A TALE OF TWO DECADES: A STUDY OF CHANGING UNDERWEIGHT AND OVERWEIGHT FACTORS IN INDIAN WOMEN (15-49) BETWEEN 1999 AND 2019

Capstone Project

Presented to the Faculty of the Graduate School

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Master of Professional Studies | Global Development

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Dedicated to

This work is dedicated to my beloved daughter, Aavya Vashistha.

Your presence has been a constant source of inspiration and joy, reminding me of the importance of balance, determination, and the pursuit of knowledge. Your boundless curiosity, infectious laughter, and endless love have been my constant motivation and reminder of the importance of striving for a better future. May this endeavor contribute to a world where your dreams can flourish.

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I am appreciative of all my friends, colleagues, and well-wishers who shared their insights and engaged in meaningful discussions, enriching the quality of this study.
Lastly, I want to acknowledge all those who, directly or indirectly, contributed to the successful completion of this research. Your support and encouragement have been immeasurable.

Abstract

This study examines underweight and overweight factors among Indian women aged 15 to 49, using 1999 and 2019 Demographic and Health Survey data. Univariate summary stats, visualizations, and logistic regressions analyze changing dynamics. Education's influence shifts from protective in 1999 to complex associations in 2019. Age consistently impacts both conditions. Physical work correlates with lower overweight odds. Rural residency's impact changes, reflecting healthcare improvements. Access to amenities consistently affects health outcomes. Findings inform adaptable policies for India's evolving health landscape.

Table of Contents

Abbreviations

1. BMI: Body Mass Index
2. CEB: Children Ever Born
3. DBM: Double Burden of Malnutrition
4. DHS: Demographic and Health Survey
5. GHI: Global Hunger Index
6. MPI: Multidimensional Poverty Index
7. NCD: Non Communicable Diseases
8. UNDP: United Nations Development Programme
9. UNICEF: United Nations Children's Fund

1. Introduction

In April 2023, India surpassed China to become the world's most populous country. A growing population of young and skilled Indian workers have led to a remarkable economic growth, making India one of the fastest-growing large economies and a formidable force on the global economic stage. The economic growth and the resulting opportunities have catapulted millions of people out of poverty. According to a recent report by the United Nations Development Programme (UNDP), the number of people living in multidimensional poverty fell to 16.4% of India's population in 2021 from 55% in 2005.[1] As of July 2023, the Multi-dimensional Poverty Index (MPI) of India is 0.069.[2] This is a significant drop from 0.300 in 1999.[3] Yet, these impressive economic opportunities and benefits do not translate equitably to all people.

Women in India experience severe challenges in seeking employment opportunities and their labor force participation continues to remain low because of barriers like poor educational opportunities, unpaid care work and domestic duties, and restrictions placed on them by the strongly patriarchal systems within which they work. [4] In India,

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[1] 25 countries halved multidimensional poverty within 15 years, but 1. 1 billion remain poor | united nations development programme. (n.d.). UNDP. Retrieved July 31, 2023, from https://www.undp.org/press-releases/25-countries-halved-multidimensional-poverty-within-15-years-11-billion-remain-poor

[2] Nations, U. (2023). *2023 global multidimensional poverty index(Mpi)*. United Nations. https://hdr.undp.org/content/2023-global-multidimensional-poverty-index-mpi

[3] Alkire, S., & Seth, S. (2013). Multidimensional poverty reduction in India between 1999 and 2006: Where and how? SSRN Electronic Journal. https://doi.org/10.2139/ssrn.2292941

[4] Labour Force Participation of Women in India: Some facts, some queries. (n.d.). STICERD. Retrieved July 31, 2023, from https://sticerd.lse.ac.uk/textonly/india/publications/working_papers/ARCWP40-BhallaKaur.pdf

the geographical focus on this work, female labor participation is the lowest among all countries in South Asia, with four out of five women not engaged in the labor force. [5] [6] The uneven economic opportunities translate into a downstream impact on women's nutrition.[7] Women with limited economic opportunities face challenges in accessing nutritious food, leading to a higher likelihood of malnutrition.[8] UNICEF estimates that a quarter of women of reproductive age in India are undernourished and their diets are often too poor to meet their nutritional needs.[9] Poor nutrition can perpetuate a poverty trap when malnutrition leads to stunted physical and cognitive development, which in turn, can limit their ability to seize economic opportunities later in life, perpetuating an intergenerational cycle of undernutrition.[10]

Although several public health scholars have examined social determinants of women's health[11], there is a scarcity of research that longitudinally examines such linkages and

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[5] Kamdar, B. (2020, July 31). Women Left Behind: India's Falling Female Labor Participation. The Diplomat. Retrieved July 31, 2023, from https://thediplomat.com/2020/07/women-left-behind-indias-falling-female-labor-participation/

[6] Frayer, L., & Kumar, R. (2023, January 4). It's a mystery: Women in India drop out of the workforce even as the economy grows. NPR. Retrieved July 31, 2023, from https://www.npr.org/sections/goatsandsoda/2023/01/04/1146953384/why-women-in-india-are-dropping-out-the-workforce-even-as-the-economy-grows

[7] Women's Empowerment, Food Security, and Nutrition Transition in Africa. (2022, December 24). NCBI. Retrieved July 31, 2023, from https://www.ncbi.nlm.nih.gov/pmc/articles/PMC9819006/

[8] Duflo, E., & Banerjee, A. (2011). Poor economics (Vol. 619). New York, NY, USA: PublicAffairs.

[9] Women's nutrition | UNICEF India. (n.d.). Retrieved August 1, 2023, from https://www.unicef.org/india/what-we-do/womens-nutrition

[10] Alderman, H. (2006). Long term consequences of early childhood malnutrition. *Oxford Economic Papers*, *58*(3), 450–474. https://doi.org/10.1093/oep/gpl008

[11] NIH - Data Science. Retrieved August 1, 2023, from https://datascience.nih.gov/fhir-initiatives/common-data-elements-and-social-determinants-of-health

factors in the context of women's malnutrition in India. To fill this critical gap, this study sought to answer the following research questions:

1. How do different education levels impact women's nutritional status?
2. How do different employment opportunities impact women's nutritional status?
3. What is the temporal impact of education and employment on women's nutritional status?

To answer these questions, I quantitatively analyzed secondary data sourced from the Demographic and Health Surveys (DHS) program that conducts nationally-representative household surveys periodically in several developing countries to capture data on several global development indicators of population, health, and nutrition, among others. (*Demographic and Health Survey (DHS)*, n.d.) Using this data, I used statistical methods including descriptive analysis and logistic regressions that revealed critical insights on how education and employment opportunities shape nutritional status for Indian women of reproductive age.

2. Related Research

More than a billion women and adolescent girls are malnourished globally.[12] India has over 189 million malnourished people, most of whom are women and children, and ranks 107th out of the 121 countries in the 2022 Global Hunger Index (GHI) with a level

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[12] Malnutrition in women and girls has soared 25% in crisis-hit countries. (2023, March 29). The World Economic Forum. Retrieved August 1, 2023, from https://www.weforum.org/agenda/2023/03/malnutrition-poverty-women-inequality-pregnancy/

of hunger that is serious.[13] Patriarchal norms in India dictate women to often eat last and the least, resulting in every second woman being anemic, every third woman with low body mass index (BMI), and every fourth child born with low birth weight. [14]

These statistics have motivated a number of public health scholars to study factors that impact women's nutritional status as well as broader health, economic, and well-being impacts of malnourishment. Dahiya and Viswanathan[15] used the data from India Human Development Survey for 2005-06 to examine the factors which influence the BMI of women between 20 and 40 years of age in India and found caste, religion, per capita consumption expenditure, and wealth to be important variables in explaining variations in BMI. Reddy[16] studied the relationship between socioeconomic and behavioral variables and BMI among socioeconomically heterogeneous populations in Hyderabad, India, and found a positive association between socioeconomic status and BMI. Similarly, Gouda and Prusty[17] analyzed data from the National Family Health Survey (NFHS) 2005-2006 to examine the prevalence of overweight and obesity among

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[13] Hunger Index 2022: India. (n.d.). Global Hunger Index. Retrieved August 1, 2023, from https://www.globalhungerindex.org/pdf/en/2022/India.pdf

[14] Chakraborty, S. (2022, December 2). India suffers because women eat the last and the least. Https://Planet.Outlookindia.Com/. https://planet.outlookindia.com/opinions/india-suffers-because-women-eat-the-last-and-the-least-news-413250

[15] Dahiya, S., & Viswanathan, B. (2015). Women's malnutrition in India: The role of economic and social status. Margin: The Journal of Applied Economic Research, 9(3), 306–332. https://doi.org/10.1177/0973801015579756

[16] Reddy, B. N. (1998). Body mass index and its association with socioeconomic and behavioral variables among socioeconomically heterogeneous populations of Andhra Pradesh, India. Human Biology, 70(5), 901–917. https://www.jstor.org/stable/41465685

[17] (*Overweight and Obesity Among Women by Economic Stratum in Urban India*, n.d.) NCBI. Retrieved August 1, 2023, from https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4089075/

women from different economic strata in urban India. They found non-poor women to be three times more at risk of being obese and demonstrated obesity to increase with age, education, and parity of women. Islam et al.[18] used multinomial logistic regression on DHS data to identify risk factors of malnutrition for women in Bangladesh and found that several variables like age, region, wealth index, education, marital status, cooking fuel, and drinking water source are the potential factors that predict the nutrition status of women. Rokade et al.[19] examined data of nearly 4,000 tribal women in Maharashtra, India to identify the prevalence and determinants of nutritional status and found more than half of the total women to be anemic, with most of them spatially located in the Northwest districts of Maharashtra. Dunneram and Jeewon[20] conducted a meta-review of studies published on improving nutritional outcomes for women in multiple countries and concluded that community-based interventions that use multilevel strategies are critical in improving health outcomes and modifying health behaviors.

