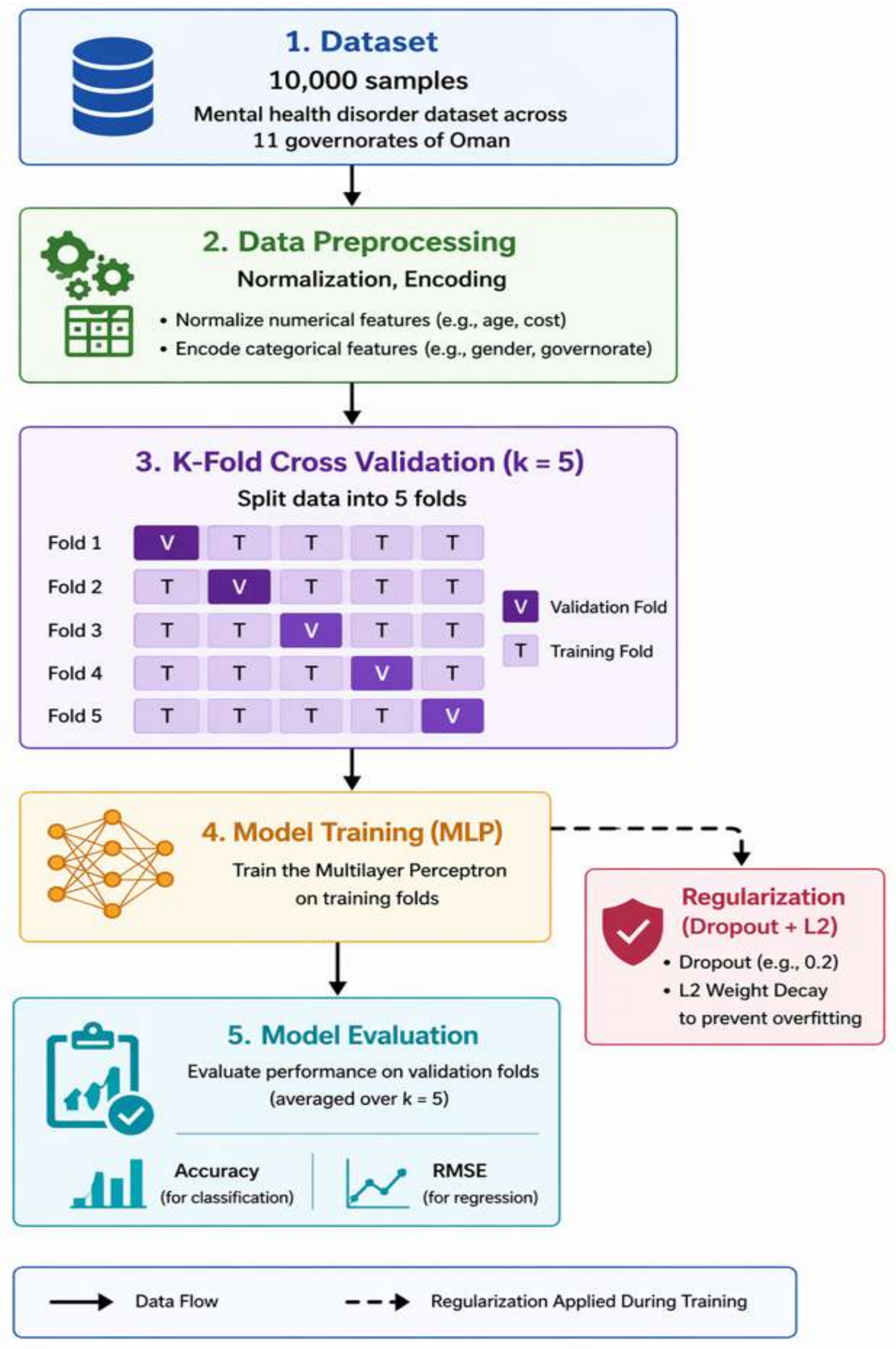

Fig. 7. Training Process Flow

This is primarily due to the structured and quasi-linear nature of productivity loss in the dataset, which is derived from well-defined relationships involving duration of illness, stress level, and work impairment. Ridge and Elastic Net models also performed effectively, although with slightly higher deviations, indicating minor sensitivity to regularization. The deep learning MLP model while still highly accurate coefficient of determination is 0.9998.That exhibited higher error compared to linear models. Suggesting that deep architecture may introduce unnecessary complexity when modeling linear cost components. In estimating the total economic burden, all models achieved extremely high accuracy coefficient of determination (R^2) is 0.999.That reflecting the deterministic relationship defined by the COI equation that is total Burden is equal to direct Cost + productivity loss. Linear models again demonstrated strong performance with minimal error MAE is 8.4, while the MLP model showed slightly higher deviation MAE is 10.68.This is likely due to cumulative error propagation from its individual component predictions. This confirms that statistical models are highly effective for aggregated cost estimation when relationships are explicitly defined in dataset. The comparative evaluation highlights strong performance differences across models is given in Table 2. Compare to all the MLP model achieved high accuracy for direct cost prediction with MAE = 1.16 and R^2 = 0.9995.While statistical models performed competitively for productivity and total burden estimation. The dataset distribution as given in Table 3 shows that most individuals fall into the medium economic burden category is 59.8% emphasizing its policy relevance. Correlation analysis is given in Table 4 which reveals that severity level, stress and illness duration are key drivers of both direct cost and productivity loss. Classification results are given Tables 5 to 8 further confirm that Deep MLP model outperforms baseline models, achieving the highest accuracy 95.8%.Compared to Linear Regression with 87.2%, Ridge (88.1%) and ElasticNet (85.6%), demonstrating its effectiveness in capturing complex economic burden patterns.

