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The Predictors of Multimorbidity (defined as diabetes + hypertension) Amongst Males Aged 15-54 in India: An Analysis of the NFHS-5

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Abstract

Research Question: "What are the predictors of multimorbidity (defined as having diabetes + hypertension) amongst males aged 15-54 in India?"

Methods: Using mixed-effect multi-level binary logistic regression models, data from the 2019-2021 India NFHS-5 were analyzed. Separate multivariable analyses were conducted for males from urban and rural areas so the association between common predictors of interest (sociodemographic & lifestyle), and multimorbidity could be determined.

Results: Various predictors (listed below) were found to have a statistically significant association to multimorbidity with some variation across urban and rural areas:

Urban areas: Age, region of residence, wealth, religion, occupation, and BMI.

Rural areas**:** Age, education, region of residence, wealth, occupation, caste, BMI, alcohol consumption, media exposure, and tobacco consumption.

Conclusion: Findings from this study may have possible implications for policymakers across India. With high-risk characteristics that are predictive of multimorbidity being identified, preventative and healthcare strategies may be improved.

Keywords

India, Multimorbidity, Diabetes and hypertension multimorbidity, NFHS-5, National Family Health Survey-5, Predictors, Predictors of multimorbidity, Male multimorbidity

Summary for Lay Audience

Multimorbidity, commonly defined as the co-existence of two or more health conditions within an individual, has been a growing concern in India due to its associated challenges and burdens. With many different combinations of conditions being possible, specific combinations have emerged as being of greater concern. One such example is diabetes and hypertension. Both conditions have been found to be rapidly growing, with their multimorbidity becoming one of the most prevalent in India. More specifically, research has also found that males may be at a greater risk for both conditions with additional reports of increased prevalence when compared to females. Therefore, it has become of interest to determine which characteristics of the population, such as sociodemographic and/or lifestyle factors, may contribute to or protect against this specific multimorbidity. By understanding the association these factors share with multimorbidity, their role as a 'predictor' of the health outcome can be better understood. This thesis aimed to investigate and answer the following research question: "What are the predictors of multimorbidity (defined as diabetes + hypertension) amongst males aged 15-54 in India?"

Using the 2019-2021 India National Family Health Survey as a nationally representative data source, males aged 15-54 from urban and rural areas were analyzed separately. After employing relevant statistical methods, the direct association between each predictor of interest and multimorbidity was determined. Both urban and rural areas had statistically significant findings with the following factors being found to be predictors of multimorbidity.

Urban areas: Age, region of residence, wealth, religion, occupation, and BMI.

Rural areas**:** Age, education, region of residence, wealth, occupation, caste, BMI, alcohol consumption, media exposure, and tobacco consumption.

What these findings suggest is that various sociodemographic and lifestyle factors exist among men in both urban and rural areas of India that may be used to better predict diabetes and hypertension multimorbidity outcome. Policymakers across India should take these findings into consideration to further improve preventative and healthcare strategies and possibly reduce multimorbidity-related burden.

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Table of Contents

Abstract ii

Summary for Lay Audience iii

Acknowledgments iv

Table of Contents v

List of Tables ix

List of Figures x

List of Abbreviations xi

Chapter 1 1

1 Introduction 1

1.1.1 Structure of Thesis 3

Chapter 2 4

2 Literature review 4

2.1 Background information regarding India 4

2.1.1 Geography 4

2.1.2 Population demographics 6

2.1.3 Economy 8

2.1.4 Health status and issues 8

2.2 Multimorbidity 12

2.2.1 Definition of multimorbidity 12

2.2.2 Common disease patterns in multimorbidity 14

2.2.3 Prevalence of multimorbidity in India 15

2.2.4 Burden of multimorbidity 20

2.2.5 Diabetes & hypertension multimorbidity in India 25

2.3 Predictors of multimorbidity 31

2.3.1 Summary of studies relevant to predictors ... 31
2.3.2 Predictors of multimorbidity in India ... 37
2.4 Current state of literature ... 45
2.4.1 Gaps in the literature ... 46
2.5 Current study ... 49
2.5.1 Rationale and objectives of study ... 49
2.5.2 Research question ... 49
Chapter 3 ... 50
3 Methods ... 50
3.1 Source of data ... 50
3.1.1 Survey of interest – (NFHS-5) ... 51
3.1.2 Survey sampling design ... 51
3.1.3 Study population ... 52
3.1.4 Ascertainment of final dataset ... 52
3.1.5 Relevant institutions and permissions ... 53
3.2 Study framework ... 53
3.3 Defining variables ... 55
3.3.1 Dependent variable ... 55
3.3.2 Independent variables ... 60
3.4 Statistical methods ... 67
3.4.1 Software ... 67
3.4.2 Merging datasets ... 67
3.4.3 Missing data ... 68
3.4.4 Statistical analysis ... 70
Chapter 4 ... 73
4 Results ... 73

4.1 Univariate analysis 73
4.1.1 Distribution of multimorbidity 73
4.1.2 Distribution of sociodemographic factors 73
4.1.3 Distribution of lifestyle factors 75
4.2 Urban Area - bivariate & multivariable analysis 78
4.2.1 Sociodemographic factors 78
4.2.2 Lifestyle predictors 79
4.2.3 Characteristics of urban area multi-level model 80
4.3 Rural Area - bivariate & multivariable analysis 83
4.3.1 Sociodemographic factors 83
4.3.2 Lifestyle predictors 84
4.3.3 Characteristics of rural area multi-level model 85
4.4 Multivariable analysis comparison urban vs. rural 88
Chapter 5 92
5 Discussion 92
5.1 Summary of study findings 92
5.1.1 Univariate analysis 92
5.1.2 Statistically significant predictor-MM associations 93
5.2 Interpretation of findings 94
5.2.1 Findings consistent with literature 94
5.2.2 Findings inconsistent with literature 100
5.2.3 Insignificant Predictors 102
5.3 Study contribution and Implications for Policy and Practice 103
5.4 Limitations 106
5.4.1 Data 106
5.4.2 Methodological 107

5.5 Future research 108

5.6 Conclusion 109

References 110

Permission(s)/License(s) 131

Curriculum Vitae 133

List of Tables

Table 1: Summary of studies reviewed for predictors of multimorbidity in India 31

Table 2: Categories of independent variables (predictors) 65

Table 3: Missing data summary for diabetes and hypertension variables 68

Table 4: Summary of missing data for the dependent and independent variables.................. 69

Table 5: Univariate analysis of dependent and independent variables split by urban and rural areas. 76

Table 6: Bivariate and multivariable analyses of sociodemographic & lifestyle predictors of multimorbidity for urban area residents (n=22,411)... 81

Table 7: Bivariate and multivariable analyses of sociodemographic & lifestyle predictors of multimorbidity for rural area residents (n=66,768). 86

Table 8: Comparison of significant multivariable analysis findings between urban and rural areas - sociodemographic and lifestyle predictors of multimorbidity. 88

List of Figures

Figure 1: Map of India (States and Union Territories) 5

Figure 2: Multimorbidity prevalence distribution - urban and rural areas of India 17

Figure 3: Aging population multimorbidity prevalence variations across states/union territories 19

Figure 4: Prevalence of diabetes across urban and rural areas 26

Figure 5: Prevalence of hypertension across urban and rural areas.. 28

Figure 6: Analytical framework.. 54

Figure 7: Criteria used to define possible cases of multimorbidity. 59

List of Abbreviations

ABPM	Ambulatory Blood Pressure Monitoring
AHRQ	Agency for Healthcare Research and Quality
BMI	Body Mass Index
CARRS	Cardiometabolic Risk Reduction in South Asia Surveillance
CEB	Census Enumeration Block
CD	Communicable Disease
CHARLS	China Health and Retirement Longitudinal Study
CI	Confidence Interval
CRD	Chronic Respiratory Disease
CVD	Cardiovascular Disease
DALY	Disability Adjusted Life Year
DHS	Demographic and Health Surveys
EGPRN	European General Practice Research Network
GDP	Gross Domestic Product
HBPM	Home Blood Pressure Monitoring
ICC	Intraclass Correlation Coefficient
IIPS	International Institute for Population Sciences
LASI	Longitudinal Ageing Study in India
LMICs	Low- and Middle-income Countries
LRT	Likelihood Ratio Test
MCA	Multiple Correspondence Analysis
MCAR	Missing Completely at Random

MCPE	Monthly per Capita Consumption-Expenditure
MM	Multimorbidity
MoHFW	Ministry of Health and Family Welfare
NCD	Non-Communicable Disease
NFHS	National Family Health Survey
NSS	National Sample Survey
OBC	Other Backward Class
OOPE	Out-of-Pocket Expenditure
PCA	Principle Components Analysis
PPS	Probability Proportional to Size
PSU	Primary Sampling Unit
SC	Scheduled Caste
SES	Socioeconomic Status
ST	Scheduled Tribe
TB	Tuberculosis
TV	Television
UNFPA	United Nations Population Fund
USAID	United States Agency for International Development
WHO	World Health Organization
WHO-SAGE	World Health Organization Study on Global Ageing and Adult Health

Chapter 1

1 Introduction

Multimorbidity, which is commonly defined as the coexistence of two or more chronic health conditions in an individual (WHO, 2016), has become a public health concern across India. In recent decades India has continued to experience rapid urbanization and economic development, causing a health and epidemiological transition (Basto-Abreu et al., 2022; Luna & Luyckx, 2020). Characteristics of this transition include changing lifestyles, decreases in overall mortality rates, and increases in life expectancy (Narain, 2016; Nethan & Mehrotra, 2017; Yadav & Arokiasamy, 2013). These changes have contributed to uncontrolled increases in the prevalence of non-communicable diseases (NCDs). NCDs have thus caused drastic increases in morbidity rates and have also been linked to nearly 60% of all deaths in India (Nethan & Mehrotra, 2017; MOHFW, 2022). Furthermore, as individuals are now generally living longer, an increasing number of individuals are also being diagnosed with multiple NCDs causing a surge in the prevalence of multimorbidity.

This rapid increase in multimorbidity prevalence has been especially alarming due to its associated burdens. Those affected by multimorbidity typically experience a reduction in quality of life due to factors such as disability, polypharmacy, and financial strain (Rosbach & Andersen, 2017; Sum et al., 2018). This burden also goes beyond the individual level, because there are further implications for the health systems of India. Those diagnosed often have increased medical needs due to complex disease interactions (Johnston et al., 2018). This results in more resource-intensive treatments with individuals requiring patient-centered approaches for their healthcare (Prathapan et al., 2020; Balakrishnan et al., 2022). Unfortunately, India's healthcare systems are currently not well suited to handle such comprehensive treatments as they have historically taken a more vertical approach to care (Balakrishnan et al., 2022; Pati et al., 2014; Prenissl et al., 2022; Singh et al., 2018). Within vertical care, programs and healthcare providers tend to focus resources and effort on the solution of individual conditions, rather than taking a more holistic approach (Mournier-Jack et al., 2017; Druetz, 2018; Kirwin et al., 2022).

As such, predictors of multimorbidity have become a topic of interest for researchers. Many relevant studies have chosen to broadly analyze various population characteristics such as sociodemographic and lifestyle factors to determine if they may have a protective or risk-increasing effect on multimorbidity outcomes. Such findings may benefit relevant policymakers and healthcare providers to better approach multimorbidity.

However, most of the existing research regarding predictors of multimorbidity has been general. Studies have chosen to consider broad operational definitions and therefore there exists great heterogeneity in the number of and types of conditions considered (Debsarma et al., 2022; Puri & Singh, 2022; Mishra et al., 2021; Singh et al., 2018; Puri et al., 2021a; Puri et al., 2021b; Khan et al., 2022; Chauhan et al., 2022b; Prenissl et al., 2022). Due to this, the significance and effect of commonly analyzed predictors may not apply to all combinations of conditions in multimorbidity. Studies have placed minimal emphasis on determining what the predictors of specific multimorbidities may be, even though it has been well-established that there are specific combinations of conditions emerging that are of increased concern (Rajoo et al., 2021; Zhang et al., 2022; Roberston et al., 2022).

Of particular interest is the combination of diabetes and hypertension, which are each respectively two of the fastest-growing chronic health conditions in India (Anjana et al., 2023; Puri et al., 2021a; Pradeepa & Mohan, 2021; Geldsetzer et al., 2018; Anchala et al., 2014). Both conditions have been found to share an associative pattern, commonly appearing in multimorbidity diagnoses and together being one of the most prevalent multimorbidities (Mini & Thankappan, 2017, Prenissl et al., 2022; Sinha et al., 2022b; Rajoo et al., 2021; Zhang et al., 2022; Roberston et al., 2022). More specifically, this is of concern amongst the male population who have been estimated to have increased odds and prevalence of both conditions (when compared to females) (Neupane et al., 2014; Jayawardena et al., 2012; Anjana et al., 2023).

Therefore, there exists an evident gap in knowledge that could be filled to better inform relevant parties across India. By gaining knowledge regarding high-risk characteristics for some of the more prevalent multimorbidity condition combinations, some burden may be alleviated. This study aimed to investigate the predictors of multimorbidity (defined as diabetes + hypertension) amongst males in India. To carry out this research, this study utilized data from the 2019-2021 National Family Health Survey, which contains health-related information pertaining to a national sample of males aged 15-54 (IIPS & ICF, 2021).

1.1.1 Structure of Thesis

This thesis is organized into five chapters: 1) Introduction, 2) Literature Review, 3) Methods, 4) Results, and 5) Discussion.

Chapter two, the literature review, builds on this chapter. Presented is contextual information regarding India with a more in-depth review of what is currently known regarding multimorbidity in terms of prevalence, common combinations of conditions, and associated burdens. Diabetes and hypertension are further explored and discussed. What follows is a review of relevant studies from which trends regarding the effects of common predictors of multimorbidity are summarized. Chapter two concludes by summarizing the evident gaps in the literature to produce this study's research question. Chapter three then details the research methods utilized within this study to answer the research question. Described within this chapter are the datasets utilized, operational definitions of the independent and dependent variables analyzed, and all relevant statistical methods. Chapter four presents this study's findings from all statistical analyses completed including univariate, bivariate, and multivariable analyses. Lastly, chapter five concludes this thesis. This chapter opens with a summary and interpretation of findings in which a comparison is made to existing literature. This chapter then ends with a brief description of how the thesis contributes to literature, its implications, study limitations, and possible future research.

Chapter 2

2 Literature review

In this chapter, information pertaining to India, multimorbidity, its predictors, and the purpose/objectives of this study are discussed. Section 2.1 begins by introducing background information regarding India and its current health status. Next, section 2.2 provides contextual information regarding multimorbidity and its presence in India with a focus on diabetes and hypertension multimorbidity. Section 2.3 describes the literature regarding previously studied predictors of multimorbidity. Section 2.4 highlights the current state of the literature and the gaps that currently exist. Lastly, section 2.5 explains the rationale of this study, summarizing what the objectives are and what we aim to contribute. The literature databases utilized were Google Scholar and PubMed. Amongst these databases, only relevant journals, papers, reports, and articles written/available in English were considered.

2.1 Background information regarding India

2.1.1 Geography

Situated in the southern region of Asia, The Republic of India, more commonly referred to as India, is a country that first became an independent nation on August 15th, 1947. During this time, geographical boundaries were defined through a partition that divided the British Raj into India and Pakistan. The partitioning left India as the 7th largest country in the world, covering approximately 3,287,782 km^2 of area within southern Asia (Nag & Sengupta, 1992). India's borders feature over 7,500 km of coastline along with approximately 15,100 km of land borders (Saddiki, 2017; Das, 2010). The countries that border the geographic land area of India are Pakistan, China, Afghanistan, Nepal, Myanmar, Bangladesh, and Bhutan. Additionally, there is maritime bordering with Sri Lanka, Pakistan, Indonesia, Thailand, Myanmar, Bangladesh, and Maldives. Within India, there are 36 entities that comprise the nation known as states (n=28) and union territories (n=8) (Boland-Crewe & Lea, 2022; Gov. India, n.d.).

The 28 states consist of: Andhra Pradesh, Arunachal Pradesh, Assam, Bihar, Chhattisgarh, Goa, Gujarat, Haryana, Himachal Pradesh, Jharkhand, Karnataka, Kerala, Madhya Pradesh, Maharashtra, Manipur, Meghalaya, Mizoram, Nagaland, Odisha, Punjab, Rajasthan, Sikkim, Tamil Nadu, Telangana, Tripura, Uttar Pradesh, Uttarakhand, and West Bengal.

The 8 union territories consist of: Andaman and Nicobar Islands, Chandigarh, Dadra and Nagar, Delhi, Jammu & Kashmir, Lakshadweep, Ladakh, and Puducherry.

Figure 1: Map of India (States and Union Territories)

Source: Maps of India - https://www.mapsofindia.com/maps/india/india-political-map.htm

2.1.2 Population demographics

The population of India is currently estimated to be 1.41 billion, with an average annual growth of 0.90% (UNFPA, 2022). India is currently the 2nd most populated country in the world, hosting approximately 18% of the global population. The median age is 28.7 years, with females being 29.5 years and males being 28 years (Central Intelligence Agency, 2023). Regarding population composition, India is slightly male-dominant. It is approximated that 51.96% of the population is male and 48.04% female (UN, 2019). The at-birth life expectancy of males and females is currently 65.5 years and 69.2 years respectively (Central Intelligence Agency, 2023). The distribution of population age is approximated to be that 26.30% of the population is aged 0-14, 17.50% is aged 15-24, 41.60% is aged 25-54, and 14.60% is aged 55+ (Central Intelligence Agency, 2023).

Urban/Rural Areas – Across India, the population is also disproportionately split between urban and rural areas. It is estimated that approximately 35.39% of the population lives in urban areas and 64.61% lives in rural areas (UN, 2019). Some key differences that have been found to exist between urban and rural areas are education, occupation, quality of housing, and health/medical services (Das & Pathak, 2012; Census of India, 2011).

Languages - India is also home to a diverse set of languages. In the last census of India (2011), over 121 different languages were listed as being spoken across the country (Pruthi, 2018). Amongst these, 22 were identified as official languages and 99 as non-scheduled languages (not officially recognized by Indian Government) (Pruthi, 2018). It was found that 5 different languages represented over 70% of the mother tongue spoken as reported by Indians. These 5 languages were Hindi 43.63%, Bengali 8.03%, Marathi 6.86%, Telugu 6.70%, and Tamil 5.70% (Pruthi, 2018).

Education - Currently, India has seen its highest literacy rates since gaining its independence in 1947. In the first post-independence census which occurred in 1951, it was found that literacy was extremely low with only 27.00% of men and 9.00% of females being considered literate (Kingdon, 2007). However, due to the framework of India's newly found constitution at the time, it was declared that free and compulsory schooling would be provided across India for primary and secondary education (Kingdon, 2007). This had led to drastic improvements as per the 2011 census, with the literacy rate rising to 82.10% amongst males and 65.50% amongst females (Central Intelligence Agency, 2023; Gov. India, n.d).

Religion - India is also home to a variety of religions. The 2011 census revealed that India's religious composition consisted mostly of Hindus, Muslims, and Christians (Kramer, 2021). Approximately 79.80% of the nation self-identify as Hindus, 14.20% as Muslim, and 2-3% as Christian (Kramer, 2016). The remaining individuals either identify with smaller religious groups or none.

Caste - Another unique characteristic of India is the caste system which has traditionally been used as a form of social segregation. Within the caste system, specific communities/groups have been perceived as being of lower status in the social hierarchy. This has resulted in these groups being highly disadvantaged, suffering from marginalization socially, economically, and in education (Vart et al., 2015). As per India's constitution, some of these communities/groups have been "scheduled", i.e., the Government of India has acknowledged them as being marginalized. The common categories used to describe these groups are scheduled castes (SC), scheduled tribes (ST), and other backward classes (OBC). SCs represent approximately 22% of the population (Tong, 2022). These individuals are the most disadvantaged because historically they have been segregated socially and ritually through being labeled as the "untouchables" (Vart et al., 2015; Sankaran et al., 2017). Similarly, there exists STs, which are approximately 10% of the nation's population (Tong, 2022). STs are indigenous communities that rejected the caste system and have been marginalized geographically (Vart et al., 2015; Kramer, 2021). Lastly, there are the OBCs which represent approximately 42% of the population (Tong, 2022). These are the individuals that are disadvantaged either educationally, socially, or both (Kramer, 2021). To ensure fairness and reduce disadvantage amongst marginalized groups, the Government of India provides benefits and opportunities. Currently, the Government of India has implemented various affirmative action programs. What these ensure is 15%, 7.50%, and 27% of government jobs and 'seats' in higher education institutions are allocated to SCs, STs, and OBCs respectively (Kramer, 2021). Those that are not categorized into any scheduled groups are considered to be of general category or no caste/tribe (Tong, 2022).

2.1.3 Economy

India's economy is highly diverse and encompasses many different sectors. Some of these include agriculture, industries, and services. These sectors contribute the majority to the gross domestic product (GDP) with agriculture composing 15.40%, industry 23%, and services 61.50% (Central Intelligence Agency, 2023). Amongst these contributors to the economy, the largest workforce is in agriculture. Recent estimates place slightly less than half the workforce of India in the agricultural industry (World Bank, 2021a). India relies heavily on the agricultural sector due to 60.80% of India's land being agriculturally suitable (Central Intelligence Agency, 2023). However, the service sector is the largest contributor to economic growth, while only employing less than one-third of the workforce (Central Intelligence Agency, 2023). The actual GDP of India is approximately 3.18 trillion US dollars as of 2021 (World Bank, 2021b), with a per capita GDP of $2,256 which is below the global average (World Bank, 2021c). It is also approximated that the economy has grown steadily for the past 3 decades, with an average increase of 7% (Central Intelligence Agency, 2023). For a country experiencing great economic growth, the general population is relatively poor. Additional demographics report that over 21% of Indians live below the poverty line and unemployment has reached approximately 6% (Central Intelligence Agency, 2023).

When compared to other countries, one key limitation of India's economy is its allocation to healthcare funding. India currently allocates some of the lowest funding to health when considered as a percentage of their GDP (Narain, 2016). This minimal investment and ever-increasing expenses for residents have resulted in an increased health burden, especially for those who are poor (Narain, 2016).

2.1.4 Health status and issues

Rapid urbanization (2.33% increase annually) and continuous economic development have fostered changes that can best be described as a health and epidemiological transition (Narain, 2016; Nethan & Mehrotra, 2017; Yadav & Arokiasamy, 2013). In recent decades, mortality rates have nearly been halved, dropping from 14.9 to 7.1 per 1000 persons and life expectancy is at its highest (Narain 2016; Nethan & Mehrotra, 2017; Yadav & Arokiasamy, 2013). This has contributed to the elderly population increasing in size and contributing to a greater composition of India's population. Additionally, India has also been experiencing lifestyle changes and insufficient investment in healthcare and promotion (Narain 2016; Nethan & Mehrotra, 2017). These changes have all fostered a state of increasing morbidity rates and health-related burdens amongst the population of India. Contributing to this increasing burden are various health conditions.

Historically, one of the largest contributors to the health burden in India had been communicable diseases (CDs). In past decades, the primary focus in India was on CDs which caused a considerable number of deaths due to their infectious spread. CDs such as polio, tetanus, tuberculosis (TB), malaria, gastroenteritis, and pneumonia were some of the most common health issues across the nation (Yadav & Arokiasamy, 2013; Desiraju, 2021). As India has continued to make strides in its health sector, various conditions have effectively been eradicated such as polio and tetanus. However, certain conditions such as TB and various vector-borne diseases such as malaria are still of major public health concern (Desiraju, 2021). Recently, in 2017 it had been estimated that there were 9.5 million cases of malaria in India with 94% of the population being at risk (Desiraju, 2021). Similarly, mortality due to TB has seen a reduction from 42 per 100,000 persons to 23 per 100,000 since the 1990s (Desiraju, 2021). While India continues to display gradual improvements in controlling and responding to CDs, its current health infrastructure continues to hinder the country's ability to rapidly detect and respond to outbreaks (Desiraju, 2021). Until India invests further in preventative and response methods, communicable diseases will continue to affect the population.

In recent decades, NCDs have emerged as the leading cause of health burden in India. The WHO defines NCDs to be health conditions that are generally chronic and are not transmissible inter-personally (WHO, 2022). While focus had remained on communicable diseases, the health transition occurring has resulted in NCDs becoming rampant across India. This presence of CDs and the rapidly increasing presence of NCDs concurrently has produced a state of dual burden. It is estimated that deaths due to NCDs have nearly doubled from causing approximately 37% of total deaths in 1990 to approximately 60% (5.87 million) in 2016 (Nethan & Mehrotra, 2017; MOHFW, 2022). With many of these deaths occurring prematurely (occurring before reaching average life expectancy), there is a substantial loss of productive/working years amongst the population (Srivastava & Bachani, 2011). Thus, the burden of these NCDs affects not only the health of the Indian population but also the economy. Some of the most prominent NCDs contributing to morbidity and mortality are cardiovascular diseases, hypertension, diabetes, chronic respiratory diseases (CRDs), and cancers (Nethan & Mehrotra, 2017; MOHFW, 2022). Burden of these NCDs has only been projected to increase unless sufficient efforts are made in the prevention of the NCDs and the control of their risk factors (Srivastava & Bachani, 2011).

In terms of causes, the majority of NCDs are thought to share certain common biological and modifiable behavioural risk factors. These include increasing age, poor diet, obesity, insufficient physical activity, and consumption of tobacco and alcohol (WHO, 2022; Nethan & Mehrotra, 2017), which have been found to be increasingly prevalent in India. As previously mentioned, the population has been aging due to decreasing mortality rates and increasing life expectancies. Thus, a greater composition of the population is elderly. Diet has also been found to be changing in recent decades. Tak et al. analyzed household consumption data from 1993 to 2012 and found that the consumption of key micronutrient-rich foods such as fruits and vegetables to be approximately 154g per person per day for rural residents and 181g per person per day for urban residents (Tak et al., 2019). These numbers are particularly alarming as they are well below the 400g per person per day recommended by the WHO. An increasing number of households are thought to be lacking in either fruit, vegetable, or meat consumption with others having increasing consumption of processed foods (Tak et al., 2019).

Obesity has also become highly prevalent in India. Since the 1970's obesity prevalence nearly quadrupled from 7% to recent approximations of 28.60% (Nethan & Mehrotra, 2017; Anjana et al., 2023). Increasing obesity can be considered an outcome of worsening diets along with sub-optimal physical activity across the Indian population.

