Title page

Latent Class Analysis of Chronic Disease Co-occurrence, Clustering and their determinants in India using SAGE India, Wave-2

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Abstract

Background: The presence of multi-morbidity in an individual has an adverse impact on health outcomes, healthcare costs, and quality of life and poses challenges in resource allocation, health service delivery, and policy formulation. This study seeks to shed light on the factors associated with the self-reported multi-morbidity latent classes in India.

Methods: The present study utilizes data from the nationally representative survey "Study on Global AGEing and Adult Health (SAGE-Wave 2, 2015)". The eligible sample size was 6,298 adults aged 50 years and older. Latent Class Analysis was performed to uncover latent subgroups of multi-morbidity. Multinomial logistic regression was carried -out to identify the factors linked to observed latent class membership.

Results: The LCA grouped our sample of men and women over the age of 49into three groups: mild MM risk (30%), moderate MM risk (41%), and severe MM risk (29%). In the mild MM risk group, the most prevalent diseases were asthma and arthritis, and the major prevalent disease in the moderate MM risk group is low near/distance vision, followed by depression, asthma, and lung disease. Angina, diabetes, hypertension, and stroke were the major diseases in the severe MM risk category. Individuals with higher ages were at increased risk of having moderate MM risk OR: 1.18*** (1.16–1.19) and severe MM risk OR: 1.15*** (1.13–1.16). Females were 3.36% more likely to have a moderate relative risk ratio (RRR: 3.36*** CI: 2.67–4.25) and 2.82 times more likely to have severe MM risk (RRR: 2.82*** CI: 2.19–3.61).

Conclusion: The clustering of diseases highlights the importance of integrated disease management in primary care settings and improving the healthcare system to accommodate the ' 'individual's needs. Implementing preventive measures and tailored interventions, strengthening the health and wellness centers, and delivering comprehensive primary health care services for secondary and tertiary level hospitalization may cater to the needs of multimorbid patients.

Keywords: *LCA; multi-morbidity; chronic disease; SAGE ; older adults; India.*

Introduction

Chronic diseases have emerged as a significant global health challenge, substantially impacting both developed and developing nations. According to the World Health Organization (WHO), chronic diseases account for approximately 74% of all global deaths, with 77% of these deaths occurring in low- and middle-income countries like India (1). These diseases, also known as non-communicable diseases (NCDs), encompass a diverse range of conditions, including cardiovascular diseases, diabetes, chronic respiratory diseases, and cancers, which collectively contribute to a substantial portion of global morbidity, mortality, and healthcare costs (2). Over the past few decades, the global burden of disease has shifted from communicable to non-communicable diseases, reflecting demographic and epidemiological transitions (3). This shift is primarily attributed to rapid urbanization, sedentary lifestyles, unhealthy dietary practices, and the ageing of populations (4).

Chronic diseases often exhibit complex interrelationships. Evidence suggests that individuals with one chronic disease are more susceptible to developing other chronic conditions (5). The co-occurrence or clustering of multiple chronic conditions within an individual, known as multi-morbidity (MM), is gaining attention due to its adverse impact on health outcomes, healthcare costs, and quality of life. The simultaneous presence of multiple chronic conditions can exacerbate each other effects, leading to worse health outcomes and higher healthcare costs (6). The clustering of chronic diseases poses challenges in resource allocation, health service delivery, and policy formulation (7). Furthermore, research has unveiled the intriguing concept of disease clustering, wherein certain chronic diseases tend to co-occur more frequently than expected by chance alone. For instance, cardiovascular diseases and diabetes often cluster, sharing common risk factors such as obesity and hypertension (8).

Multimorbidity is not solely an issue of ageing populations; it affects individuals across different age groups (6), with a significant impact on older adults (9). NCDs disproportionately affect people in low- and middle-income countries, where more than three-quarters of global NCD deaths (31.4 million) occur (1). Research has highlighted the existence of health inequalities, with chronic diseases disproportionately affecting vulnerable and marginalized communities (10). As populations age and societies undergo epidemiological transitions, the burden of these diseases is anticipated to rise. According to estimates, 4.7 million people in India died in 2017 from NCDs, accounting for 49% of all causes of death (11), reflecting the significant health challenge posed by chronic diseases.

India stands at the intersection of an epidemiological transition where the burden of chronic diseases increases alongside persistent challenges related to infectious diseases and maternal and child health (12). Reports suggest that cardiovascular diseases (27%) are the leading cause of mortality in India, followed closely by respiratory diseases (9%), cancer (6%), and diabetes (2.4%) (11,13). Recent studies have highlighted the prevalence of multi-morbidity globally, underscoring the need for comprehensive approaches to disease management and healthcare planning (4). In India, where communicable diseases have historically dominated the public health agenda, the increasing prevalence of chronic diseases presents a dual burden. In India, the co-occurrence of conditions like diabetes and cardiovascular diseases has been widely documented (14). In India, the prevalence of chronic diseases is estimated to be 63%, which is expected to rise to 70% by 2030 (15). This transition requires a paradigm shift in policy and practice to accommodate the evolving health landscape.

