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Decomposing rural-urban differences in depression prevalence: a cross-sectional analysis of two community-based southern Indian cohorts

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ABSTRACT

Introduction Depression is a growing public health concern in India but its prevalence is uneven across the country, possibly influenced by several sociodemographic factors. We aimed to assess the rural-urban disparity in the prevalence of depression and their associated sociodemographic and lifestyle-related factors.

Methods Participants were middle-aged and older adults (≥45 years) from two parallel, prospective cohorts from rural (CBR-SANSCOG, n=4493) and urban (CBR-TLSA, n=972) southern India. We used cross-sectional data from the baseline clinical and biochemical assessments of the above two cohorts. The Geriatric Depression Scale (GDS-30) was used to screen for depression (cut-off ≥10). Logistic regression was used to assess the relationship between place of residence (rural vs urban) and prevalence of depression, adjusting for age, sex, education, income, marital status, Body Mass Index (BMI), alcohol use, tobacco use and number of comorbidities. The Fairlie decomposition analysis was used to decompose the rural-urban disparity.

Results We found that the prevalence of depression was significantly higher in rural than in urban participants (14.49% vs 8.23%, p<0.001). The fully adjusted binary logistic regression model showed that rural-dwelling individuals were 1.57 times more likely to have depression than urban residents (AOR: 1.57, 95% CI: 1.03, 2.39). In the decomposition analysis, the variables included in this model (age, sex, education, income, marital status, BMI, alcohol use, tobacco use and number of comorbidities) explained 35.21% of the rural-urban disparity in the prevalence of depression, with sex and marital status being the significant contributors.

Conclusion Participants in our rural cohort had significantly higher odds for depression as compared to their urban counterparts, with sociodemographic factors playing a key role in this disparity. This underscores the need for scaling up mental health services in the rural communities of India including training primary healthcare providers to promptly identify and manage depression.

WHAT IS ALREADY KNOWN ON THIS TOPIC

⇒ Previous studies have found that individuals in rural areas in India are less likely to access mental health treatment and face barriers such as stigma and lack of awareness about mental health. However, the disparities in the prevalence of depression and the differential impact of sociodemographic and lifestyle-related factors on depression between urban and rural populations in India have not been investigated adequately.

WHAT THIS STUDY ADDS

⇒ This is one of the few large (n=5465), community-based studies examining rural-urban disparity in depression in middle-aged and older adults in the Indian population and brings to light the significantly higher odds of rural participants having depression as compared to their urban counterparts. We have also decomposed this rural-urban disparity to demonstrate that the sociodemographic and lifestyle-related factors included in our model explained 35.21% of this disparity.

HOW THIS STUDY MIGHT AFFECT RESEARCH, PRACTICE OR POLICY

⇒ Gaining a better understanding on the factors contributing to the above disparity would facilitate policymakers to design population-specific, targeted strategies for rural communities for the prevention, early detection and effective management of depression.

INTRODUCTION

Health disparity is a rising concern in the healthcare and research sector worldwide. It refers to inequities in healthcare access and outcomes between groups that could differ based on factors such as geographical area, socioeconomic status, ethnicity, etc.[1] Understanding these differences is important since they could account for a considerable extent of preventable morbidity and mortality. Further, objectively measuring disparities among disadvantaged groups would help in devising targeted strategies to improve their health, thereby ensuring health equity.