Both males and females over the age of 20 have been reported to be highly physically inactive across urban and rural areas of the country. It was found that approximately 54.40% of the population was inactive with males' prevalence of inactivity being 45.70% and females 63% (Anjana, 2014). Furthermore, urban areas displayed significantly greater inactivity, with an inactivity prevalence of 65% as compared to 50% in rural areas (Anjana, 2014). With the WHO recommending at least 150 minutes of physical activity per week, it is alarming that more than half the country is not reaching the minimum recommendation.

The WHO recently estimated that approximately 29% of adults aged 15+ in India consume tobacco (smoked or smokeless) (WHO, 2022). With over 250 million adults utilizing tobacco, its negative impacts have become a public health concern. To worsen the scenario, India is the second largest producer and consumer of tobacco internationally (WHO, 2022). With cheap access to tobacco, this risk factor has become rampant across India. Consumption of alcohol has also been found to be increasing across India. Recent estimates of alcohol consumption indicate that approximately 29.20% of men and 1.20% of women over the age of 15 consume alcohol (Balasubramani et al., 2021). In sum, as the behavioural habits of the population worsen and the trend of increasing prevalence of NCD risk factors continues, NCDs will continue to burden India.

India has implemented methods of prevention and monitoring for NCDs and has adopted WHO's *Action Plan of Global Strategy for the Prevention and Control of Noncommunicable Diseases* (Nethan & Mehrotra, 2017). To achieve the health objectives set forth by this initiative, various health programs have been developed and implemented at the national scale (Nethan & Mehrotra, 2017). To monitor the progression of NCDs, India has also contributed to various surveys that are conducted periodically (Nethan & Mehrotra, 2017). Of interest is the National Family Health Survey (NFHS), which obtains extensive national estimates of population health (Nethan & Mehrotra, 2017).

Regardless of India's efforts thus far, increasing NCD burden has reached a point where an increasing number of individuals have begun to be diagnosed with more than one health condition (Sinha et al., 2022b). This has brought up concern regarding a concept known as multimorbidity.

2.2 Multimorbidity

Within this section, information regarding multimorbidity is summarized. The section opens by exploring various definitions of multimorbidity within existing literature. Next, contextual information about its prevalence, common combinations, and burden are discussed with a focus on India. Lastly, one of the most frequently associated combinations of NCDs contributing to multimorbidity is further explored – diabetes and hypertension.

2.2.1 Definition of multimorbidity

Multimorbidity (MM) is a term that is often confused with co-morbidity when discussing the occurrence of multiple health conditions. Often utilized interchangeably with comorbidity, there exists a distinction between both terms. Both terms in general are utilized to describe scenarios of multiple chronic conditions within an individual, but the difference lies in the priority of the morbidities (Harrison et al., 2021). In comorbidity, there is often an index disease that is of priority interest during the clinical course of a patient (Harrison et al., 2021). Any additional health conditions that may exist concurrently or arise during the clinical course, are comorbidities (Harrison et al., 2021). In MM, all concurrently occurring chronic conditions are of equal importance. No priority is given to a specific condition, with focus simply being on understanding the state of multiple morbidities coexisting within individuals (Harrison et al., 2021).

Although this differentiation between comorbidity and MM has been well established, there still exists variation in how MM is specifically defined with certain health agencies and researchers defining MM differently. Some examples are as follows; the Agency for Healthcare Research and Quality (AHRQ) in the United States defines MM as the following (Bierman, n.d.):

- *"The presence of two or more chronic physical or mental health conditions"*

Another group of researchers in Australia (Britt and Colleagues) have proposed that it should be considered if multiple organ systems are affected and thus proposed that MM is best defined as:

- *The involvement of two or more organ domains by chronic diseases (Britt et a., 2008)*

The European General Practice Research Network (EGPRN) conducted a systematic review regarding MM definitions. They produced a comprehensive definition of MM that has been labelled as clinically relevant (Le Reste et al., 2015):

- *"Multimorbidity is any combination of chronic disease with at least one other disease (acute or chronic) or biopsychosocial factor (associated or not) or somatic risk factor."*

The World Health Organization (WHO) defined MM as the following (WHO, 2016):

- *"Multimorbidity is the co-existence of two or more chronic health conditions within an individual.*"

It must be acknowledged that MM has no universally accepted definition and that not all researchers may be referring to the same definition within literature. However, amongst the variations in definitions, that set forth by the WHO is most commonly used (Johnston et al., 2018).

Further heterogeneity exists in literature regarding the operational definition of MM with respect to which specific conditions are considered, how many are considered, and how they are grouped (Fortin et al., 2012; Johnston et al., 2018, Diederichs, Berger & Bartels, 2011; Le Reste et al., 2015). Researchers have generally considered their respective research topic and the availability of data when determining which health conditions will contribute to their definition of MM. Two different systematic reviews on MM's operational definitions found that amongst their reviewed studies, the number of diseases included in definitions varied per study from as low as 4 conditions to as high as 185 (Diederichs et al., 2011). Across these studies, inconsistencies also existed regarding which conditions would be considered possible contributors to MM. It was found that certain conditions such as diabetes, stroke, cardiovascular diseases, hypertension, and cancer were considered within most definitions, and other studies considered conditions that have been of less frequent interest (e.g., depression, kidney disease, etc.) (Diederichs et al., 2011). Additionally, studies have also grouped specific conditions differently. Some studies have chosen to consider all health conditions separately and others have grouped conditions that may be clinically interrelated together. When grouped, these conditions have been treated as a single diagnosis contributing to MM (e.g., anxiety and depression as mood disorders, melanoma, carcinoma, and lymphoma as cancers, etc.) (Mercer et al., 2009). Certain studies have also expanded the minimum threshold of conditions required beyond at least 2 concurrent conditions. The most common threshold seen is 2 or more (2+) health conditions to define MM however, select studies have defined MM as 3 or more concurrent conditions (Fortin et al., 2012; Johnston et al., 2018).

With such extensive variations in how MM has been measured and defined in literature, there are challenges in interpreting and comparing results across multiple studies. When approaching literature regarding MM, researchers should be careful and acknowledge the complexities in its definition.

2.2.2 Common disease patterns in multimorbidity

While MM has generally been used to broadly define the co-existence of two or more chronic health conditions within an individual, some chronic conditions have been reported to co-exist more frequently than others (Rajoo et al., 2021; Robertson et al., 2022). In a recent systematic review, studies exploring MM in various Asian countries were pooled to determine patterns of chronic conditions that clustered more frequently. This clustering of conditions was referred to as associative patterns of MM, defined as the co-occurrence of conditions beyond chance (Rajoo et al., 2021). Three associative patterns were found to exist most frequently: 1) cardiovascular and metabolic diseases, 2) degenerative diseases, and 3) pulmonary diseases (Rajoo et al., 2021). The most common amongst these associative patterns was that of cardiovascular and metabolic diseases. Within this pattern of disease clustering, the most common diseases reported were hypertension and diabetes (Rajoo et al., 2021).

Similar results have been found by other studies regarding the contribution of specific conditions to MM. In another systematic review regarding Asian populations, dyad MM disease patterns were explored. MM in this review was defined as the co-existence of several medical conditions in an individual with no index condition of interest (Zhang et al., 2022). The four most common dyad disease patterns were: 1) hypertension and diabetes, 2) hypertension and arthropathies, 3) hypertension and heart disease, and 4) hypertension and metabolic disorders (Zhang et al., 2022). Hypertension and diabetes were found to be two of the most commonly contributing conditions (Zhang et al., 2022).

In a study conducted by Robertson and colleagues in Scotland, MM clusters were explored amongst hospitalized patients. They defined MM as “having recorded diagnoses of 2 or more chronic conditions” (Robertson et al., 2022). Amongst the study population of adults aged 18+ years, 27.40% were found to have MM with condition counts ranging from 2 to 11 (Robertson et al., 2022). It was found that the most common conditions reported in MM diagnoses were hypertension (56.50%), diabetes (27%), and chronic kidney disease (26%) (Robertson et al., 2022). Additionally, most commonly occurring together were 1) diabetes and hypertension, and 2) chronic kidney disease and hypertension (Robertson et al., 2022).

Across various literature, similar associative patterns for conditions contributing to MM have been found to exist (Rajoo et al., 2021; Zhang et al., 2022; Roberston et al., 2022). Specific conditions such as diabetes and hypertension have clearly contributed to MM diagnosis often and have been frequently found to co-exist in MM.

2.2.3 Prevalence of multimorbidity in India

In India, studies conducted regarding MM have found variable estimates of prevalence, which may be due to the varying number and types of conditions taken into consideration, and the use of different data sources/study populations.

Recent estimates of MM prevalence in India have been broad, ranging from as low as 1.30% to as high as 83%. In a nationally representative study conducted using *National Family Health Survey* (NFHS) data from 2015-2016, MM was explored amongst those aged 15-49 years and was defined as having two or more conditions of 5 self-reported chronic conditions: anemia, diabetes, asthma, obesity, and hypertension (Prenissl et al., 2022). Prevalence was reported to be 7.20%, with urban areas being 9.20% and rural 5.80% (Prenissl et al., 2022). Similarly, in a study conducted utilizing data from The *World Health Organization Study on Global Ageing and Adult Health* (WHO-SAGE), adults 18 and older from six different states were studied (West Bengal, Assam, Maharashtra, Rajasthan, Karnataka, and Uttar Pradesh), and MM was defined as the presence of two or more of the following self-reported conditions: angina, diabetes, arthritis, cataracts, asthma, hypertension, depression, stroke, and chronic lung disease (Pati et al., 2014). Prevalence was found to be 8.90% (Pati et al., 2014). The slight differences may be due to the inclusion of different health conditions, with both studies only sharing commonalities in consideration of diabetes, hypertension, and asthma.

Furthermore, in a study conducted regarding Southern Asia, MM was explored in urban areas of India and Pakistan amongst adults aged 20 years or older. The *Cardiometabolic Risk Reduction in South Asia Surveillance Study* (CARRS study) found MM prevalence to be 9.4% (Singh et al., 2018). This study analyzed data regarding adults from urban areas of New Delhi, Chennai, and Karachi; MM was defined as the presence of two or more of the following chronic conditions (determined through biomarker and self-reported data): hypertension, diabetes, heart disease, stroke, or kidney disease (Singh et al., 2018).

Urban areas of India have been found to be disproportionately impacted by MM as compared to rural areas (Prenissl et al, 2022; Chauhan et al., 2022a; Khan et al., 2022). Two nationally representative studies utilizing the 2017-2018 *Longitudinal Ageing Study in India* (LASI) data explored urban and rural prevalence differences in adults 45+ years in age (Chauhan et al., 2022a; Khan et al., 2022). Khan and colleagues defined MM as the presence of two or more of the following self-reported conditions: hypertension or high blood pressure, diabetes or high blood sugar, stroke, cancer/malignant tumor, chronic lung diseases, chronic heart diseases, arthritis, rheumatism, osteoporosis, bone/joint disease, neurological/psychiatric problems, and high cholesterol, and studied adults aged 45+ years (Khan et al., 2022). Chauhan et al. (2022a) defined MM as the presence of two or more chronic conditions with consideration of hypertension, stroke, diabetes, chronic heart disease, cancer/malignant tumor, bone/joint disease, high cholesterol, neurological/psychiatric disease, and any chronic lung disease, and studied adults aged 60+ years (Chauhan et al., 2022a). Both studies utilized the same LASI dataset but differed slightly in the conditions considered within their definition of MM and their population age of interest. However, both studies still reported a significant difference in the prevalence of MM between urban and rural areas, with both finding a greater prevalence within urban (Chauhan et al., 2022a; Khan et al., 2022). Khan and colleagues estimated an urban area prevalence of 69.60% and a rural prevalence of 59.50% (Khan et al., 2022). Chauhan and colleagues estimated a prevalence of 19.10% in rural areas and 35.40% in urban (Chauhan et al., 2022a).

Prenissl et al. (2022) also found that prevalence of MM was higher in urban areas as seen in Figure 2.

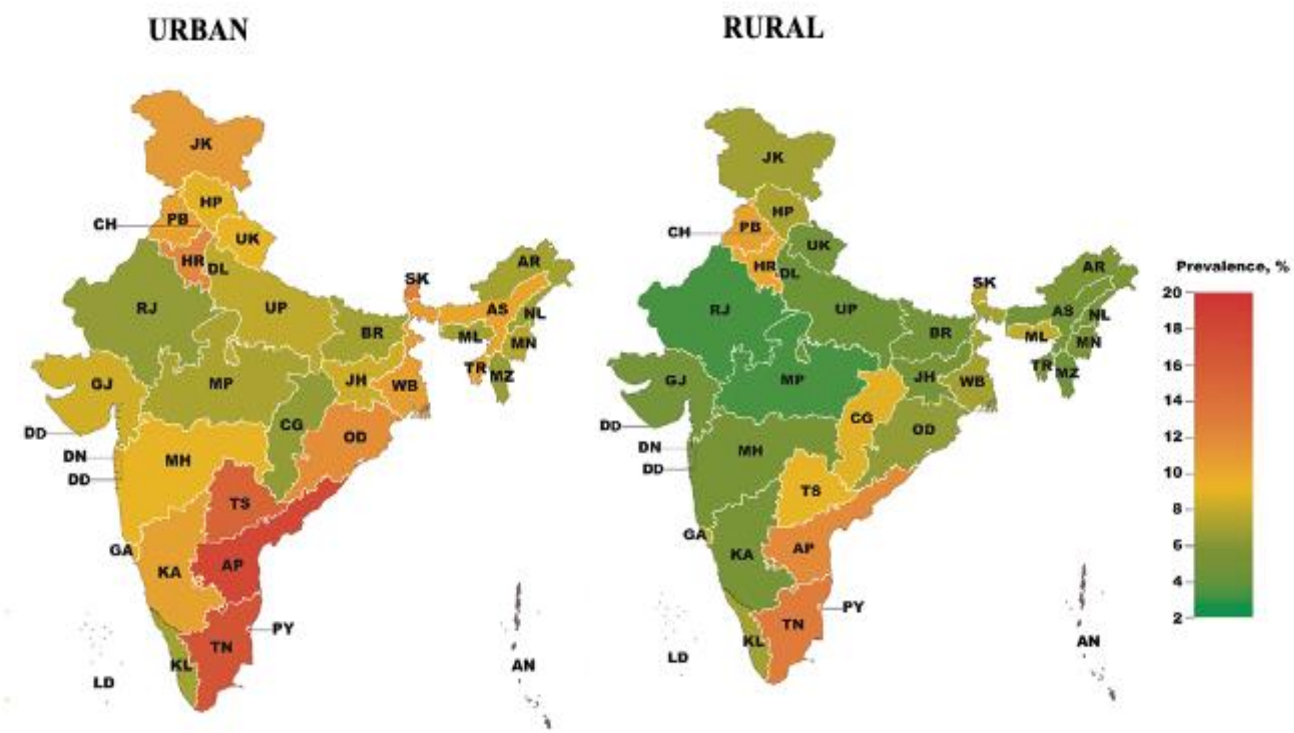

Figure 2: Multimorbidity prevalence distribution - urban and rural areas of India

Source: Pattern of multimorbidity in India: A nationally representative cross-sectional study of individuals aged 15-49 years – (Prenissl et al., 2022)
https://journals.plos.org/globalpublichealth/article?id=10.1371/journal.pgph.0000587

Many studies have also reported a strong positive association between age and MM prevalence across India. It has been estimated that the younger population has a much lower prevalence of MM. With the specific definition of MM utilized by Pati et al., the prevalence of MM was found to be as low as 1.30% for those aged 18-29 years (Pati et al., 2014). However, in studies conducted regarding the elderly population, prevalence has been found to dramatically increase with increasing age. National prevalence estimates were reported to be 62.70% amongst those aged 45 years or greater, with an increase to 73.90% amongst those over the age of 75 (Khan et al., 2022).

Amongst this older adult population, major discrepancies in prevalence have also been noted across the states/union territories. Some states/union territories such as Punjab & Kerala have seen prevalence as high as 83% and 78% respectively amongst their population above the age of 45 years (Khan et al., 2022). Meanwhile, certain states/union territories have seen much lower prevalence. Nagaland and Chhattisgarh have reported a prevalence of 42.60% and 44.60% respectively (Khan et al., 2022). The following figure displays the prevalence of MM as defined by Khan et al., across states/union territories. The legend included provides colour coordinates prevalence estimates (as a percentage) for each state/union territory.

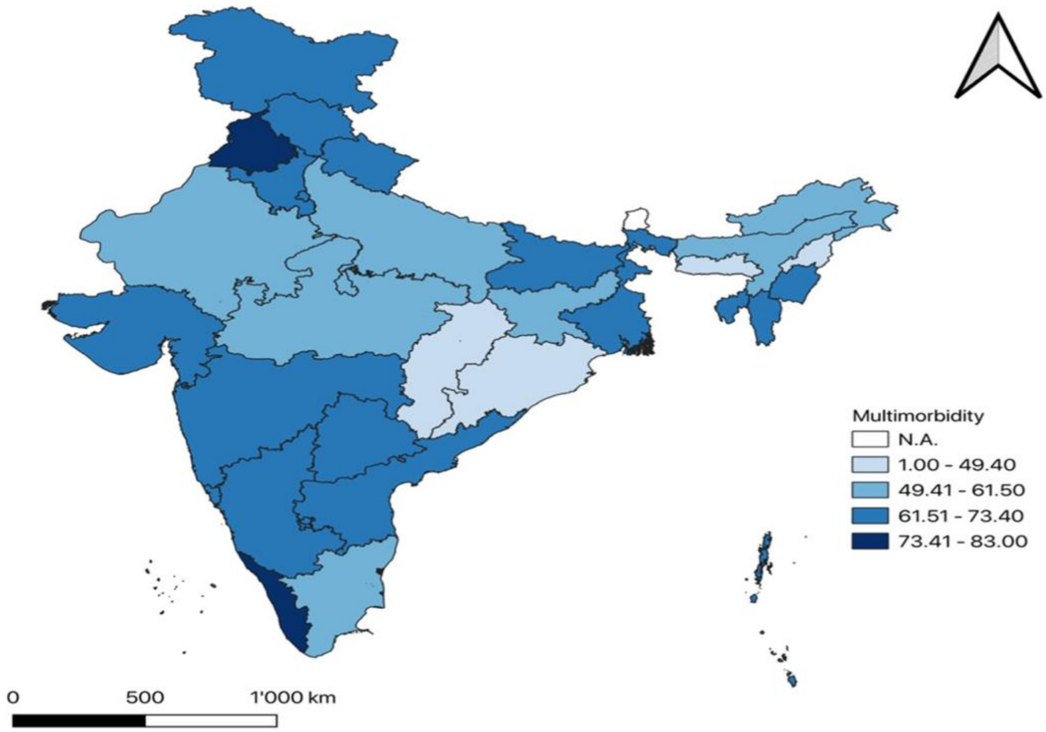

Figure 3: Aging population multimorbidity prevalence variations across states/union territories

Source: Multimorbidity and its associated risk factors among older adults in India – (Khan et al., 2022). https://bmcpublichealth.biomedcentral.com/articles/10.1186/s12889-022-13181-1/figures/2

Many of the studies exploring MM in India have similarly defined MM as the co-occurrence/co-existence of two or more chronic conditions within the same individual/respondent. Additionally, most of these studies have approached defining MM using self-reported data. Variation still exists regarding which specific conditions were considered in each study, with some conditions being considered more frequently (such as diabetes, hypertension, stroke, chronic heart disease, and cancer). However, patterns can still be deduced from the commonalities that do exist among studies. Age has been found to be a significantly associated risk factor for MM and prevalence has consistently been shown to increase with age (Singh et al., 2018). Additionally, a clear trend of differences in prevalence across geographical areas have been found with greater prevalence in urban areas.

Differences have also been noted in the most common MM disease combination, which could be a function of the varying MM definition used by researchers. For example, Prenissl and colleagues indicate that the four most prevalent combinations of conditions found amongst the study population of ages 15-49 were 1) hypertension and obesity (2.95%), 2) hypertension and anemia (2.18%), 3) anemia and obesity (1.19%) and 4) hypertension and diabetes (1.04%) (Prenissl et al., 2022). Sinha and colleagues report the common dyads to be 1) obesity and oral conditions – 7.92%, 2) oral conditions and hypertension – 5.31%, 3) hypertension and obesity – 5.24%, and 4) hypertension and diabetes – 2.18% (Sinha et al., 2022b). In a study focusing on MM amongst adults aged over 60 years, data collected by the *United Nations Population Fund* (UNFPA) was analyzed. States were sampled from across India and included Punjab, Himachal Pradesh, Tamil Nadu, Kerala, Maharashtra, West Bengal, and Orissa (Mini & Thankappan, 2017). The most prevalent reported specific multimorbidities were 1) arthritis and hypertension – 7.50%, 2) arthritis and cataracts – 5.30%, and 3) diabetes and hypertension – 4.70% (Mini & Thankappan, 2017). Across each of these studies, hypertension has shown a clear trend of being one of the most prevalent conditions involved in top-reported multimorbidities. Additionally, consistent with findings from section 2.2.2 is the associative tendency of hypertension with diabetes. The combination of hypertension and diabetes has been reported consistently across studies as one of the most prevalent multimorbidities in India.

2.2.4 Burden of multimorbidity

As MM continues to grow as a public health concern, its burden is felt at various levels amongst countries all around the world. Both high income countries and low- and middle-income countries (LMICs) are impacted, with MM contributing to worsened health outcomes and straining healthcare systems (Sum et al., 2018; Tran et al., 2022; Basto-Abreu et al., 2022; Singh et al., 2018; Khan et al., 2022; Prathapan et al, 2020).

2.2.4.1 Burden amongst Individuals

Various studies exploring MM have reported increased levels of disability, reduction of quality of life, increasing burden due to treatment, and financial burden amongst those affected (Rosbach & Andersen, 2017; Sum et al., 2018; Laires & Perelman, 2018; La et al., 2022; Afshar et al., 2015; Prathapan et al, 2020).

A recent systematic review found a reduction in quality of life and an increasing burden of treatment due to extensive interaction with healthcare systems, polypharmacy issues, and lifestyle changes (Rosbach & Andersen, 2017). Many individuals reported that the time required to arrange and attend doctors' visits, maintain continuous and coordinated medication consumption, and change to their lifestyles was extremely difficult to execute. A Portuguese study examined the burden of MM in individuals aged 25-79 years and found an increased burden (Laires & Perelman, 2018). The study defined MM as the presence of at least two or more self-reported chronic conditions from hypertension, diabetes, heart disease, stroke, asthma, allergies, kidney disease, depression, liver cirrhosis, urinary incontinence, obstructive pulmonary disease, and arthrosis (Laires & Perelman, 2018). Utilizing self-reported data regarding functional capacity, many respondents reported being much more limited in daily activities due to their MM (Laires & Perelman, 2018). As MM interferes with the ability of individuals to carry out day-to-day tasks and introduces new health-related commitments, those affected are burdened by disability and reduced quality of life. This can result in a negative impact on psychological well-being as well (Prathapan et al, 2020).

Furthermore, those affected by MM may experience financial burdens. Increases in out-of-pocket expenditure (OOPE) on medication has been associated with MM in both-high income and LMICs. A systematic review examining 14 studies from Canada, Australia, South Korea, India, and the USA found that as the number of health conditions increases, so did OOPE on medication (Sum et al., 2018). Compared to those with no conditions, those with dyad MM had nearly 5.2 times the OOPE on medications associated with their conditions and those with MM involving 3 or more conditions had nearly 10.1 times the OOPE (Sum et al., 2018). Within this review, the most commonly studied conditions included diabetes, hypertension, stroke, respiratory diseases, and arthritis (Sum et al., 2018).

Further supporting this is a recent study conducted in Asia utilizing India WHO-SAGE data from 2015 and *China Health and Retirement Longitudinal Study* (CHARLS) data from 2015 (La et al., 2022). For both countries, amongst adults over the age of 45 years MM was defined as two or more self-reported long-term conditions (La et al., 2022). For those from India, 9 conditions were considered (angina, arthritis, diabetes, asthma, chronic lung disease, hypertension, cataracts, stroke, and depression), and for those from China 14 conditions were considered (hypertension, dyslipidemia, diabetes, heart disease, chronic lung disease, stroke, cancer, digestive disease, liver disease, kidney disease, memory disease, depression, psychological/emotional illness, and arthritis), with the only commonalities being hypertension, diabetes, stroke, arthritis, chronic lung disease, and depression (La et al., 2022). Amongst the Chinese sample studied, for each additional chronic condition diagnosed, OOPE on medication was estimated to increase by 18.50% (La et al., 2022). For the Indian population, the OOPE increase was estimated to be 20.90% (La et al., 2022). With increased expenditure on medication needed for the multiple conditions an individual is living with, families may face financial strain. India specifically has one of the highest OOPEs related to healthcare; the World Bank estimates nearly 85.60% of costs accrued due to healthcare are paid OOPE (Narain 2016).

2.2.4.2 Burden amongst health systems

MM also burdens health systems around the world due to its complex and resource-intensive nature. In the previously mentioned study conducted in Portugal by Laires & Perelman, healthcare utilization was reported to be higher with increasing number of morbidities (Laires & Pelerman, 2018). Per additional morbidity diagnosed, the risk of hospitalization was found to increase by 26% (Laires & Pelerman, 2018). Additionally, those affected by MM were found to access healthcare to a greater extent, having more general practice appointments, specialist appointments, and hospital admissions (Laires

& Pelerman, 2018). As individuals with MM utilize health services to a greater extent, they contribute strain to the health systems that support them. Further supporting this is a systematic review from the UK that identified increased healthcare utilization and the costs associated with providing care to those with MM. Within this systematic review, the majority of studies defined MM as two or more health conditions but varied greatly in which conditions were considered (Soley-Bori et al., 2020). Consistent across all studies was the consideration of conditions regarding the endocrine, cardiovascular, and circulatory systems (Soley-Bori et al., 2020). Within primary care, the odds of individuals with MM utilizing health services were found to be 2.56 times greater than those who did not have MM (OR=2.56) (Soley-Bori et al., 2020). Not only was MM associated with increased odds of use, but MM was found to be positively associated with increased costs for primary care providers (Soley-Bori et al., 2020). Compared to those without any morbidity, individuals with MM incurred between 1.55 to 2.85 times more costs for primary care providers (Soley-Bori et al., 2020).