Understanding chronic diseases prevalence, patterns, and co-occurrence is pivotal for effective healthcare planning and disease prevention strategies. There is a need to explore how chronic diseases cluster across different populations, geographical regions, and socio-economic strata (16). The purpose of this study was to use self-reported diagnosed morbidity health condition factors in a latent class analysis (LCA) utilizing data from the WHO-SAGE India Wave 2 to categorize Indian people aged 50 and older according to multi-morbidity risk. This study also looks at the determinants, i.e., socio-demographic, anthropometric, and behavioural factors linked to the multi-morbidity latent classes. This article contributes to the growing body of knowledge by providing an updated overview of chronic diseases' prevalence and the current situation in India. It sheds light on the intricate interplay of these ailments in India and underscores the urgency of addressing their co-occurrence and clustering. By synthesizing existing literature and epidemiological data, this study seeks to shed light on the intricate interplay between chronic conditions, thereby contributing to the design of holistic and context-specific healthcare strategies.

Data and Methods

Data

The data for this study were drawn from the second wave (follow-up of SAGE-1) of the Study on Global Aging and Adult Health (SAGE-Wave 2, 2015) for India. SAGE is a comprehensive survey that assesses various aspects of health and well-being among older adults. The dataset encompasses a wide range of socio-demographic, lifestyle, and health-related variables. The survey was conducted in 2015 in six states of India: Assam, Karnataka, Maharashtra, Rajasthan, Uttar Pradesh, and West Bengal. The SAGE India Wave-2 survey covered 9116 individuals from 8152 households (17). Individuals aged 50 and above were only considered in this study sample. After excluding the samples with missing information, the eligible sample size for the analysis was 6,298 individuals.

Variables

This analysis included nine chronic health conditions namely angina pectoris, arthritis, asthma, chronic lung disease, diabetes mellitus, hypertension, stroke, visual impairment, and depression. All of these conditions (except visual impairment) were assessed through a question about ever being diagnosed with the disease by a health professional. The specific question was, “Have you ever been told by a health professional or doctor that you have (disease name)?” SAGE measured near and distance vision for both eyes using the CAPI-enabled vision test. Near vision was measured using a prescribed distance of 40 centimeters, distance vision was measured at four meters. The respondent was classified as having morbidity if they had two or more morbid conditions simultaneously.

The variables employed in this study include age (categorized into four groups: 50–59 years, 60–69 years, 70–79 years, and 80 years and above), sex (as male and female), marital status (distinguished as those cohabiting and those not cohabiting), education (categorized into four levels: no formal education, less than primary school, secondary school, and college and above), and place of residence (urban and rural). Adding salt at the dining table is coded as yes or no. Individuals' consumption of tobacco and alcohol was coded as "ever" and "never." The variable "Ever Worked" indicates whether the respondent has ever worked or not, categorized as yes or no. Physical activity was categorised as vigorous, moderate, light, or no activity. For self-rated health, the respondents were asked how they would rate their health in general, and the response was categorized as good if they reported (good or very good), moderate, and bad if they reported their health as bad or very bad. The respondents were asked, "Overall, in the last 30 days, how much of a problem did you have with sleeping, such as falling asleep, waking up frequently during the night, or waking up too early in the morning?" and their response was recorded as "none," "mild, "moderate, "severe and "extreme" or "can't do." The sleep quality was coded as good when the response was non-mild and bad if the response was moderate, severe, extreme, or if he couldn't sleep.

Adult health-related physical activity is divided into four categories: vigorous , moderate, light, and no physical inactivity. Individuals who engage in vigorous exercise spend at least 75 minutes per week engaging in activities that cause significant increases in breathing or heart rate, such as heavy lifting, digging, or chopping wood. Individuals who engage in moderately intense exercise that causes small increases in breathing or heart rate, such as brisk walking, carrying light loads, cleaning, cooking, or washing clothes, for at least 150 minutes each week are considered to be engaged in moderate activity. Individuals who engage in a walk or use a bicycle (pedal cycle) for at least 150 minutes a week are considered to have "light physical activity," and no involvement in any of the above categories is considered "no activity." SAGE incorporated a separate health examination and biomarkers module, including measures of anthropometry that measured weight, height, waist (in cm), and hip circumferences (in cm). The BMI values for individuals were categorized as underweight if their BMI was below 18.5, normal if their BMI ranged between 18.5 and 24.9, and overweight or obese if their BMI ranged from 25.0 and above.