The pertinence of this issue was highlighted when the World Health Organization (WHO)

forming the Commission on Social Determinants of Health to advocate and support policy changes to address the disparity in social determinants of health.[2] The impact of health disparities is reflected in almost every aspect of healthcare, namely diagnosis, clinical decision-making, treatment quality, preventive care and psychosocial support. Further, there is compelling evidence that health disparities negatively impact a wide array of medical conditions, such as diabetes, hypertension, heart disease, stroke, cancer, trauma, infectious diseases, etc.[3–7]

When compared with the knowledge on disparities related to physical conditions, the literature on inequalities in mental health is limited. This is dismaying since mental health is an important aspect of health that could be potentially influenced maximally by health disparities. However, the bulk of the prior studies that have explored health disparities in mental healthcare have been conducted in high-income countries and the literature from low-income and middle-income countries (LMICs) is minimal. Moreover, previous literature has focused on disparities among specific racial/ethnic groups, immigrants, sexual minorities, and economically deprived groups but studies among rural, marginalized, ageing populations in LMICs are limited.[8–10]

Depression is a common mental disorder that is a growing public health concern worldwide. Several sociodemographic and cultural factors could substantially influence depression prevalence. A US study that used data from the National Survey of American Life to understand the association between place of residence and race/ethnicity found that the prevalence of depression was influenced by rural residency among women belonging to specific ethnic groups.[11] Other studies have highlighted the disparities in depression prevalence in relation to racial and ethnic differences.[12 13]

In India, depression is a rising challenge and contributes the maximum to disability due to mental disorders.[14] Older adults are at higher risk of depression, which could be attributed to multiple factors, such as higher rates of physical illness, social isolation and financial dependency.[15] Also, with India's changing demographic patterns, the proportion of older persons is fast increasing (projected to reach 19.1% by 2050). Thus, the burden due to depression in the older population could pose a major public health challenge in the coming years.[16]

However, this burden may not be uniform across the country and there could be several sociodemographic factors contributing to these differences. A recent large-scale, Indian study on the ageing population reported that there were significant differences observed across different states as well as between rural and urban areas.[17] This study also observed inequalities with respect to sex, education and socioeconomic status.[18]

In the above scenario, we aimed to study the sociodemographic and lifestyle-related factors associated with the rural-urban disparity in the prevalence of depression in a middle-aged and older adult population from Karnataka in southern India. We hypothesised that the rural residents in our study would have a higher prevalence of depression than urban residents, and a substantial proportion of this disparity would be explained by the sociodemographic and lifestyle-related factors included in our model.

METHODS

Participants were from two prospective ageing cohort studies that are ongoing in rural and urban Karnataka. The rural cohort is the Centre for Brain Research-Srinivaspura Aging, NeuroSenescence and COGnition (CBR-SANSCOG) study conducted in the villages of Srinivaspura of Kolar district, in Karnataka state in southern India. In contrast, the urban cohort is the Centre for Brain Research-Tata Longitudinal Study on Ageing (CBR-TLSA) conducted in Bangalore city in the same state. As per the most recent Census of India (2011), an area is classified as 'urban' if it has a minimum population of 5000 persons, a minimum population density of 400 persons per square kilometre, and if at least 75% of the main working population is not in the agricultural sector. Areas not fulfilling this criteria are classified as 'rural'.[19 20] According to the above definitions, the study sites where the participants were recruited—Srinivaspura villages and Bangalore city—are rural and urban, respectively.

Both the above parent studies are designed as longitudinal cohorts with long-term follow-up, where participants undergo comprehensive clinical, cognitive, biochemical, genetic and neuroimaging assessments, with the aim of identifying risk and protective factors for dementia. The CBR-SANSCOG cohort comprises a typical rural community of primarily farmers engaged in mango cultivation, with low migration rates. They mainly hail from a low socioeconomic background and are less educated. On the other hand, the CBR-TLSA cohort participants are well-educated and belong to a middle or upper socioeconomic status.