Of further concern is the burden MM imposes on LMIC health systems. MM has been estimated to have nearly a 10–15-year earlier onset amongst LMICs as compared to high income countries (Barnett et al., 2012). This may result in prolonged strain on healthcare systems in which care will have to be provided for a longer duration of time. Additionally, as many LMICs are still managing and responding to communicable diseases, countries such as Sri Lanka report adverse effects on health systems as healthcare workers attempt to concurrently battle rapidly emerging MM (Prathapan et al., 2020).

Reports of burden on health systems due to MM have also become prominent in India. MM has been associated with increased hospitalization and service use. In a study conducted by Pati and colleagues, WHO-SAGE data was utilized to determine healthcare utilization amongst adults aged 18 and older across 6 Indian states (West Bengal, Assam, Maharashtra, Rajasthan, Karnataka, and Uttar Pradesh) (Pati et al., 2014). To study the association of MM and healthcare utilization, respondents were asked questions regarding how many outpatient department visits they had in the past 12 months and if they had an overnight stay in a hospital in the past 3 years (Pati et al., 2014). Findings reported that the mean number of outpatient department visits in a span of 12 months was 2.24 amongst those with no morbidities but, 6.16 amongst those affected by multimorbidity, nearly 3 times more (Pati et al., 2014). Additionally, amongst those requiring hospital care, only 9% of individuals with no morbidity required an overnight stay, meanwhile amongst those affected by multimorbidity, 29% reported an overnight stay (Pati et al., 2014). With increases in healthcare utilization and hospitalization, those affected by MM ultimately have increased use of medical resources (Khan et al., 2022). Furthermore, when individuals present to healthcare providers with MM, their complex health issues pose a challenge. In LMICs such as Nepal and India, health systems have generally been found to take a more vertical approach, which makes them better prepared for individual/singular health conditions (Mournier-Jack et al., 2017; Balakrishnan et al., 2022; Pati et al., 2014; Prenissl et al., 2022; Singh et al., 2018). Vertical approaches to healthcare can be defined as highly selective interventions that are oriented towards specific conditions (Druetz, 2018; Mournier-Jack et al., 2017; Kirwin et al., 2022). Such approaches allow for reduced budget allocations and maximize treatment outcomes. However, diagnosis of various combinations of morbidities such as NCDs requires more 'horizontal' patient-centered approaches due to complex disease interactions (Prathapan et al., 2020; Balakrishnan et al., 2022). Horizontal approaches to healthcare can be defined as systematic improvements that provide more comprehensive and holistic treatments (Mournier-Jack et al., 2017). Such approaches may be the superior intervention method for health systems to implement in response to varying combinations of conditions (Druetz, 2018; Mournier-Jack et al., 2017; Kirwin et al., 2022). However, even though horizontal/patient-focused approaches may better assist those individuals affected by MM, health systems face further strain as more resources must be allocated to provide such care.

2.2.5 Diabetes & hypertension multimorbidity in India

Diabetes can broadly be described as a non-communicable metabolic disease that affects the uptake of sugars (CDC, 2022; Kharroubi & Darwish, 2015). When we consume food, our body breaks it down into its constituent sugars (such as glucose) to provide us with an energy source. Once broken down, these sugars enter the bloodstream affecting blood sugar levels which ultimately trigger a reaction in the body to release insulin (CDC, 2022). Insulin acts to support the uptake of these sugars into cells but, for those diagnosed with conditions such as diabetes, there can be issues in production or a resistance to insulin (CDC, 2022; Kharroubi & Darwish, 2015). Diabetes is generally categorized as type 1 and type 2. Type 1 is characterized as when the body is unable to produce insulin due to an autoimmune response and in diabetes type 2, the body can produce insulin but, cannot correctly regulate the uptake of sugars due to insulin resistance (CDC, 2022; Kharroubi & Darwish, 2015). Diabetes can generally be diagnosed by analyzing the glucose content within the plasma of an individual. A fasting plasma glucose reading equal to or greater than 126 mg/dL (≥7.0 mmol/L) signifies diabetes (ADA, n.d.); for those non-fasting, a random plasma glucose level greater than or equal to 200 mg/dL (≥11.1 mmol/L) is generally thought to signify diabetes (ADA, n.d.).

In recent decades the burden of diabetes has been increasing in India steadily. The prevalence of diabetes has recently been estimated to be 11.40% (95% CI: 10.20, 12.50) amongst those aged 20 years and older (approximately 101 million cases) (Anjana et al., 2023). However, urban areas have been estimated to be affected disproportionately with a diabetes prevalence of 16.40% (95% CI: 14.60, 18.20) as compared to rural areas which have an estimated prevalence of 8.90% (95% CI: 8.10, 9.70) (Anjana et al., 2023). A visualization of these findings is presented in Figure 4, where for nearly every state/union-territory, urban areas have greater prevalence as compared to rural areas. (The colour-coordinated legend within the figure is in terms of prevalence as a percentage).

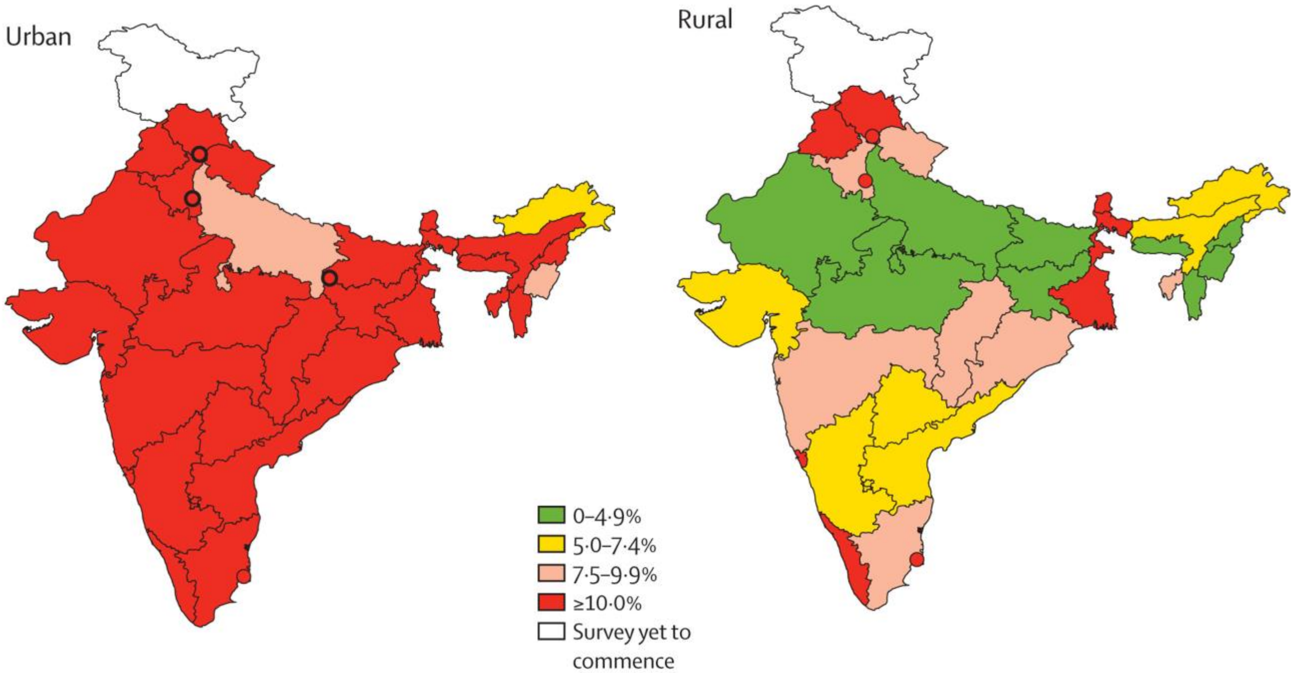

Figure 4: Prevalence of diabetes across urban and rural areas

Source: Metabolic non-communicable disease health report of India: The ICMR-INDIAB national cross-sectional study (ICMR-INDIAB-17) – (Anjana et al., 2023). https://www.sciencedirect.com/science/article/pii/S2213858723001195
Publication: The Lancet Diabetes & Endocrinology. Publisher: Elsevier. Copyright Clearance Permission - Agreement for use of the above figure from the publisher is contained within the "Permission(s)/License(s)" section of this thesis. The agreement consists of the license details and the terms and conditions provided by Elsevier and Copyright Clearance Center.

Overall, a near 2-3-fold increase has been noted since the 1980's (Pradeepa & Mohan, 2021; Geldsetzer et al., 2018). This increasing trend of diabetes prevalence is estimated to continue for decades to come (Pradeepa & Mohan, 2021). The number of disability-adjusted life years (DALYs) due to diabetes have also rapidly increased in past decades. DALYs describe the burden of disease on the health of those affected, with each DALY representing a loss of one year of full health. In the 1990s, DALYs due to diabetes were estimated to be a total of 3.8 million amongst the Indian population but, have nearly tripled to 10.4 million DALYs in 2016 (Tripathy, 2018). Deaths due to diabetes have also seen a rapid increase in the past decades. Diabetes mortality rate has risen from an estimated 10 deaths per 100,000 population in the 1990s to 23.1 deaths per 100,000 in 2016 (Tripathy, 2018).

Furthermore, diabetes has produced an economic burden. The direct costs (prevention, diagnosis, treatment/medication, and care) and indirect costs (transportation, disability, loss of productivity, etc.) associated with diabetes, impose a significant burden on individuals and households (Oberoi & Kansra, 2020). For each person with diabetes, the total annual expenditure on diabetes care has been estimated to be ₹10,000 in urban areas and ₹6,260 in rural areas ($1 CAD ≈ ₹ 60) (Bansode & Jungari, 2019). For a country with many individuals residing in poverty, these additional costs could be an immense financial strain. As diabetes continues to worsen, it is soon expected that India will contribute the largest number of cases to global prevalence (Oberoi & Kansra, 2020).

Hypertension is a non-communicable cardiovascular disease in which blood pressure becomes higher than normal. Normal blood pressure is described as less than 120/80 mmHg meaning that an individual’s systolic pressure is below 120 mmHg and their diastolic is below 80 mmHg (CDC, 2021). For those that are diagnosed with hypertension, their blood pressure has increased to the point where various cardiovascular issues become of concern (e.g., possible heart attack, stroke, etc.) (CDC, 2021). Cut-offs to diagnose hypertension depend on the measurement method, the population of interest, and healthcare professionals (CDC, 2021; Shah et al., 2020). In India, the cut-offs for hypertension diagnosis vary depending on the method and context of measurement as per the 2019 Indian Guidelines of Hypertension – Edition 4 (Shah et al., 2020). For ambulatory blood pressure monitoring (ABPM), cut-offs for diagnosis of hypertension are a 24-hour mean blood pressure of ≥ 130/80 mmHg (Shah et al., 2020). For office/clinical measurements taken by a healthcare provider, a diagnosis of hypertension often has a slightly higher cut-off of blood pressure ≥ 140/90 mmHg (Shah et al., 2020). For home blood pressure monitoring (HBPM) methods such as when automated oscillometric machines are utilized, the cut-off for hypertension is a blood pressure of ≥ 135/85 mmHg (Shah et al., 2020).

Hypertension has become one of the most prevalent morbidities in India. In the late 1990s/early 2000s, urban areas were estimated to have a prevalence of 2-15% and rural areas 2-8% (Shah et al., 2022). Prevalence has increased in past decades with recent national estimates being 35.50% (95% CI: 33.80, 37.30) amongst those aged 20 years and older (Anjana et al., 2023; Geldsetzer et al., 2018; Anchala et al., 2014). More specifically it has been estimated that in urban areas hypertension prevalence is 40.70% (95% CI: 38.20, 43.20) and 33.00% (95% CI: 31.60, 34.30) in rural areas (Anjana et al., 2023). The following Figure 5 provides a visualization of how the prevalence of hypertension in each state/union-territory is generally greater in urban areas. (Colour-coordinated legend in the center of Figure 5 is in terms of prevalence as a percentage.)

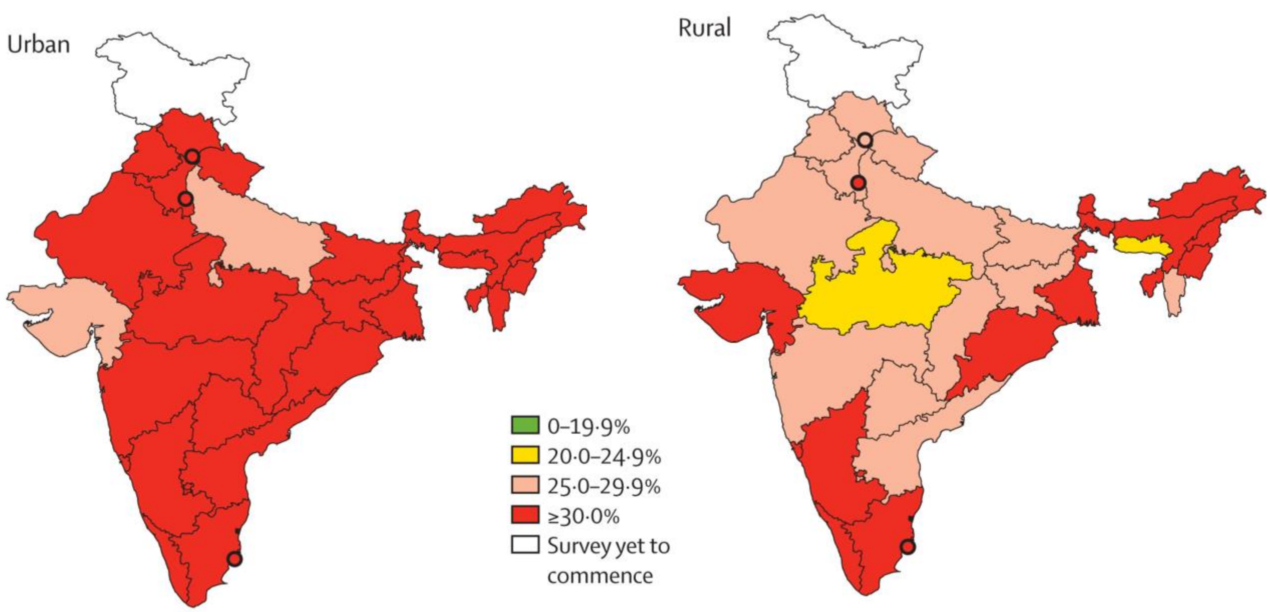

Figure 5: Prevalence of hypertension across urban and rural areas

Source: Metabolic non-communicable disease health report of India: The ICMR-INDIAB national cross-sectional study (ICMR-INDIAB-17) - – (Anjana et al., 2023).

https://www.sciencedirect.com/science/article/pii/S2213858723001195
Publication: The Lancet Diabetes & Endocrinology. Publisher: Elsevier. Copyright Clearance Permission - Agreement for use of the above figure from the publisher is contained within the

Overall hypertension is thought to affect over 200 million adults across India. Amongst those affected, only about one out of 10 individuals living with hypertension have their blood pressure under control (Sahoo et al., 2022). Due to hypertension being a risk factor for subsequent cardiovascular diseases (CVDs), this underwhelming rate of individuals with their blood pressure under control is alarming. With CVDs contributing to nearly 1.6 million deaths annually in India and an estimated economic loss of $94 billion, control of hypertension becomes ever important (Sahoo et al., 2022; Das et al., 2021).

A recent study that utilized cross-sectional data from three rounds of the *National Sample Survey* (NSS) conducted from 1994-1995 to 2018, found that the two fastest growing morbidities in India are diabetes and hypertension (Puri et al., 2021a). The specific MM of the two conditions has been analyzed in recent studies utilizing self-reported data from various data sources. These studies have reported various prevalence estimates for diabetes and hypertension MM based on the age of the chosen study populations. Prevalence estimates of diabetes and hypertension MM have been found to range from 1.04% to 4.7%. In the nationally representative study utilizing 2015-2016 NFHS data regarding individuals aged 15-49 years, prevalence was estimated to be 1.04% amongst the population (Prenissl et al., 2022). Sinha and colleagues also reported on diabetes and hypertension MM but, amongst a slightly older population (ages 45+ years) and utilizing more recent data (2017-2018 LASI). Findings of diabetes and hypertension MM prevalence were 2.18% (Sinha et al., 2022b). Lastly, in a study conducted amongst individuals aged 60+ years old, diabetes and hypertension prevalence were reported to be 4.70% (Mini & Thankappan, 2017). Prevalence of diabetes and hypertension MM in India has shown an increasing trend amongst the aging population.

Furthermore, these specific conditions have also been found to disproportionately affect males and females. In two different systematic reviews and meta-analyses conducted regarding India, the odds of having diabetes and hypertension have been found to be greater amongst men as compared to females. In South Asia, pooled estimates place male odds of hypertension as 19% greater than those of females (Neupane et al., 2014). Similarly, pooled estimates of the odds of diabetes amongst males are 21% greater as compared to females (Jayawardena et al., 2012). Supporting such findings was a recent nationally representative study conducted regarding metabolic NCDs which found that when comparing males and females aged 20+ years old, males were found to have a greater prevalence of both diabetes and hypertension (Anjana et al., 2023). Prevalence of diabetes and hypertension amongst males were respectively estimated to be 12.10% (95% CI: 10.90, 13.30) and 38.70% (95% CI: 36.80, 40.70) (Anjana et al., 2023). Meanwhile, for females, prevalence estimates were a lesser 10.70% (95% CI: 9.60, 11.80) and 32.60% (95% CI: 31.00, 34.20) respectively for diabetes and hypertension (Anjana et al., 2023).

Although the prevalence of diabetes and hypertension MM has been studied as a component of existing studies, being established as one of the most prevalent combination of conditions in India, there exists no literature that has focused on the predictors of their MM. Furthermore, with males being affected to a greater extent by both diabetes and hypertension as compared to females, lacking in specific is research regarding diabetes and hypertension MM amongst the men of India.

2.3 Predictors of multimorbidity

Within this section of the literature review, the primary focus is reviewing studies that have analyzed predictors of MM. Predictors are factors that may act to contribute to or help in preventing specific health outcomes such as MM. Within the existing literature, there are many predictors that have been studied for their possible association to MM.

2.3.1 Summary of studies relevant to predictors

The following table provides a summary of studies relevant to MM in India which were reviewed. Within this table is information pertaining to each study examined such as: the authors, dataset utilized, sample population, operational definition of MM used, and which predictors they found to be statistically significant. In the subsequent sections, findings and trends regarding each predictor are discussed.

Table 1: Summary of studies reviewed for predictors of multimorbidity in India

First Author	**1) Dataset Utilized** **2) Sample population**	**Definition of MM**	**Statistically Significant Findings** **(**Risk Ratios, Odds ratios, predicted probabilities)
Prenissl et al., 2022 (Urban portion of analysis)	1 - National Family Health Survey (NFHS) – 4th Edition (2015-2016) 2 - Nationally representative sample of Males and females aged 15-49 years. (n=617,374 women and n=95,448 men)	Having two or more of the following chronic conditions: anemia, diabetes, asthma, obesity, and hypertension.	Risk Ratio (RR) - Urban Age: 15-24 (Ref.) 25-34 = 2.65 (95% CI: 2.51, 2.80) 35-44 = 5.05 (95% CI: 4.79, 5.33) 45-49 = 6.84 (95% CI: 6.47, 7.23) Education: None (Ref.) Some primary = 1.08 (95% CI: 1.02, 1.15) Completed Primary = 1.10 (95% CI: 1.04, 1.17) Middle = 1.09 (95% CI: 1.05, 1.13) Post-Secondary = 0.92 (95% CI: 0.87, 0.96) Wealth: Poorest (Ref.) Poorer = 1.31 (95% CI: 1.25, 1.37) Middle = 1.52 (95% CI: 1.45, 1.59) Richer = 1.64 (95% CI: 1.56, 1.72) Richest = 1.72 (95% CI: 1.64, 1.81) Marital Status: Single (Ref.) Married = 1.30 (95% CI: 1.25, 1.35) Tobacco consumption: Not smoking tobacco (Ref.) Smoking tobacco = 0.91 (95% CI: 0.84, 0.97)

Table 1 – Continued

First Author	**1) Dataset Utilized** **2) Sample population**	**Definition of MM**	**Statistically Significant Predictors** (Risk Ratio, Odds ratio, predicted probabilities)
Prenissl et al., 2022 (Rural portion)	1 - National Family Health Survey (NFHS) – 4th Edition (2015-2016) 2 - Nationally representative sample of Males and females aged 15-49 years. (n=617,374 women and n=95,448 men)	Having two or more of the following chronic conditions: anemia, diabetes, asthma, obesity, and hypertension.	RR- Rural Age: 15-24 (ref.) 25-34 = 2.21 (95% CI: 2.12, 2.30) 35-44 = 3.95 (95% CI: 3.79, 4.11) 45-49 = 5.42 (95% CI: 5.19, 5.66) Education: None (ref.) Some primary = 1.13 (95% CI: 1.08, 1.18) Completed Primary = 1.13 (95% CI: 1.08, 1.17) Middle = 1.09 (95% CI: 1.06, 1.12) Secondary = 1.08 (95% CI: 1.03, 1.14) Wealth: Poorest (Ref.) Poorer = 1.10 (95% CI: 1.06, 1.15) Middle = 1.27 (95% CI: 1.22, 1.32) Richer = 1.55 (95% CI: 1.48, 1.61) Richest = 2.05 (95% CI: 1.96, 2.14) Marital Status: Single (Ref.) Married = 1.37 (95% CI: 1.32, 1.42) Tobacco consumption: Not smoking tobacco (Ref.) Smoking tobacco = 0.89 (95% CI: 0.84, 0.94) No smokeless consumption (Ref.) Smokeless consumption = 1.05 (95% CI: 1.01, 1.09)
Chauhan et al., 2022b	1 - LASI: 2017-2018 2 - Nationally representative sample of adults aged 60+ years (n= 31,373)	The presence of two or more co-occuring chronic diseases from: hypertension, diabetes, cancer, chronic lung disease, stroke, arthritis, chronic heart diseases, bone/joint disease, high cholesterol, and neurological problems.	Risk Ratio (RR): Education: None (Ref.) Below primary = 1.74 (95% CI: 1.40, 2.15) Primary = 2.04 (95% CI: 1.67, 2.48) Secondary = 2.26 (95% CI: 1.88, 2.70) Higher Education = 2.12 (95% CI: 1.49, 3.04) Urban/Rural Residence: Rural (Ref.) Urban = 2.35 (95% CI: 2.02, 2.74) Wealth: Poorest (Ref.) Poorer = 1.53 (95% CI: 1.26, 1.85) Middle = 1.79 (95% CI: 1.47, 2.18) Richer = 2.06 (95% CI: 1.71, 2.48) Richest = 2.86 (95% CI: 2.29, 3.55) Marital Status: Married (Ref.) Never Married = 0.43 (95% CI: 0.20, 0.90) Tobacco consumption: None (Ref.) Consuming tobacco = 0.76 (95% CI: 0.67, 0.87)

Table 1 – Continued

First Author	1) Dataset Utilized 2) Sample population	Definition of MM	Statistically Significant Predictors (Risk Ratio, Odds ratio, predicted probabilities)
Khan et al., 2022	1 - Longitudinal Ageing Study in India (LASI) (2017 – 2018) 2 - Nationally Representative sample of Males and females aged 45+ years (n=72,250) (52% women and 48% men)	The presence of two or more of: hypertension, diabetes, cancer, any chronic lung diseases, any chronic heart diseases, arthritis, psychiatric problems, and high cholesterol.	Adjusted Odds ratio (AOR): Age: 45 (Ref.) 46-60 = 1.97 (95% CI: 1.88, 2.07) 61-75 = 3.00 (95% CI: 2.83, 3.18) 75+ = 3.33 (95% CI: 3.05, 3.62) Education: None (Ref.) Primary = 1.13 (95% CI: 1.08, 1.18) Secondary = 1.13 (95% CI: 1.08, 1.17) Post-Secondary = 1.09 (95% CI: 1.06, 1.12) Urban/Rural Residence: Rural (Ref.) Urban = 1.41 (95% CI: 1.36, 1.46) Wealth: Poorest (Ref.) Poorer = 1.24 (95% CI: 1.18, 1.31) Middle = 1.38 (95% CI: 1.31, 1.45) Richer = 1.63 (95% CI: 1.55, 1.72) Richest = 1.93 (95% CI: 1.82, 2.03) Religion: Hindu (Ref.) Muslim = 1.31 (95% CI: 1.24, 1.38) Other religions = 1.21 (95% CI: 1.15, 1.27) Occupation: Currently working (Ref.) Currently not working = 1.49 (95% CI: 1.42, 1.56) Caste: SC (Ref.) ST = 0.88 (95% CI: 0.84, 0.93) OBC = 0.56 (95% CI: 0.53, 0.60) Other castes = 0.86 (95% CI: 0.82, 0.89) Marital Status: Currently married (Ref.) Widowed = 1.08 (95% CI: 1.03, 1.13) Alcohol Consumption: Never consumed (Ref.) Has ever consumed = 1.20 (95% CI: 1.14, 1.25)

Table 1 – Continued

First Author	1) Dataset Utilized 2) Sample population	Definition of MM	Statistically Significant Predictors (Risk Ratio, Odds ratio, predicted probabilities)
Puri et al., 2021a	1 - National Sample Survey (NSS) – 2018 Round 2 - Nationally Representative sample of adults aged 45+ years (n=130,553).	Simultaneous occurrence of two or more of the following chronic morbidities: diabetes, hypertension, cancer, neurological disorder, goiter/thyroid disorder, hearing disorder, mental disorder, tuberculosis, heart disease, and vision disorder.	RR: Age: 45-49 (Ref.) 55-59 = 2.15 (95% CI: 1.27, 3.62) 60-64 = 5.50 (95% CI: 3.39, 8.94) 65-69 = 6.58 (95% CI: 3.99, 10.84) 70+ = 10.26 (95% CI: 6.40, 16.43) Wealth: Poor (Ref.) Middle = 2.15 (95% CI: 1.17, 3.95) Rich = 4.59 (95% CI: 2.55, 8.24) Religion: Hindu (Ref.) Non-Hindu = 1.76 (95% CI: 1.38, 2.24)
Puri et al., 2021b	1 - NFHS – 4th Edition (2015-2016) 2 - Nationally representative sample of females aged 15-49 (n= 661,811)	The presence of two or more of the following chronic health: diabetes, hypertension, asthma, cancers, tuberculosis, heart disease, and thyroid disorder.	Predicted Probabilities: Age: 15-19 (Ref.) = 0.55%*** 35-39 = 3.92%*** 20-24 = 0.78%*** 40-44 = 5.75%*** 25-29 = 1.46%*** 45-49 = 7.81%*** 30-34 = 2.44%*** Religion: Hindu (Ref.) = 1.88% Muslims = 2.35% *** Other Religions = 2.06% * BMI: Underweight (Ref.) = 1.23% Normal = 1.74%*** Overweight = 3.44%*** Obese = 63.45%*** Alcohol Consumption: None (Ref.) = 1.94% Consume Alcohol = 2.28%*** Consumption of a healthy diet: Unhealthy diet (Ref.) = 1.79% Healthy diet = 2.11%*** Tobacco consumption: None (Ref.) = 1.94% Consume Tobacco = 2.51%*** *p<0.05, **p<0.01, ***p<0.001