Although these studies uncover linkages between nutritional status, health and wellbeing, and other social determinants of women's health, only a few scholars have conducted longitudinal studies to identify shifts in patterns and relationships between

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[18] Islam, Md. M., Rahman, Md. J., Islam, M. M., Roy, D. C., Ahmed, N. A. M. F., Hussain, S., Amanullah, M., Abedin, Md. M., & Maniruzzaman, Md. (2022). Application of machine learning based algorithm for prediction of malnutrition among women in Bangladesh. International Journal of Cognitive Computing in Engineering, 3, 46–57. https://doi.org/10.1016/j.ijcce.2022.02.002

[19] Rokade, S., Mog, M., & Mondal, N. A. (2020). Nutritional status among tribal women in Maharashtra, India: Spatial variations and determinants. Clinical Epidemiology and Global Health, 8(4), 1360–1365. https://doi.org/10.1016/j.cegh.2020.05.012

[20] Jeewon, R. (n.d.). Healthy Diet and Nutrition Education Program among Women of Reproductive Age: A Necessity of Multilevel Strategies or Community Responsibility. NCBI. Retrieved August 1, 2023, from https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4539058/

these variables over time. Jose and Navaneetham[21] used the National Family Health Survey to analyze levels of women's malnutrition in India between 1998-99 and 2005-06. They found that iron-deficiency anemia increased among women from disadvantaged social and economic groups and maternal malnutrition caused child malnutrition and increased prevalence of chronic diseases. Luhar et al.[22] analyzed data between 1998 and 2016 to examine trends in the prevalence of overweight and obesity among adults in India by socioeconomic position. They found that the overweight and obesity prevalence increased among men and women in both rural and urban areas and concluded that obesity and overweight is no longer a disease of affluence. While these studies are closest to this work, in part because they conduct temporal analysis, these studies do not temporally analyze the impact of levels of education and different types of work on the nutritional status of women, which is the core contribution of my work.

3. Data Description

3.1. Data Source

Secondary data was sourced from DHS (Demographic and Health Survey) data for India for 1999 and 2019. The DHS data are nationally representative household survey data that capture information on a wide range of indicators in the areas of population, health, and nutrition. (*Demographic and Health Survey (DHS)*, n.d.). In my analysis, I have

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[21] Jose, S., & Navaneetham, K. (2008). A factsheet on women's malnutrition in India. Economic and Political Weekly, 43(33), 61–67. https://www.jstor.org/stable/40277858

[22] Luhar, S., Mallinson, P. A. C., Clarke, L., & Kinra, S. (2018). Trends in the socioeconomic patterning of overweight/obesity in India: A repeated cross-sectional study using nationally representative data. BMJ Open, 8(10), e023935. https://doi.org/10.1136/bmjopen-2018-023935

considered data collected on women between the age of 15 and 49 years. The India DHS 1998-99 DHS-IV data has a household sample size of 92,486 and 90,303 women. The India DHS 2019-2021 DHS-VII data has a household sample size of 636,669 and 724,115 women.

3.2. Key Variables

Variables examined for this study are: age (V012), highest education level (V106), occupation type (V717), CEB (Children Ever Born) (V201), type of place of residence (urban or rural) (V102), BMI defined as weight in kilograms divided by the square of her height in meters (V 445). Since 1999 data did not carry wealth index, and in order to have homogeneity across variables between 1999 and 2019 data, proxy indicators for wealth are considered such as: Type of toilet facility in the household (V116), Whether the household has: electricity (V119), a radio (V120), a television (V121).[23]

3.3. Variable Recoding

The BMI values (V445) are being categorized into two categories: overweight and underweight. The cutoff criteria for defining overweight and obesity among the South Asian population are slightly different from those of the rest of the population. This is because several studies are determining the risk of diabetes and cardiovascular

[23] Standard Recode Manual for DHS7 [DHSG4]. (2018, September 10). The DHS Program. Retrieved July 31, 2023, from https://dhsprogram.com/pubs/pdf/DHSG4/Recode7_DHS_10Sep2018_DHSG4.pdf

disorders at lower BMI values in the South Asian population compared to the White population [24]

- Underweight BMI values 18.5 or less are coded as 1 and all else as 0
- Overweight BMI values 23 or more are coded as 1 and all else as 0

Education level (V106) is being coded into four categories:

- No Education = 0
- Primary Level = 1
- Secondary Level = 2
- Higher Level = 3

The type of toilet structure (V116) is being simplified and grouped as the presence or absence of access to any kind of toilet structure versus open defecation. This is being coded as follows:

- The values 10, 11, 12, 13, 20, 21, 22, 23, 41, 42, 43, and 44, which represent having access to some type of toilet structure, are being coded as 0.
- The values 30 and 31, which represent no access to some type of toilet structure, are being coded as 1.

The type of residency location (V102) is being categorized:

- Urban = 1 and Rural = 2.

Access to Electricity (V119)

- No electricity = 0 and Has electricity = 1

[24] Misra, A. (2015, April 22). Ethnic-Specific Criteria for Classification of Body Mass Index: A Perspective for Asian Indians and American Diabetes Association Position Statement. PubMed. Retrieved July 31, 2023, from https://pubmed.ncbi.nlm.nih.gov/25902357/

Radio (V120)

- No radio = 0 and Has radio = 1

Television (V121)

- No TV = 0 and Has TV = 1

For this study, the occupation type is being regrouped into work that requires strenuous physical or manual labor into one category, and desk jobs or similar tasks are considered non-physical work. The overall occupation variable (V717) is being coded as follows:

- Not working = 0
- Non-physical labor (having values 1, 2, 3, 7) = 1
- Physical labor (having values 4, 5, 6, 8) = 2

Figure 1.

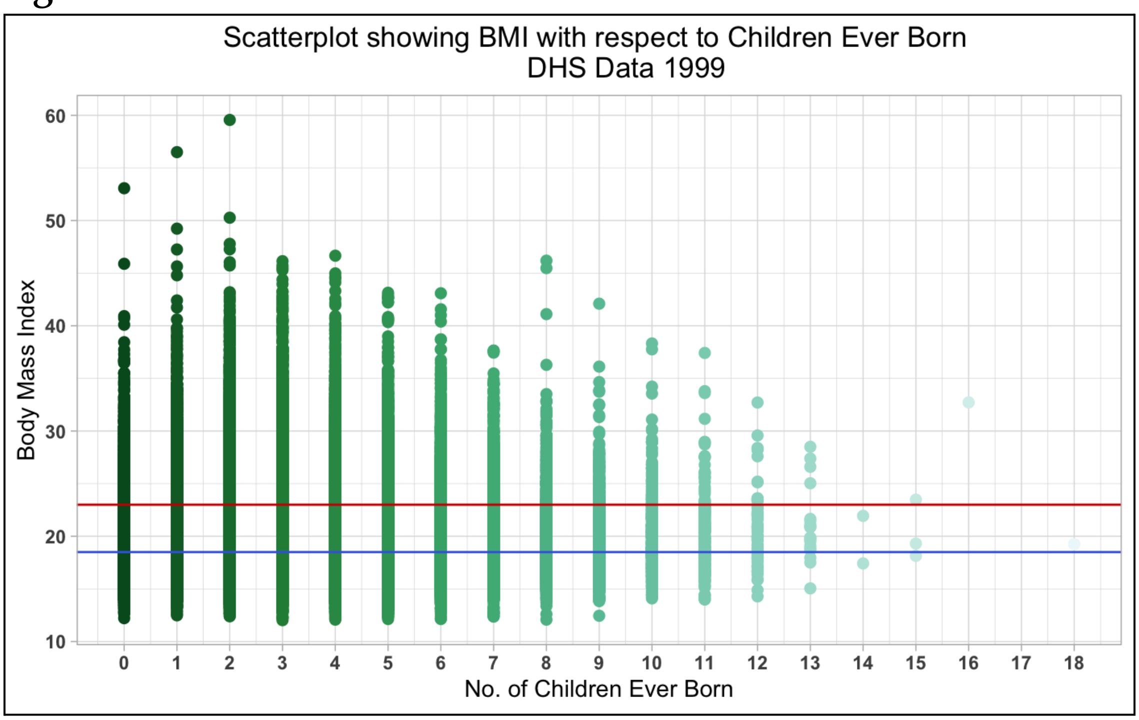
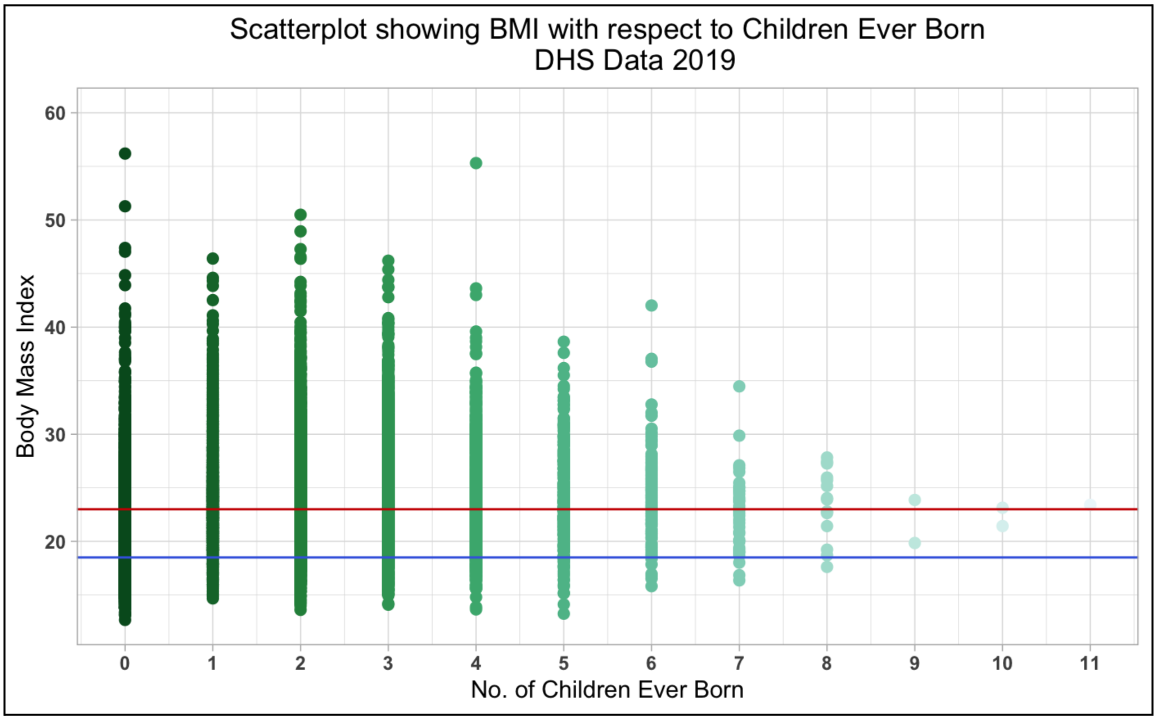