The information on the wealth quintile is grouped into five categories: poorest, poorer, middle, richer, and richest. The respondent's caste is categorised into Scheduled Tribes (STs), Scheduled Castes (SCs), Others, and Other Backward Classes (OBC), and their religion is distinguished as Hinduism, Islam, and others based on their religious beliefs. A wealth index was derived from household ownership of durable goods, dwelling characteristics (type of floors, walls, and cooking stoves), and access to services such as improved water, sanitation, and cooking fuel (18). Using a Bayesian post-estimation (empirical Bayes) method, households were arranged on the asset ladder, where the raw continuous income estimates were transformed in the final step into quintiles (17). The SAGE survey focused on six states, Assam, Karnataka, Maharashtra, Rajasthan, Uttar Pradesh, and West Bengal.

Statistical Methods

The bivariate analysis explored associations between pairs of chronic diseases and demographic variables. To uncover latent subgroups of individuals with similar patterns of chronic disease occurrences among the eligible participants, the Latent Class Analysis (LCA) was carried out in STATA (Version 16). Angina, arthritis, chronic lung disease, near/distance vision, asthma, stroke, depression, diabetes, and hypertension were included as observable markers in the current investigation. The Bayesian information criterion (BIC), which has been proven to offer reliable indications of class enumeration with categorical outcomes, was used to identify the ideal number of latent classes (19). The lowest values of the BIC show the model that best fits the data when comparing several feasible class models.

Each participant was classified into one class based on the most significant calculated probability of membership once the best model was chosen. The optimal number of latent classes was determined using the BIC, and three latent classes were considered in the study. The three latent classes were termed "Mild MM risk," "Moderate MM risk," and "Severe MM risk" based on the probabilities of having each of nine chronic conditions with low probability to moderate and severe probability [supplementary Table A].

Multinomial logistic regression was performed to identify the socio-demographic, anthropometric, and behavioural variables linked to observed latent class membership.. The current work uses STATA terminology to refer to multinomial logistic regression. For each explanatory variable, relative risk ratios, 95% CIs, and p values are presented. The outcomes of these analyses will provide valuable insights into the interconnectedness of chronic diseases and inform targeted interventions for improving the health and well-being of older adults in India.

Results

The demographics of the participants are summarised in Table 1a. Most participants fell within the age groups of 50–59 years (43%) and 60–69 years (34%). The study population was almost evenly divided between males and females. The majority of participants reported residing in rural areas (78%), cohabiting (77%), and having no formal education. 67% never smoked, and 88% never consumed alcohol. More than two-thirds of the participants (69%) reported ever working, and 55.74% were physically active. The distribution of BMI indicated that 20% of participants were underweight, 56% had a normal BMI, and 24% were categorized as overweight or obese. The distribution of self-rated health showed that 37% of participants rated their health as good and 49% as moderate. Among participants, 72% reported good sleep quality, while 28% reported bad sleep quality. Participants were distributed across various states, with Uttar Pradesh having the highest representation (21%), and Assam having the least (10%).

[Table 1a]

The study examined the existence of morbidity conditions among the 6,298 respondents. [Table 1b]. The major prevalent morbidity in the sampled respondents is hypertension (24%), followed by arthritis (19%), diabetes (11%), asthma (5%), angina (4%), depression (3%), lung disease (2%) and stroke (2%). Around half of the respondents (52%) reported low near and distance vision. The distribution of participants based on the number of reported morbidities is as follows: 42% reported one, 21% reported two, and 12% reported three or more morbidities. Among the participants, 33% had multiple co-morbidities, while the remaining 67% did not report having multiple co-morbidities.

[Table 1b]

Bivariate analysis explored the relationships between background characteristics and three latent classes [Table 2]. Notably, respondents aged 50–59 were predominantly distributed in moderate MM (61.32%) and severe MM (22.55%), while those aged 80 and above were notably concentrated in minimal MM risk (57.49%). Males were predominantly in moderate MM (49.98%), while females showed a higher distribution in minimal MM risk (35.99%) and severe MM (32.66%). For those with no formal education, rural residents were more likely to belong to the minimal MM risk category, while respondents with college and above education and urban residents were notably present in the severe MM category (48.4%). BMI demonstrated significant clustering. Underweight participants with bad sleep quality were primarily at minimal MM risk (59.12% and 41.21%, respectively), whereas overweight and obese participants were notably concentrated at severe MM (53.1%). Respondents without salt available were predominantly distributed in moderate MM (43.93%), while those with salt available were notably present in severe MM (31.44%). Respondents who had ever smoked were predominantly distributed in moderate MM (41.91%), while alcohol users were notably distributed in severe MM (33.44%). Individuals who ever worked, had vigorous physical activity, and had moderate self-rated health were primarily found in moderate MM (45.86%, 50.08%, and 34.54%, respectively). at the same time, those with bad self-rated health were notably concentrated in minimal MM risk (47.62%). Wealth quantiles exhibited distinctive clustering. The poorest and poorer wealth quantiles were predominantly found in minimal MM risk (53.82% and 43.15%, respectively), while the richest quantile was notably concentrated in severe MM (47.11%).