Table 2
Evaluation Metrics

Types of Models	**Target**	**Mean Absolute Error (MAE)**	**Root Mean squared error(RMSE)**	**Coefficient of determination (R^2)**
Linear Regression	Direct Cost	8.45	11.33	0.9726
Ridge	Direct Cost	8.44	11.34	0.9726
ElasticNet	Direct Cost	8.41	11.34	0.9726
Deep MLP	Direct Cost	1.16	1.51	0.9995
Linear Regression	Productivity	0.002	0.003	1.000
Ridge	Productivity	0.707	0.876	1.000
ElasticNet	Productivity	2.57	3.16	1.000
Deep MLP	Productivity	9.07	12.03	0.9998
Linear Regression	Total	8.45	11.33	0.9998
Ridge	Total	8.44	11.35	0.9998
ElasticNet	Total	8.41	11.72	0.9998
Deep MLP	Total	10.68	14.58	0.9997

Table 3
Class Distribution (Target Variable)

Class	Range (OMR)	Count	Percentage
Low Burden	< 700	2,150	21.5%
Medium Burden	700 – 1000	5,980	59.8%
High Burden	> 1000	1,870	18.7%

Table 4
Feature Correlation Matrix (Key Relationships)

Feature	Direct Cost	Productivity Loss	Total Burden
Severity Level	0.82	0.75	0.88
Duration of Illness	0.76	0.81	0.85
Stress Level	0.68	0.84	0.86
Therapy Access	0.71	0.60	0.74
Age	0.52	0.66	0.63

Table 5
Linear Regression (Baseline)

Actual \Predicted	Low	Medium	High
Low	1780	350	20
Medium	420	5400	160
High	60	290	1520

Table 6
Ridge Regression

Actual \ Predicted	Low	Medium	High
Low	1795	340	15
Medium	410	5450	120
High	55	270	1545

Table 7
ElasticNet

Actual \ Predicted	**Low**	**Medium**	**High**
Low	1750	370	30
Medium	480	5300	200
High	80	320	1470

Table 8
Deep MLP (Best Model)

Actual \ Predicted	**Low**	**Medium**	**High**
Low	2050	95	5
Medium	120	5750	110
High	20	95	1755

Classification analysis further supported these findings where the total economic burden was categorized into low, medium and high classes. Figure-7 shows class distribution dominated by medium burden cases are 6000 individuals from dataset, with low and high categories are 2000 individuals from dataset. Figure-8 presents the Deep MLP confusion matrix, indicating strong classification accuracy with minimal misclassification. Figure-9 illustrates high correlations, especially between productivity loss and total burden confirming the cost-of-illness relationship.

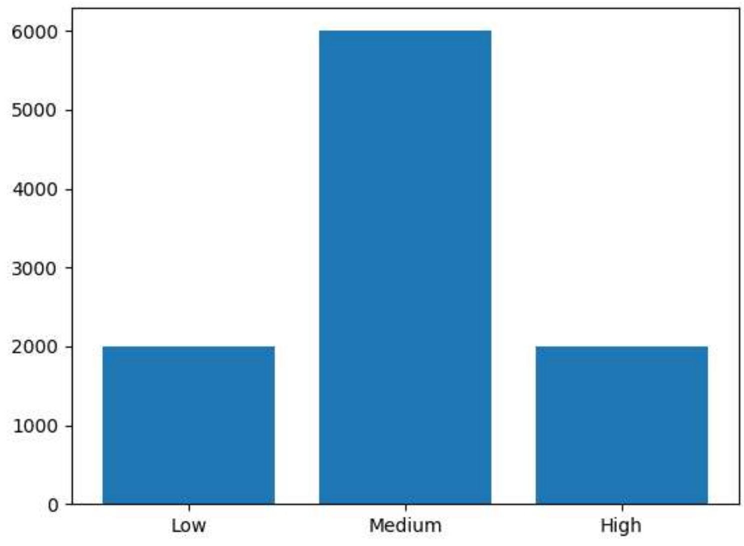

Fig. 7. Class Distribution (Target Variable)