The CBR-SANSCOG study follows an area sampling strategy wherein eligible participants from the villages of Srinivaspura 'taluk' (equivalent of a subdistrict) are recruited systematically. These villages are divided into groups according to the coverage of the Primary Health Centres (PHCs) in the taluk. PHCs are the basic units of India's public healthcare infrastructure, with each PHC covering a specific population that would include a number of villages. The CBR-SANSCOG recruitment team approaches the village community through the support of ASHAs (accredited social health activists), who are trained female community health workers from the village itself and serve as an integral part of India's National Rural Health Mission. All consenting participants are recruited after screening for study eligibility. After all potential participants in the villages covered by a particular PHC are recruited, the villages in the next PHC are targeted. Further details on the recruitment, data collection and assessments in the CBR-SANSCOG

study have been published elsewhere.[21] In contrast, CBR-TLSA participants are recruited through convenience sampling. Potential participants in urban Bangalore are made aware of the study through advertisements in newspapers and social media, in addition to conducting awareness campaigns in large apartment complexes or retirement communities.[22 23]

The inclusion criteria for the present study were (i) age ≥45 years at the time of recruitment, (ii) residency in rural Srinivaspura for at least 5 years and enrolled in the CBR-SANSCOG cohort or residency in urban Bangalore for at least 5 years and enrolled in the CBR-TLSA cohort, and (iii) completion of baseline clinical assessments as part of the respective cohorts.

The exclusion criteria were (i) known diagnosis of dementia or diagnosed during the detailed clinical assessments (Clinical Dementia Rating, CDR score ≥ 1), (ii) diagnosis of psychosis, bipolar disorder or substance dependence (except nicotine), (iii) any severe or terminal medical illness likely to hamper participation in the studies, and (iv) any significant hearing or vision or locomotor impairment limiting the study evaluations.

The present study included a total of 5465 participants belonging to the CBR-SANSCOG (n=4493) and CBR-TLSA (n=972) cohorts, who had complete data on the outcome variable that is depression. The baseline data was retrieved during the periods January 2018 to October 2022 in CBR-SANSCOG and July 2015 to October 2022 in CBR-TLSA (These periods included the three waves of the COVID-19 pandemic in India). The data collection procedures in both these cohorts have been harmonised. The sociodemographic and clinical data for both cohorts were collected digitally by trained clinicians or nurses using hand-held tablets and the Open Data Kit platform. The following study assessments were conducted.

Assessments

1. Depression: The 30-item version of the Geriatric Depression Scale (GDS-30) was used to screen for depression.[24] This scale was administered in the local languages (Kannada or Telugu) by clinicians who underwent specific training and inter-rater reliability exercises to ensure conformity in the data collection. The GDS-30 is a well-validated, self-reported tool to screen for depression in the older adult population. It has 30 straightforward questions that have to be answered as 'yes' or 'no'. Each question carries one point and the maximum score that can be obtained is 30. In our study, a cut-off score of 10 or more was used to identify depression, which has previously demonstrated an 82% sensitivity and 76% specificity.[25] The GDS has also been widely used with a cut-off of 10 to screen for depression in the Indian population.[26 27]
2. Sociodemographic information: Sociodemographic information such as age, sex, marital status, education and income were collected. Education in years was categorised into illiterate (0 years), primary/middle school (1–9 years), high school/diploma (10–13 years) and graduate/postgraduate (14 years and above). Marital status was categorised as living with a partner (married) and living without a partner (never married/divorced/separated/widowed). Income was categorised into less than 50 000 INR and more than equal to 50 000 INR.
3. Body Mass Index (BMI): This was calculated using the formula, weight (in kilograms) divided by the square of the height (in metres). Participants were categorised into underweight (BMI: <18.5 kg/m^2), normal weight (BMI: 18.5–22.9 kg/m^2), overweight (BMI: 23–24.9 kg/m^2) and obesity (BMI: ≥ 25 kg/m^2) based on Asia Pacific BMI criteria.[28]
4. Tobacco use: Tobacco use was assessed using the self-report question, 'Have you ever smoked tobacco [cigarette, beedi, cigar, hookah] or used smokeless tobacco [such as chewing tobacco, gutka, pan masala, etc]'. If answered yes, current tobacco use was assessed using the follow-up question, 'Do you currently smoke, chew, or sniff tobacco or have you quit?'.
5. Alcohol use: Alcohol use was assessed using the self-report question, 'Have you ever consumed any alcoholic beverages such as beer, wine, liquor, country liquor, etc.?' If answered yes, current alcohol use was assessed using the follow-up question, 'Do you currently drink any alcoholic beverages such as beer, wine, liquor, etc. (in the last 1 year)?'.
6. Comorbidities: Diabetes, hypertension, dyslipidaemia, cardiac illness, stroke, transient ischaemic attack, Parkinson's disease, thyroid disease, renal disease, cancer, arthritis, and respiratory illness were the comorbidities assessed and the number of comorbidities was categorised into none, one, and two or more. For comorbidities where objective measurements were available (diabetes-fasting blood glucose, hypertension-systolic and diastolic blood pressure, and dyslipidemia-abnormal levels of total cholesterol or triglycerides or low-density lipoprotein or high-density lipoprotein), a combination of self-reported and objective measures was used. For the other comorbidities where objective measurements were not available, only self-reported information was used. The blood collection procedure for the biochemical investigations was uniform between the two cohorts and the laboratory assays were carried out in nationally accredited laboratories.