[Table 2]

[Figure 1]

In the mild MM risk group, the most prevalent diseases were asthma and arthritis, and the major prevalent disease in the moderate MM risk group is low near/distance vision, followed by depression, asthma, and lung disease. Diseases such as angina, diabetes, hypertension, and stroke were the major diseases in the severe MM risk category [Figure 1].

The results obtained from multinomial logistic regression employed to understand the associations between background characteristics and the latent classes are presented in Table 3. Age, sex, marital status, education, BMI, working, physical activity, self-rated health, sleep quality, waist circumference, wealth quintile, caste, and state were significantly associated with moderate MM and severe MM. However, salt availability at the table, alcohol use, ever smoking, and urban residence were significantly associated with an increased risk of having severe MM risk with reference to individuals in the mild MM risk category. In this multinomial logit model, we used the mild MM risk group as the reference. Individuals with higher ages were at increased risk of having moderate MM risk OR: 1.18*** (1.16–1.19) and severe MM risk OR: 1.15*** (1.13–1.16). Females were 3.36% more likely to have a moderate relative risk ratio (RRR: 3.36*** CI: 2.67–4.25) and 2.82 times more likely to have severe MM risk (RRR: 2.82*** CI: 2.19–3.61). Individuals with higher education were 2.51 times more likely to belong to the severe MM class and 83% less likely to belong to the severe MM class relative to the minimal MM risk group. Being obese or overweight was associated with a twice higher likelihood of being in the severe group. Bad self-rated was associated with an 8-fold higher likelihood of being in the moderate MM risk group and a 16-fold greater likelihood of being in the severe group. Individuals in the highest wealth quintile were more likely to belong to the severe MM class than those in the poorest wealth quintile. Residing in an urban area, smoking, alcohol consumption, not working ever, OBC, and other castes were associated with an increased likelihood of being in the severe group.

[Table 3]

Discussion

This study show that the prevalence of single morbidity was the highest (42%), while the coexistence of morbidity was prevalent in 32% of the sampled individuals. The LCA model's application significantly reduced the complexity of the data and enabled us to identify significant variations across the multimorbid population's subgroups. The LCA grouped our sample of men and women over the age of 50 and above into three groups: mild MM risk (30%), moderate MM risk (41%), and severe MM risk (29%). In the mild MM risk group, the most prevalent diseases were asthma and arthritis, and the major prevalent disease in the moderate MM risk group was low near/distance vision, followed by depression, asthma, and lung disease. Diseases such as angina, diabetes, hypertension, and stroke were the major diseases in the severe MM risk category. The presence of these various non-communicable diseases in the study region could indicate that they share common risk factors, have a similar pattern of occurrence, or are linked causally (20). Previous research that employed the LCA technique to explain patterns of chronic illness coexistence in older populations has produced varied findings regarding the number of clusters found. For instance, two latent class clusters, namely low co-morbidity and hypertension-diabetes-arthritis, were identified in a study conducted in India based on individuals aged 15–64 years (21). A study reported six clusters, i.e., "relatively healthy", "hypertension", "gastrointestinal disorders-hypertension-musculoskeletal disorders", "musculoskeletal disorders-hypertension-asthma", "metabolic disorders", and "complex cardiometabolic disorders" using data from the Longitudinal Ageing Study in India, 2017–2018, among individuals aged 45 years and above (22). Similar to our findings, a study conducted in South Africa reported three groups: minimal MM risk, concordant (hypertension and diabetes), and discordant (angina, asthma, chronic lung disease, arthritis, and depression) (23). A similar study conducted in Jamaica revealed four distinct profiles: a relatively healthy class (52.70%), with a single or no morbidity, and three multimorbid classes, i.e., metabolic (30.88%), vascular-inflammatory (12.21%), and respiratory (4.20%) (Craig et al., 2021) and other parts of the world (20).

Very few studies have been conducted in India to understand the prevalence and predictors of multi-morbidity in India using probability-based classification of chronic disease coexistence (21,22). It is challenging to compare these studies since the results may differ depending on the number and kind of diseases included in the study, the characteristics of the sample, or the methodology used to gather disease data. Previous studies have reported higher chances of individuals being in the "Hypertension-Diabetes-Arthritis" group (21) and latent classes with a higher prevalence of diabetes and hypertension (22). Compared with the mild MM risk group, an increase in age, being female, and not cohabitating were associated with belonging to the moderate MM group, while tobacco use and an increase in age were associated with belonging to the severe MM group. In line with the previous findings, higher age was significantly associated with an increased relative risk of being at moderate or severe MM risk (20,22,23,24,25).