Figure 2.



Figures 1 and 2 show scatterplot BMI vs CEB for 1999 and 2019 DHS survey data for Indian women between ages 15 and 49 years. We can observe distinct trends in the overall number of children ever born between 1999 and 2019 DHS data. The values below the blue line mark the 18.5 BMI value as the cutoff for women who are underweight and the values above 23 BMI value represent women who are overweight or obese.

4. Methodology

To investigate the association between education and underweight status, I performed data visualizations, descriptive analysis, and univariate and binomial logistic regressions. I used open-source R software[25] for statistical analysis and descriptive data

[25] R: the r project for statistical computing. (n.d.). Retrieved August 1, 2023, from https://www.r-project.org/

visualization on the Rstudio[26] environment. Both numerical and nominal variables were used to analyze and conduct statistical analysis. Numerical data like BMI values were grouped and coded into categories. Similarly, nominal variables like highest education level, access to a toilet, electricity, and other assets were used for multinominal logistic regression with education levels as the independent variable and prevalence of underweight and overweight as dependent variables, and age, CEB, occupation type, urban or rural residence, access to toilet and assets as control variables.

Figure 2.

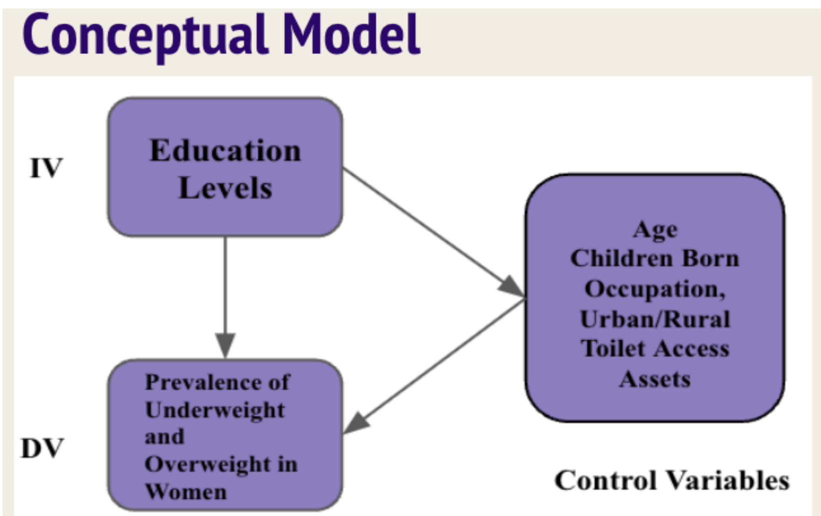


Figure 3. Logistic regression model with Education Level as the independent variable (IV), the prevalence of underweight and overweight in women as the dependent variable (DV), and Control for the variables like age, CEB, occupation type, type of residence location, assets in the form of radio, television, and access to toilet facilities as indirect measures of wealth.

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[26] Posit. (n.d.). Posit. Retrieved August 1, 2023, from https://www.posit.co/

5. Statistical analysis

5.1. Summary Statistics

Figure 4.

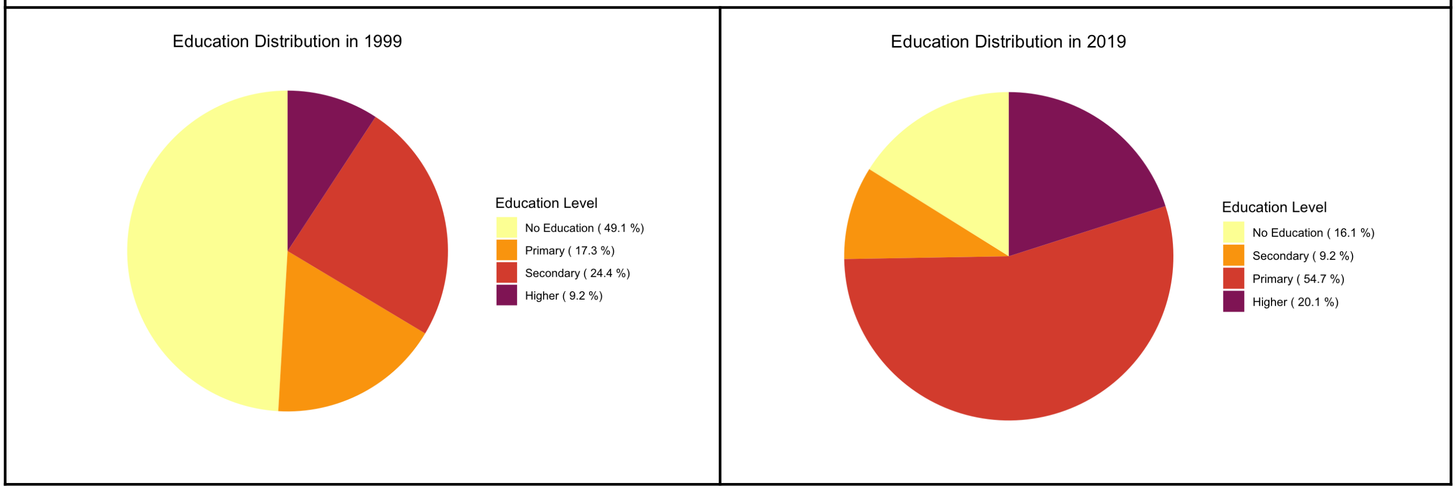


Figure 5.

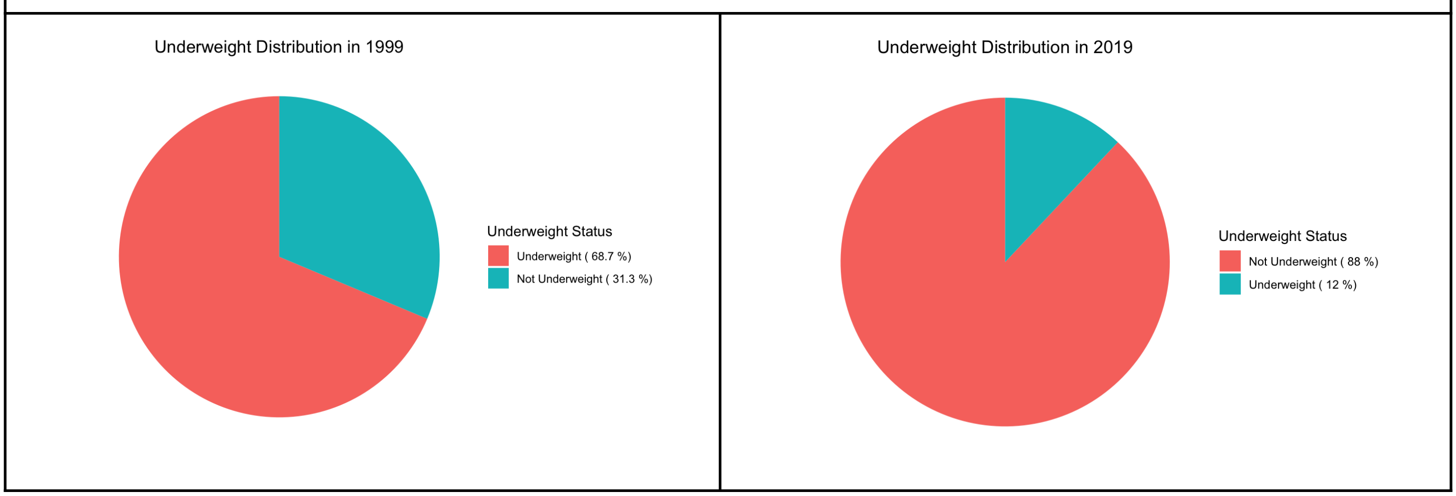


Figure 6.