Statistical analysis

To examine the association between categorical covariates and the place of residence, the χ^2 test was used, whereas continuous covariates were tested for group differences using the independent t-test. Missing values in the clinical variables and covariates were imputed using the Multiple Imputations by Chained Equations (MICE) method. We generated 10 imputed datasets and all the analysis results were pooled using Rubin's rule.[29] Multivariable binary logistic regression was used to estimate the association between the place of residence and depression, adjusting for covariates such as age, sex, marital status, education,

Table 1 Sample characteristics of the rural and urban cohorts

Characteristics	Rural, n=4493 (%)	Urban, n=972 (%)	P value
Age, mean (SD), range	58.91 (9.89), (45, 100)	63.66 (9.48), (45, 91)	<0.001
Age <65 years	3014 (67.08)	508 (52.26)	
Age ≥65 years	1479 (32.92)	464 (47.74)	
Sex			0.093
Female	2352 (52.35)	480 (49.38)	
Male	2141 (47.65)	492 (50.62)	
Marital status*			<0.001
Not living with a partner	759 (19.85)	94 (12.89)	
Living with a partner	3065 (80.15)	635 (87.11)	
Education*			<0.001
Illiterate	1791 (42.25)	25 (2.57)	
Primary/middle school	1.525 (35.98)	25 (2.57)	
High school/diploma	741 (17.48)	166 (17.08)	
Graduate/postgraduate	182 (4.29)	756 (77.78)	
Body Mass Index*			<0.001
Underweight	536 (12.05)	5 (0.58)	
Normal	1699 (38.20)	145 (16.82)	
Overweight	841 (18.91)	148 (17.17)	
Obesity	1372 (30.85)	564 (65.43)	
Body Mass Index, range	(12.34, 37.51)	(14.90, 37.65)	
Tobacco use*			<0.001
No	2927 (65.16)	927 (95.96)	
Yes	1565 (34.84)	39 (4.04)	
Alcohol use*			<0.001
No	4206 (93.61)	816 (84.47)	
Yes	287 (6.39)	150 (15.53)	
Income*			<0.001
Less than 50 000 INR	3481 (78.76)	7 (0.73)	
More or than equal to 50 000 INR	939 (21.24)	955 (99.27)	
Number of comorbidities*			<0.001
None	853 (19.20)	38 (3.94)	
One	1976 (44.48)	231 (23.94)	
Two or more	1613 (36.31)	696 (72.12)	
Depression			<0.001
No	3842 (85.51)	892 (91.77)	
Yes	651 (14.49)	80 (8.23)	
Diabetes*			<0.001
No	3618 (80.53)	638 (65.71)	
Yes	875 (19.47)	333 (34.29)	
Hypertension*			<0.001
No	3010 (66.99)	352 (36.29)	
Yes	1483 (33.01)	618 (63.71)	
Arthritis*			0.001
No	4273 (95.34)	897 (92.76)	
Yes	209 (4.66)	70 (7.24)	