The unequal gender distribution within the moderate and severe latent classes is also noteworthy , women are more likely to fall into the moderate and severe MM risk categories, pointing to gender-specific variations in life course trajectories of health. This finding is supported by studies conducted in different settings (20,26). Studies conducted in Jamaica (25,27,28) and the broader Caribbean region (29) have also found that women are more likely to be affected by various non-communicable diseases (NCDs), which is why they also bear a higher burden of having multiple chronic conditions. While this could be attributed to several factors, such as women seeking healthcare more readily and getting diagnosed earlier, the exact causes of this gender disparity are still unknown and need further exploration. The United Nations projected that Indians over the age of 60 would double by 2050, constituting almost 19.6 percent of the total population (30). To enhance healthcare and social service planning and improve the health and quality of life for the elderly in India, it would be beneficial to study the burden and socio-economic distribution of multi-morbidity in this population.

The majority of the individuals in the moderate and severe MM risk categories point towards long-term healthcare facilities, highlighting the potential for improved healthcare systems to accommodate the individuals needing care. The higher prevalence of asthma in moderate MM risk groups highlights the necessity for smoking prevention and cessation initiatives that specifically target this demographic. Poor environmental conditions, such as air pollution, continue to be a significant indicator of multiple health conditions in low- and middle-income countries (LMICs) (31). Arthritis, which is highly prevalent in the moderate MM class, generally has a multi-factorial aetiology and is considered a product of an interplay between systemic and local factors (32). Since the number of individuals with arthritis is likely to increase shortly due to population aging, it will have a growing impact on healthcare and public health systems in the future. The preponderance of angina, diabetes, hypertension, and stroke in the severe MM risk group supports the idea that there could be common physiological mechanisms involved, where the existence of one condition raises the likelihood of another, either due to shared environmental or biological risk factors (33).

In keeping with previous literature, study found that increased waist and hip circumference also exacerbated the risk of falling into moderate and severe MM risk categories (34). The impeccable association between an unhealthy eating pattern, obesity, being overweight, and morbidity is widely recognized (35,36). Different modifiable lifestyle factors, such as smoking, alcohol intake, consumption of fruits and vegetables, physical activity, and risk factors like obesity (measured by BMI), have all been linked to multi-morbidity (37). The clustering of diseases as shown by LCA highlights the importance of integrated disease management in primary care settings. Clinicians, decision-makers, and researchers must prioritize the requirements and care procedures for patients living with or at risk of multi-morbidity based on the clustering of multi-morbidity and lifestyle risk factors. Patients diagnosed with a disease in primary care may be periodically tested for additional chronic illnesses as per the clusters of the disease identified. Increased access to high-quality healthcare services, particularly in primary healthcare settings where many people with multi-morbidity go years without receiving a diagnosis and most of those receiving treatment frequently experience uncontrolled disease.

Limitations

This study looks at latent classes of a wide range of chronic illnesses in a large, nationwide sample with a representative age distribution, using a relatively recent and reasonable approach to identify the multi-morbidity pattern. But some restrictions need to be made clear. A longitudinal analysis over a long period is required to estimate the incidence of transitions between latent classes and to identify characteristics associated with the development of multi-morbidity of increasing severity because the cross-sectional nature of the data used precludes drawing any conclusions about the temporality or causation between the chronic diseases under investigation. Second, some self-reported ailments served as the study's foundation. Therefore, if clinical data or information about other chronic conditions had been available, the patterns of multi-morbidity may have changed. In our study, we examined nine chronic diseases that have the potential to be fatal or restrict daily activities and were included in the SAGE Study. However, participants may have had other chronic diseases that were not included in the list. To improve overall relevance, future studies are suggested to encompass a broader range of chronic diseases. Though there are restrictions, the results of this study strongly support the importance of examining multi-morbidity patterns with LCA. Moreover, replicating these results in another sample further boosts confidence in their applicability.

Conclusions

Since understanding multi-morbidity can help in developing more efficient strategies for treatment and prevention, this study reveals different population segments with distinct disease patterns. Detecting emerging pathophysiological patterns in older adults as they accumulate multiple health conditions can be crucial for preventing and managing multi-morbidity. Identifying these patterns at an early stage is important to intervene effectively and address the underlying factors contributing to developing other diseases. By recognizing and addressing these patterns, healthcare professionals can implement preventive measures and tailor interventions to help reduce the risk of another disease in older adults. It is necessary to customize treatment plans for patients belonging to different multi-morbidity categories, to strengthen the health and wellness centers, to strengthen and deliver comprehensive primary health care (PHC) services for the entire population, and to implement the Pradhan Mantri Jan Arogya Yojana (PMJAY) for secondary and tertiary level hospitalization services. Dealing with multi-morbidity poses a challenge for managing the treatment burden for individuals with multiple diseases. The current healthcare system, which is fragmented and specialized, needs to incorporate and strengthen prevention and public health strategies as per the healthcare needs of patients from different disease segments. Furthermore, the multimorbid segments generally have less favourable socio-demographic characteristics compared to the relatively healthy group. Therefore, effective and high-quality care for multimorbid patients should integrate healthcare and social care beyond individual silos.