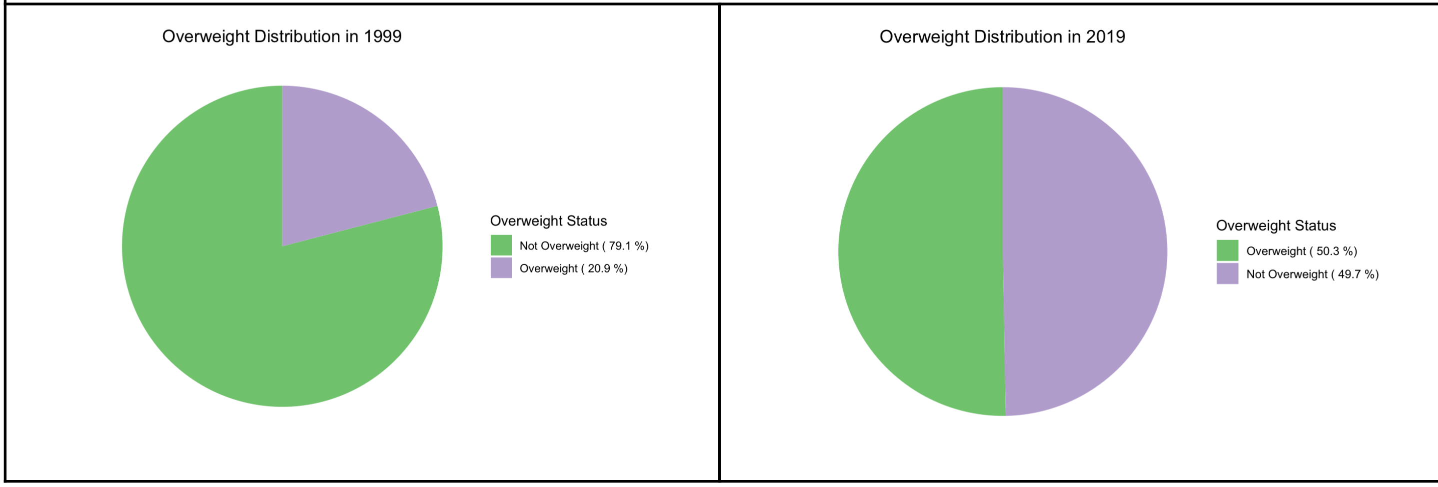
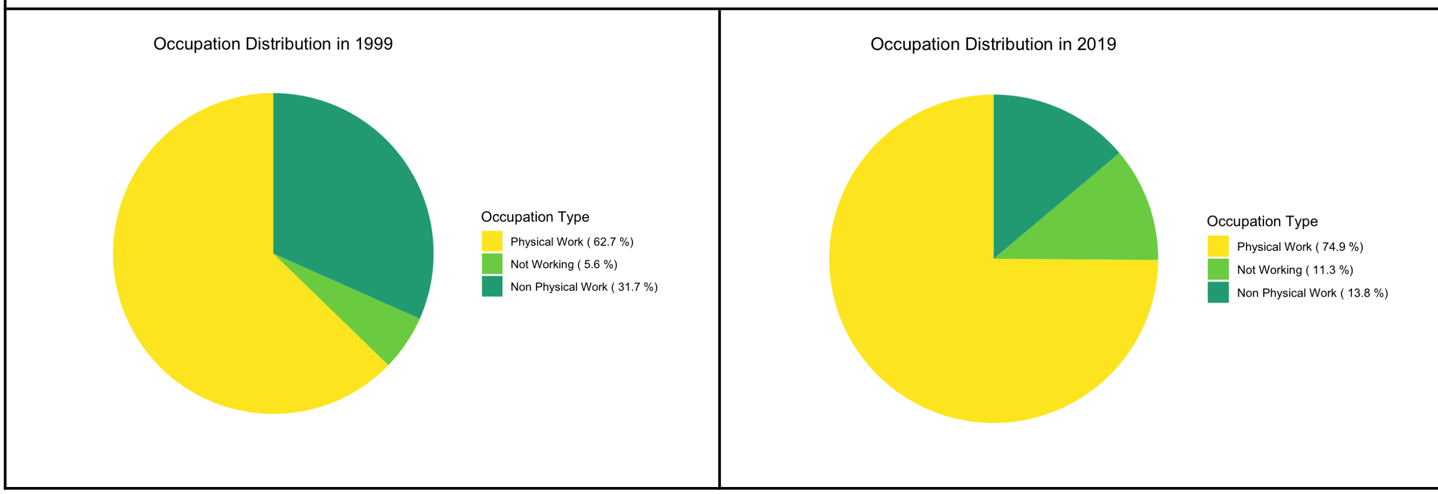


Figure 7.



Figures 4, 5, 6, and 7 show simple visualization of pie charts comparing how data varies in 1999 and 2019 for education level, underweight, overweight, and occupation-related variables considered in our analysis.

Looking at the pie charts in Figure 4, we can see a significant reduction among those with no education which was approximately 50% in 1999 to 16% in 2019, while women having higher education has doubled from 9.2% in 1999 to 20.1% in 2019. In Figure 5, we see a comparison between the prevalence of underweight women reduced from 68.7% in 1999 to 12% in 2019.

Similarly, in Figure 6, we see the prevalence of women being overweight increased from 21% in 1999 to 50% in 2019.

Despite a significant increase in the percentage of women having primary education and higher education, we see a drop in women being gainfully employed meaning the number of women not working increased from 5.6% in 1999 to 11.3 % in 2019. However perplexing, it aligns with the findings reported in related prior work[27, 28, 29].

"The findings in this paper indicate that a number of factors were responsible for the recent sharp decline in estimated labour force participation rates among working-age women. Some factors, such as increased attendance in education and higher household income levels, are no doubt a positive reflection of rapid economic development. Additionally, we find evidence that changes in measurement methodology across survey rounds is likely to have contributed to the estimated decline in female participation, due to the difficulty of differentiating between domestic duties and contributing family work."[28]

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[27] Kapsos, S. S. (2014, August 11). *Why is female labour force participation declining so sharply in India?* [Publication]. http://www.ilo.org/global/research/publications/papers/WCMS_250977/lang--en/index.htm

[28] Sanghi, S., Srija, A., & Vijay, S. S. (2015). Decline in rural female labour force participation in india: A relook into the causes. Vikalpa: The Journal for Decision Makers, 40(3), 255–268. https://doi.org/10.1177/0256090915598264

[29] Verick, S. (2014). Women's labour force participation in India: Why is it so low? https://www.ilo.org/wcmsp5/groups/public/---asia/---ro-bangkok/---sro-new_delhi/documents/genericdocument/wcms_342357.pdf

Figure 8.

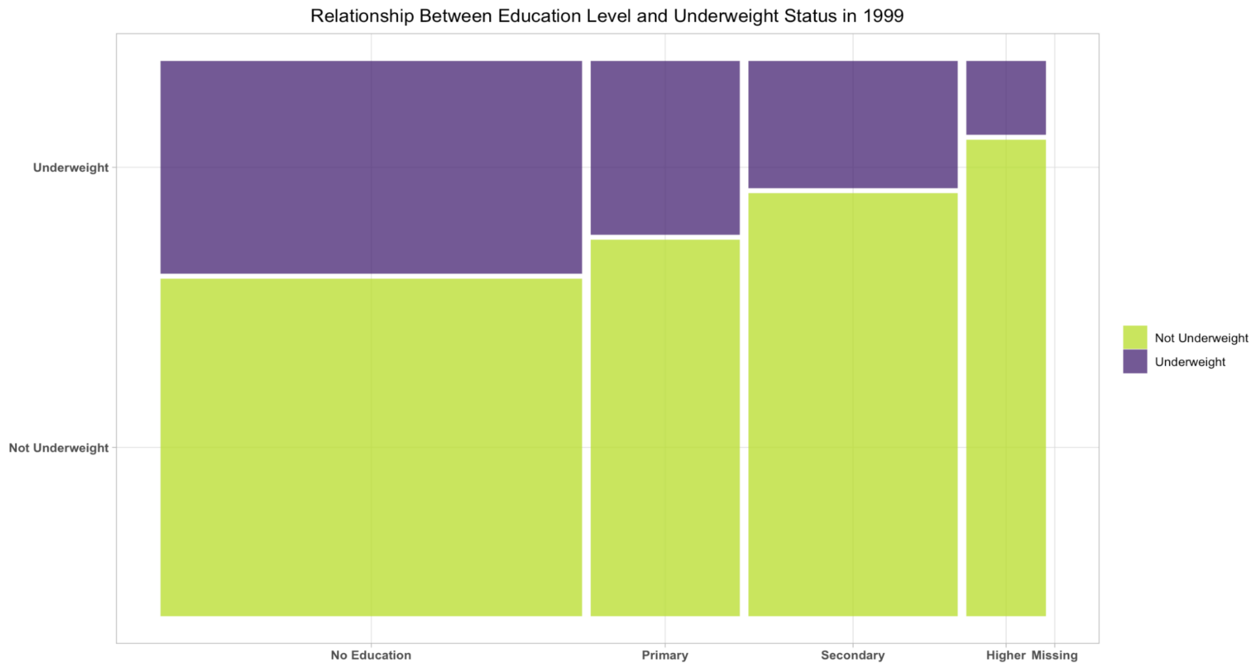


Figure 9.