Table 1 – Continued

First Author	1) Dataset Utilized 2) Sample population	Definition of MM	Statistically Significant Predictors (Risk Ratio, Odds ratio, predicted probabilities)
Debsarma et al., 2022	1 - World Health Organization, Study on Global AGEing (WHO-SAGE) – India (2015) 2- Females aged 18+ years from Assam, Karnataka, Maharashtra, Rajasthan, Uttar Pradesh, and West Bengal (n=4898)	Having two or more of the following self-reported conditions: hypertension, diabetes, lung disease, stroke, angina, depression, paralysis, asthma, coughing, phlegm, wheezing, shortness of breath, tightness in chest, arthritis, cataracts and backpain.	AOR: Age: 18-34 (Ref.) 35-49 = 4.32 (95% CI: 1.74, 10.75) 50-59 = 6.87 (95% CI: 2.76, 17.13) 60-69 = 8.90 (95% CI: 3.33, 23.79) 70+ = 30.55 (95% CI: 7.66, 121.77) Education: No Education (Ref.) Primary education = 0.48 (95% CI: 0.28, 0.82) Occupation: Currently not working (Ref.) Currently working = 0.52 (95% CI: 0.32, 0.83)
Puri & Singh, 2022	1 - LASI: 2017-2018 2 - Nationally Representative sample of Males and females aged 45+ years (n=59,764)	The simultaneous occurrence of two or more or the following chronic conditions: hypertension, stroke, diabetes, high cholesterol, cancer, asthma, chronic obstructive pulmonary disease, musculoskeletal disorders, chronic heart disease, chronic bronchitis, gastrointestinal disorders, urinary incontinence, chronic renal failure, neurological/psychiatric disorders, thyroid disease, and skin disease.	RR: **p<0.05, ***p<0.01 Age: 45-49 (Ref.) 65-69 = 2.92*** 50-54 = 1.42*** 70-74 = 3.26*** 55-59 = 2.23*** 75-79 = 3.63*** 60-64 = 2.41*** 75+ = 3.39*** Education: 0 years (Ref.) < 5 years = 1.52*** 5-9 years =1.33*** 10+ years = 1.26*** Urban/Rural Residence: Rural (Ref.) Urban = 1.29*** Religion: Hindu (Ref.) Muslims = 1.37 *** Caste: SC (Ref.) ST = 0.53 *** Other castes = 1.09** Occupation: Never worked (Ref.) Currently not working = 1.19*** Currently working = 0.62*** BMI: Normal (Ref.) Underweight = 0.64*** Overweight = 1.85*** Obese = 3.26*** Tobacco Consumption: Never used tobacco (Ref.) Smoke Tobacco = 1.10** Smoked + smokeless tobacco = 1.40***

Table 1 – Continued

First Author	1) Dataset Utilized 2) Sample population	Definition of MM	Statistically Significant Predictors (Risk Ratio, Odds ratio, predicted probabilities)
Mishra et al., 2021	1 - NFHS – 4th Edition (2015-2016) 2 - Nationally Representative sample females aged 15-49 (n=699686)	Having two or more of: diabetes, hypertension, asthma, cancer, thyroid conditions, and heart diseases.	AOR: Age: 15-24 (Ref.) 25-34 = 2.2 (95% CI: 2.00, 2.42) 35+ = 6.4 (95% CI: 5.80, 7.00) Education: No Education (Ref.) Primary education = 1.10 (95% CI: 1.03, 1.17) Post-Secondary = 0.72 (95% CI: 0.66, 0.79) Region of Residence: North India (Ref.) East India = 1.28 (95% CI: 1.19, 1.37) North-East India = 1.24 (95% CI: 1.14, 1.34) West India = 0.70 (95% CI: 0.63, 0.77) South India = 1.32 (95% CI: 1.23, 1.42) Religion: Hindu (Ref.) Muslims = 1.48 (95% CI: 1.40, 1.56) Christians = 1.28 (95% CI: 1.17, 1.40) Caste: SC (Ref.) ST = 0.77 (95% CI: 0.71, 0.84) OBC = 0.88 (95% CI: 0.83, 0.93) Marital Status: Never married (Ref.) Others = 1.27 (95% CI: 1.12, 1.43) BMI: Normal (Ref.) Underweight = 0.75 (95% CI: 0.70, 0.81) Overweight = 2.02 (95% CI: 1.93, 2.13) Obese = 3.73 (95% CI: 3.52, 3.96) Alcohol Consumption: Don't consume (Ref.) Consume = 1.18 (95% CI: 1.04, 1.33) Media Exposure: unexposed (Ref.) Exposed = 1.19 (95% CI: 1.12, 1.28) Tobacco Consumption: Don't smoke tobacco (Ref.) Smoke tobacco = 1.87 95% CI: 1.65, 2.10) Don't chew tobacco (Ref.) Chews tobacco = 1.18 (95% CI: 1.10, 1.26)

Table 1 – Continued

First Author	1) Dataset Utilized 2) Sample population	Definition of MM	Statistically Significant Predictors (Risk Ratio, Odds ratio, predicted probabilities)
Singh et al., 2018	1 - (CARRS Surveillance Study) 2010-2011 2 - South Asian Urban adults aged 20+ years (New Delhi, Chennai, Karachi) n= 16287	The presence of two or more of the following chronic conditions: hypertension, diabetes, heart disease, stroke, or kidney disease	Prevalence Ratio (PR): Age (Continuous): = 1.11 (95% CI: 1.10, 1.11) Education: Primary (Ref.) Post-Secondary = 0.76 (95% CI: 0.61, 0.97) Occupation: Professional/non-physically intensive (Ref.) Physically intensive = 0.68 (95% CI: 0.53, 0.87) Current Alcohol Consumption: No (Ref.) Yes = 1.68 (95% CI: 1.39, 2.01)

2.3.2 Predictors of multimorbidity in India

2.3.2.1 Age

Age has been found to be one of the most prominent predictors of MM with a significant positive association (Singh et al., 2018, Prenissl et al., 2022, Khan et al., 2022; Puri et al., 2021a; Mishra et al., 2021; Debsarma et al., 2022; Puri et al., 2021b; Puri & Singh, 2022). This finding remains consistent across nearly all the studies reviewed even though studies designs have varied greatly. Data sources that have been used to analyze this predictor have included NFHS (2015-2016), LASI (2017-2018), NSS (2018), CARRS (2010-2011), and WHO-SAGE (2015). Additionally, studies have been chosen to analyze varying age demographics ranging from 15-75+ years old, with varying operational definitions of MM. Regardless, the only clear variation across each study's findings has been the reported magnitudes of age's effect on MM outcome.

2.3.2.2 Education

There exist conflicting findings regarding the effect of education as a predictor of MM with studies reporting both positive and negative statistically significant associations

(Khan et al., 2022; Prenissl et al., 2022; Singh et al., 2018; Mishra et al., 2021: Debsarma et al., 2022; Puri & Singh, 2022; Chauhan et al., 2022b). Education has once again been studied and found to be a significant predictor using various datasets, sample populations, and definitions of MM but, with no consensus findings. Rather some studies have reported specific education levels to increase risk/odds of MM and other studies have reported the opposite.

A majority of the studies reviewed have chosen to utilize those who are illiterate/have no formal education as a reference group, and then analyze the effects of increasing education. Some studies have reported a trend that when compared to those with no education, risk/odds of MM appear to be greater amongst all other education levels, with risk peaking amongst those with solely primary level education and gradually decreasing for each subsequent level of education completed (Khan et al., 2022; Prenissl et al., 2022; Puri & Singh, 2022). However, other analyses have reported a different trend for urban areas with reports of an absolute decrease in the risk of MM for those with post-secondary education (in reference to those with no education) (Prenissl et al., 2022; Singh et al., 2018).

Chauhan et al. (2022b) and Debsarma et al. (2022) then report findings unlike any other study. Chauhan and colleagues found a trend that all levels of education have an approximate 2 times increase in risk of MM compared to no education (Chauhan et al., 2022b). Debsarma and colleagues reported that primary education nearly halves the odds of MM as compared to those no education (Debsarma et a., 2022). While studies have frequently found an education-MM association, understanding this association is difficult due to the variations in both direction and magnitudes of effect.

2.3.2.3 Urban/rural residence

There is agreement across various nationally representative studies that urban areas are associated with a statistically significant increased risk for MM as compared to rural areas (Khan et al., 2022; Puri & Singh, 2022; Chauhan et al., 2022b). The risk increase associated with living in urban areas as compared to rural areas has been found to vary across studies with reports of risk increase ranging from 29%-135% (Khan et al., 2022;

Puri & Singh, 2022; Chauhan et al., 2022b). Prenissl et al. (2022) also include residence in urban or rural areas within their study analysis, but not as a predictor. Unlike other studies, they chose to split their analysis into urban and rural areas and reported differing findings across each area regarding their predictors of interest.

2.3.2.4 Region of residence

One of the few studies to produce measures of effect between regions of residence and MM was done by Mishra and colleagues. Geographical areas were grouped into regions of North, Central, East, North-East, West, and South India. Amongst the regions analyzed, all but Central India had a statistically significant association to MM reported with reference to North India. West India had the lowest odds of MM with approximately a 30% reduction in odds. All other regions displayed an increase in odds of MM with South India having the greatest increase in odds of MM at 32% (with reference to North India) (Mishra et al., 2021).

Supporting this is previous discussions from section 2.2.3, in which the studies conducted by Prenissl et al. (2022) and Khan et al. (2022) found varying prevalence estimates of MM depending on the specific regions that survey respondents resided within. Across both studies, results were consistent with those of Mishra et al., with South India being found to have some of the highest MM prevalence rates (as seen in Figures 2 and 3). These studies chose not to report measures of effect for regions, making associative patterns more difficult to understand.

2.3.2.5 Wealth

'Wealth' has consistently displayed a statistically significant positive relationship with MM outcome. When defining wealth, some studies have chosen to consider a wealth index in which ownership of goods and residential features are considered (Prenissl et al., 2022; Chauhan et al., 2022b; Puri & Singh 2022; Puri et al., 2021b). Other studies have chosen to consider monthly per capita consumption-expenditure (MPCE) (Khan et al., 2018; Puri et al., 2021a). Regardless, a similarity amongst a majority of these studies is the categorization of wealth into quantiles, with studies comparing increasing wealth to a reference category of lowest relative wealth. All studies found that as a respondent's quantile of wealth increases (regardless of how wealth is defined), there is increased risk/odds of MM. There does however exist variation across studies in magnitudes of effect reported between the wealth-MM, but this may be due to the varying study designs frequently discussed (sample population, dataset, MM definition).

Furthermore, limitations may exist in how wealth has been analyzed within existing literature due to a majority of previous researchers not analyzing urban and rural areas separately. Past analyses have chosen to analyze both areas within a single model but, urban and rural areas of India have been found to differ greatly in both average consumption of goods and services, and per-capita incomes, with urban areas generally being considered 'richer' (Balasubramanian et al., 2021). With each area varying greatly in characteristics that are used to measure 'wealth', the understanding of the wealth-MM association can be improved by segregating wealth analysis by area.

2.3.2.6 Religion

Common findings are that with reference to Hindus, other religious groups are at greater risk for MM (Puri et al., 2021a; Mishra et al., 2021; Khan et al., 2022; Puri et al., 2021b; Puri & Singh, 2022). Studies have varied in how they analyze religions. Some studies such as that by Puri and colleagues have simply analyzed 'non-Hindus' with reference to Hindus but, made no specification regarding which religions were specifically considered when defining 'non-Hindu' (Puri et al., 2021b). Other studies have chosen to analyze specific religious groups such as Muslims and Christians as their own category. It has been frequently reported that both Muslims and Christians have increased risk/odds for MM as compared to Hindus, with Muslims having the greatest risk (Khan et al., 2022; Puri & Singh 2022; Mishra et al., 2021; Puri et al., 2021b; Mishra et al., 2021).

2.3.2.7 Marital status

Findings regarding the association of marital status to MM have generally been indecisive with some studies reporting a significant association (Prenissl et al., 2022; Chauhan et al., 2022b; Khan et al., 2022; Mishra et al., 2022), and others reporting no association (Debsarma et al., 2022; Puri & Singh, 2022). Amongst the studies that have reported statistically significant associations, single individuals have been reported to have the lowest risk, with married individuals having a significant increase in risk of MM (Prenissl et al., 2022, Chauhan et al., 2022b). More specifically, it has also been reported that those that have once been married but are now divorced, deserted, separated, or widowed have the highest risk/odds of MM (Khan et al., 2022; Mishra et al., 2022). Prenissl and colleagues once again found that there exists a discrepancy in this predictor's association with MM across urban and rural areas. In both areas the risk of MM was greater for married individuals, as compared to single but, the effect was slightly stronger in rural areas (Prenissl et al., 2022).

2.3.2.8 Caste

Caste has also been found to be a significant predictor of MM, but findings are conflicting. Using LASI and NFHS data, studies have generally found that in reference to SCs, all other marginalized castes acknowledged by the Indian government (STs and OBCs) have reduced risk/odds of MM (Khan et al., 2022; Puri & Singh, 2022; Mishra et al., 2021). However, there does exist conflicting findings regarding how other castes (non-marginalized) are affected. Some studies have found that being a member of other castes has a protective effect against MM, similar to STs and OBCs (when compared to SCs) (Khan et al., 2022; Mishra et al., 2021). Thus, these studies have concluded that SCs have the greatest odds of MM. In Puri and Singh's study, other castes were reported to have a greater risk for MM as compared to SCs. Within the literature reviewed, there appears to be no clear trend of how caste behaves as a predictor with measures of effect varying in direction and magnitude. The only consensus that can be made is that more studies than not have found SCs (often considered the most disadvantaged group) to have the greatest risk/odds of MM.

2.3.2.9 Occupation

Occupation has broadly been studied as a predictor of MM in India. Within the studies that have analyzed the occupation-MM association, nearly all reported statistically significant findings that working individuals have reduced risk/odds of MM (as compared to those who are currently not working or have never worked) (Puri & Singh, 2022; Chauhan et al., 2022b; Debsarma et al., 2022; Khan et al., 2022). The analysis of the occupation-MM association was taken even further by Singh and colleagues who analyzed specific occupations as a part of their study. They found that with reference to those employed in professional (non-physically intensive jobs), individuals working jobs that are generally physically intensive/demanding had a 32% reduced relative prevalence of MM (Singh et al., 2018).

2.3.2.10 BMI

BMI has been found to have a strong positive association to MM that has consistently been reported as statistically significant (Puri et al., 2021b; Mishra et al., 2021; Puri & Singh, 2022). All studies that have analyzed the BMI-MM association have utilized the common categories of underweight, normal, overweight, and obese BMI. Each study tended to use normal BMI as their reference category and then compared all other BMI categories. With reference to those with normal BMI, every study found similar results that those who were underweight had reduced risk/odds of MM, those who were overweight had increased risk/odds of MM, and obese individuals had the greatest risk (Puri et al., 2021b; Mishra et al., 2021; Puri & Singh, 2022). The strength of this association is evidently strong with obese individuals having a 3.50-3.75 increase in risk/odds of MM as compared to normal BMI individuals (Mishra et al., 2021; Puri & Singh, 2022). For a simpler perspective, Puri et al. (2021b) presented this association in terms of predicted probabilities. They found that normal BMI individuals were predicted to have a 1.74% probability of having MM, but for obese individuals, this probability rose drastically to 63.45% (Puri et al., 2021b).

However, each these studies utilized the common WHO cut-offs for BMI: underweight ($< 18.5\, kg/m^2$), normal ($18.5\, kg/m^2 - 24.9\, kg/m^2$), overweight, ($25\, kg/m^2 - 29.9\, kg/m^2$) and obese ($> 30\, kg/m^2$). South Asian countries such as India have increased obesity risk and thus, have been recommended reduced cut-offs for BMI: underweight ($< 18.5\, kg/m^2$), normal ($18.5\, kg/m^2 \leq BMI < 23\, kg/m^2$), overweight, ($23\, kg/m^2 \leq BMI < 25\, kg/m^2$) and obese ($> 25\, kg/m^2$) (WHO, 2000; Weir & Jan, 2022; Aziz et al., 2014).

2.3.2.11 Alcohol consumption

Alcohol has also been well established as a predictor of MM with nearly all relevant studies reporting statistically significant findings (Khan et al., 2022; Mishra et al., 2021; Puri et al., 2021b; Singh et al., 2018). Such findings may have been expected as alcohol has commonly been thought to be a risk factor for NCDs, which contribute to MM outcomes (WHO, 2022; Nethan & Mehrotra, 2017). Most studies have approached alcohol consumption as a simple binary variable. Using various data sources such as CARRS, NFHS, and LASI, studies have found that consumption of alcohol is positively associated with MM, meaning the risk/odds of MM are greater amongst those who chose to consume alcohol.

2.3.2.12 Diet

Diet has also been reported to contribute to the increasing prevalence of NCDs and hence indirectly MM (WHO, 2022). This is alarming for India, as it is currently estimated in both urban and rural areas, individuals on average are consuming less than 50% of the recommended servings of key micronutrient-rich foods such as fruits and vegetables (Tak et al., 2019). As diets continue to worsen through insufficient consumption of nutrient-rich foods and increase consumption of processed foods, health outcomes may worsen (Tak et al., 2019).

However, the consumption of a healthy diet has been minimally studied as a predictor of MM. Puri et al. (2021b) conducted one of the sole studies to include diets within their analysis. Within their analysis, data regarding the consumption of fruits, vegetables, fish, milk, bean, fried food, egg, meats/chicken, and aerated drink was considered. Utilizing a multiple correspondence analysis (MCA), scores were generated for each respondent based on their consumption habits of the previously mentioned foods (Puri et al., 2021b). These scores were used to categorize respondents into one of the following categories: 1) unhealthy diet and 2) healthy diet (Puri et al., 2021b). Statistically significant findings were reported when comparing the probability of MM for those with unhealthy diets as compared to healthy diets. They concluded that those who did not consume a healthy diet had a 2.11% probability of having MM, meanwhile those who did consume a healthy diet had a 1.79% probability (Puri et al., 2021b). However, this study was solely conducted amongst a nationally representative sample of females, with no generalizability for males. This is because although diets within a household may be similar, we cannot assume the dietary habits of males may be exactly the same.

2.3.2.13 Media exposure

Media exposure was only explored by Mishra and colleagues (female-focused study), with a significant association reported. Media exposure was treated as a binary variable, in which those women who watched tv, listened to the radio, and read newspapers/magazines (all 3) were treated as being "exposed" to media (Mishra et al., 2021). Those who did not practice all three of these forms of media exposure were defined as "not exposed". They found that in reference to those who were unexposed to media, the women exposed to media had 19% increased odds of MM (Mishra et al., 2021). However, media exposure can be better approached methodologically if data permits. In recent decades, much of the Indian population has begun to have access to the internet and mobile phones (Ninan, 2019). It is estimated that from 2016-2018, a 65% growth in internet consumption occurred with there now being over 500 million Indians on the internet (Ninan, 2019). Thus, India is in a new era of media exposure, with access readily available at any time. This changing media landscape must be considered in subsequent studies to improve analysis of media exposure.

2.3.2.14 Tobacco consumption

Tobacco has been found to be a significant predictor of MM across multiple studies, however, depending on the study at hand both positive and negative associations have been reported. Studies have approached the analysis of tobacco differently. Some studies have broadly studied any tobacco consumption (Puri et al., 2021b; Chauhan et al., 2022b), and other studies have chosen to separate analysis of smoked and chewed tobacco (Prenissl et al., 2022; Mishra et al., 2021; Puri & Singh, 2022).

Prenissl et al. (2022) and Chauhan et al. (2022b) were two studies to report that smoking tobacco has a protective effect against MM. These findings are interesting as tobacco has generally been considered to worsen health outcomes and has been well established as a contributor to NCDs and hence MM (WHO, 2022; Nethan & Mehrotra, 2017). Both studies offered minimal further elaboration on these findings beyond speculation. All other studies that were reviewed reported opposite findings with tobacco consumption reported to increase risk/odds of MM (Mishra et al., 2021; Puri & Singh, 2022; Puri et al., 2021b). However, the studies by Mishra et al. (2021) and Puri et al. (2021b) each only considered the female population of India. Meanwhile, the studies done by Prenissl et al. (2022), Chauhan et al. (2022b), and Puri & Singh (2022) each considered both males and females and had conflicting findings. Although these discussed findings have all been reported as statistically significant, the inconsistencies across studies make it difficult to interpret the true effect of tobacco on MM amongst the Indian population.

2.4 Current state of literature

In the current state of literature, MM has been broadly explored across India. Various studies have been conducted at the national level regarding various operational definitions of MM. Prevalence has been reported to vary across India based on factors such as state of residence, urban and rural areas, and age of the population (Pati et al., 2014; Khan et al., 2022; Prenissl et al., 2022; Singh et al., 2018). However, there also exist specific multimorbidities that are of greater concern. Associative patterns have been noted regarding conditions that may contribute to MM. One of the most common disease patterns reported has been that of cardiovascular and metabolic diseases (Rajoo et al., 201). Within this broad category of conditions, the two most commonly reported have been diabetes and hypertension together. Diabetes and hypertension have been reported to be the fastest-growing morbidities in India and the most common dyad MM (Zhang et al., 2022; Puri et al., 2021a). Additionally, within literature, the diabetes and hypertension combination has commonly been found to be one of the most prevalent multimorbidities in India. The population is also affected disproportionately by diabetes and hypertension depending on urban/rural residence and gender. Recent papers have reported that males in South Asia have approximately 20% increased odds for both diabetes and hypertension (Neupane et al., 2014; Jayawardena et al., 2012). Furthermore, both diabetes and hypertension have been found to be more prevalent amongst males (when compared to females) and in urban areas (when compared to rural areas) (Anjana et al., 2023).

Regarding what factors may be used to predict MM outcome, various predictors have been analyzed within literature. Of major interest has been the association of various sociodemographic and lifestyle characteristics of individuals. Sociodemographic predictors include age, education, region of residence, urban/rural residence, wealth, religion, current marital status, occupation, and caste. Lifestyle predictors include BMI, alcohol consumption, healthy diet, media exposure, and tobacco consumption. However, these predictors have been studied for varying operational definitions of MM, amongst varying study populations and using different datasets. Due to these, there have been many different measures of effect, magnitudes of effect, and in some cases even directions of effect reported.

2.4.1 Gaps in the literature

2.4.1.1 Predictors of diabetes + hypertension multimorbidity

There exist various gaps within literature pertaining to MM in India. Firstly, lacking is an analysis focused on the predictors of diabetes and hypertension MM. Within current literature, MM has been extensively studied. Studies have chosen to operationally define MM differently however, consistent across literature is that definitions have been broad, and have incorporated many conditions. However, there has been no specific analysis conducted on specific multimorbidities of concern. It has been established that not only is the MM of diabetes and hypertension one of the most common in India, but the two conditions are highly associative (Rajoo et al., 2021; Zhang et al., 2022; Robertson et al., 2022). With diabetes and hypertension both being the two of the fastest-growing morbidities in India (Puri et al., 2021a), there currently exists a gap in knowledge regarding how common predictors may be associated with this specific MM.

2.4.1.2 Analysis of predictors amongst male population

Furthermore, there exists little to no focus on the male perspective of MM within India. Most studies that have been conducted regarding India have either analyzed a mix of both males and females or solely studied females (as seen within studies reviewed within this thesis). However, males have been found to be disproportionately affected by both diabetes and hypertension, with studies estimating the odds and prevalence of both hypertension and diabetes being greater amongst males as compared to females (Neupane et al., 2014; Jayawardena et al., 2012; Anjana et al., 2023). By analyzing predictors of diabetes and hypertension MM amongst males, who may be at an increased risk for this health outcome, an evident gap in literature can be filled.

2.4.1.3 Urban and rural area analysis

In recent decades, urbanization has been occurring at an overwhelming rate across the world. Much of this urbanization has been focused in LMICs, specifically countries within Asia and Africa (Ranzani et al., 2022). As LMICs have continued to experience rapid urbanization, this transition from rural to urban areas has contributed to health disparities amongst populations. Residing in urban areas has generally been characterized as providing various benefits that can contribute to improving health outcomes of populations. Benefits include but are not limited to better access to healthcare, improved sanitation, improved water supply sources, clean energy, etc. (Ranzani et al., 2022). However, there also exist various negative effects associated with residing in urban areas. Urban areas have often been associated with various health risks such as but not limited to decreased physical activity, increased air pollution, increased access to processed foods, etc. (Ranzani et al., 2022). Due to the two areas being different, studies relevant to India have often included analysis of how residing in urban or rural areas may affect MM outcomes. However, most of these studies have analyzed the effect of residing in urban or rural areas by treating area of residence as another predictor variable. Nearly all findings have well established that residing in urban areas increases risk/odds of MM (Puri & Singh, 2022; Khan et al., 2022; Chauhan et al., 2022b; Hossain et al., 2021).