Declarations

Competing interest

The authors declare that they have no competing interest

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Data sharing statement

This study uses secondary data which is available on request through https://www.iipsindia.ac.in/content/lasi-wave-i

Ethics approval

SAGE was approved by the World Health ' 'Organization's Ethical Review Committee. Additionally, partner organizations in each country implementing SAGE obtained ethical clearance through their respective institutional review bodies.

Consent to participate

Not applicable

Consent for publication

Not applicable

Contributor statement

SS, and NS, Conceived and designed the research paper. SS analyzed the data. NS wrote the manuscript. All authors reviewed the manuscript.

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Informed consent

Written informed consent was obtained from all study participants.

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Table 1a: Descriptive statistics of participants characteristics, SAGE, Wave-2, 2015

Background Characteristics		**Frequency**	**Percentage (%)**
Age (in years)	50-59	2,620	42.95
	60-69	2,318	36.67
	70-79	1,107	16.57
	80+ and above	253	3.81
Sex	Male	2,954	49.88
	Female	3,344	50.12
Marital Status	Cohabiting	4,752	77.34
	Not-cohabiting	1,546	22.66
Education	No formal education	3,139	46.72
	Less than primary	1,709	27.56
	Secondary school	1,102	19.21
	College and above	348	6.51
Body Mass Index (BMI)	Underweight	1,655	20.2
	Normal	3,461	55.47
	Overweight/Obese	1,182	24.33
Salt available at dining table	No	1,803	28.71
	Yes	4,495	71.29
Smoking	Never	4,158	66.47
	Ever	2,140	33.53
Alcohol consumption	Never	5,585	88.3
	Ever	713	11.7
Ever Worked	Yes	4,220	68.51
	No	2,078	31.49
Physical activity	Vigorous Activity	1,036	16.59
	Moderate Activity	1,619	25.02
	Light Activity	874	14.13
	No Activity	2,769	44.26
Self-rated Health	Good	2,216	36.58
	Moderate	3,073	48.45
	Bad	1,009	14.97
Sleep Quality	Good	4,479	71.9

	Bad	1,819	28.1
Waist Circumference	Mean ± SD		85.17±11.48
Hip Circumference	Mean ± SD		90.88±10.19
Wealth Quantiles	Poorest	1,195	17.23
	Poorer	1,155	17.49
	Middle	1,166	17.86
	Richer	1,303	21.09
	Richest	1,479	26.34
Place of Residence	Rural	5,012	77.89
	Urban	1,286	22.11
Caste	Scheduled tribe	471	7.14
	Scheduled caste	1,029	15.29
	Others	1,888	30.95
	OBC	2,910	46.61
Religion	Hinduism	5,277	83.57
	Islam	779	12.41
	Others	242	4.02
State	Assam	661	10.19
	Karnataka	693	11.33
	Maharashtra	1,059	17.45
	Rajasthan	1,295	21.57
	Uttar Pradesh	1,346	20.72
	West Bengal	1,244	18.74
Total		6,298	

Table 1b: Descriptive statistics of type of morbidity prevalent among the participants, SAGE, Wave-2, 2015

Morbidity condition		Frequency	Percentage (%)
Angina	No	6,079	96.25
	Yes	219	3.75
Arthritis	No	5,089	80.58
	Yes	1,209	19.42
Asthma	No	5,952	94.63
	Yes	346	5.37
Diabetes	No	5,655	88.63
	Yes	643	11.37
Hypertension	No	4,884	76.15
	Yes	1,414	23.85
Lung Disease	No	6,150	97.70
	Yes	148	2.30
Stroke	No	6,149	97.53
	Yes	149	2.47
Vision	Normal	2,893	47.72
	Low near/distance vision	3,405	52.28
Depression	No	6,142	97.49
	Yes	156	2.51
Number of morbidities	0	1,562	25.14
	1	2,739	42.32
	2	1,294	20.91
	3	502	8.26
	4	157	2.57

		5	40	0.73
		6	1	0.01
		7	2	0.03
		8	1	0.01
Have Multi-morbidity	No		4,301	67.46
	Yes		1,997	32.54
Total			6,298	

Table 2: Characteristics of participants by latent class category (n=6,298), SAGE, Wave-2, 2015