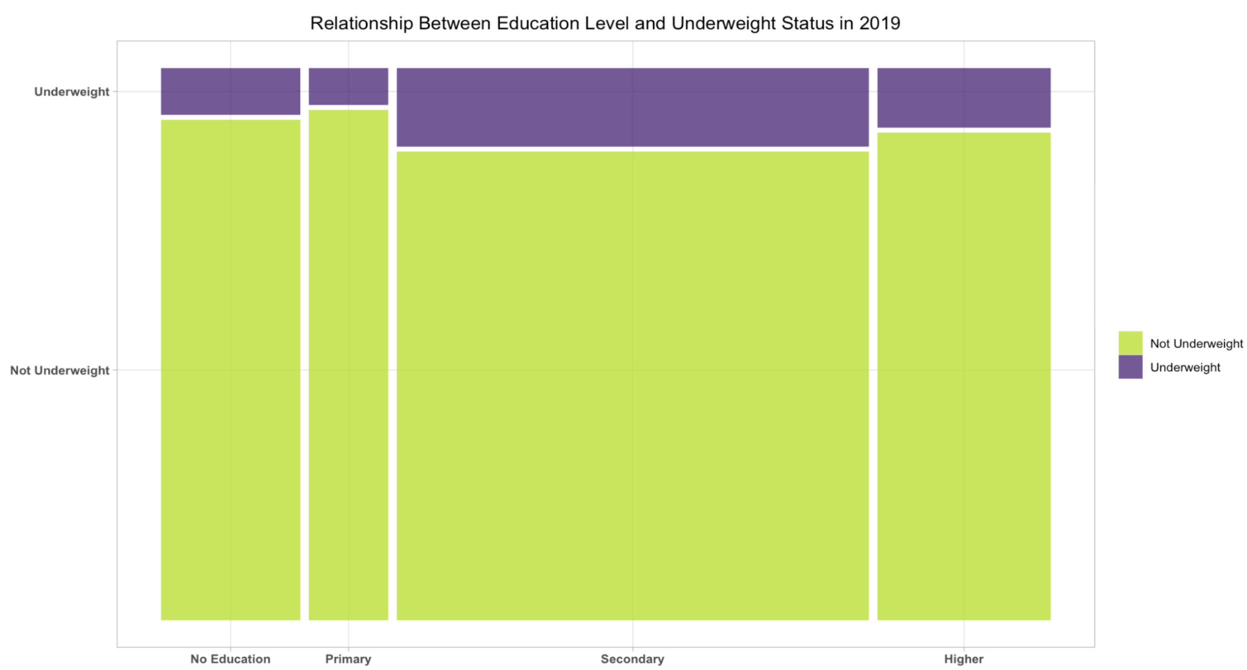


Figure 10.

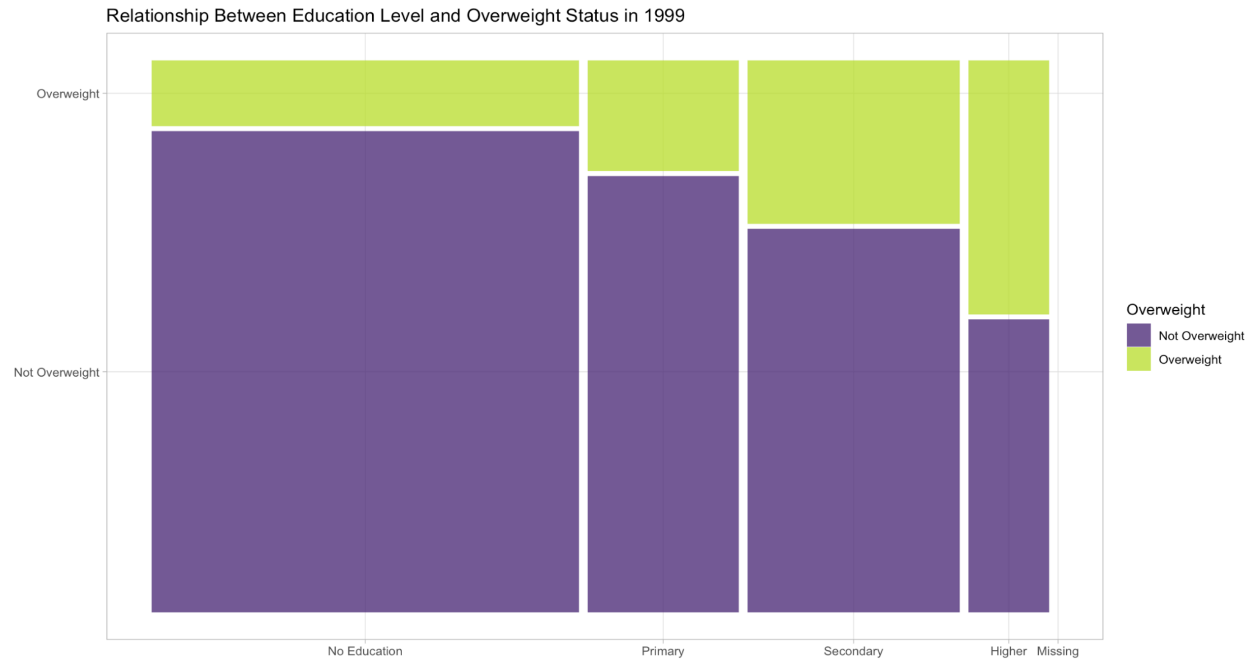
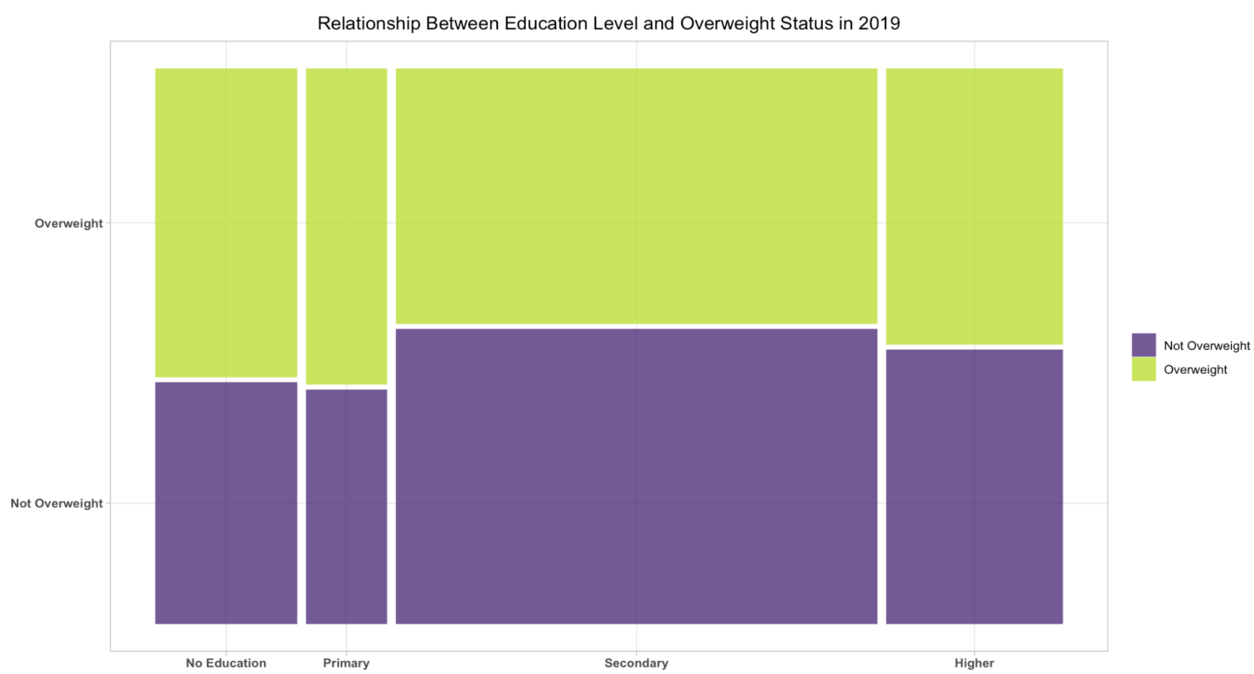


Figure 11.



Figures 8, 9, 10, and 11 are mosaic plots. Mosaic plots provide a visual summary of the distribution of data across multiple categorical variables. Visually inspecting the tile sizes and areas help identify emerging relationships between the variables.

- The width of the tiles represents the proportion of observations in each category of the first variable.
- The height of the tiles represents the proportion of observations in each category of the second variable.
- The area of each tile represents the joint proportion of both categories.

The horizontal axis represents the different education levels, and each tile's width represents the proportion of individuals in each education category. The vertical axis represents the underweight or overweight status, and each tile's height represents the proportion of individuals in each category. The area of each tile corresponds to the joint proportion of individuals belonging to a specific combination of education level and underweight or overweight status.

Figures 8 and 9 show the relationship between education level and underweight in 1999 and 2019, respectively. We can see that there is a significant drop in the proportion of women who are underweight. At the same time, we observe a reduction in the proportion of women under the “No Education” category. Likewise, Figures 10 and 11 show the relationship between education and overweight in 1999 and 2019, respectively. Visually it is clear there is a significant increase in the proportion of counts of individuals who are categorized as overweight. The summary statistics present valuable insights into the changes in education level, underweight, overweight, and occupation-related variables among women in 1999 and 2019. Although the visual observations from the pie charts and mosaic plots provide a snapshot of the changes, they do not delve into the statistical significance of these relationships or control for potential confounding factors. Hence, conducting analysis using logistic regression, with education level as the independent variable and underweight/overweight status as the dependent variable while controlling for other relevant variables, is necessary to validate and quantify the observed relationships, understand the trends over time, and determine the independent effect of education level on underweight and overweight status among women.