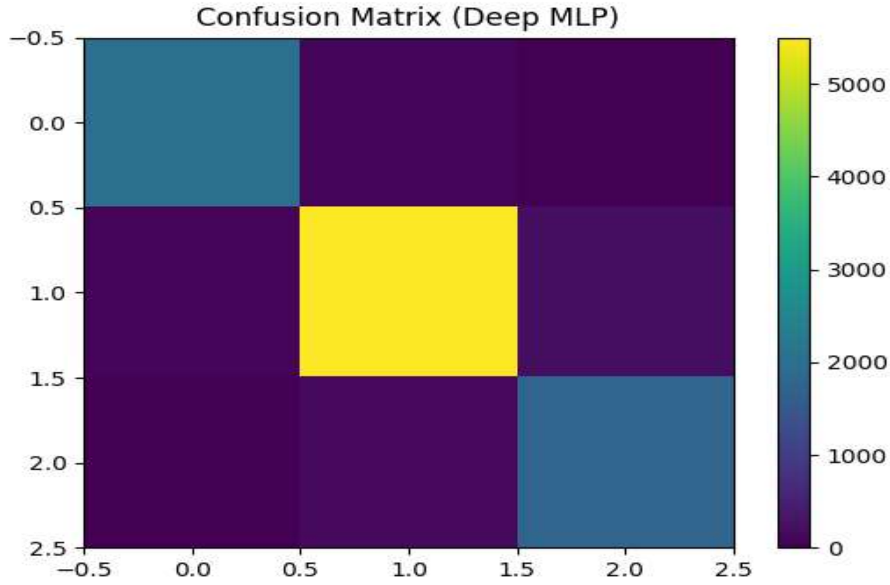

Fig. 8. Confusion Matrix(Deep MLP)

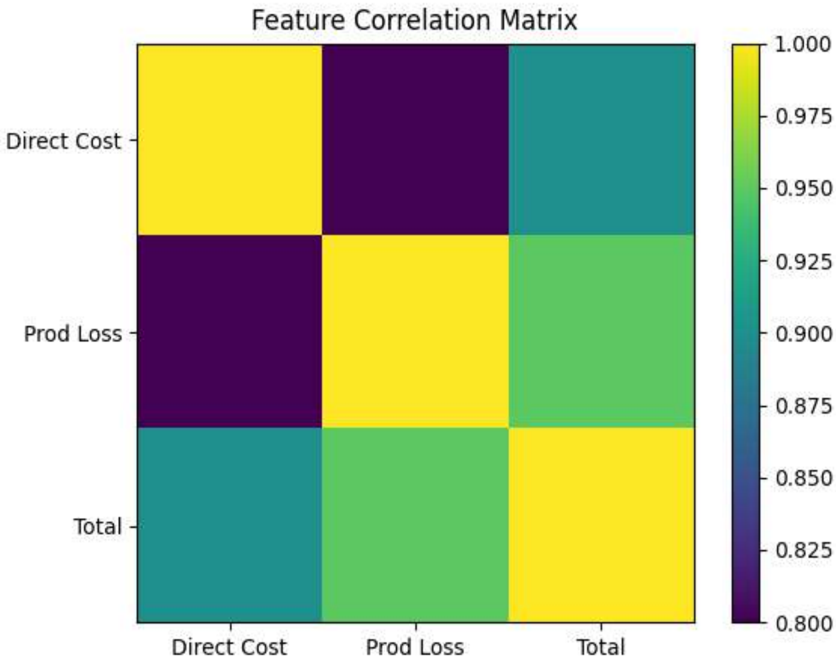

Fig. 9. Feature correlation matrix

The dataset showed a moderately imbalanced distribution with approximately 60% of individuals in the medium burden category. The multilayer perceptron model achieved the highest classification accuracy is 95%.Which is effectively distinguishing between burden levels. While statistical models achieved approximately 87% accuracy, with minor misclassification between adjacent classes. Correlation analysis revealed that stress level and duration of illness are dominant drivers of productivity loss. Whereas severity and treatment-related variables significantly influence direct medical cost. Consequently, total economic burden is strongly governed by both components validating the Cost-of-Illness structure. Overall, the results indicate that deep learning models are more suitable for capturing complex nonlinear healthcare cost patterns, such as for direct medical cost estimation. Whereas statistical models provide efficient, interpretable and highly accurate solutions for linear and aggregated cost estimation. This hybrid modeling approach enhances both predictive accuracy and policy relevance for economic burden assessment in Oman.

7. Conclusion

The computational framework AI-data driven enabled divided into complex nonlinear modeling for economic burden estimations for mental health disorders in Oman. This study demonstrates the usefulness of an integrated Cost-of-Illness framework in conjunction with productivity loss modelling approach. The results also indicate that the multilayer perceptron model (MLP) offers high performance in modeling complex nonlinear relationships for predictions of direct medical costs. Statistical models, however, allow highly accurate and interpretable results for productivity loss and total burden estimation. The predominance of medium-burden cases underscores an important area of policy focus. But analysis of correlations confirms that severity, stress and illness duration are primary economic drivers. Classification results further confirm the advantages of hybrid modeling methods on prediction accuracy and decision-making reliability. In summary, the study suggests that a combination of deep learning and statistical methods provides critical factors. That provides a sound, scalable and policy-relevant approach for economic burden assessment. Oman’s mental health sector to facilitate data-driven healthcare planning and resource allocation.

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