Background Characteristics		Moderate MM Risk	Mild MM Risk	Severe MM Risk	*p-value*
Age (in years)	50-59	16.13	61.32	22.55	<0.01
	60-69	33.51	34.82	31.67	
	70-79	53.39	12.96	33.65	
	80+ and above	57.49	1.34	41.17	
Sex	Male	24.48	49.98	25.53	<0.01
	Female	35.99	32.66	31.34	
Marital Status	Cohabiting	25.43	48.02	26.55	<0.01
	Not-cohabiting	46.72	18.37	34.91	
Education	No formal education	45.29	34.87	19.84	<0.01
	Less than primary	24.63	44.71	30.67	
	Secondary school	10.88	49.72	39.41	
	College and above	3.37	48.22	48.4	
Body Mass Index (BMI)	Underweight	59.12	32.71	8.17	<0.01
	Normal	28.48	46.51	25.01	
	Overweight/Obese	10.32	36.58	53.1	
Salt available at dining table	No	33.78	34.79	31.44	<0.01
	Yes	28.83	43.93	27.24	
Smoking	Never	29.03	40.99	29.97	<0.01
	Ever	32.67	41.91	25.42	
Alcohol consumption	Never	31.23	40.98	27.78	<0.01
	Ever	22.84	43.72	33.44	
Ever Worked	Yes	28.91	45.86	25.23	<0.01
	No	33.17	31.4	35.43	
Physical activity	Vigorous Activity	27.48	50.08	22.44	<0.01
	Moderate Activity	34.43	33.65	31.92	
	Light Activity	28.09	44.53	27.38	
	No Activity	29.62	41.31	29.07	
Self-rated Health	Good	17.26	62.22	20.52	<0.01
	Moderate	34.69	34.54	30.76	
	Bad	47.62	12.06	40.33	
Sleep Quality	Good	25.97	49.27	24.76	<0.01
	Bad	41.21	20.93	37.86	
Waist Circumference	Mean ± SD	81.00±10.15	84.20±10.38	92.34±11.50	
Hip Circumference	Mean ± SD	87.34±9.03	90.47±9.20	96.31±10.84	
Wealth Quantiles	Poorest	53.82	34.88	11.3	<0.01
	Poorer	43.15	39.08	17.77	
	Middle	34.1	43.02	22.89	

	Richer	21.68	45.62	32.7	
	Richest	10.53	42.36	47.11	
Place of Residence	Rural	34.96	43.04	22	<0.01
	Urban	13.65	35.19	51.16	
Caste	Scheduled tribe	33.11	52.55	14.34	<0.01
	Scheduled caste	36.93	41.13	21.95	
	Others	24.94	41.06	34	
	OBC	31.15	39.8	29.05	
Religion	Hinduism	30.47	42.12	27.42	<0.01
	Islam	33.63	33.3	33.06	
	Others	15.37	49.05	35.59	
State	Assam	14.67	47.12	38.21	<0.01
	Karnataka	25.48	35.2	39.33	
	Maharashtra	25.55	47.15	27.3	
	Rajasthan	25.29	48.46	26.25	
	Uttar Pradesh	43.6	38.77	17.63	
	West Bengal	36.94	30.95	32.11	
Total		**30.25**	**41.3**	**28.45**	

Figure 1: Latent class membership of morbidity condition, SAGE, Wave 2,2015

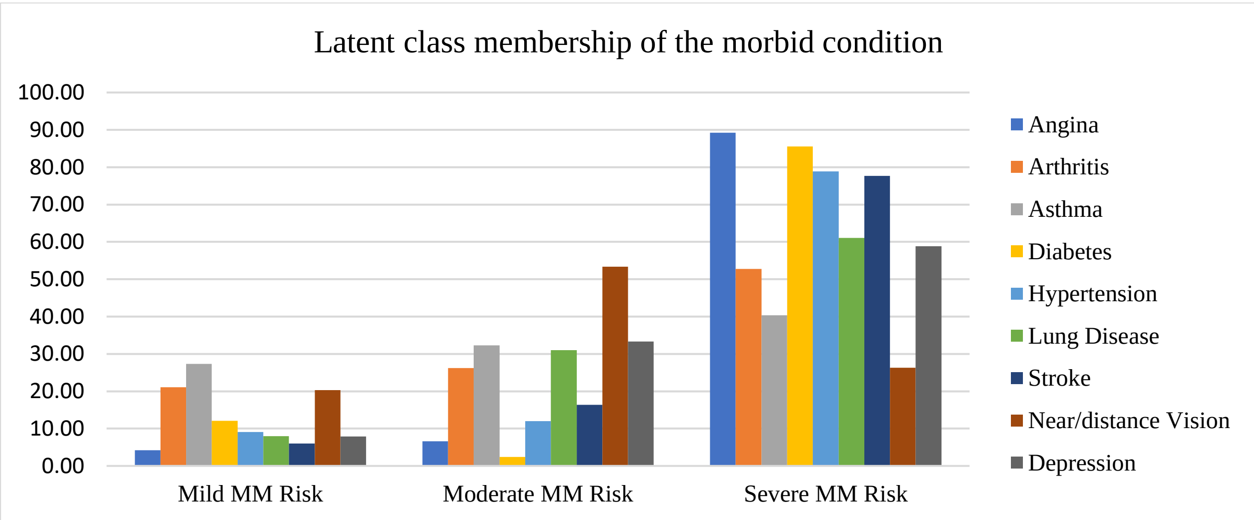

Table 3: Multinomial logistics regression analysis for factors associated with LCA-based multi-morbidity clusters as the exposure (Relative Risk Ratios and 95% CI), SAGE, Wave-2, 2015