Continued

Table 1 Continued

Characteristics	Rural, n=4493 (%)	Urban, n=972 (%)	P value
Lung disease*			0.069
No	4392 (97.99)	956 (98.86)	
Yes	90 (2.01)	11 (1.14)	
Cancer*			<0.001
No	4435 (99.57)	951 (98.35)	
Yes	19 (0.43)	16 (1.65)	
Renal disease*			0.002
No	4447 (99.84)	960 (99.28)	
Yes	7 (0.16)	7 (0.72)	
Thyroid disease*			<0.001
No	4355 (97.82)	849 (87.89)	
Yes	97 (2.18)	117 (12.11)	
Parkinson's disease*			0.014
No	4452 (99.96)	964 (99.69)	
Yes	2 (0.04)	3 (0.31)	
Dyslipidaemia*			<0.001
No	1626 (36.19)	170 (17.51)	
Yes	2867 (63.81)	801 (82.49)	
Stroke*			0.290
No	4465 (99.38)	958 (99.07)	
Yes	28 (0.62)	9 (0.93)	
Cardiac illness*			<0.001
No	4401 (97.95)	866 (89.56)	
Yes	92 (2.05)	101 (10.44)	
TIA*			<0.001
No	4491 (99.96)	959 (99.28)	
Yes	2 (0.04)	7 (0.72)	

*Cases may not be equal due to missing values.
TIA, transient ischaemic attack.

income, BMI, alcohol and tobacco use, and number of comorbidities. The results were presented as OR along with 95% CI. The Fairlie decomposition technique, which is a non-linear approximation of the Blinder-Oaxaca decomposition technique to logit and probit models[30] was used to decompose the rural-urban disparity in the prevalence of depression. It also estimates the contribution of each variable in explaining the disparity. A positive coefficient would mean that the variable was making a positive contribution to the rural-urban disparity and a negative coefficient would mean that the variable was making a negative contribution to the rural-urban disparity in the prevalence of depression if the inequality was positive, which was the case here. The Fairlie command in STATA V.18[31] was used to perform this analysis with 1000 replications and randomised order of variables with pooled estimates. A p value of <0.05 was considered statistically significant in all the analyses.

RESULTS

Out of the total of 5465 study participants, 4493 were from rural and 972 from urban areas. The missing data of the participants is shown in online supplemental table 1.

Participant characteristics

The rural participants had a significantly lower mean age (58.91 years) than the urban participants (63.66 years). Rural participants had a significantly higher proportion of participants who were illiterate (42.2% vs 2.6%), had income below 50 000 rupees (78.76% vs 0.73%) and were not living with a partner (19.85% vs 12.89%) than their urban counterparts. The comparative participant characteristics of the rural and urban cohorts are shown in table 1. We assessed potential multicollinearity between sociodemographic variables by calculating their correlations. While some variables showed weak correlations, these relationships are unlikely to have influenced the

Table 2 Crude and adjusted associations between the place of residence and the prevalence of depression

Characteristics	COR (95% CI)	AOR (95% CI)
Residence		
Urban (reference)		
Rural	1.89 (1.48, 2.41)*	1.57 (1.03, 2.39)*
Sex		
Male (reference)		
Female		1.47 (1.20, 1.79)*
Age		1.00 (0.99, 1.01)
Marital status		
Not living with a partner (reference)		
Living with a partner		0.64 (0.51, 0.79)*
Education		
Graduate/postgraduate (reference)		
Illiterate		1.45 (0.95, 2.21)
Primary/middle		1.35 (0.90, 2.03)
High school/diploma		0.97 (0.65, 1.46)
BMI		
Normal (reference)		
Underweight		1.11 (0.85, 1.46)
Overweight		1.03 (0.82, 1.30)
Obesity		0.96 (0.78, 1.19)
Tobacco use		
No (reference)		
Yes		1.10 (0.92, 1.32)
Alcohol use		
No (reference)		
Yes		1.25 (0.89, 1.74)
Income		
Less than 50 000 INR (reference)		
Equal to or more than 50 000 INR		1.12 (0.91, 1.39)
Number of comorbidities		
None (reference)		
One		0.93 (0.74, 1.17)
Two or more		1.14 (0.90, 1.46)