5.2 Univariate Logistic Regressions for DHS 1999 Dataset

Model Specification:

$$log\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 \times Education$$

Where

- p is the probability of being underweight or overweight.
- Education is the value of the education variable for a given individual.
- β_0 is the intercept coefficient.
- β_1 is the coefficient associated with the "Education" predictor.

5.2a. Underweight vs Education Level in 1999: Methodology, Results and Discussion

Univariate logistic analysis gives us an initial reference point for understanding the relationship between education and underweight and overweight status.

The model utilized a binary outcome variable, "Underweight" or “Overweight” which was categorized as a factor. The predictor variable of interest was "Education" which was categorized into three levels: Primary, Secondary, and Higher education.

Following is the output for the univariate logistic regression for underweight.

```
Call:
glm(formula = Underweight ~ Education, family = binomial, data =
mutate(tidydata_1999,
    Underweight = as.factor(Underweight)))

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-0. 9887  -0.9887  -0.7249   1.3786   2.0055

Coefficients:
                   Estimate Std. Error z value Pr(>|z|)
(Intercept)        -0.46150    0.01016  -45.44   <2e-16 ***
EducationPrimary   -0.31188    0.02058  -15.15   <2e-16 ***
EducationSecondary -0.74070    0.01951  -37.97   <2e-16 ***
EducationHigher    -1.40581    0.03499  -40.18   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 103567  on 83310  degrees of freedom
Residual deviance: 100565  on 83307  degrees of freedom
```

Results for Underweight vs Education in 1999

The intercept coefficient, denoting the estimated log-odds of being underweight when education is held constant, was found to be statistically significant (Estimate = -0.46150, z = -45.44, $p < 0.001$). This indicates that individuals with zero education level had a particular baseline likelihood of being underweight. Education emerged as a crucial predictor variable.

The coefficient estimates for each education level were as follows:

EducationPrimary: The coefficient estimate for individuals with primary education was -0.31188 (z = -15.15, $p < 0.001$), suggesting a significant negative relationship between primary education and the odds of being underweight compared to those with no education.

EducationSecondary: For those with secondary education, the coefficient estimate was -0.74070 (z = -37.97, $p < 0.001$). This underscores a substantial inverse association between secondary education and the likelihood of being underweight.

EducationHigher: Individuals with higher education exhibited a coefficient estimate of -1.40581 (z = -40.18, $p < 0.001$), underscoring a highly significant negative link between higher education and the odds of being underweight.

The outcomes of the logistic regression analysis emphasize a compelling relationship between education levels and underweight status. The negative coefficient estimate for all education levels (Primary, Secondary, and Higher) signify that higher levels of education are associated with decreased odds of being underweight.

5.2b. Underweight vs Education Level in 2019: Methodology, Results, and Discussion

```
Call:
glm(formula = Underweight ~ Education, family = binomial, data =
mutate(tidydata_2019,
    Underweight = as.factor(Underweight)))

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-0.5561  -0.5561  -0.4793  -0.4219   2.3249

Coefficients:
                   Estimate Std. Error z value Pr(>|z|)
(Intercept)        -2.37448    0.08139 -29.174  < 2e-16 ***
EducationPrimary   -0.25877    0.14529  -1.781   0.0749 .
EducationSecondary  0.58609    0.08867   6.610 3.85e-11 ***
EducationHigher     0.26867    0.10443   2.573   0.0101 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 8831.9  on 12037  degrees of freedom
Residual deviance: 8738.0  on 12034  degrees of freedom
```

The intercept is estimated to be -2.37448. It represents the log-odds of being underweight when an individual is in the reference category ie; when education is not categorized as “no education”.

EducationPrimary: The coefficient for "EducationPrimary" is -0.25877. This indicates that individuals with Primary education have a lower log-odds of being underweight compared to the reference category. The corresponding p-value is 0.0749, which implies that the effect of Primary education on underweight prevalence is not statistically significant at the conventional 0.05 significance level.

EducationSecondary: The coefficient for the "EducationSecondary" category is 0.58609. This suggests that all else being equal, individuals with Secondary education have a higher log-odds of being underweight compared to the reference category. The associated low p-value (3.85e-11) indicates strong evidence of the significance of this effect.

EducationHigher: The coefficient for the "EducationHigher" category is 0.26867. This implies that holding other factors constant, individuals with Higher education have a higher log-odds of being underweight compared to the reference category. The associated p-value (0.0101) suggests that this effect is statistically significant.

5.2c. Overweight vs Education Level in 1999: Methodology, Results and Discussion

The model's structure involved a binary response variable, "Overweight," which was transformed into a categorical factor variable. The focal predictor variable, "Education," was divided into three tiers: Primary, Secondary, and Higher education. Following is the output for the univariate logistic regression for overweight.

```
Call:
glm(formula = Overweight ~ Education, family = binomial, data =
mutate(tidydata_1999, Overweight = as.factor((Overweight))))

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.1174  -0.6721  -0.5053  -0.5053   2.0599

Coefficients:
                   Estimate Std. Error z value Pr(>|z|)
(Intercept)        -1.99384    0.01523 -130.94   <2e-16 ***
EducationPrimary    0.62090    0.02571   24.15   <2e-16 ***
EducationSecondary  1.14041    0.02161   52.76   <2e-16 ***
EducationHigher     1.85091    0.02747   67.39   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)
    Null deviance: 85524  on 83310  degrees of freedom
Residual deviance: 79890  on 83307  degrees of freedom
```

Results for Overweight vs Education in 1999

The intercept coefficient was statistically significant (Estimate = -1.99384, z = -130.94, $p < 0.001$), signifying that individuals with no education exhibited a certain baseline likelihood of being overweight.

EducationPrimary: Individuals with primary education demonstrated a positive coefficient estimate of 0.62090 (z = 24.15, $p < 0.001$). This implies a significant positive association between primary education and the odds of being overweight compared to those with no education.

Education Secondary: For individuals with secondary education, the coefficient estimate was 1.14041 (z = 52.76, $p < 0.001$), pointing to a substantial positive connection between secondary education and the likelihood of being overweight.

EducationHigher: Those with higher education recorded a coefficient estimate of 1.85091 (z = 67.39, $p < 0.001$), indicating a pronounced positive correlation between higher education levels and the odds of being overweight.

The positive coefficient estimates for all education levels (Primary, Secondary, and Higher) underscore that higher education levels are associated with an increased probability of being overweight.

5.2d. Overweight vs Education Level in 2019: Methodology, Results and Discussion

I now present the logistic regression analysis conducted to examine the relationship between education levels and overweight prevalence in the year 2019. The analysis explores the coefficient estimates, standard errors, z-values, and p-values to understand the significance of education levels (Primary, Secondary, Higher) in predicting the likelihood of being overweight.

```
Call:
glm(formula = Overweight ~ Education, family = binomial, data =
mutate(tidydata_2019,
    Overweight = as.factor((Overweight))))

Deviance Residuals:
   Min       1Q   Median       3Q      Max
-1.307  -1.117  -1.117   1.239   1.239

Coefficients:
                   Estimate Std. Error z value Pr(>|z|)
(Intercept)         0.24476    0.04577   5.348 8.91e-08 ***
EducationPrimary    0.05455    0.07616   0.716 0.473800
EducationSecondary -0.38904    0.05202  -7.479 7.49e-14 ***
EducationHigher    -0.23814    0.06125  -3.888 0.000101 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 16688  on 12037  degrees of freedom
Residual deviance: 16601  on 12034  degrees of freedom
```

Intercept: The intercept is estimated to be 0.24476 with a standard error of 0.04577. This represents the log-odds of being overweight when an individual is in the reference category.

EducationPrimary: The coefficient for the "EducationPrimary" category is 0.05455 with a standard error of 0.07616. Individuals with Primary education have slightly higher log-odds of being overweight compared to the reference category “NoEducation”. However, the p-value (0.473800) indicates that this effect is not statistically significant.

EducationSecondary: The coefficient for the "EducationSecondary" category is -0.38904 with a standard error of 0.05202. Individuals with Secondary education have significantly lower log-odds of being overweight compared to the reference category “NoEducation”. The associated p-value (7.49e-14) indicates strong statistical significance.

EducationHigher: The coefficient for the "EducationHigher" category is -0.23814 with a standard error of 0.06125. Individuals with Higher education have lower log-odds of being overweight compared to the reference category. The p-value (0.000101) suggests that this effect is statistically significant.

5.3 Comparative Analysis of Education and Underweight/Overweight Prevalence: 1999 vs. 2019

This section presents a comparative analysis of the relationship between education levels and underweight/overweight prevalence in the years 1999 and 2019. Univariate Logistic regression models were employed to assess the impact of education levels (Primary, Secondary, Higher) on the likelihood of being underweight or overweight.

5.3a. Comparative Analysis of Univariate Logistic Regressions of Underweight Prevalence and Education Levels: 1999 vs. 2019

Comparing the two years' results:

The intercept values differ, indicating potential changes in baseline underweight prevalence between 1999 and 2019.The effects of education categories are consistent across both years. Individuals with Secondary and Higher education levels have significantly different odds of being underweight compared to the reference category. The effect of Primary education is marginally significant in 1999 and not significant in 2019. The comparative analysis of underweight prevalence and education levels in 1999 and 2019 demonstrates consistent findings in the relationship between education and underweight prevalence. Further research could explore potential contextual factors that might contribute to the observed changes and consistencies.