It must also be considered that due to the differences in characteristics between urban and rural areas, other predictors of MM may behave differently within each area. Certain factors within one area may share a stronger association with MM as compared to the other or there may be variations in which specific predictors are significant. That is why the analysis approach taken by researchers Prenissl et al. (2022) is intuitive. Prenissl and colleagues have conducted one of the sole studies regarding India to separate their analysis of MM predictors between urban and rural respondents (Prenissl et al., 2022). Although Prenissl and colleagues did not provide any evident rationale for splitting their analysis, the results they reported support the decision. Referring to Table 1 presented in section 2.3.1, it can be seen that across the separate urban and rural analyses conducted not only were there differences in magnitudes of effect between common significant predictors but, certain categories of predictors were significant in one analysis but not the other. Conducting a separate urban and rural analysis ultimately allowed for the determination of varying significances of predictors and magnitudes of effect. This is especially of interest for diabetes and hypertension, which have both been found to have greater prevalence in urban areas as compared to rural areas (Anjana et al., 2023)

That is why incorporating this specific analysis method into future relevant research (such as filling in the gap of predictors of diabetes + hypertension multimorbidity) is crucial. With MM being reported to burden not only those affected but also their families and the health systems that support them, understanding what may be contributing to MM depending on the area of residence becomes ever important. LMICs such as India have an earlier onset of MM by nearly 10-15 years which may contribute to prolonged burden (Barnett et al., 2012). By separating the analysis of predictors into urban and rural, populations with high-risk characteristics in each area can specifically be targeted for practices such as preventative measures, screenings, and treatment to possibly help reduce burden (Janes et al., 2008).

2.4.1.4 Use of latest data available

Lastly, within much of the literature that currently exists regarding predictors of MM older datasets have been utilized. Amongst various studies reviewed, there have been common data sources used such as the 2015-2016 NFHS-4, and 2017-2018 LASI, etc. However, these datasets are ultimately outdated with certain data collection organizations conducting more recent surveys and releasing newer data that is more reflective of India’s current population. Recently, the Demographic and Health Surveys (DHS) Program released the latest iteration of their nationally representative NFHS series (NFHS-5), which was conducted from 2019-2021 (IIPS & ICF, 2021). With minimal analysis of this dataset having been conducted, its use is warranted to fill in the prior discussed gaps regarding predictors of MM (defined as diabetes + hypertension) amongst the male population of India.

2.5 Current study

2.5.1 Rationale and objectives of study

The current study aims to fill in a knowledge gap regarding predictors of diabetes and hypertension MM amongst males. This research will help to improve understanding of high-risk characteristics amongst the male sex for this specific instance of MM. Additionally, findings may possibly be used to contribute to and improve preventative and intervention strategies. To conduct this research, the latest data regarding the male Indian population will be utilized. To date, nearly all relevant literature on MM has been conducted using 2017-2018 data or older. Recently, the DHS program released the latest iteration of the NFHS series. The National Family Health Survey – 5 was conducted in 2019-2021 and contains the latest health-related information regarding men aged 15-54 (IIPS & ICF, 2021). With approximately 60% of India's male population being aged 15-54, this dataset captures a great portion of males in India (Central Intelligence Agency, 2023). This study will be the first of its kind to study predictors of diabetes and hypertension MM amongst men in India. Additionally, this study will be one of the first to separate the analysis of predictors from an urban/rural perspective.

2.5.2 Research question

Thus, the specific research question posed for this thesis is as follows:

What are the predictors of multimorbidity (defined as diabetes + hypertension) amongst males aged 15-54 in India?

Chapter 3

3 Methods

Within this chapter, the methods that were utilized to carry out this study are summarized in detail. Section 3.1 introduces the methods by describing the source of data. Section 3.2 briefly summarizes predictors of MM that have been of interest in existing literature. Next, section 3.3 provides definitions for the dependent variable and various independent variables. Lastly, Section 3.4. explains the statistical methods that were implemented.

In sum, these methods discussed are the basis of how the research question: "*What are the predictors of multimorbidity (defined as diabetes + hypertension) amongst males aged 15-54 in India?"* was explored. This study was done to identify significant predictors of this specific MM in both urban and rural areas of India. By identifying population characteristics that are associated with higher odds of MM, clinicians and policymakers can focus resources on prevention, intervention, and treatment amongst those most at risk.

3.1 Source of data

The source of data used for this research project was the nationally representative India National Family Health Survey (NFHS) 2019-2021, which is also commonly referred to as the India NFHS-5. The NFHS-5 is the fifth and latest survey in the NFHS series that has been conducted in India (IIPS & ICF, 2021). In India, these surveys began with the first National Family Health Survey, NFHS-1 which was conducted in 1992-1993 (IIPS & ICF, 2021; Dandona, Pandey & Dandona, 2016). Since then, the NFHS-2 has been conducted in 1998-1999, NFHS-3 in 2005-2006, NFHS-4 in 2015-2016, and NFHS-5 in 2019-2021 (IIPS & ICF, 2021; Dandona et al, 2016). The NFHS series are nationally representative surveys that have aimed to provide high-quality information regarding the population of India. Each successive survey has served to not only provide the latest information regarding the Indian population but, to also increase the range and accuracy of information collected (IIPS & ICF, 2021). When compared to the earlier surveys, the latest NFHS surveys have improved exponentially through the addition of anthropometric measurements, biochemical testing, male-focused interviews, and increased sample sizes (IIPS & ICF, 2021).

3.1.1 Survey of interest – (NFHS-5)

The NFHS-5 was conducted beginning June 17th, 2019, and continued through 2 stages until its conclusion on April 30th, 2021 (IIPS & ICF, 2021). During this time, information from 101,839 men aged 15-54 and 724,115 women aged 15-49 was collected across 636,399 households (IIPS & ICF, 2021). Data was collected through the implementation of four survey questionnaires/schedules (IIPS & ICF, 2021). These consisted of a male-focused questionnaire, a female-focused questionnaire, a household questionnaire, and a biomarker schedule (IIPS & ICF, 2021). In sum, these questionnaires/schedules resulted in a wide array of information being collected. Collected information ranged from demographics, socioeconomic characteristics, health-related data, and various anthropometric/biomarker data (height, weight, blood pressure, blood glucose, etc.) (IIPS & ICF, 2021).

3.1.2 Survey sampling design

For the NFHS-5, a stratified two-stage sampling method was employed (IIPS & ICF, 2021; Elkasabi, Ren & Pullum, 2020). The NFHS-5 aimed to provide information not only at the national and state level but also district level estimates (IIPS & ICF, 2021). All 707 districts acknowledged in India on March 31st, 2017 were considered for sampling (IIPS & ICF, 2021). Within each district, there was stratification into either urban or rural areas. For the first stage of the sampling, to obtain rural samples, villages in rural areas were selected as primary sampling units (PSUs) utilizing a probability proportional to size (PPS) method (IIPS & ICF, 2021). Similarly for the first stage, to obtain urban samples, Census Enumeration Blocks (CEBs) were selected in urban areas as PSUs (IIPS & ICF, 2021). This resulted in 30,456 PSUs being selected across all of India, of which 30,198 PSUs had field work completed in them (IIPS & ICF, 2021).

Each of these PSUs acted as a rural or urban cluster and from these, the second stage of sampling was conducted (Elkasabi et al., 2020). During the second stage of sampling, 22 random households were selected from each cluster (IIPS & ICF, 2021). These 22 households were selected through an equal probability systematic selection method by utilizing an updated household list after the PSUs were selected in the first stage (IIPS & ICF, 2021). From these households, first, a household representative was interviewed for household data (IIPS & ICF, 2021). Next, eligible men and women residing in the households were interviewed for male and female-specific data (IIPS & ICF, 2021).

3.1.3 Study population

This study focuses on the predictors of multimorbidity amongst males in India and therefore data relevant to the men involved in the NFHS-5 was utilized. 111,179 males were eligible to be interviewed for the NFHS-5 but, only 101,839 men completed the interview process (a response rate of 91.60%) (IIPS & ICF, 2021). All men who were eligible to participate in the survey were aged 15-54 (IIPS & ICF, 2021). For this study, all 101,839 males interviewed were eligible to be included in the analysis, with exclusions arising from subsequent missing data/modeling constraints.

3.1.4 Ascertainment of final dataset

The primary dataset used was the 2021 NFHS-5 male recode (IAMR7DFL.dta) which contains most of the data collected that pertains to the 101,839 males involved in the NFHS-5 (ICF, 2021). As a secondary dataset, the household recode (IAHR7DFL.dta) dataset was also used (ICF, 2021). From this household dataset, information regarding male height and weight was merged into the primary dataset. To merge this data into the primary male-focused dataset, identifier variables were utilized. To match male respondents in the household dataset to those same males within the primary dataset, the relevant identifier variables utilized were respondent number, cluster number, household number, and type of residence (Rutstein, 2006). This allowed for height and weight data from the household dataset to be merged into the men’s dataset and to be linked to the correct respondent. From the household dataset, a total of 101,839 observations were matched to the primary male recode dataset. The statistical process to merge these datasets is described further in section 3.4.2. The final merged dataset contained all male relevant information needed for analysis to be completed.

3.1.5 Relevant institutions and permissions

Each NFHS has been both funded and conducted by the Ministry of Health and Family Welfare (MoHFW), Government of India, with support from the International Institute for Population Sciences (IIPS), Mumbai, and ICF, USA (IIPS & ICF, 2021). The ICF contributed technical assistance through the DHS program, which is funded by United States Agency for International Development (USAID) (IIPS & ICF, 2021). For the NFHS-5 all relevant protocols and contents of the questionnaires/schedules were approved by both the ICF review board along with the IIPS review board.

Respondents consented to all data collected and permission to access and utilize this data was obtained by request from the DHS Program website. The NFHS-5 is available as an open access data source. Due to the NFHS data being publicly available data in which respondent identities and information are not available, our study was exempt from Research Ethics Board review.

3.2 Study framework

The analytical framework utilized for this study was re-analyzing the various predictors of MM that have been established/of interest as per the literature review. These predictors can be broadly categorized as sociodemographic and lifestyle factors as summarized in the following Figure 6. Each predictor will be analyzed for its possible association with diabetes and hypertension MM, with the same model being utilized in the separate urban and rural area analyses.

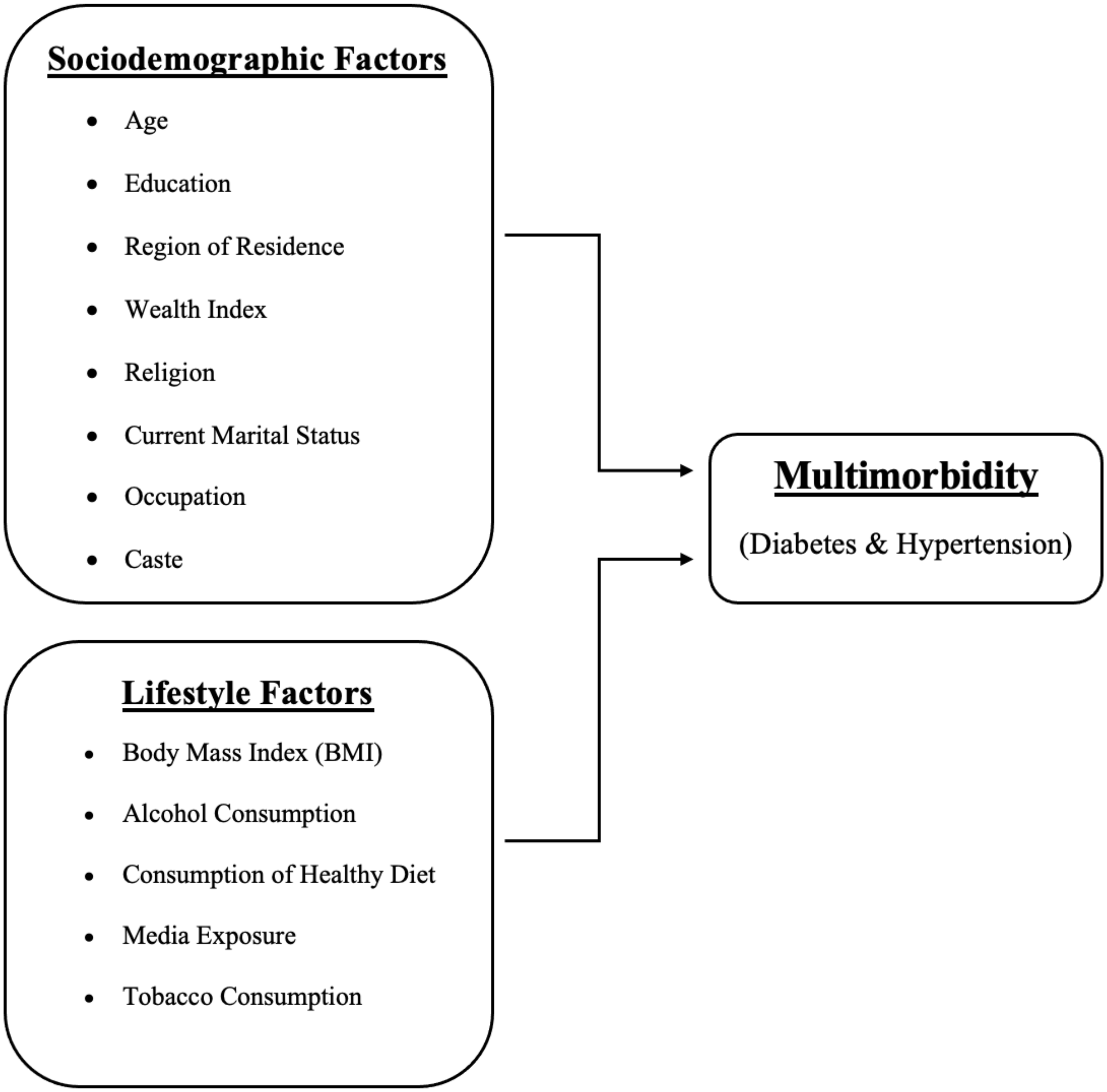

Figure 6: Analytical framework

3.3 Defining variables

3.3.1 Dependent variable

3.3.1.1 Diabetes

Multiple data elements were considered when defining a survey respondent as a 'possible case of diabetes'. Responding yes to/meeting at least one of the following criteria categorized a respondent as a possible case of diabetes:

1) **"Do you currently have diabetes?"**
2) **"Are you currently taking prescribed medication to lower your blood glucose level?"**
3) **"Have you been told you have high blood glucose on 2 or more occasions by a doctor or other health professional?"**
4) **A non-fasting plasma glucose level reading of ≥ 200 mg/dL (≥ 11.1 mmol/L).**
5) **A fasting plasma glucose level reading of ≥ 126 mg/dL (≥ 7.0 mmol/L).**

The first three criteria we considered were derived from closed-ended questions that respondents were asked during the surveying process. Respondents were asked:

- "Do you currently have diabetes?" - YES or NO
- "Are you currently taking prescribed medication to lower your blood glucose level?" - YES or NO
- "Have you been told you have high blood glucose on two or more occasions by a doctor or other health professional?" - YES or NO

The final two criteria we considered when defining possible cases of diabetes were derived from glucose level estimates of respondents. During the surveying process, field agents conducted one glucose test on each respondent who consented. Using an Accu-Chek Performa Glucometer, estimates of capillary blood glucose levels were determined

(Sacks et al., 2011; IIPS & ICF, 2021). Within the dataset, glucose level estimates were distributed as capillary level estimates in units of mg/dL. However, glucose level cut-offs for defining diabetes are often expressed in terms of plasma glucose levels which are not the same as capillary blood glucose levels (Sacks et al., 2011). Plasma glucose levels are on average 11% greater than those found in a capillary blood sample (Sacks et al., 2011). Thus, to correct this difference, we increased capillary blood glucose level estimates by a multiple of 1.11 within the dataset to convert to plasma glucose level estimates (Sacks et al., 2011).

Within literature, there exists different plasma glucose level cut-offs for defining cases of diabetes depending on the fasted state of an individual. Amongst individuals defined as fasting, their cut-off for being categorized as a possible case of diabetes is a fasting plasma glucose level greater than or equal to 126 mg/dL (≥ 7.0 mmol/L) (ADA, n.d.). A fasting state is widely accepted to be when an individual has not eaten or drank anything (except water) for 8 continuous hours (ADA, n.d.). For individuals who are non-fasting, their cut-off for being categorized as a possible case of diabetes is a random plasma glucose level greater than or equal to 200 mg/dL (≥ 11.1 mmol/L) (ADA, n.d.). A non-fasting state can be considered when an individual has consumed any food or drank anything aside from water in the past 8 hours (ADA, n.d.).

Thus, the fasting state of respondents was determined based on the following questions asked during the surveying process:

- "When was the last time you had something to eat?"
- "When was the last time you had something to drink other than plain water?"

Both questions were asked in units of time (hours) prior to the survey and biomarker testing. Thus, for those who responded 8 hours or more to both questions, we defined them as fasting and they had a plasma glucose level cut-off of ≥ 126 mg/dL (≥ 7.0 mmol/L) as one of their possible criteria to be categorized as possibly diabetic. For those who responded less than 8 hours to either question, they were defined as non-fasting and had a plasma glucose level cut-off of ≥ 200 mg/dL (≥ 11.1 mmol/L) as one of their possible criteria to be categorized as a possible diabetic.

3.3.1.2 Hypertension

Responding yes to/meeting at least one of the following criteria categorized a respondent as a possible case of hypertension:

1) **"Do you currently have hypertension?"**
2) **"Are you currently taking prescribed medication to lower your blood pressure?"**
3) **"Have you been told you have high blood pressure on 2 or more occasions by a doctor or other health professional?"**
4) **Average systolic blood pressure reading of ≥ 135mmHg and an average diastolic blood pressure reading of ≥ 85mmHg (≥ 135/85)**

The first three criteria we considered were derived from closed-ended questions that respondents were asked during the surveying process. Respondents were asked:

- "Do you currently have hypertension?" - YES or NO
- "Are you currently taking prescribed medication to lower your blood pressure?" - YES or NO
- "Have you been told you have high blood pressure on two or more occasions by a doctor or other health professional?" - YES or NO

The final criteria considered when defining possible cases of hypertension was derived from systolic and diastolic blood pressure readings. During the surveying process, the NFHS-5 field teams utilized Omron Blood Pressure Monitors to carry out blood pressure readings (measured in mmHg) (IIPS & ICF, 2021). They took blood pressure readings three times for each respondent with an interval time of five minutes between readings (IIPS & ICF, 2021). The findings were reported as three separate systolic variables (first, second, and last reading) and three separate diastolic variables (first, second, and last reading) within the dataset. This method of blood pressure data collection adheres to that outlined by the WHO in their WHO STEPS surveillance manual (WHO, 2005).

As per WHO recommendations, prior to utilizing this blood pressure data for analysis, we averaged the final two readings for each systolic and diastolic pressure. Thus, we averaged the final two systolic pressure reading variables into a singular average systolic pressure reading variable. The same was done to the two final diastolic pressure reading variables to produce a singular average diastolic pressure reading variable. To determine a blood pressure value cut-off for defining hypertension, we referred to the Indian Guidelines of Hypertension – Edition 4. Within these guidelines, it is highlighted that when home measurement methods are done such as using automated oscillometric machines, there are specific cut-offs for defining a case of hypertension (Shah et al., 2020). When using oscillometric machines, the cut-off is a mean systolic blood pressure reading equal to or greater than 135 mmHg and a mean diastolic blood pressure reading equal to or greater than 85 mmHg (Shah et al., 2020). These cut-offs apply to our research as the data collected by field agents was collected utilizing an Omron Blood Pressure Monitor, which is a type of automated oscillometric measuring device (Ostchega et al., 2012). Thus, when defining possible cases of hypertension, one of the possible criteria they could meet was having an average systolic blood pressure reading of $\geq$135 mmHg and an average diastolic blood pressure reading of $\geq$85 mmHg.[1]

[1] In Canada, blood pressure cut-off values for the diagnosis of hypertension are lowered for those affected by diabetes as per the Canadian Cardiovascular Harmonized National Guideline Endeavour (C-CHANGE) (Tobe et al., 2018). However, within the Indian context no evidence or guidelines could be found to substantiate a similar approach.

3.3.1.3 Multimorbidity

Within this study, MM was defined as the co-existence of both diabetes and hypertension within an individual. If a respondent met any of the criteria outlined for being a possible case of diabetes and additionally also met any of the criteria outlined for being a possible case of hypertension, they were considered a possible case of MM. The following Figure 7 provides a summary of all possible criteria.

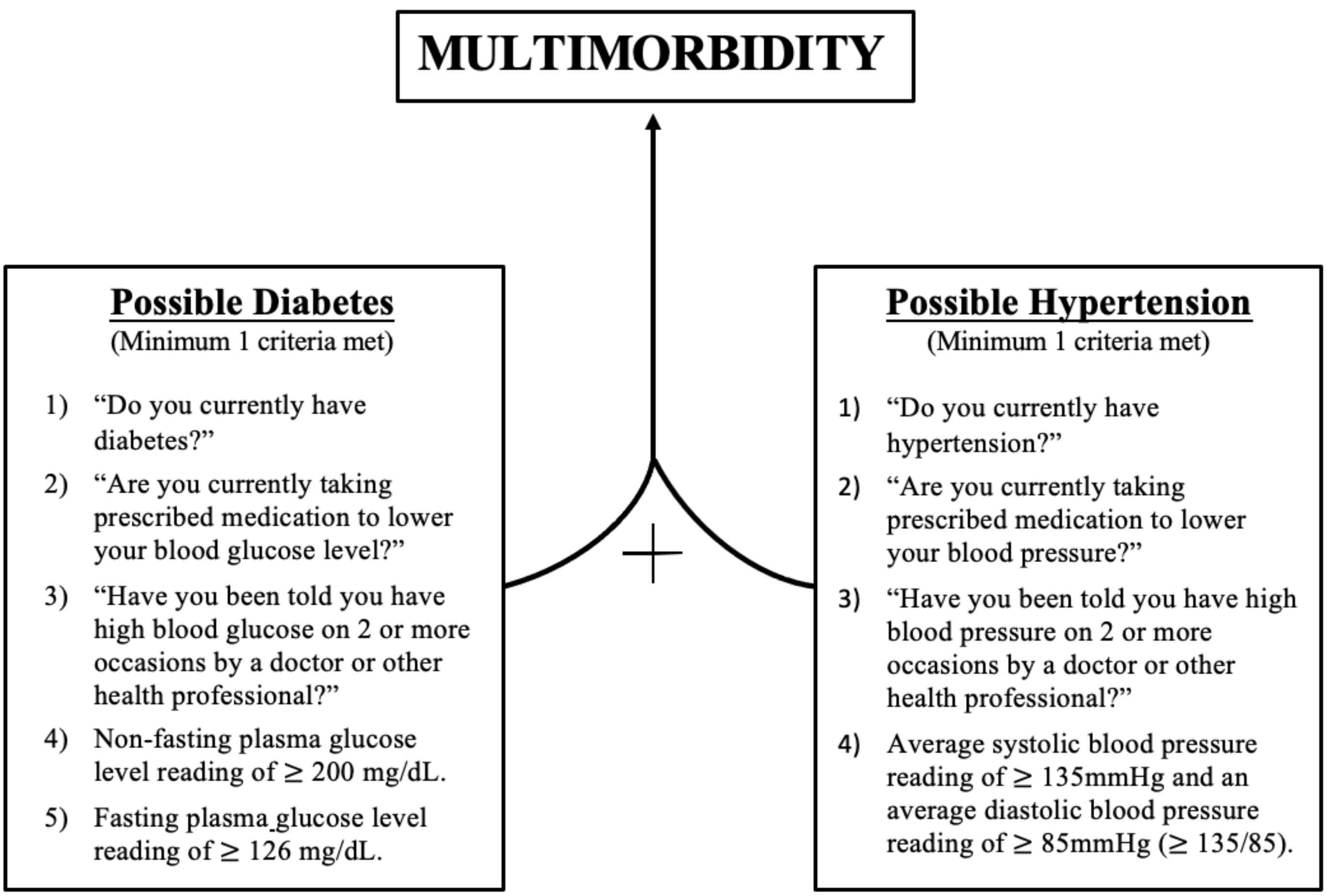

Figure 7: Criteria used to define possible cases of multimorbidity.

3.3.2 Independent variables

3.3.2.1 Sociodemographic independent variables

Age – Age was defined as the respondent's age at the time that the survey took place. Respondents were asked "In what month and year were you born?" to determine their age (IIPS, n.d.). Age ranged in values from a minimum of 15 years of age to a maximum of 54 years of age. Age was treated as a continuous variable.

Education – Education was defined as the self-reported maximum level of education respondents had obtained. Respondents were asked, "What is the highest grade/standard you have completed in school?" (IIPS, n.d.). Based on collected data, respondents were categorized into specific categories associated with their educational attainment. Education was recoded to a 4-category variable: 'No education', 'Incomplete primary', 'incomplete secondary' and, 'Completed secondary or higher'. Those respondents who replied as having completed no grades of schooling were categorized as 'No education'. Those respondents who reported completing any grade between 1-5, were categorized as 'incomplete primary education'. The respondents who replied as completing any grade between 6-11 were categorized as 'incomplete secondary education' which encompasses those who completed primary education and began but did not complete secondary education. Lastly, those that completed secondary education or had obtained higher education beyond the 12th grade/standard, were categorized as 'Completed secondary or higher'.

Region of Residence – Region of residence was defined as the general geographic area of India in which a respondent resided. Before beginning the interview, field agents noted down various information regarding respondents which included which state/union territory the respondent reside within. For this variable, states and union territories were combined into six categories: North India, Central India, East India, North-East India, West India, and South India. The DHS program defined each category as containing the following regions (IIPS & ICF, 2021):

1) North India: Chandigarh, Delhi, Haryana, Himachal Pradesh, Jammu & Kashmir, Ladakh, Punjab, Rajasthan, and Uttarakhand.

2) Central India: Chhattisgarh, Madhya Pradesh, and Uttar Pradesh.

3) East India: Bihar, Jharkhand, Odisha, and West Bengal.

4) North-East India: Arunachal Pradesh, Assam, Manipur, Meghalaya, Mizoram, Nagaland, Sikkim, and Tripura.

5) West India: Dadra and Nagar, Goa, Gujarat, and Maharashtra.

6) South India: Andaman and Nicobar Islands, Andhra Pradesh, Karnataka, Kerala, Lakshadweep, Puducherry, Tamil Nadu, Telangana.