*p value <0.05
AOR, Adjusted Odds Ratio; BMI, Body Mass Index; COR, Crude Odds Ratio.

main findings. The detailed correlational analysis is provided in online supplemental table 2.

Factors associated with depression

The prevalence of depression was significantly higher in rural (14.49%) than in urban (8.23%) participants. The crude binary logistic regression showed that individuals in rural areas were 1.89 times more likely to have depression than those in urban areas (COR: 1.89, 95% CI: 1.48 to 2.41). After adjusting for covariates (age, sex, marital status, education, income, BMI, alcohol and tobacco use, and number of comorbidities), rural residents had 1.57 times higher odds of having depression than urban residents (AOR: 1.57, 95% CI: 1.03 to 2.39). Further, females were 1.47 times more likely to be depressed than males (AOR: 1.47, 95% CI: 1.20 to 1.79). Individuals living with a partner had significantly lower odds of having depression than those living without a partner (AOR: 0.64, 95% CI: 0.51 to 0.79) (table 2 and figure 1).

Decomposition analysis

The rural-urban disparity in the prevalence of depression was 6.26% and the set of covariates included in this model explained 35.21% of this disparity. The variables that significantly explained the rural-urban disparity in the prevalence of depression were sex (2.11%) and marital status (6.13%) (table 3).

DISCUSSION

In a diverse nation such as India, identifying health disparities and understanding the factors associated with them are paramount to delivering equitable healthcare to all individuals. In this study, we aimed to assess the rural-urban disparity in the prevalence of depression among middle-aged and older adults from the southern Indian state of Karnataka and also, identify the associated sociodemographic and lifestyle-related factors. We found that rural residents had 1.57 times higher odds of having depression than urban residents despite adjusting for covariates. Further, our decomposition analysis revealed that the rural-urban disparity in the prevalence of depression was 6.26% and that the sociodemographic and lifestyle-related factors included in our model explained 35.21% of this disparity.

Though there have been previous studies from other parts of the world to understand this subject, predominantly from high-income countries, these insights may not be applicable to low-income and middle-income countries such as India, since the patterns of rural-urban differences may be highly population-specific. For example, a recent meta-analysis of studies on rural-urban differences in the prevalence of depression among older adults (aged 60 years or older) revealed that the odds for depression were higher only in developed countries and no association was observed in developing countries.[32] Further, studies from different countries among participants aged 45 to 85 years have shown conflicting findings[33–35] and a possible reason for this could be the varying definitions of rural and urban areas, depending on the country and the population size.

Prior studies on the comparative prevalence of depression between rural and urban Indian populations have also shown mixed results. Findings from the recent National Mental Health Survey in India revealed that urban adults were at three times higher odds of having depression than rural residents. Among studies focusing on the older