5.3b. Comparative Analysis of Univariate Logistic Regressions of Overweight Prevalence and Education Levels: 1999 vs. 2019

Comparing the results between 1999 and 2019:

The intercept values differ, suggesting potential changes in baseline overweight prevalence between the two years. The effects of education levels on overweight prevalence are consistent between 1999 and 2019. Both Secondary and Higher education levels are associated with significantly higher log-odds of being overweight in 1999 and significantly lower log-odds in 2019. The comparative analysis of overweight prevalence and education levels in 1999 and 2019 demonstrates consistent findings in the relationships. While Primary education's impact varies slightly between the two years, both Secondary and Higher education consistently exhibit significant associations with overweight prevalence. These results highlight the influence of education on overweight prevalence and suggest that the direction of effects may change over time. Further research could explore potential underlying mechanisms and contextual factors driving these patterns.

Overall Analysis

Comparing the results between 1999 and 2019 reveals dynamic shifts in the relationship between education levels and weight-related outcomes:

Underweight: While education levels were consistently associated with reduced odds of underweight in 1999, the pattern has changed in 2019. Secondary education now shows a positive association with underweight prevalence, and Higher education continues to be negatively associated.

Overweight: The positive associations between education levels and overweight prevalence observed in 1999 persist in 2019, with Secondary and Higher education showing reduced odds of overweight.

The comparative analysis highlights the evolving dynamics of the relationship between education and weight-related outcomes over the two decades.

6. Multiple Logistic Regressions: DHS 1999 Dataset

Model Specification:

$$log\left(\frac{p}{1-p}\right) = \beta_0 + \sum_{i=1}^{10} = \beta_i \times Predictor_i$$

Where

- p represents the probability of an individual being underweight or overweight
- β_0 is the intercept term.
- β_i are the coefficients associated with each of the 10 predictor variables.
- $Predictor_i$ represents the value of the ith predictor variable.

6.1 Methodology

Data Source

The dataset used for analysis is derived from the DHS 1999 India dataset, containing information about education, age, residency, occupation, reproductive history, access to utilities, and sanitation facilities. The binary response variable, 'Underweight,' or 'Overweight' categorizes individuals as either underweight/overweight or not.

6.1a. Results for Underweight vs Education in 1999

The model's results are presented in the "Coefficients" section of the output. Each predictor variable's coefficient estimate indicates the change in the log-odds of being underweight associated with a one-unit change in the predictor, holding other predictors constant.

```
Call:
glm(formula = Underweight ~ Education + Age + Residency + Occupation
+
    CEB + Electricity + Radio + Television + Telephone + Toilet,
    family = binomial, data = mutate(tidydata_1999, Underweight =
as.factor(Underweight)))

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.2761  -0.9354  -0.6540   1.2544   2.4157

Coefficients:
                             Estimate Std. Error z value Pr(>|z|)
(Intercept)                 -0.365386   0.040391  -9.046  < 2e-16 ***
EducationPrimary            -0.058990   0.021759  -2.711  0.00671 **
EducationSecondary          -0.200910   0.023028  -8.725  < 2e-16 ***
EducationHigher             -0.356642   0.041636  -8.566  < 2e-16 ***
Age                         -0.018230   0.001135 -16.059  < 2e-16 ***
ResidencyRural               0.030155   0.022063   1.367  0.17171
OccupationNon Physical Work -0.202278   0.042866  -4.719 2.37e-06 ***
OccupationPhysical Work      0.177934   0.017214  10.336  < 2e-16 ***
CEB                          0.030533   0.004656   6.558 5.46e-11 ***
ElectricityHas Electricity  -0.110424   0.018789  -5.877 4.18e-09 ***
RadioHas Radio              -0.109346   0.017160  -6.372 1.87e-10 ***
TelevisionHas TV            -0.276759   0.021185 -13.064  < 2e-16 ***
TelephoneHas Telephone      -0.614680   0.041237 -14.906  < 2e-16 ***
ToiletNo Toilet              0.530437   0.020717  25.604  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 103567  on 83310  degrees of freedom
Residual deviance:  97071  on 83297  degrees of freedom
```

Education: Individuals with primary, secondary, or higher education are less likely to be underweight compared to those with no formal education. The coefficients for primary, secondary, and higher education are statistically significant ($p < 0.01$).

Age: Older individuals are less likely to be underweight. Age has a significant negative effect on the log-odds of underweight ($p < 0.01$).

Occupation: Individuals engaged in non-physical work were significantly associated with a decreased likelihood of being underweight (both $p < 0.01$).

CEB (Children Ever Born): The positive coefficient estimate suggests that an increase in the number of children ever-born is associated with a higher likelihood of being underweight ($p < 0.01$).

Access to Utilities: Lack of access to electricity and radio is associated with a higher likelihood of being underweight (both $p < 0.01$).

Sanitation Facilities: Lack of access to a toilet is associated with an increased likelihood of being underweight while having no toilet is highly significant ($p < 0.01$).

Residency: Rural residency is not significantly associated with underweight prevalence ($p > 0.05$).

Television and Telephone Access: The coefficients for television and telephone access are negative but not statistically significant ($p > 0.05$)

6.1b. Results for Overweight vs Education in 1999

```
Call:
glm(formula = Overweight ~ Education + Age + Occupation + Residency +
    CEB + Electricity + Radio + Television + Telephone + Toilet,
    family = binomial, data = mutate(tidydata_1999, Overweight =
as.factor(Overweight)))
Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.8560  -0.6453  -0.4099  -0.2503   2.8454
Coefficients:
                             Estimate Std. Error z value Pr(>|z|)
(Intercept)                 -3.783780   0.054218 -69.788  < 2e-16 ***
EducationPrimary             0.229475   0.028440   8.069 7.10e-16 ***
EducationSecondary           0.416470   0.027284  15.264  < 2e-16 ***
EducationHigher              0.542627   0.037564  14.445  < 2e-16 ***
Age                          0.066085   0.001350  48.969  < 2e-16 ***
OccupationNon Physical Work -0.001992   0.036374  -0.055  0.95634
OccupationPhysical Work     -0.420986   0.024996 -16.842  < 2e-16 ***
ResidencyRural              -0.338637   0.023000 -14.724  < 2e-16 ***
CEB                         -0.042714   0.005994  -7.126 1.03e-12 ***
ElectricityHas Electricity   0.479832   0.030060  15.962  < 2e-16 ***
RadioHas Radio               0.057919   0.020595   2.812  0.00492 **
TelevisionHas TV             0.499922   0.024755  20.194  < 2e-16 ***
TelephoneHas Telephone       0.533699   0.029037  18.380  < 2e-16 ***
ToiletNo Toilet             -0.501900   0.025126 -19.975  < 2e-16 ***
---Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)
    Null deviance: 85524  on 83310  degrees of freedom
Residual deviance: 69800  on 83297  degrees of freedom
```

EducationPrimary, EducationSecondary, EducationHigher: These variables represent different levels of education compared to the baseline level “no education”. They are all statistically significant ($p < 0.001$), indicating that different levels of education have a significant impact on the odds of being overweight.

Age: Older individuals exhibit a higher likelihood of being overweight. Age has a coefficient of 0.066085. For each one-unit increase in age, the log-odds of being overweight increase by 0.066085. Age is highly statistically significant ($p < 0.001$).

Occupation: The predictor variable "OccupationNon Physical Work" shows no significant association with overweight prevalence ($p = 0.95634$). However, "OccupationPhysical Work" is significantly associated, with individuals in this category being less likely to be overweight ($p < 0.001$).

Residency: Individuals in rural areas are less likely to be overweight ($p < 0.001$).

CEB (Children Ever Born): A higher number of children ever born is associated with a decreased likelihood of being overweight. For each one-unit increase in CEB, the log-odds of being overweight decrease by 0.042714 and is statistically significant. ($p < 0.001$).

Access to Utilities: Having access to electricity, radio, television, and telephone is positively associated with overweight prevalence (all p-values < 0.001).

Sanitation Facilities: Lack of access to a toilet is significantly associated with a decreased likelihood of being overweight ($p < 0.001$).

6.1c. Results for Underweight vs Education in 2019

```
Call:
glm(formula = Underweight ~ Age + Education + Occupation + Residency
+
    CEB + Electricity + Radio + TV + Telephone + Toilet, family =
binomial, data = mutate(tidydata_2019, Underweight =
as.factor(Underweight)))
Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.3597  -0.5436  -0.3536  -0.2185   3.2229
Coefficients:
                             Estimate Std. Error z value Pr(>|z|)
(Intercept)                  1.263689   0.527511   2.396 0.016595 *
Age                         -0.109051   0.005887 -18.523  < 2e-16 ***
EducationPrimary            -0.585750   0.152726  -3.835 0.000125 ***
EducationSecondary          -0.497213   0.106935  -4.650 3.32e-06 ***
EducationHigher             -0.704778   0.124501  -5.661 1.51e-08 ***
OccupationNon Physical Work -0.070842   0.105757  -0.670 0.502948
OccupationPhysical Work      0.064559   0.094273   0.685 0.493468
ResidencyRural              -0.201592   0.062371  -3.232 0.001229 **
CEB                         -0.032361   0.036611  -0.884 0.376744
ElectricityHas Electricity   0.531637   0.506302   1.050 0.293701
RadioHas Radio              -1.028394   0.105860  -9.715  < 2e-16 ***
TVHas TV                    -0.053809   0.086646  -0.621 0.534587
TelephoneHas Telephone      -0.091487   0.233389  -0.392 0.695063
ToiletNo Toilet              0.466735   0.121388   3.845 0.000121 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
(Dispersion parameter for binomial family taken to be 1)
    Null deviance: 8831.9  on 12037  degrees of freedom
Residual deviance: 7660.8  on 12024  degrees of freedom
```

Age: A one-unit increase in age is associated with a decrease of approximately 0.109 in the log odds of being underweight. The p-value (< 2e-16) indicates that age is highly significant in predicting underweight.