Wealth Index – Wealth index was defined as which quantile of 'wealth' respondents belonged to. The construction of a wealth index is done in a specific method by the DHS program. During the survey process, households were asked questions regarding household assets and utility services (Rutstein et al., 2004; IIPS, n.d.). Common inquiries include but are not limited to water supply/source, sanitation facilities, domestic servants, electricity, ownership of agricultural land, persons sleeping per room, type of flooring in home, etc. (Rutstein et al., 2004). For household assets, consumer goods were inquired about such as radio, television, telephone, type of vehicle, appliances, bicycle, computer, sewing machine, etc. (Rutstein et al., 2004; IIPS, n.d.). Filmer and Pritchett's principle components analysis (PCA) is used by the DHS to construct the wealth index (Rutstein et al., 2004; Filmer & Pritchett, 2001). Using the PCA method, indicator variables can be assigned a weight and then the weighted sum of these indicator variables is used to produce a wealth index value for each household (Rutstein et al., 2004; Filmer & Pritchett, 2001). Once a wealth index value was determined for all relevant households (and hence their respective individual residents), the scores were ranked from least to greatest. This distribution of scores was created in 5 equal categories known as quintiles. The categories ranged from the lowest scores to the greatest which were labeled as the following: poorest (1^{st} quintile), poorer (2^{nd} quintile), middle (3^{rd} quintile), richer (4^{th} quintile), and richest (5^{th} quintile).

Religion – Religion was defined as which religious group a respondent self-identified as belonging to. Respondents were asked "What is your religion?" with response options being Hindu, Muslim, Christian, Sikh, Buddhist/Neo-Buddhist, Jain, Jewish, Parsi/Zoroastrian, no religion or other (IIPS, n.d.). These were recoded into Hindu, Christian, Muslim, and other. The “other” category was used to represent many of the less frequently reported religions such as: Sikh, Buddhist/Neo-Buddhist, Jain, Jewish, Parsi/Zoroastrian, other or no religion.

Current Marital Status – Current Marital status was defined as per the self-reported marital status at the time of the interview. Respondents were asked “What is your current marital status?” with the reply options being married, never married, deserted, separated/no longer living together, divorced, or widowed (IIPS, n.d.). For this variable, respondents were recoded into two categories which were either married or single. Married was defined as those who self-reported being married at the time of the survey. Single was defined as those that self-reported they are divorced, widowed, deserted, had never been married, or are no longer living together/separated.

Occupation – Occupation was defined as per the self-reported occupation at the time of the survey. Respondents were asked an open-ended question “What is your occupation, that is, what kind of work do you mainly do?” (IIPS, n.d.). With the NFHS team receiving a broad range of responses, we recoded occupations into five categories: ‘not working’, ‘agricultural’, ‘professional/services/technical/managerial/clerical/sales’, ‘skilled and unskilled manual’, and ‘other’.

Caste – Caste was defined as which caste respondents self-reported as belonging to. Respondents were asked “Do you belong to a scheduled caste, a scheduled tribe, other backward class, or none of these?” and response options were scheduled caste, scheduled tribe, other backward class (OBC) or none (IIPS, n.d.). This variable was left as categorical with these four original categories.

3.3.2.2 Lifestyle independent variables

BMI – BMI was defined as the category of body mass index to which respondents belonged. BMI is a simple measure in which weight and height information is used to place individuals into certain categories of estimated body fat proportions (Weir & Jan, 2022; Aziz et al., 2014). During the surveying process, respondents had their weight (kg) and height (m) measured by field agents. However, BMI values for each respondent were not distributed within the dataset. Thus, to determine the BMI value for each respondent, we transformed their height and weight data using the following equation: $BMI = \frac{weight\ (kg)}{[height(m)]^2}$ (CDC, 2022). There were four categories of BMI that we recoded respondents into: underweight, normal, overweight, and obese. To determine which BMI values would be recoded into each category, we referred to the following BMI cut-offs relevant to the Indian population (Weir & Jan, 2022; Aziz et al., 2014; WHO, 2000):

1) Underweight: BMI value less than 18.5 kg/m^2
2) Normal: BMI value equal to or greater than 18.5 kg/m^2, but less than 23 kg/m^2 ($18.5\,kg/m^2 \leq BMI < 23\,kg/m^2$)
3) Overweight: BMI value equal to or greater than 23 kg/m^2 but, lesser than 25 kg/m^2 ($23\,kg/m^2 \leq BMI < 25\,kg/m^2$)
4) Obese: BMI value greater equal to or greater than 25 kg/m^2

Thus, in accordance with these cut-offs, we categorized respondents into the appropriate BMI category.

Alcohol Consumption – Alcohol consumption was defined as the self-reported status regarding if a respondent consumed alcohol or not. Respondents were asked "Do you drink alcohol?" and could reply with yes or no. This variable was left as categorical with these two original categories.

Healthy Diet Consumption – For healthy diet consumption, self-reported data regarding the frequency of consumption of fruits and dark green leafy vegetables was considered. Respondents were asked the following two questions:

- "How often do you yourself eat the following food items: daily, weekly, occasionally, or never?" Fruits.
- "How often do you yourself eat the following food items: daily, weekly, occasionally, or never?" Dark green leafy vegetables.

Defining those who have a 'healthy diet' was done in 2 steps. Firstly, respondents that self-reported daily or weekly consumption for each: 1) fruits and 2) dark green leafy vegetables, were recoded as having sufficient consumption of each respective food. In the second step, a variable called "Healthy diet consumption" was produced. Those who had sufficient consumption of both fruits and dark green leafy vegetables were coded as having a healthy diet, with others being coded as having an unhealthy diet.

Media Exposure – For media exposure, self-reported data regarding use of internet, television (TV), radio, newspaper/magazine, and mobile phone was considered. Respondents were asked the following five questions:

1) "Do you listen to the radio?" YES or NO
2) "Do you watch television?" Yes or NO
3) "Do you read a newspaper or magazine? Yes or NO
4) "Do you have any mobile phone that you yourself use?" YES or NO
5) "Have you ever used the internet?" YES or NO

A new variable called "Media Exposure" was produced which took into consideration each of these forms of media exposure. Within this variable, each respondent was computed a discrete score ranging from 0-5 by summing up the number of "YES" responses they gave. Meaning that a respondent with a value of 0 did not utilize the internet, TV, radio, newspaper/magazine, or a mobile phone. Oppositely, a value of 5 means a respondent self-reported using all sources of media discussed.

Tobacco Consumption – Tobacco consumption was defined as the self-reported status of if a respondent consumed tobacco or not. Respondents were asked the following questions:

- "Do you currently smoke cigarettes every day, some days, or not at all?"
- "Do you currently smoke bidis every day, some days, or not at all?"
- "Do you currently smoke or use tobacco in any other form?" YES or NO

- If YES - "In, what other form do you currently smoke or use tobacco? Cigar, pipe, hookah, gutkha/paan masala with tobacco, khaini, pan with tobacco, other chewing tobacco, snuff, or any other methods."

A binary tobacco consumption variable was created which took into consideration all these various methods of consumption. For this variable, consumption of tobacco through any method resulted in a respondent being coded as 1 and if a respondent had no consumption of tobacco, they were coded as 0. Thus, if a respondent replied with smoking cigarettes at any frequency and/or smoking bidis at any frequency they were coded as 1. Additionally, if any respondent reported consumption through any one of: smoking cigars, smoking pipe, smoking hookah, smoking gutkha/paan masala with tobacco, chewing paan with tobacco, snorting snuff, chewing khaini, using any other sort of chewing tobacco or consumption in any other method, they were also coded as 1. Those respondents that self-reported no consumption of tobacco through any method were coded 0.

Table 2: Categories of independent variables (predictors)

Variables	**Categories**
Sociodemographic Variables	
Age	- Continuous (Range: 15-54)
Education	- No education - Incomplete Primary - Incomplete Secondary - Completed Secondary or Higher
Region	- North India - Central India - East India - North-East India - West India - South India
Wealth Index	- Poorest - Poorer - Middle - Richer - Richest

Table 2 – Continued

Variables	Categories
<u>Sociodemographic Variables</u>	
Religion	- Hindu - Muslim - Christian - Other
Current marital Status	- Single - Married
Occupation	- Professional/services/technical/managerial/ clerical/sales - Not working - Agricultural - Skilled/unskilled manual - Other
Caste	- Scheduled Caste - Scheduled Tribe - Other Backward Classes (OBC) - None
<u>Lifestyle Variables</u>	
BMI	- Underweight - Normal - Overweight - Obese
Alcohol Consumption	- No - Yes
Healthy Diet Consumption	- No - Yes
Media Exposure	- Discrete (Range: 0-5)
Tobacco Consumption	- No - Yes

3.4 Statistical methods

3.4.1 Software

Statistical software package STATA 17, edition BE (Basic) (STATA Corp, 2021), was used to carry out all tasks such as merging datasets, defining/creating variables, and to conduct all analyses.

3.4.2 Merging datasets

From the NFHS-5 survey, two different datasets were pooled together to create a final dataset which was used for analysis. Dataset IAMR7DFL.dta (male recode) was the primary dataset utilized for analysis. Information regarding male height and weight (required to calculate the BMI of respondents) was not available in this dataset. Thus, dataset IAHR7DFL.dta (household recode) was also utilized. Within this dataset, since only height and weight data were needed, all other variables were dropped prior to merging. The merging process was conducted using STATA's many-to-one merge command. For each male observation in the primary male recode dataset (master), the merge command determines the corresponding observation in the secondary household recode dataset (using). The merge command can determine which male observations in the *master* dataset correspond to the same males in the *using* dataset due to identifier variables. Commonly utilized identifier variables for DHS data include respondent number, cluster number, household number, and type of residence (Rutstein, 2006). The merge command was completed successfully, with all 101,839 men from the primary male recode dataset being correctly matched to those from the secondary household dataset.

Amongst the matched respondents, height data pertaining to 96,030 males and weight data pertaining to 96,054 males was merged in. The remaining observations were instances of missing data, refusal to participate, and absence during measurement of height and weight.

3.4.3 Missing data

The DHS Program defines a missing value for a variable as when a respondent either chose not to provide an answer to the question or if the respondent was not asked the relevant question (The DHS Program, n.d.). Additionally, any response given as “I don’t know” was recoded as a missing value.

For the dependent variable (multimorbidity), there were 7,596 missing observations (7.46%). The MM variable was constructed by using the diabetes and hypertension variables described in sections 3.3.1.1 and 3.3.1.2. The hypertension variable had 9,356 missing observations (9.19%). The diabetes variable had 8,328 missing observations (8.18%). Amongst these missing observations for the diabetes and hypertension variables, 6,126 were common (missing data for both diabetes and hypertension, thus contributing to missing observations of MM). An additional 1264 missing observations of diabetes were defined as possible cases of hypertension, thus also contributing to missing observations for MM. Similarly, 206 of the missing observations for hypertension were defined as possible cases of diabetes thus, also contributing to missing observations for MM. Together, these sum to the 7,596 missing observations for MM as seen in the following table 2.

Table 3: Missing data summary for diabetes and hypertension variables

	Diabetes			TOTAL
Hypertension	0	1	missing data	
0	72,115	3,031	938	76,084
1	12,638	2,497	1,264	16,399
Missing data	3,024	206	6,126	9,356
TOTAL	87,777	5,734	8,238	101,839

→ contributes to multimorbidity missing data.

For independent variables, only caste, occupation, and BMI had missing data. The caste variable had 4,951 missing observations (4.86%). The occupation variable had 243 missing observations (0.24%). Lastly, the BMI variable had 5,931 missing observations of data (5.82%). All other independent variables, which are age, education, region, wealth index, religion, current marital status, alcohol consumption, healthy diet, media exposure, and tobacco consumption, had no missing data (101,839 observations each).

Table 4: Summary of missing data for the dependent and independent variables

Variable	Missing observations - n (%)
Multimorbidity (outcome)	7,596 (7.46%)
Caste	4,951 (4.86%)
Occupation	243 (0.24%)
BMI	5,931 (5.82%)

To account for this missing data, we utilized a listwise deletion method also known as complete case analysis within STATA. When using listwise deletion if any respondent was missing data for even one of the independent variables (≥ 1), their entire observation was excluded from any multivariable statistical analysis model. It was assumed that data was missing completely at random (MCAR). Under such an assumption, the use of listwise deletion will still produce accurate standard error estimates while maintaining minimized introduction of bias (Allison, 2009). However, one downside is that due to entire observations being discarded, a large amount of data can possibly be lost. For our analysis, listwise deletion brought the final observation count for all relevant multivariable analyses to a total of 89,179 (22,411 urban observations and 66,768 rural observations). Thus, a total of 12,660 observations (12.43% of respondents) were excluded from multivariable analysis.

3.4.4 Statistical analysis

3.4.4.1 Survey weights

When analyzing survey data such as the NFHS, it is common practice to implement survey weights. As the NFHS series utilizes a two-stage sampling method, generally two weights are required (one for each stage) to correctly *svyset* the dataset within STATA. By implementing survey weights for all stages of sampling, certain analysis methods such as multi-level modeling (as implemented in section 3.4.4.4) can be completed using weighted data. However, the weights for each stage of sampling are currently unavailable for the NFHS-5, and thus the data at hand cannot be *svyset* appropriately. This has resulted in all subsequent analyses being conducted utilizing unweighted data.

3.4.4.2 Univariate analysis

For the univariate analysis of the continuous/discrete variables (age and media exposure), the mean values and standard deviations were determined. For the univariate analysis of the categorical variables (multimorbidity, education, region, wealth index, religion, marital status, occupation, caste, BMI, alcohol consumption, healthy diet, and tobacco consumption), frequency distribution of observations were determined. For each of these variables, the univariate analysis was split into urban and rural respondents. For each variable (multimorbidity, sociodemographic factors, and lifestyle factors) it was also tested if differences in univariate findings across urban and rural areas were statistically significant. To do so, chi-square tests of independence ($\mathcal{X}^2$) and t-tests were conducted respectively for categorical and continuous/discrete variables. The univariate analysis served to better understand the data at hand and additionally, served to compare urban vs. rural findings for each variable. The univariate analysis was conducted using unweighted data.

3.4.4.3 Bivariate analysis

Bivariate analysis was conducted to determine the unadjusted statistical association between each independent variable with MM. To carry out each bivariate analysis, an unadjusted binary logistic regression was run between each independent variable and the outcome variable. For each independent variable, a separate odds ratio (OR) was determined for rural and urban respondents by running two separate models. Additionally, the associated p-value and 95% confidence interval was determined for each OR. The bivariate analysis was conducted using unweighted data.

3.4.4.4 Multivariable analysis

Multivariable analysis was conducted to determine adjusted statistical associations between each independent variable with MM. To determine these adjusted odds ratio (AOR) estimates, multi-level mixed-effect binary logistic regression models were created. DHS surveys tend to follow a multi-level data structure due to the two-stage sampling design implemented (Elkasabi et al., 2020). This nested data structure can result in possible correlation between observations from a specific cluster and thus, to ensure the accuracy of estimates, and correct for any possible nesting effects, a two-level model design was implemented. Level 1 of the models was the male respondents and for level 2, the cluster variable analyzed was districts (random intercept) so that any possible intra-district correlation of observations could be taken into consideration. A separate model was created for both urban and rural area respondents to determine area-specific associations between predictors of interest and MM. Doing so allowed for urban and rural area predictors to be contrasted. The multivariable analyses were done using unweighted data.

Additionally, to test the goodness-of-fit of using multi-level mixed-effect binary logistic regression to model the relationship between the predictors of interest and MM, a likelihood ratio test (LRT) was done. The LRT test was conducted against a regular non-multilevel binary logistic regression to determine which model may be a better fit for the data being analyzed. The LRT was done for both multivariable analyses (urban and rural).

Lastly, multicollinearity and interaction were tested for within both multivariable models. To determine if multicollinearity exists between any variables, variance inflation factor (VIF) values were determined for each variable, and a mean VIF for the model. To test for interaction, interaction terms were created for the following variable combinations:

1) Wealth – Education
2) Wealth – Occupation
3) Wealth – Tobacco consumption
4) Wealth – Alcohol consumption
5) Wealth – Media Exposure
6) Wealth – Religion
7) Education – Region
8) Education – BMI
9) BMI – Region

Chapter 4

4 Results

Within this chapter is an overview of findings from all analyses completed. Section 4.1 contains the univariate analysis for the dependent (MM) and all independent variables (sociodemographic and lifestyle factors) split by urban and rural areas. Sections 4.2 and 4.3 respectively focus on urban and rural areas and present the bivariate and multivariable analysis results for the associations between the predictors of interest and MM. Lastly, section 4.4 provides a side-by-side comparison of significant predictors of MM found from the urban and rural multivariable analyses.

4.1 Univariate analysis

Table 5 (univariate results) is presented following section 4.1.3 and summarizes the descriptive statistics for all variables analyzed in this study. Univariate analysis was done using unweighted data.

4.1.1 Distribution of multimorbidity

Of the 101,839 males sampled in the NFHS-5, a total of 94,243 had sufficient data to determine their MM (diabetes + hypertension) status. With the analysis being split into urban and rural areas, there were respectively 23,922 and 70,321 observations for each area. Amongst males from urban areas, a higher percentage were found to be possible cases of MM as compared to rural areas. Within urban areas, 909 males (3.8%) were defined as having MM, and within rural areas 1,588 (2.3%). A statistically significant difference in the distribution of multimorbidity was found across urban and rural areas ($p<0.001$).

4.1.2 Distribution of sociodemographic factors

The first set of independent variables analyzed in the univariate analysis was the sociodemographic factors. For all sociodemographic factors, a statistically significant difference in findings across urban and rural areas was found (as per chi-square tests and t-tests, $p<0.001$). Amongst these factors, age was analyzed as a continuous variable. The age range of the males sampled was 15 to 54 years with the mean age in urban areas being slightly greater than that of rural areas. The mean age and standard deviation was 32.5 ($\pm$11.1) in urban areas and 32.1 ($\pm$11.3) in rural areas.

The remaining sociodemographic factors were categorical variables and were analyzed for their distribution of observations (Table 5). A greater proportion of males had higher levels of education in urban areas as compared to rural areas. Approximately 31.1% of males residing in urban areas had completed secondary school-level education or higher. Meanwhile, in rural areas, the proportion was lower at 18.3%. Rural areas exhibited a greater proportion of males having lower education levels as compared to urban areas. Distribution of region of residence also varied as there was no clear trend. Amongst those males residing in urban areas, the majority were from North India (24.1%) and the least were from the North-East region (11.3%). For those residing in rural areas, the majority were from Central India (24.6%), with the least being from the Western region (10.2%).

Wealth was found to have notable disparities across urban and rural areas. Wealth was measured using a wealth index which placed all males sampled into quintiles ranging from poorest, poorer, middle, richer, and richest. Amongst males from urban areas, a much greater proportion belonged to richer quintiles of wealth's. Oppositely, in rural areas a greater proportion of males were found to belong to the poorer quintiles of wealth. In urban areas 41.2% of males belonged to the richest quintile (5^{th}) of wealth. In rural areas, only 8.8% belonged to the same quintile. Oppositely, only 3.0% of males from urban areas belonged to the poorest quintile of wealth however, in rural areas, this proportion was 25.2%.

The distribution of religious groups was similar across urban and rural areas with Hindus being the majority in both areas at approximately 75%. The only notable difference was the proportion of Muslims, with urban areas having a slightly higher proportion (16.3%) as compared to rural areas (10.4%). Marital status distributions were also nearly identical with approximately 60% of men being married in both areas as opposed to single (never in union, divorced, widowed, separated, deserted). In rural areas, agriculture was the predominant occupation as 41.1% of the sampled males belonged to this category.

However, in urban areas, the broad category of professional, services, technical, managerial, clerical, and sales-related occupations were most common at 37.8%. Other occupational categories were similar in proportion of observations across urban and rural areas.

Lastly, caste composition was analyzed for which similar proportions of males identified as belonging to an SC (~20%) or OBC (~40%) in both rural and urban areas. Proportions for STs and those who identify with none of the highly marginalized castes differed across urban and rural areas. In urban areas 10.8% of males identified as being in an ST and 26.7% identified as being in 'none' (not in a ST, SC, or OBC). In rural areas, 23.1% of males identified as being in a ST and 17.1% as none (not in a ST, SC, OBC). Hence in urban areas a slightly less proportion of males belong to the highly marginalized castes.

4.1.3 Distribution of lifestyle factors

For all lifestyle factors, a statistically significant difference in findings across urban and rural areas was also found ($p<0.001$). In urban areas, only 37.8% of men were found to have normal BMI as compared to 47.1% in rural areas. Instead, a greater proportion of urban area males had higher BMIs. In urban areas 19.9% of males were overweight and 26.7% were obese (as per their BMI). In rural areas, the proportion for overweight and obese BMI were a lesser 17.6% and 19.7% respectively. The proportion of males with underweight BMI in urban and rural areas respectively were 11.2% and 15.6%. It was also found that in urban areas 62.5% of males consumed a 'healthy diet', whereas in rural areas only 46.8% did. For the lifestyle factors media exposure was analyzed as a continuous variable. It was found that media exposure was slightly greater in urban areas. With media exposure being measured on a scale of 0-5 for each observation, the mean media exposure and standard deviation was 3.4 ($\pm$1.2) in urban areas and 2.8 ($\pm$1.3) in rural areas. Alcohol consumption was also similar across urban and rural areas with approximately 25% of males self-reporting that they consume alcohol. Tobacco consumption however was greater in rural areas with nearly half of the sampled males reporting consumption (46.1%). In urban areas, the proportion was lower at 35.9%.

Table 5: Univariate analysis of dependent and independent variables split by urban and rural areas.

	Urban	Rural
Variable	**n (%)**	**n (%)**
Dependent Variable		
Multimorbidity* (n=94,243)		
No	23,013 (96.2%)	68,733 (97.7%)
Yes	909 (3.8%)	1,588 (2.3%)
Independent Variables		
Sociodemographic factors		
Age (years)*		
Mean ± SD	32.5± 11.1	32.1± 11.3
Education*		
No education	1,875 (7.1%)	10,394 (13.8%)
Incomplete primary	2,268 (8.6%)	9,442 (12.5%)
Incomplete secondary	14,046 (53.2%)	41,761 (55.4%)
Completed secondary or higher	8,231 (31.1%)	13,822 (18.3%)
Region*		
North India	6,368 (24.1%)	14,766 (19.6%)
Central India	4,692 (17.8%)	18,550 (24.6%)
East India	3,057 (11.5%)	12,140 (16.1%)
North-East India	2,979 (11.3%)	11,881 (15.7%)
West India	3,873 (14.7%)	7,715 (10.2%)
South India	5,451 (20.6%)	10,367 (13.8%)
Wealth Index*		
Poorest (1st Quintile)	786 (3.0%)	19,010 (25.2%)
Poorer (2nd Quintile)	2,238 (8.5%)	20,361 (27.0%)
Middle (3rd Quintile)	4,580 (17.3%)	17,135 (22.7%)
Richer (4th Quintile)	7,921 (30.0%)	12,288 (16.3%)
Richest (5th Quintile)	10,895 (41.2%)	6,625 (8.8%)
Religion*		
Hindu	19,301 (73.0%)	57,910 (76.8%)
Muslim	4,297 (16.3%)	7,815 (10.4%)
Christian	1,661 (6.3%)	5,606 (7.4%)
Other	1,161 (4.4%)	4,088 (5.4%)
Current Marital Status*		
Single (never in union, divorcee, widowed, separated, deserted)	10,747 (40.7%)	27,715 (36.8%)
Married	15,673 (59.3%)	47,704 (63.2%)

Table 5 - Continued

Variable	Urban n (%)	Rural n (%)
Independent Variables		
Occupation*		
Professional/services/Technical/ managerial/clerical/sales	9,954 (37.8%)	11,574 (15.4%)
Not working	5,359 (20.3%)	13,882 (18.5%)
Agricultural	1,929 (7.3%)	30,935 (41.1%)
Skilled & unskilled manual	7,723 (29.3%)	16,207 (21.5%)
Other	1,394 (5.3%)	2,639 (3.5%)
Caste*		
Scheduled caste	4,719 (19.0%)	14,541 (20.2%)
Scheduled tribe	2,694 (10.8%)	16,660 (23.1%)
OBC (other backward classes)	10,820 (43.5%)	28,506 (39.6%)
None	6,649 (26.7%)	12,319 (17.1%)
Lifestyle factors		
BMI*		
Underweight	2,738 (11.2%)	11,144 (15.6%)
Normal	9,192 (37.8%)	33,671 (47.1%)
Overweight	4,844 (19.9%)	12,605 (17.6%)
Obese	7,568 (31.1%)	14,146 (19.7%)
Alcohol Consumption*		
No	20,066 (75.9%)	55,325 (73.4%)
Yes	6,354 (24.1%)	20,094 (26.6%)
Healthy Diet*		
No	9,913 (37.5%)	40,133 (53.2%)
Yes	16,507 (62.5%)	35,286 (46.8%)
Media exposure (score 0-5)*		
Mean $\pm$ SD	3.4 $\pm$ 1.2	2.8 $\pm$ 1.3
Tobacco consumption*		
No	16,941 (64.1%)	40,671 (53.9%)
Yes	9,479 (35.9%)	34,748 (46.1%)

Statistically significant Chi-square test and t-test results between urban and rural findings denoted with asterisks (*) besides independent variable.

** $p<0.001$, ** $p<0.01$, *** $p<0.05$*

4.2 Urban Area - bivariate & multivariable analysis

Bivariate and multivariable analyses were first conducted regarding males from urban areas to determine associations between the predictors of interest and MM. For bivariate analysis, a binary logistic regression was conducted producing unadjusted OR estimates. For the multivariable analysis, a multi-level mixed-effect binary logistic regression was conducted producing adjusted OR estimates. These findings are summarized in Table 6 following section 4.2.3. Each analysis was done using unweighted data.

4.2.1 Sociodemographic factors

Within the urban area bivariate analysis, select sociodemographic factors (or specific categories) were found to have a statistically significant association with MM. However, some of these factors or categories became insignificant once covariates were adjusted for in the subsequent multivariable analysis.