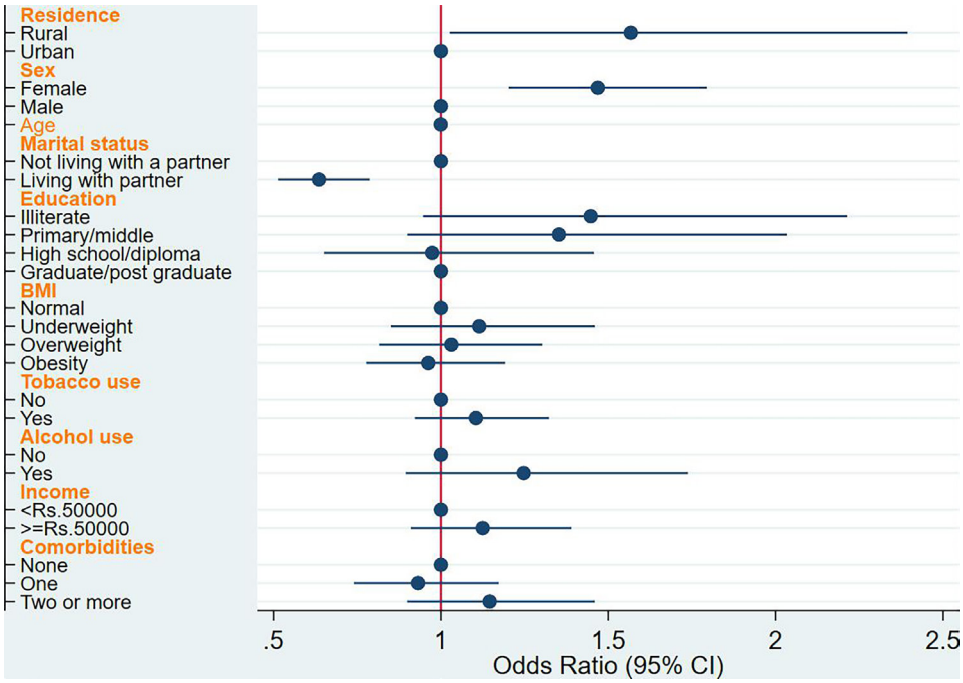

Figure 1 This figure is a forest plot depicting the associations of the place of residence and other sociodemographic and lifestyle-related factors with the prevalence of depression.

population of 60 years and above, findings from the Longitudinal Study on Ageing in India (LASI) revealed that though there was no association between depressive symptoms and place of residence during childhood or adulthood, there was a significant positive association observed between current rural residency and depressive symptoms in older women but not men.[36] On the other hand, a study on 3038 older adults (>60 years) in a hospital setting in northern India observed that urban residency was associated with a higher prevalence of depression after adjusting for other sociodemographic factors.[37]

Table 3 Decomposition of the rural-urban gap in prevalence of depression

Terms of decomposition		Depression
Difference (rural-urban)		0.06260
Explained (%)		0.022039 (35.21%)
Unexplained (%)		0.040561 (64.79%)
Variable	**Beta coefficient**	**Contribution %**
Age	0.00026 (0.00218)	0.42
Sex	0.00132 (0.00067)*	2.11
Marital status	0.00384 (0.00112)*	6.13
Education	0.03033 (0.01618)	48.45
BMI	0.00317 (0.00438)	5.06
Tobacco use	0.00384 (0.00365)	6.14
Alcohol use	−0.00256 (0.00216)	−4.09
Income	−0.01057 (0.00999)	−16.89
Number of comorbidities	−0.00759 (0.00402)	−12.12

Standard errors are presented in parentheses.
*p value <0.05.
BMI, Body Mass Index.

In our study, the higher prevalence of depression in our rural participants is likely due to their socioeconomic disadvantages, lesser access to healthcare facilities and higher psychosocial stressors. It is also likely due to the adverse psychological impact of the recent COVID-19 pandemic on this marginalised community as revealed by a recent study on this population. [38] With respect to the specific factors associated with the observed rural-urban differences, the present study found that sociodemographic factors such as female sex, and not living with a partner were significantly associated with higher odds of having depression. Our findings are similar to that of previous studies from LMICs that have explored sociodemographic factors potentially contributing to rural-urban disparities in the prevalence of depression among middle-aged and older adults.[37 39 40]