Reference (Mild MM risk)		Relative Risk Ratios	Relative Risk Ratios
Background Characteristics		**Moderate MM Risk**	**Severe MM Risk**
Age (in years)		1.18***(1.16-1.19)	1.15***(1.13-1.16)
Sex	Male®		
	Female	3.36***(2.67-4.25)	2.82***(2.19-3.61)
Marital Status	Cohabiting®		

	Not-cohabiting	2.13***(1.74-2.62)	2.31***(1.86-2.88)
Education	No formal education®		
	Less than primary	0.59***(0.48-0.72)	1.62***(1.3-2.01)
	Secondary school	0.28***(0.21-0.37)	2.2***(1.71-2.84)
	College and above	0.11***(0.06-0.21)	2.51***(1.72-3.67)
Body Mass Index (BMI)	Underweight®		
	Normal	0.41***(0.33-0.5)	1.27*(0.97-1.66)
	Overweight/Obese	0.17***(0.12-0.25)	1.89***(1.32-2.72)
Salt available at dining table	No®		
	Yes	0.88 (0.73-1.06)	0.77**(0.63-0.95)
Smoking	Never®		
	Ever	0.96 (0.8-1.15)	1.34***(1.1-1.63)
Alcohol consumption	Never®		
	Ever	1.21 (0.91-1.6)	2.24***(1.71-2.93)
Ever Worked	Yes®		
	No	0.82*(0.66-1)	1.73***(1.38-2.16)
Physical activity	Vigorous Activity®		
	Moderate Activity	1.11 (0.87-1.42)	0.99 (0.76-1.28)
	Light Activity	0.77*(0.58-1.03)	0.73**(0.54-0.99)
	No Activity	0.74**(0.59-0.94)	0.61***(0.48-0.79)
Self-rated Health	Good®		
	Moderate	2.98***(2.51-3.55)	3.56***(2.96-4.28)
	Bad	7.61***(5.72-10.12)	15.56***(11.49-21.08)
Sleep Quality	Good®		
	Bad	2.61***(2.18-3.14)	3.06***(2.53-3.7)
Waist Circumference	Mean ± SD	1.03***(1.02-1.05)	1.08***(1.06-1.1)
Hip Circumference	Mean ± SD	1 (0.98-1.02)	1 (0.98-1.01)
Wealth Quantiles	Poorest®		
	Poorer	0.86 (0.68-1.09)	1.15 (0.83-1.6)
	Middle	0.6***(0.47-0.77)	1.2 (0.88-1.65)

	Richer	0.38***(0.3-0.49)	1.54***(1.13-2.09)
	Richest	0.26***(0.19-0.34)	2***(1.46-2.73)
Place of Residence	Rural®		
	Urban	0.92 (0.72-1.17)	1.97***(1.61-2.4)
Caste	Scheduled tribe®		
	Scheduled caste	1.29 (0.93-1.79)	1.99***(1.33-3)
	Others	1.42**(1.03-1.96)	1.9***(1.3-2.79)
	OBC	1.71***(1.26-2.31)	2.54***(1.74-3.7)
Religion	Hinduism®		
	Islam	1.04 (0.81-1.35)	1.63***(1.26-2.11)
	Others	0.64*(0.4-1.02)	1.33 (0.9-1.97)
State	Assam®		
	Karnataka	3.18***(2.16-4.7)	0.8 (0.56-1.13)
	Maharashtra	2.55***(1.78-3.65)	0.44***(0.32-0.61)
	Rajasthan	2.23***(1.58-3.15)	0.5***(0.36-0.68)
	Uttar Pradesh	6.75***(4.77-9.55)	0.24***(0.17-0.34)
	West Bengal	6.18***(4.34-8.79)	0.55***(0.39-0.76)

Supplementary Table A: Latent class analysis fit statistics

Number of latent classes	Number of observations	LL	DF	AIC	BIC
Two class	6,298	-16579.8	38	33235.64	33492.06
Three class	**6,298**	**-16336.7**	**67**	**32807.37**	**33259.49**
Four class	6,298	-16372.5	94	32933.01	33567.32
Five class	6,298	-16290	117	32814.07	33603.58
Six class	6,298	-16227.8	153	32761.59	33794.04
Seven class	6,298	-16069.5	180	32499	33713.64
Eight class	6,298	-16060.2	206	32532.37	33922.46
Nine class	6,298	-16037.7	237	32549.45	34148.73

AIC-Akaike Information Criterion, BIC-Bayesian Information Criterion, DF-degrees of freedoms, LL-Log Likelihood