4.2.1.1 Bivariate results

Age was found to have a statistically significant positive association with MM, with a reported 11% increase in odds of MM per year increase in age. Amongst the categorical sociodemographic factors, certain categories of region of residence, wealth index, religion, current marital status, occupation, and caste were found to share a statistically significant association with MM. Males residing in East or South India respectively had 30% and 55% increased odds of MM as compared to males from North India. However, males residing in West India had 43% reduced odds of MM. Regarding wealth index, males in the middle (3rd), richer (4th), and richest (5th) quintiles of wealth respectively had 2.05, 2.55, and 3.10 times the odds of MM as compared to those in the poorest quintile (1st). For religions, Muslims were found to have 38% reduced odds of MM as compared to Hindus. Furthermore, married men had 6.54 times greater odds of MM as compared to those who were single. For occupation, those not working and those doing skilled/unskilled manual jobs respectively had 75% and 36% reduced odds of MM as compared to men in professional, services, technical, managerial, clerical, or sales occupations. Amongst caste categories, only males in SC were found to have a statistically significant association to MM with a reported 28% reduction in odds of MM as compared to those in none of the highly marginalized castes.

4.2.1.2 Multivariable results

Due to the multivariable analysis adjusting for all other covariates, the identified associations are a more accurate representation of the direct relationship between each predictor and MM.

The adjusted estimate for the age-MM association remained nearly unchanged with a reported AOR of 1.10 (95% CI: 1.09, 1.11). Residing in the East, West, or South regions of India each remained statistically significant predictors of MM (with reference to North India). Residing in either East or South India increased odds of MM respectively by 65% and 50%. Residing in West India was still found to have a protective effect, reducing odds of MM by 36%. Wealth index was still a significant predictor of MM with males in the richer and richest quintiles each respectively having AORs of 2.14 (95% CI: 1.09, 4.17) and 2.34 (95% CI: 1.18, 4.62) for MM (as compared to men from the poorest quintile). For religion, Christian men were found to have a statistically significant 38% reduction in odds of MM. For occupation, those working skilled/unskilled manual jobs were still found to have reduced odds of MM with an AOR of 0.78 (95% CI: 0.65, 0.95). Lastly, marital status and caste both had no significant findings for the multivariable analysis. Education was the sole urban area sociodemographic predictor to have no significant findings in association to MM for both the bivariate and the multivariable analysis.

4.2.2 Lifestyle predictors

For lifestyle predictors (BMI, alcohol consumption, healthy diet, media exposure, tobacco consumption) all were found to be significant within the bivariate analysis. However, after adjusting for covariates in the multivariable analysis the only lifestyle predictor to remain a statistically significant predictor of MM was BMI.

4.2.2.1 Bivariate results

Within the urban bivariate analysis, BMI was found to have a strong positive association with MM. When compared to males with normal BMI, those who were overweight and obese each respectively had 2.08 and 3.60 times the odds of MM. Underweight males had a 60% reduction in odds of MM. Consuming alcohol and consuming tobacco were each respectively found to increase the odds of MM by 57% and 24%. A healthy diet was found to increase odds of MM by 27%. Lastly, was the continuous variable for media exposure, which was found to have an OR of 1.10 (95% CI: 1.04, 1.17), meaning for each unit increase in media exposure score, odds of MM increased by 10%.

4.2.2.2 Multivariable results

For the urban multivariable analysis, only the overweight and obese categories of BMI remained statistically significant predictors of MM. Males who were overweight and obese respectively had AORs of 1.40 (95% CI: 1.12, 1.75) and 2.09 (95% CI: 1.72, 2.54) (as compared to males with normal BMI).

4.2.3 Characteristics of urban area multi-level model

Within the multivariable analysis, possible clustering at the district level was acknowledged by treating districts as a random intercept. For this multi-level mixed-effect binary logistic regression, the intraclass correlation coefficient (ICC) was reported to be 0.15. This implies that approximately 15% of the variability in MM outcome can be attributed to the districts which sampled males reside in. When testing the adequacy of this multi-level mixed-effect binary logistic regression as compared to a regular non-multi-level binary logistic regression, the LRT yielded a value of 98.46 ($p<0.001$). Thus, implying that the chosen multi-level model is a better fit for the data at hand.

Regarding multicollinearity, no independent variable was found to have a VIF value of concern, with the models average VIF value being equal to 3.47. All interaction terms tested were insignificant, and therefore excluded from the final model.

Table 6: Bivariate and multivariable analyses of sociodemographic & lifestyle predictors of multimorbidity for urban area residents (n=22,411).

Independent variables	Unadjusted OR (95% CI)	*P*	Adjusted OR (95% CI)	*P*
Sociodemographic factors				
Age	**1.11 (1.10, 1.12)**	<0.001	**1.10 (1.09, 1.12)**	<0.001
Education				
No education	-		-	
Incomplete primary	1.14 (0.83, 1.57)	0.409	1.12 (0.79, 1.59)	0.518
Incomplete secondary	0.88 (0.68, 1.14)	0.336	1.00 (0.73, 1.37)	0.990
Completed secondary or higher	0.93 (0.71, 1.22)	0.603	1.00 (0.71, 1.42)	0.991
Region				
North India	-		-	
Central India	0.90 (0.72, 1.12)	0.344	1.17 (0.83, 1.63)	0.370
East India	**1.30 (1.04, 1.64)**	0.023	**1.65 (1.14, 2.38)**	0.008
North-East India	1.25 (0.99, 1.58)	0.057	1.46 (0.96, 2.22)	0.073
West India	**0.57 (0.43, 0.75)**	<0.001	**0.64 (0.43, 0.96)**	0.030
South India	**1.55 (1.28, 1.87)**	<0.001	**1.50 (1.08, 2.06)**	0.014
Wealth Index				
Poorest (1st Quintile)	-		-	
Poorer (2nd Quintile)	1.30 (0.66, 2.54)	0.449	1.22 (0.60, 2.49)	0.581
Middle (3rd Quintile)	**2.05 (1.10, 3.80)**	0.024	1.81 (0.92, 3.53)	0.084
Richer (4th Quintile)	**2.55 (1.39, 4.69)**	0.002	**2.14 (1.09, 4.17)**	0.026
Richest (5th Quintile)	**3.10 (1.69, 5.66)**	<0.001	**2.34 (1.18, 4.62)**	0.015
Religion				
Hindu	-		-	
Muslim	**0.62 (0.50, 0.77)**	<0.001	0.76 (0.58, 1.00)	0.053
Christian	0.83 (0.62, 1.10)	0.194	**0.62 (0.40, 0.95)**	0.027
Other	0.88 (0.63, 1.22)	0.442	0.95 (0.63, 1.43)	0.814
Current Marital Status				
Single	-		-	
Married	**6.54 (5.26, 8.15)**	<0.001	1.32 (1.00, 1.75)	0.053
Occupation				
Professional/services/Technical/ managerial/clerical/sales	-		-	
Not working	**0.25 (0.19, 0.32)**	<0.001	1.31 (0.95, 1.82)	0.098
Agricultural	0.80 (0.62, 1.02)	0.074	0.84 (0.63, 1.11)	0.222
Skilled & unskilled manual	**0.64 (0.55, 0.76)**	<0.001	**0.78 (0.65, 0.95)**	0.011
Other	0.87 (0.66, 1.15)	0.322	1.02 (0.74, 1.40)	0.920

Table 6 - Continued

Independent variables	Unadjusted OR (95% CI)	*P*	Adjusted OR (95% CI)	*P*
Sociodemographic factors				
Caste				
None	-		-	
Scheduled caste	**0.72 (0.58, 0.89)**	0.003	0.93 (0.72, 1.19)	0.558
Scheduled tribe	1.03 (0.81, 1.30)	0.818	1.34 (0.95, 1.88)	0.097
OBC (other backward classes)	1.03 (0.87, 1.21)	0.744	1.07 (0.87, 1.30)	0.525
Lifestyle factors				
BMI				
Normal	-		-	
Underweight	**0.40 (0.26, 0.63)**	<0.001	0.65 (0.40, 1.06)	0.084
Overweight	**2.08 (1.70, 2.56)**	<0.001	**1.40 (1.12, 1.75)**	0.004
Obese	**3.60 (3.03 4.29)**	<0.001	**2.09 (1.72, 2.54)**	<0.001
Alcohol Consumption				
No	-		-	
Yes	**1.57 (1.36, 1.81)**	<0.001	1.15 (0.97, 1.37)	0.118
Healthy Diet				
No	-		-	
Yes	**1.27 (1.11, 1.47)**	0.001	1.06 (0.90, 1.25)	0.485
Media exposure (score 0-5)	**1.10 (1.04, 1.17)**	0.001	1.02 (0.94, 1.10)	0.689
Tobacco consumption				
No	-		-	
Yes	**1.24 (1.08, 1.42)**	0.002	1.12 (0.94, 1.33)	0.218

Random effect (Random Intercept)	**Variance of intercepts (95% CI)**
Group Variable: Districts	0.57 (0.41, 0.79)
Intraclass correlation coefficient (95% CI)	**LR test - multivariable analysis:**
0.15 (0.11, 0.19)	Multi-level model vs. regular binary logistic regression: = 98.46 (p<0.001)

4.3 Rural Area - bivariate & multivariable analysis

Like section 4.2, bivariate and multivariable analyses were once again conducted but instead for rural areas. All rural area findings are summarized in Table 7 following section 4.3.3. Both analyses were done using unweighted data.

4.3.1 Sociodemographic factors

For the rural area analyses, certain sociodemographic factors (or specific categories) were found to have a significant association with MM in the bivariate analysis however in the multivariable analysis certain factors/categories became insignificant or significant.

4.3.1.1 Bivariate results

Within the rural bivariate analysis, age was found to have a statistically significant positive association to MM with an AOR of 1.09 (95% CI: 1.09, 1.10). Amongst the categorical sociodemographic factors, certain categories of region of residence, wealth index, current marital status, occupation, and caste were found to share a statistically significant association to MM. Males residing in East or South India respectively had 57% and 107% increased odds of MM as compared to those from North India. However, those residing in West India had 21% reduced odds of MM.

All categories of wealth index were found to be significant with an increasing trend in odds of MM. Males in the poorer (2nd), middle (3rd), richer (4th), and richest (5th) quintiles of wealth respectively had 1.30, 1.72, 2.08, and 2.60 times the odds of MM as compared to those in the poorest quintile. Those who were married were found to have 4.42 times greater odds of MM as compared to single men. For occupations, all categories analyzed had significant findings. With reference to those working professional, services, technical, managerial, clerical, or sales occupations, those men with occupations in agriculture, skilled/unskilled manual, other, and not working respectively had 41%, 41%, 26%, and 80% reduced odds of MM. Amongst caste categories, only those in STs had a statistically significant association to MM, with a reported 30% reduction in odds of MM when compared to those in none (not in SC, ST, OBC).

4.3.1.2 Multivariable results

The rural area multivariable analysis yielded the following statistically significant adjusted estimates for the association of sociodemographic factors and MM.

Reported for the age-MM association was an AOR of 1.09 (95% CI: 1.09, 1.10). Education was found to be a significant predictor of MM, with males who have incomplete primary- and incomplete secondary- education each respectively having 30% and 24% increased odds of MM as compared to those with no education. Males residing in Central, East, North-East, and South India each respectively had 41%, 120%, 58% and 87% increased odds of MM as compared to men residing in North India. Wealth index was found to have a statistically significant positive association with MM. When compared to the poorest quintile, males in the poorer, middle, richer, and richest quintiles respectively had 20%, 42%, 53%, and 93% increased odds of MM. Males with occupations in agriculture or skilled/unskilled manual jobs were respectively found to have 29% and 18% reduced odds of MM. Lastly, males who were in a SC had 20% increased odds of MM compared to men who were not in a highly marginalized caste.

Marital status became an insignificant predictor in the multivariable analysis and religion was the sole urban area sociodemographic predictor to have no significant findings in association to MM for both the bivariate and the multivariable analysis.

4.3.2 Lifestyle predictors

Each lifestyle predictor (BMI, alcohol consumption, healthy diet, media exposure, tobacco consumption) had statistically significant findings within the rural bivariate analysis. In the rural multivariable analysis, all lifestyle predictors remained significant except for a healthy diet.

4.3.2.1 Bivariate results

Within the bivariate analysis, BMI was found to have a statistically significant positive association with MM. When compared to males with normal BMI, those who were underweight had 48% reduced odds of MM, and those who were overweight and obese each respectively had 1.96- and 3.63-times greater odds of MM. Consuming alcohol was found to increase odds of MM by 55% and consuming tobacco was found to increase odds of MM by 11% (when compared to not consuming). A healthy diet was found to increase odds of MM by 17%. Lastly, the continuous variable for media exposure was found to have an OR of 1.10 (95% CI: 1.04, 1.17), meaning for each unit increase in media exposure score, odds of MM increased by 10%.

4.3.2.2 Multivariable results

BMI, alcohol consumption, media exposure, and tobacco consumption each remained significant predictors of MM after the multivariable analysis. It was found that when compared to those with normal BMI, those who were underweight had 23% reduced odds of MM, and those who were overweight and obese respectively had 46% and 128% increased odds of MM. Those who consumed alcohol were found to have 1.25 (95% CI: 1.10, 1.42) times greater odds of MM as compared to non-consumers. Media exposure had an AOR of 1.08 (95% CI: 1.02, 1.14), thus for each unit increase in media exposure score, odds of MM increased by 8%. Lastly, tobacco consumption was instead found to be protective in rural areas with an AOR of 0.86 (95% CI: 0.76, 0.97).

4.3.3 Characteristics of rural area multi-level model

Within the rural area multivariable analysis, the reported ICC was equal to 0.09. This implies that approximately 9% of the variability in MM outcome can be attributed to the districts in which sampled males reside. An LRT was conducted once again for the rural area multivariable analysis to determine the goodness-of-fit of the multi-level mixed-effect binary logistic regression as compared to a regular binary logistic regression (non-multi-level). The LRT yielded a value of 122.73 ($p<0.001$), implying that the conducted multi-level model better was a better fit. Furthermore, multicollinearity was not of concern for the rural model either as no independent variable was found to have an extreme VIF value, with the models average VIF value being equal to 2.75. All interaction terms tested were also insignificant, and therefore excluded from the final model.

Table 7: Bivariate and multivariable analyses of sociodemographic & lifestyle predictors of multimorbidity for rural area residents (n=66,768).

Independent variables	Unadjusted OR (95% CI)	*P*	Adjusted OR (95% CI)	*P*
Sociodemographic factors				
Age	**1.09 (1.09, 1.10)**	<0.001	**1.09 (1.09, 1.10)**	<0.001
Education				
No education	-		-	
Incomplete primary	1.16 (0.96, 1.39)	0.123	**1.30 (1.06, 1.59)**	0.010
Incomplete secondary	0.93 (0.80, 1.07)	0.315	**1.24 (1.04, 1.49)**	0.019
Completed secondary or higher	0.87 (0.73, 1.05)	0.141	1.13 (0.89, 1.43)	0.304
Region				
North India	-		-	
Central India	0.98 (0.83, 1.16)	0.842	**1.41 (1.11, 1.79)**	0.005
East India	**1.51 (1.27, 1.78)**	<0.001	**2.20 (1.72, 2.83)**	<0.001
North-East India	1.19 (1.00, 1.42)	0.053	**1.58 (1.19, 2.10)**	0.002
West India	**0.79 (0.63, 0.99)**	0.045	0.94 (0.69, 1.27)	0.680
South India	**2.07 (1.76, 2.44)**	<0.001	**1.87 (1.47, 2.38)**	<0.001
Wealth Index				
Poorest (1st Quintile)	-		-	
Poorer (2nd Quintile)	**1.30 (1.10, 1.52)**	0.002	**1.20 (1.00, 1.44)**	0.046
Middle (3rd Quintile)	**1.72 (1.47, 2.01)**	<0.001	**1.42 (1.17, 1.72)**	<0.001
Richer (4th Quintile)	**2.08 (1.77, 2.45)**	<0.001	**1.53 (1.24, 1.90)**	<0.001
Richest (5th Quintile)	**2.60 (2.17, 3.11)**	<0.001	**1.93 (1.50, 2.47)**	<0.001
Religion				
Hindu	-		-	
Muslim	1.02 (0.87, 1.20)	0.805	1.22 (0.98, 1.52)	0.076
Christian	0.89 (0.73, 1.09)	0.273	0.82 (0.62, 1.09)	0.170
Other	1.20 (0.97, 1.47)	0.086	1.01 (0.78, 1.32)	0.924
Current Marital Status				
Single	-		-	
Married	**4.42 (3.79, 5.15)**	<0.001	1.03 (0.84, 1.24)	0.802
Occupation				
Professional/services/Technical/ managerial/clerical/sales	-		-	
Not working	**0.20 (0.16, 0.25)**	<0.001	0.87 (0.67, 1.13)	0.286
Agricultural	**0.59 (0.52, 0.67)**	<0.001	**0.71 (0.61, 0.82)**	<0.001
Skilled & unskilled manual	**0.59 (0.51, 0.69)**	<0.001	**0.82 (0.69, 0.96)**	0.016
Other	**0.74 (0.57, 0.96)**	0.026	1.01 (0.76, 1.33)	0.969

Table 7 – Continued

Independent variables	Unadjusted OR (95% CI)	*P*	Adjusted OR (95% CI)	*P*
Sociodemographic factors				
Caste				
None	-		-	
Scheduled caste	0.92 (0.78, 1.08)	0.317	**1.20 (1.00, 1.44)**	0.048
Scheduled tribe	**0.70 (0.59, 0.82)**	<0.001	0.97 (0.78, 1.20)	0.770
OBC (other backward classes)	0.92 (0.80, 1.06)	0.247	1.02 (0.87, 1.19)	0.818
Lifestyle factors				
BMI				
Normal	-		-	
Underweight	**0.52 (0.41, 0.65)**	<0.001	**0.77 (0.60, 0.98)**	0.032
Overweight	**1.96 (1.70, 2.25)**	<0.001	**1.46 (1.26, 1.70)**	<0.001
Obese	**3.63 (3.22, 4.09)**	<0.001	**2.28 (2.00, 2.60)**	<0.001
Alcohol Consumption				
No	-		-	
Yes	**1.55 (1.40, 1.73)**	<0.001	**1.25 (1.10, 1.42)**	<0.001
Healthy Diet				
No	-		-	
Yes	**1.17 (1.06, 1.29)**	0.002	1.00 (0.89, 1.12)	0.999
Media exposure (score 0-5)	**1.11 (1.07, 1.15)**	<0.001	**1.08 (1.02, 1.14)**	0.005
Tobacco consumption				
No	-		-	
Yes	**1.11 (1.00, 1.23)**	0.036	**0.86 (0.76, 0.97)**	0.017

Random effect (Random Intercept)	Variance of intercepts (95% CI)
Group Variable: Districts	0.31 (0.24, 0.41)
Intraclass correlation coefficient (95% CI)	**LR test - multivariable analysis:**
0.09 (0.07, 0.11)	Multi-level model vs. regular binary logistic regression: = 122.73 (p<0.001)

4.4 Multivariable analysis comparison urban vs. rural

Statistically significant findings from the urban and rural area multivariable analyses varied. Certain predictors were found to have similar findings while other predictors only had a significant association to MM in one of the areas. Table 8 provides a side-by-side comparison of significant predictors of MM found in each multivariable analysis.

Table 8: Comparison of significant multivariable analysis findings between urban and rural areas - sociodemographic and lifestyle predictors of multimorbidity.

Independent variables	Urban - Adjusted OR (95% CI)	Rural - Adjusted OR (95% CI)
Sociodemographic factors		
Age	**1.10 (1.09, 1.12)**	**1.09 (1.09, 1.10)**
Education		
No education	Ref.	Ref.
Incomplete primary	-	**1.30 (1.06, 1.59)**
Incomplete secondary	-	**1.24 (1.04, 1.49)**
Completed secondary or higher	-	-
Region		
North India	Ref.	Ref.
Central India	-	**1.41 (1.11, 1.79)**
East India	**1.65 (1.14, 2.38)**	**2.20 (1.72, 2.83)**
North-East India	-	**1.58 (1.19, 2.10)**
West India	**0.64 (0.43, 0.96)**	-
South India	**1.50 (1.08, 2.06)**	**1.87 (1.47, 2.38)**
Wealth Index		
Poorest (1st Quintile)	Ref.	Ref.
Poorer (2nd Quintile)	-	**1.20 (1.00, 1.44)**
Middle (3rd Quintile)	-	**1.42 (1.17, 1.72)**
Richer (4th Quintile)	**2.14 (1.09, 4.17)**	**1.53 (1.24, 1.90)**
Richest (5th Quintile)	**2.34 (1.18, 4.62)**	**1.93 (1.50, 2.47)**
Religion		
Hindu	Ref.	Ref.
Muslim	-	-
Christian	**0.62 (0.40, 0.95)**	-
Other	-	-
Current Marital Status		
Single	Ref.	Ref.
Married	-	-

Table 8 – Continued

Independent variables	**Urban - Adjusted OR (95% CI)**	**Rural - Adjusted OR (95% CI)**
Sociodemographic factors		
Occupation		
Professional/services/Technical/ managerial/clerical/sales	Ref.	Ref.
Not working	**-**	**-**
Agricultural	**-**	**0.71 (0.61, 0.82)**
Skilled & unskilled manual	**0.78 (0.65, 0.95)**	**0.82 (0.69, 0.96)**
Other	**-**	**-**
Caste		
None	Ref.	Ref.
Scheduled caste	**-**	**1.20 (1.00, 1.44)**
Scheduled tribe	**-**	**-**
OBC (other backward classes)	**-**	**-**
Lifestyle factors		
BMI		
Normal	Ref.	Ref.
Underweight	-	**0.77 (0.60, 0.98)**
Overweight	**1.40 (1.12, 1.75)**	**1.46 (1.26, 1.70)**
Obese	**2.09 (1.72, 2.54)**	**2.28 (2.00, 2.60)**
Alcohol Consumption		
No	Ref.	Ref.
Yes	**-**	**1.25 (1.10, 1.42)**
Healthy Diet		
No	Ref.	Ref.
Yes	**-**	**-**
Media exposure (score 0-5)	-	**1.08 (1.02, 1.14)**
Tobacco consumption		
No	Ref.	Ref.
Yes	**-**	**0.86 (0.76, 0.97)**

Age was a significant predictor of MM in both areas with a similar magnitude of effect. In rural areas each year increase in age increased odds of MM by 9% and in urban areas by 10%. For education, there were no significant findings in the urban area analysis. However, in rural areas, males who had incomplete primary or incomplete secondary education both had increased odds of MM when compared to those with no education. Regions of residence with a significant association to MM also varied across urban/rural areas. Urban area men from East and South India had increased odds of MM and those from West India had reduced odds when compared to those from North India. However, rural area males residing in Central, East, North-East, or South India were each associated with statistically significant increases in odds of MM. For wealth, only the richer and richest quintiles had significant associations to MM in urban areas however in rural areas all quintiles did. Increasing wealth resulted in increased odds of MM when compared to the poorest quintile of males. However, the magnitude of the effect of wealth on MM outcome for the richer and richest quintiles was slightly greater in urban areas as compared to rural. Religion was only significant in urban areas, with Christians having 38% reduced odds of MM as compared to Hindus. For occupations, skilled/unskilled manual occupations had a protective effect against MM in both areas with a similar magnitude of effect. Specific to rural areas, agricultural occupations also had a statistically significant protective effect. Lastly, for the sociodemographic predictors, caste was found to only have significant findings in rural areas. It was found that males in SCs had 20% increased odds of MM as compared to men in none of SC, ST, or OBCs. The only sociodemographic predictor to be insignificant for its association with MM in both areas was marital status.

Amongst the lifestyle predictors, BMI was a significant predictor of MM in both areas with a strong positive association. In rural areas, being underweight, overweight, and obese BMIs had a significant association to MM however, in urban areas only overweight and obese BMI were significant. The effect of BMI was similar in both areas.

Alcohol consumption, media exposure, and tobacco consumption were each only significant in rural areas, with no significant multivariable findings in the urban model. Alcohol consumption and increasing media exposure each increased odds of MM and tobacco consumption was found to decrease odds of MM. The only lifestyle predictor to be insignificant for its association with MM in both areas was the consumption of a healthy diet.

Chapter 5

5 Discussion

This chapter begins with a brief summary of this study's findings. Section 5.2 follows with interpretations of found associations between predictors and MM. Comparison is made to existing literature to determine consistencies and inconsistencies regarding the significance and effect of each predictor analyzed. Subsequent sections proceed to discuss this study's contribution & implications, limitations, possible future research, and final concluding remarks.

5.1 Summary of study findings

This study aimed to answer the research question: *"What are the predictors of multimorbidity (defined as diabetes + hypertension) amongst males aged 15-54 in India?"*. After completing analyses for urban and rural areas separately, various results of interest were found.

5.1.1 Univariate analysis

Amongst this study's findings, first were results from the univariate analysis. Various population characteristics were analyzed such as distribution of sociodemographic factors, lifestyle factors, and MM. For each of these variables there was a statistically significant differences in findings across urban and rural areas, further supporting the decision to split the analyses into separate urban and rural models.

However, due to prior issues discussed regarding the unavailability of sampling weights for the new NFHS-5, data could not be weighted prior to analysis. This resulted in univariate findings being unweighted and therefore, incomparable to existing literature which has commonly presented national prevalence estimates based on weighted data. Sampling weights act to correct for any imperfections (e.g., non-coverage, non-response, unequal probabilities, etc.) in sampling that may cause bias and affect a sample's representativeness of the population of interest (Yansaneh, 2003). Thus, the univariate findings of this study cannot be generalized to the male population aged 15-54 in India.

Found in this study was that amongst the sampled males, the prevalence of MM is greater amongst those males residing in urban areas (3.8%) as opposed to rural areas (2.3%). Such findings may have been expected due to previous literature having established that those residing in urban areas have increased prevalence of both diabetes and hypertension and that they have increased odds/risk of MM (Anjana et al., 2023; Prenissl et al., 2022; Khan et al., 2022; Puri & Singh, 2022; Chauhan et al., 2022b). However, findings also revealed that the males sampled from urban and rural areas each respectively varied in their sociodemographic and lifestyle characteristics. With the emphasis of this study being the determination of the predictors of MM, these sociodemographic and lifestyle factors were further analyzed.

5.1.2 Statistically significant predictor-MM associations

Both bivariate and multivariable analyses were conducted to determine if statistically significant associations existed between the predictors of interest and MM, and what their direction and magnitudes of effect may be. Across urban and rural areas findings varied with the following predictors having statistically significant findings in the multivariable analyses:

Urban areas: Age, region of residence, wealth, religion, occupation, and BMI.

Rural areas: Age, education, region of residence, wealth, occupation, caste, BMI, alcohol consumption, media exposure, and tobacco consumption.