Few studies have attempted to decompose the rural-urban disparity in depression prevalence to understand the contributing factors, and their findings are consistent with ours. A large ageing cohort study in China that reported a higher prevalence of depression in rural as compared with urban older adults (>60 years) identified that females were more depressed than males, which contributed to the rural-urban disparity.[41] Similarly, another large study revealed that older adults who are living alone were at high risk of depression, which was more significant among rural participants than their urban counterparts.[42]

Our study has the advantage of a large sample size with standardised and harmonised assessment tools employed in both the rural and urban groups. Further, it has a crucial implication for promoting equity in mental healthcare among disadvantaged populations by realising the significant contribution of social factors to the observed rural-urban disparity in depression prevalence among middle-aged and older Indians. Limitations of our study include a cross-sectional study design and unequal sample sizes of the rural and urban cohorts. The different sampling methods for the two cohorts could have influenced our prevalence estimates. Particularly, since the urban cohort was recruited by convenience sampling, the educational and socioeconomic profile of our urban participants may not be representative of the whole of urban India (the majority of the urban cohort was highly educated). Further, owing to the considerable sociodemographic and cultural variations across the different states in India (differences in literacy rates and lifestyle-related factors), caution has to be exercised in generalising our findings from the state of Karnataka to the rest of India and beyond. Also, we have not taken the migration factor into account—while our rural participants are mainly an agrarian community, who have been engaged in mango cultivation in that area for a few generations, our urban participants could have previously migrated from rural or semiurban areas (our inclusion criteria in the urban cohort necessitated being a resident of urban Bangalore for at least 5 years but we did not have information on prior migration). Further, data from the two cohorts were collected at different periods, which was due to the differences in the starting of these cohorts (CBR-TLSA: July 2015, CBR-SANSCOG: January 2018). This could imply that some of the economic changes in India, such as demonetisation in 2016 and the implementation of Goods & Service Taxes in 2017, could have had a differential impact between the rural and urban cohorts. Another limitation of the study is that we have used a self-reported screening instrument for depression (GDS-30), which is likely to have a low positive predictive value. This could explain the higher prevalence of depression in our cohorts, as compared with previous literature.[43] Finally, we found that the sociodemographic factors included in our model explained only 35.21% of the disparity, implying that there could be several other sociodemographic factors such as employment status, living arrangements, caste or religion, and lifestyle factors such as self-rated health, sleep, physical activity or social connectedness contributing to the disparity.

Our study findings add weightage to the existing literature from India on this under-researched subject of mental health disparity and could help in advocating for enhancing the rural healthcare infrastructure in India. Mental health services in rural communities need to be scaled up considerably and primary healthcare providers should be specifically trained to promptly identify and treat depression. Further, promoting primary prevention strategies for common mental health disorders such as depression, particularly focusing on socioeconomically disadvantaged populations, would go a long way in reducing the rising health and economic burden of depression in the country.

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Contributors PR, PS and JSS: Conceptualised the study, design and conduct the study. PS, PR and JSS: Analysis and interpretation of data. PR, JSS, PS and TGI: Drafting and reviewing the manuscript. All authors approved the final version of the manuscript for publication and accept responsibility to submit for publication. JSS accept full responsibility for the finished work and the conduct of the study, had access to the data and controlled the decision to publish.

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Competing interests None declared.

Patient and public involvement Patients and/or the public were not involved in the design, or conduct, or reporting, or dissemination plans of this research.

Patient consent for publication Not applicable.

Ethics approval This study involves human participants and was approved by Center for Brain Research-Institutional Ethics Committee, reference ID-CBR/42/IEC/2022-23. Participants gave informed consent to participate in the study before taking part.

Provenance and peer review Not commissioned; externally peer reviewed.

Data availability statement Data may be obtained from a third party and are not publicly available. The study's data are not yet accessible to the general public, but we intend to do so soon in accordance with the government of India's legal regulations and the institution's data-sharing policy via the Alzheimer's Disease Data Initiative (ADDI) platform.

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