(Marital status and a healthy diet were the only predictors analyzed to have no significant findings in either urban or rural areas).

5.2 Interpretation of findings

When comparing findings from this study and existing literature, there exists both consistencies and inconsistencies regarding the found effects of predictors.

5.2.1 Findings consistent with literature

Age

In this study, age was found to have a significant positive association with MM in both urban and rural areas. Each year increase of age was found to increase odds of MM by 10% and 9% respectively for urban and rural area males, thus having similar effects in both areas. Such findings can be expected as it is common knowledge that age is one of the strongest risk factors for the progression of various chronic health conditions. As individuals age their organ systems are thought to progressively dysregulate reducing their resilience to health-related issues (Fabbri et al., 2015). Thus, the formation and accumulation of chronic health conditions is thought to be accelerated. With greater susceptibility to multiple health conditions, MM becomes increasingly likely amongst those of greater age. Our findings are supported by nearly all relevant existing literature which has also reported a similar positive association between age and MM amongst the Indian population (Singh et al., 2018, Khan et al., 2022; Puri et al., 2021a; Mishra et al., 2021; Debsarma et al., 2022; Puri et al., 2021b; Puri & Singh, 2022). Ultimately it has been well established that elderly populations have drastically increased odds of MM as compared to their younger counterparts and this study is no exception.

Wealth Index

Wealth is also one of the most well-established predictors of MM with a positive association reported in nearly all relevant literature (Prenissl et al., 2022; Chauhan et al., 2022b; Puri & Singh 2022; Puri et al., 2021b). Findings from this study were in agreement with previous literature, as increasing wealth in both urban and rural areas was found to increase odds of MM. These findings were not surprising due to increased wealth being associated with less physical activity, sedentary lifestyles/occupations, and increased consumption of processed/unhealthy foods, which may all contribute to chronic health conditions and ultimately MM (Kumar et al., 2022; Chauhan et al., 2022b).

However, of particular interest was that in rural areas all quintiles of wealth were found to be associated with MM but, in urban areas only the 4th and 5th quintiles of wealth were. What may possibly contribute to such findings may be discrepancies in health systems across both areas. It is estimated that approximately 25% of India's health infrastructure, doctors, specialists, and resources, are concentrated in rural areas but they care for approximately 75% of the nation's population (Basu, 2022). As an effect of this health inequality, the quality of primary care is hindered in rural areas (Basu, 2022). Oppositely, urban area individuals are more advantaged with their health systems as they generally have improved access and receive greater resources (Banerjee, 2021), which many promote preventative and treatment measures. Therefore, even at lesser levels of wealth, urban area residents may have better-controlled progression of NCDs which could reduce the prevalence of MM. Such a scenario could contribute to the lack of significance found between wealth and MM at lesser quintiles. However, as wealth increases its associated negative implications i.e., sedentary life, unhealthy diet, etc., may contribute to rapid increases in MM prevalence that could be beyond the control of healthcare providers. This could be a cause for the significant associations we only found at higher levels of wealth.

Unfortunately, our study does not analyze any sort of healthcare/service-related factors thus, rendering such discussion about the interaction between wealth and health services as mere speculation. Under such circumstances that if we wanted to analyze such additional factors in future analyses, we could not do so using the NFHS-5 datasets as relevant variables are not available.

Although the DHS wealth index and its methodology for assessing wealth has been widely adopted in DHS reports, it has also been criticized for being too basic of an index depending on the country of interest (Rutstein, 2008). Within countries such as India, where there still exist differences in characteristics across urban and rural areas. The DHS wealth index fails to account for these differences which may possibly affect how accurately relative wealth is measured in each area (Rutstein, 2008).

Occupation

Occupations that are more physical in nature were found to have a significant protective effect against MM in both urban and rural areas. Existing literature regarding the occupation-MM association has been limited in its informativeness. Some studies have explored this topic generally only comparing risk/odds of MM for those who work with comparison to those who do not work (Puri & Singh, 2022; Chauhan et al., 2022b; Debsarma et al., 2022; Khan et al., 2022). Other researchers such as Singh et al. (2018) have conducted slightly more in-depth analyses by broadly comparing physically intensive jobs to sedentary jobs. Ultimately what previous studies have established is working, especially physically intensive jobs, reduces the odds of MM. Such findings are logically justified as physical activity is well known to have a protective effect on health.

This study expands on these found associations by analyzing more specific occupational categories. It was found that in urban areas, those who worked skilled/unskilled manual (labour) jobs had a 22% reduction in odds of MM as compared to those working more sedentary jobs (professional, services, technical, managerial, clerical, sales). Similarly in rural areas, skilled/unskilled manual jobs had a 18% reduction in odds of MM, and those working agricultural jobs also had a 29% reduction in odds of MM. The significant findings of males working agricultural jobs only having reduced odds of MM in rural areas and not urban areas might be due to the minimal amount of individuals practicing agricultural occupations within urban areas. In urban areas only 7.3% of respondents were found to engage in agriculture, meanwhile in rural areas a staggering 41.1%. Additionally, within the little agriculture that may exist in urban areas, possibly differences in agricultural practices from rural areas must be considered. As agriculture is experiencing rapid mechanization, and with urban areas being associated with greater wealth, ease of access, and availability to machinery may contribute to the reduction of agriculture's physicality (Daum, 2023).

Region of Residence

Various geographical regions of residence were also found to have statistically significant associations with MM across urban and rural area analyses. Such findings regarding the effect of region on MM have previously been found within existing literature (Mishra et al., 2021; Prenissl et al., 2022; Khan et al., 2022). However, there exists little to no discussion in these studies about why regions may vary in their odds of MM. India is thought to be highly diverse with variation across regions in certain aspects such as nutrition, rate of urbanization, physical activity, diet, occupations, environment, quality of healthcare, access to healthcare, etc. (Ramamoorthy et al., 2022; Tripathy & Thakur, 2016; Kundu & Pandey, 2020). With such inter-region differences regarding factors that may act to reduce or increase the risk for health conditions, it is possible that each area may be disproportionately affected by MM (Singh et al., 2019). Supporting this is Figures 4 and 5 in section 2.2.5, in which regions across India can be seen to have differing prevalence estimates for both diabetes and hypertension.

Caste

This study found that in rural areas, males from scheduled castes had 20% increased odds of MM as compared to men who were not in a marginalized caste. These findings are in line with previous literature amongst which the majority have found SCs to have greater risk/odds of MM when compared to other marginalized groups such as STs and OBCs (Khan et al., 2022; Puri & Singh, 2022; Mishra et al., 2021). Such findings are supported for rural areas where many individuals still firmly believe in the caste system and discriminate against groups such as the SCs (Mayell, 2021; Sahgal et al., 2022). These rural individuals may face healthcare-related difficulties such as being provided lesser information, services, and access to health programs (Patel, 2023). However, it is possible that caste was found to have no significant association with MM in urban areas due to lesser emphasis and focus on the social hierarchy. Within urban areas Indians have been found to be more accepting of individuals from marginalized castes (Sahgal et al., 2022), thus possibly reducing caste-based discrimination which may remove the health-related barriers that may indirectly contribute to MM outcome. This study found no significant associations for STs and OBCs as previous studies have.

BMI

BMI was found to have a strong positive association with MM in both urban and rural areas. Such findings can be expected with increasing BMI consistently being found to increase risk/odds of MM within existing literature (Puri et al., 2021b; Mishra et al., 2021; Puri & Singh, 2022). However, an improvement in methodology within this study was the use of BMI cut-offs that are applicable to the Indian population. Previous studies had chosen to utilize the standard WHO ranges for defining underweight, normal, overweight, and obese BMI but this is not reflective of the population of interest who has been recommended reduced cut-offs.

Media exposure

Increasing media exposure was also found to be associated with increased odds of MM. Such findings may have been foreseen as for many individuals, media exposure may be for superficial purposes such as entertainment and social media (Dar & Nagrath, 2022). If these habits become excessive, negative repercussion such as reduced physical activity have been noted which can contribute to health conditions or even other risk factors of MM such as obesity (Woessner et al., 2021). Media exposure has also previously been found to act as a risk factor for MM by Mishra et al. (2021) who conducted one of the sole studies that included analysis of the media-MM association in India. However, NFHS-5 methodology was improved taking into consideration radio, tv, and newspapers/magazines but also, internet and cellphone use which may be more representative of the current sources of media amongst the Indian population (Ninan, 2019). A significant association was only found amongst rural area males and not those of urban areas.

Alcohol

With this study approximating that 25% of males aged 15-54 in both urban and rural areas consume alcohol, which is a common risk factor for NCDs, its implications are of great concern (Balasubramani et al., 2021; WHO, 2022; Nethan & Mehrotra, 2017). Previous studies concerning MM in India are in agreement that alcohol consumption acts to increase odds/risk of MM (Khan et al., 2022; Mishra et al., 2021; Puri et al., 2021b; Singh et al., 2018). Found within this study was that in rural areas consuming alcohol increased the odds of MM by 25%. However, it was also found that in urban areas alcohol consumption and MM do not share a significant association. With alcohol being so well established as a risk factor, this lack of association is surprising. Of future consideration could be an exploration of the frequency and quantity of alcohol consumed in both urban and rural areas to corroborate/build on our findings.

Tobacco

Of further interest is that the consumption of tobacco was found to have a significant protective effect against MM for males from rural areas. Previous literature has varied in findings regarding the tobacco-MM and thus, interpretation becomes difficult (Mishra et al., 2021; Puri & Singh, 2022; Puri et al., 2021b, Prenissl et al., 2022; Chauhan et al., 2022).

With tobacco consumption being a commonly accepted risk factor for many health conditions that may contribute to MM, expecting a positive association seems intuitive. However, researchers such as Prenissl et al. (2022) and Chauhan et al. (2022) have found results similar to our own that tobacco consumption may act to reduce the odds/risk of MM. As these protective effect findings are generally not expected, interpretation is ambiguous with relevant researchers minimally discussing such findings. It is possible that such findings may also be an effect of social desirability bias (response bias). Individuals who participate in risky lifestyle behaviours (e.g., smoking, drinking alcohol, not exercising, etc.) may lie and choose to provide more socially acceptable answers regarding their habits (BCMJ, 2020). This especially pertains to those who have already been diagnosed with health conditions. If individuals have been instructed to refrain from such behaviours but choose not to, they may lie when questioned about their consumption status. With the NFHS-5 collecting self-reported data regarding tobacco consumption, any individual who chooses to provide inaccurate data may have contributed to biasing the found tobacco-MM association. There were no significant findings for urban area males.

5.2.2 Findings inconsistent with literature

Education

Education was found to have some association with MM but like existing literature, findings had no clear trend. Found in this study was that education was only associated to MM in rural areas with 30% and 24% increased odds respectively for those with incomplete primary and incomplete secondary education (when compared to those with no education). Education levels of urban area men were found to have no statistically significant association to MM. Some studies that have previously explored the education-MM association have reported similar trends where risk/odds of MM are greater for all education levels above no education, but with gradual decreases in risk/odds as greater education levels are completed up to post-secondary education (Khan et al., 2022; Puri & Singh, 2022; Mishra et al., 2021). However, Prenissl et al. (2022) found in their urban and rural split analysis that this trend exists in both urban and rural areas with the additional finding that post-secondary educated individuals in urban areas had a reduction in risk of MM when compared to those with no education. Singh et al. (2018) further supported this protective effect that post-secondary education has against MM in urban areas.

Our study's results are therefore interesting as findings regarding rural areas are somewhat in agreement with existing literature. It is generally thought that with greater education, there is better health literacy due to more knowledge regarding modifiable risk factors (Nagel et al., 2008). Higher education has commonly been associated with reducing the prevalence of health conditions, which ultimately supports that a protective effect could be expected (Nagel et al., 2008). However, in the case of this study's findings, the opposite results could be attributed to various factors. Firstly, it must be considered that educational level has been found to be positively correlated with socioeconomic status (SES) (Zou et al., 2020). Those who belong to a higher SES have generally been thought to have improved access to health services (Zou et al., 2020), and might have more opportunities for diagnosis of their health conditions. Meanwhile, those respondents with lesser education (possibly from a lower SES) may remain undiagnosed, thus giving the perception that greater education increases the odds of health issues such as MM. Many of the reviewed studies that found a similar association also lacked consideration of health services/access. As such, issues such as residual confounding must be considered (Sorjonen et al, 2021). Residual confounding can arise in situations such as when additional confounding factors are not considered i.e., unmeasured variables, or when there is an imperfect measurement of variables (Porta, 2014). These issues would possibly distort the found association between education and MM. In this study, many of the common predictors of MM in India were analyzed and adjusted for but, other possible confounders (such as health service access) that may exist are unadjusted for. Additionally, with much of the data available in the NFHS-5 being self-reported, respondents may be subject to misclassification, making found associations between specific educational categories and MM erroneous.

Furthermore, the lack of significant findings in urban areas is also a cause for interest. With univariate analysis revealing that a greater proportion of urban area males have higher levels of education (secondary level or higher), further health literacy could be assumed. Under such a scenario, urban area findings similar to those of Prenissl et al. (2022) and Singh et al. (2018) may be expected. However, another possible explanation for these unanticipated education-MM association findings could be differences between studies. Multiple systematic reviews analyzing various studies including those conducted regarding LMICs have found that differences in found associations between education and MM can often be attributed to variations in study methods (Feng et al., 2021; Pathirana & Jackson, 2018). As studies chose to explore varying definitions of MM amongst different study populations, findings in the literature are highly variable. As such, it is possible that our findings regarding the education-MM association in both urban and rural areas may be accurate and are incomparable to previous literature due to the major differences between this study and those previously conducted. With our study considering a specific MM definition amongst a specific population, further research may be needed to corroborate findings.

Religion

This study did also find a significant association between religion and MM with urban area males identifying as Christian having lower odds of MM as compared to those who identified as Hindu. However, these findings are opposite to existing literature which has consistently found that all identifying with other religious groups (e.g., Muslims, Christians, etc.) increases odds of MM when compared to those identifying as Hindu (Puri et al., 2021a; Mishra et al., 2021; Khan et al., 2022; Puri et al., 2021b; Puri & Singh, 2022). Further research may be needed to explore why this may be the case.

5.2.3 Insignificant Predictors

Marital Status & Diet

Marital status and diet were found to be significant predictors of MM within bivariate analysis but, within multivariable analyses, these two were the only predictors found to have no significant associations with MM in either urban or rural areas.

Findings regarding marital status have generally been inconsistent within literature as some studies have reported no association (Prenissl et al., 2022; Chauhan et al., 2022b; Khan et al., 2022; Mishra et al., 2022) and some have reported that married individuals have increased risk of MM (Prenissl et al., 2022, Chauhan et al., 2022b).

Findings regarding healthy diet being insignificant were surprising due to lifestyle behaviours such as poor diet commonly being associated with NCDs (WHO, 2022; Nethan & Mehrotra, 2017). Thus, it would naturally be assumed such an association would be found with MM also. Expected may have been findings similar to those of Puri et al. (2021b) who found a significant association that those who consumed a healthy diet had a lower probability of MM as compared to those who didn't eat healthy. However, possibly contributing to our study's insignificant findings may have been limitations of our diet variable. When compared to Puri and colleagues, our study solely took into consideration fruit and vegetable consumption when defining a healthy diet. The simplicity of our variable may not have accurately defined the healthiness of respondents' diets with important dietary habits being unable to be considered such as consumption of detrimental foods such fried foods, aerated drinks, etc. It is possible the complexity of defining a healthy diet is insufficient as per our methodology and therefore, future analysis with an improved diet variable may be needed to clarify any association.

5.3 Study contribution and Implications for Policy and Practice

To the best of our knowledge, this is the first study that has focused on investigating the predictors of diabetes and hypertension MM amongst the male population of India. Additionally, this is also one of the first studies to incorporate many of the sociodemographic and lifestyle predictors of MM that have been of prior interest into a single study and analyzed them from a split urban/rural analysis. With this study adjusting for more covariates within its analyses as compared to previously conducted studies, the found effects of predictors may be a better representation of their true direct association to MM. Furthermore, this study is one of the first to analyze the most recent NFHS data released by the DHS program (NFHS-5). Thus, estimates pertaining to the effect of predictors of MM may be more reflective of the current male population of India. Found within this study were both similarities and differences to literature regarding the significance and effect of predictors. It was also established that across urban and rural areas, there does exist variation in predictors.

These findings have implications for both males across India and the relevant policymakers who act to maintain/improve their health. As MM continues to rapidly grow as a nationwide health concern, so do its associated burdens. Not only does MM burden those diagnosed but also their families, health service providers, and even the nation's economy (Soley-Bori et al., 2020; Rosbach & Andersen, 2017; Sum et al., 2018; Laires & Perelman, 2018; La et al., 2022; Afshar et al., 2015; Prathapan et al, 2020; Pati et al., 2014). This study offers crucial insight for policymakers to take into consideration when attempting to allocate resources to possible preventative measures.

Relevant organizations in India have previously utilized preventative plans such as the WHO's *Action Plan of Global Strategy for the Prevention and Control of Noncommunicable Diseases*, to aid in reducing the progression of NCDs which may subsequently contribute to MM (Nethan & Mehrotra, 2017; WHO, 2013). Highlighted in this action plan are fundamental and basic guidelines that the WHO suggests in hopes of improving the health of various populations around the world. Key suggestions within the action plan are focused on controlling modifiable risk factors (i.e., lifestyle factors) and increased surveillance/monitoring of NCD progression (WHO, 2013). More specifically, this action plan presents policies that may be taken into consideration when attempting to better control common modifiable risk factors. These policies consist of but are not limited to the following (WHO, 2013):

Tobacco consumption – Implement bans on the promotion and advertisement of tobacco, provide support to those who wish to quit, increase smoke-free environments, increased mass media campaigns to warn people of dangers related to tobacco, etc.

Alcohol consumption – reduce availability and marketing of alcoholic beverages, pricing policies, increase healthcare service provider capacities to conduct increased screenings and early interventions of excessive consumption, etc.

Diet – Strengthen national nutrition policies, reduce salt intake recommendations for prepared and processed foods, increase both the affordability and availability of fruits and vegetables to promote increased consumption, increased social marketing campaigns that push for healthy dietary options, etc.

Physical activity – Improve physical education prevision during youth, planning for walking and cycling-related infrastructure, implement and campaign recommended guidelines for health maintenance through physical activity, etc.

However, this action plan is unfocused and fails to acknowledge how associations between common risk factors and health outcomes may vary depending on the nation of interest. As this is a general document that both high-income countries and LMICS can implement, its efficacy in LMICs may be reduced as crucial considerations such as the split urban/rural context are not considered. In a country such as India, urban and rural areas are still drastically different in characteristics, and as such, the creation of effective policies may not be a simple process. This becomes clearly more evident when this study’s results are taken into consideration because in India differences in predictors of MM exist across urban and rural areas. As such, policymakers must be aware that a uniform approach to health-related issues such as MM may not always be ideal, and that the urban/rural context should be kept in mind when creating policy briefs and recommendations. Evident examples of how policies may be affected are as follows:

1) BMI, a basic indicator of an individual’s general health, has been found to be a significant predictor of MM in both urban and rural areas with a positive association. What this suggests is lifestyle modifications have implications in both areas and therefore implementing policies, campaigns, screenings, etc., is of equal importance across areas. As India continues to experience rapid increases in the national prevalence of obesity (Nethan & Mehrotra, 2017; Anjana et al., 2023), it is crucial that adequate preventative measures are taken by policymakers all across India to control increasing BMIs and therefore any associated negative health outcomes.

2) Meanwhile for a risk factor such as alcohol consumption, more specific considerations may be required. This study found that in urban areas there may be no statistically significant association between alcohol and MM but, in rural areas consumption does increase odds of MM. With rural areas experiencing issues such increased consumption of illicit and country liquor (Barik et al., 2015), increased efforts and allocation of preventative resources may be better focused solely in rural areas.

By using findings from studies such as this one, preventative measures can be improved by more specifically targeting those who possess high-risk characteristics that have been found to increase odds of MM. With specific lifestyle and sociodemographic factors being found to be significant predictors of MM, policymakers can take these into consideration and implement relevant processes e.g., screening, and further health promotion, to protect those at greater risk (Tan et al., 2021). Consideration of our study’s findings in future policies may help to control increasing MM prevalence and do so in an efficient manner that does not expend resources needlessly as efforts may be focused where truly required. Thus, these findings may contribute to earlier diagnosis and commencement of treatment, therefore, helping to avoid any possible complications and burden from a prolonged state of having MM.

5.4 Limitations

Within this study there were several limitations that must be acknowledged, more specifically pertaining to data and methodology.

5.4.1 Data

Firstly, the NFHS survey data analyzed is cross-sectional (non-temporal) in nature, and therefore causality between dependent and independent variables could not be established. Additionally, only a few variables had data collected using absolute methods (i.e., biomarker testing, and anthropometric measurements). Most of the data collected in the NFHS-5 was done in an interview-style method where respondents were asked verbal questions. It is possible that respondents may introduce response bias if they unintentionally or intentionally answer questions with inaccurate information. A more specific example would be social desirability bias, in which respondents underreport their more socially undesirable attributes. Certain variables may have been more susceptible to such bias such as those regarding topics individuals may not want to discuss e.g., tobacco and alcohol consumption, diet, caste. Such biases would have implications for not only the independent variables but may also affect the dependent variable of MM. With the criteria utilized to define possible cases of each diabetes and hypertension including variables for which data was collected in an interview method, there is the possibility that bias may result in an over- or underestimation in the number of possible MM cases. As a result of such biases, found statistical associations may be unreflective of the true associations that may exist between predictors and MM within the population.

It must also be established that the NFHS-5 is only representative of males aged 15-54 in India. As such, the generalizability of this study's findings regarding the effect of predictors is limited to males within that age demographic. Inference cannot be made regarding those below the age of 15 years old and older than 55 years. However, it is currently estimated that approximately 60% of India's male population is within the age range of 15-54 (Central Intelligence Agency, 2023), thus this study's findings are applicable to a large portion of the population.

Furthermore, although the NFHS-5 collected and distributed extensive information pertaining to the sociodemographics and lifestyles of the Indian population, the survey was limited in its breadth of information pertaining to health services. Had information regarding the characteristics of health services (e.g., quality, access, private vs. rural, etc.) been collected, a more robust model may have been produced. Within this model, the association of healthcare characteristics with multimorbidity may have been explored, and any possible confounding/interaction effects adjusted for.

Lastly, within this study, no differentiation could be made between type 1 and type 2 cases of diabetes. All data relevant to diabetes (self-reported and biomarker plasma blood glucose) provided a basic understanding of a respondent's diabetes status and as such, there is insufficient evidence or clinical confirmation to determine the type of diabetes a respondent may have. However, it has recently been estimated that the majority of diabetes cases are type 2, with only approximately 9% of cases being a type 1 diagnosis (Das, 2015).

5.4.2 Methodological

Due to previously discussed issues with the availability of sampling weights, all analyses completed within this study were unweighted. This resulted in certain findings being non-comparable to literature such as the univariate analysis results. Furthermore, although our model parameters (i.e., odds ratios) could be compared with literature without the use of sampling weights, it is possible that estimates may be biased (West et al., 2015).

Limitations in the definition of certain variables must also be acknowledged. For MM, possible cases were defined utilizing various data elements available to us in the NFHS-5, i.e., interview question responses and biomarker measurements. As such, our definition of MM is presumed MM, meaning that based on the data available and the criteria we have set forth, we are presuming respondents that meet our specific criteria may be possible cases of MM. However, these are not clinically confirmed cases and therefore each found case cannot be considered a firm diagnosis. Unfortunately, this is a challenge that is present with all survey data and therefore is a common limitation of such studies. Similarly, the definition of certain predictor variables may have not been comprehensive enough. Variables such as alcohol consumption and tobacco consumption were each analyzed as binary predictors however, often the dose relationship (frequency and amount of consumption) is of interest to better understand the effect of such predictors.

Lastly, predictors analyzed using constructed variables must also be considered for methodological limitations as they may not be capturing individual characteristics accurately. The consumption of a healthy diet was a variable we constructed however, it is possible that this variable may be limited in its informativeness due to the sole consideration of fruit and vegetable consumption and not a wide range of foods. The constructed variable was far too basic and therefore our methodology may not have accurately determined a healthy vs unhealthy diet. Similarly, for media exposure, we created a variable that provided an exposure score to each respondent based on their use of five different media sources. However, frequency of use was not considered which may also have important implications in better understanding the role of media exposure as a predictor of MM.

5.5 Future research

Of interest for future research would be the continuation of study predictors of diabetes and hypertension MM amongst males in India to address the limitations of this study. With this being one of the first studies to emphasize this specific MM, there still exists further analysis needed. As this study was limited to those aged 15-54, and MM has been well established in literature to be much more prevalent amongst the elderly age demographic, analysis of predictors amongst those aged 55+ years old is of interest. NFHS data is generally limited to males aged 15-54 but, there exist other data sources such as the LASI which focuses on Indian adults aged 45+ years old. With the IIPS being expected to conduct and release the latest iteration of the LASI in the coming years, analysis could be continued (IIPS, n.d.). Also, to remedy some of the methodological limitations of this study, validation studies can be done when sampling weights are available. Doing so would support this study's findings and corroborate any drawn conclusions. Furthermore, to expand on the effects of predictors of MM, an analysis could be done using software applicable to spatial joint morbidity modeling. Under such analysis, spatial differences in the effect of predictors could be explored. This would allow for a more granular understanding of how predictors may vary across specific geographic areas of India beyond just the urban/rural perspective.

This study also provides a precedent for further research into specific operational definitions of MM. Most of the current existing literature regarding MM in India has taken into consideration a wide variety of conditions when defining MM and this has resulted in found associations being highly general. This study shows that there are both consistencies and inconsistencies in the found effects of predictors on specific MMs as compared to the wider definitions seen in literature and therefore future similar studies are warranted.

5.6 Conclusion

In conclusion, this study aimed to determine the predictors of diabetes and hypertension MM amongst males aged 15-54 in India and did so successfully, contributing to literature using its urban/rural split analysis. There are in fact variations across areas regarding the effects of predictors, with the findings having possible implications in improving the approaches taken by relevant parties across India to improve public health. As India rapidly faces health and epidemiological transitions, and MM prevalence continues to increase, such research may be crucial in controlling the associated burden.

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