EducationPrimary, EducationSecondary, EducationHigher: These variables represent different levels of education compared to the reference category "NoEducation". The coefficients are negative, indicating that higher levels of education are associated with lower log odds of being underweight. All three levels of education are statistically significant predictors.

OccupationNon Physical Work, OccupationPhysical Work: These variables represent different occupation types compared to the reference category "NoEducation". Neither occupation type shows significant associations with underweight.

ResidencyRural: Residing in a rural area is associated with a decrease of approximately 0.201 in the log odds of being underweight. The p-value (0.001229) indicates that this variable is statistically significant.

CEB: The number of children ever born (CEB) does not show a significant association with underweight.

ElectricityHas Electricity: Having electricity access is associated with an increase of approximately 0.532 in the log odds of being underweight. However, the p-value (0.293701) suggests that this variable is not statistically significant.

RadioHas Radio: Having access to a radio is associated with a decrease of approximately 1.028 in the log odds of being underweight. The highly significant p-value (< 2e-16) indicates that this variable is important.

TVHas TV: Having access to a TV does not show a significant association with underweight.

TelephoneHas Telephone: Having access to a telephone does not show a significant association with underweight.

ToiletNo Toilet: Not having access to a toilet is associated with an increase of approximately 0.467 in the log odds of being underweight. The highly significant p-value (0.000121) indicates the importance of this variable.

6.1d. Results for Overweight vs Education in 2019

```
Call:
glm(formula = Overweight ~ Age + Education + Occupation + Residency +
    CEB + Electricity + Radio + TV + Telephone + Toilet, family =
binomial(link = "logit"), data = mutate(tidydata_2019, Overweight =
as.factor(Overweight)))
Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.1328  -0.9877  -0.5186   1.0260   2.0859
Coefficients:
                             Estimate Std. Error z value Pr(>|z|)
(Intercept)                 -2.841363   0.334345  -8.498  < 2e-16 ***
Age                          0.094670   0.003125  30.292  < 2e-16 ***
EducationPrimary             0.282284   0.082549   3.420 0.000627 ***
EducationSecondary           0.428244   0.063265   6.769 1.30e-11 ***
EducationHigher              0.653220   0.076451   8.544  < 2e-16 ***
OccupationNon Physical Work -0.107496   0.063260  -1.699 0.089270 .
OccupationPhysical Work     -0.231022   0.058791  -3.930 8.51e-05 ***
ResidencyRural               0.070809   0.042639   1.661 0.096785 .
CEB                          0.015689   0.019997   0.785 0.432720
ElectricityHas Electricity  -0.755492   0.321093  -2.353 0.018629 *
RadioHas Radio               0.350227   0.055299   6.333 2.40e-10 ***
TVHas TV                     0.243315   0.062452   3.896 9.78e-05 ***
TelephoneHas Telephone       0.048868   0.140390   0.348 0.727773
ToiletNo Toilet             -0.422257   0.097846  -4.316 1.59e-05 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
(Dispersion parameter for binomial family taken to be 1)
    Null deviance: 16688  on 12037  degrees of freedom
Residual deviance: 14700  on 12024  degrees of freedom
```

Deviance Residuals:

These residuals represent the differences between the observed values and the predicted values from the model. They provide insights into how well the model fits the data. The values range from -2.1328 to 2.0859, indicating variability in the fit.

Coefficients:

Intercept: The estimated intercept of the logistic regression model is -2.841363. It represents the estimated log odds of the response variable when all predictor variables are zero.

Age: A one-unit increase in age is associated with an increase of approximately 0.0947 in the log odds of being overweight. The p-value (< 2e-16) indicates that age is highly significant in predicting overweight.

EducationPrimary, EducationSecondary, EducationHigher: These variables represent different levels of education compared to the reference category "NoEducation". The coefficients are positive, indicating that higher levels of education are associated with higher log odds of being overweight. All three levels of education are statistically significant predictors.

OccupationNon Physical Work, OccupationPhysical Work: These variables represent different occupation types compared to the reference category "Not Working". Non-physical work and physical work are not significant predictors of overweight, although the latter has a p-value of 8.51e-05 (very close to zero). A low p-value indicates that there is strong evidence against the null hypothesis, which in this case would be that the coefficient for "OccupationPhysical Work" is equal to zero (i.e., the predictor has no effect on the response).

ResidencyRural: Residing in a rural area shows a positive coefficient (0.070809), indicating a slight increase in the log odds of being overweight. The p-value (0.096785) suggests that this variable is not statistically significant at the conventional significance level (0.05).

CEB: The number of children ever born (CEB) does not show a significant association with overweight.

ElectricityHas Electricity: Having electricity access is associated with a decrease of approximately 0.755 in the log odds of being overweight. The p-value (0.018629) indicates that this variable is statistically significant.

RadioHas Radio: Having access to a radio is associated with an increase of approximately 0.350 in the log odds of being overweight. The highly significant p-value (< 2e-16) indicates that this variable is important.

TVHas TV: Having access to a TV is associated with an increase of approximately 0.243 in the log odds of being overweight. The highly significant p-value (< 2e-16) indicates that this variable is important.

TelephoneHas Telephone: Having access to a telephone does not show a significant association with overweight.

ToiletNo Toilet: Not having access to a toilet is associated with a decrease of approximately 0.422 in the log odds of being overweight. The highly significant p-value (1.59e-05) indicates the importance of this variable.

7. Findings

Comparative Analysis

In this section, we will compare the results obtained for the years 1999 and 2019 concerning the factors influencing underweight and overweight conditions. We will focus on the coefficients, their significance, and the trends observed between the two time periods.

7.1 Underweight

The logistic regression analysis revealed several key insights regarding underweight conditions in both 1999 and 2019. Notable findings include:

- **Education:** In both years, education significantly influenced underweight status. In 1999, individuals with higher education levels were less likely to be underweight, while in 2019, the effect was more nuanced, with primary and secondary education showing higher odds of being underweight.
- **Age:** Age remained a consistent predictor of underweight across both years, with older individuals having lower odds of being underweight.
- **Occupation:** In 1999, non-physical work was associated with higher odds of underweight, while physical work had the opposite effect. However, in 2019, the significance of occupation diminished.
- **Residency:** In 1999, rural residency had a non-significant effect on underweight, but in 2019, it showed a significant negative influence, indicating improved conditions in rural areas.

- **Access to Amenities:** Access to amenities such as electricity, radio, television, and telephone consistently correlated with reduced odds of being underweight in both years.

7.2 Overweight

Similar to underweight, we observed interesting trends for overweight conditions in 1999 and 2019:

- **Education:** Education remained a significant factor in both years. Higher education levels were associated with increased odds of overweight individuals in 1999, whereas in 2019, primary and secondary education had this effect.
- **Age:** The positive correlation between age and overweight conditions was consistent across both years.
- **Occupation:** Physical work consistently had a negative impact on overweight status in both years. However, the significance of non-physical work varied between the two periods.
- **Residency:** In 1999, rural residency had a strong positive influence on overweight status, which reversed in 2019, suggesting changes in lifestyle and access to resources.
- **Access to Amenities:** Access to amenities showed a consistent pattern. Having electricity, radio, television, and telephone access reduced the odds of overweight in both years.

8. Discussion

The results from this study offer valuable insights into the changes in factors influencing underweight and overweight conditions over two decades. Several key points emerge from the comparative analysis:

- **Changing Educational Dynamics:** The shifting impact of education on underweight and overweight conditions reflects the socio-economic transitions India has undergone over the studied period. In 1999, higher education appeared to serve as a shield against underweight, possibly reflecting a correlation between education and access to resources. However, by 2019, primary and secondary education displayed stronger associations with both underweight and overweight statuses. This change suggests that education's role in shaping health outcomes has evolved, possibly influenced by changing aspirations, urbanization, and employment opportunities.

- **Age-Old Traditions and Health:** The consistent correlation between age and underweight and overweight conditions holds deep implications within the Indian context. Traditional norms often prioritize the well-being of others over self-care. The findings suggest that older women tend to have lower odds of being underweight but higher odds of being overweight. Meaning, as women aged, the odds of being overweight increased, highlighting the need for targeted interventions to address changing health needs across different life stages.

- **Occupation and Lifestyle:** The significance of occupation on underweight and overweight conditions underscores the changing nature of work in India. The transition from physical to non-physical work could reflect a shift from physically demanding tasks to sedentary jobs, which, combined with dietary habits, contributes to the changing health landscape. Addressing this dynamic requires holistic interventions that consider workplace ergonomics, physical activity promotion, and nutrition education.

- **Rural-Urban Dynamics:** The transformation of the rural residency effect on underweight and overweight status highlights the complexities of rural-urban dynamics. In 1999, rural residency's lack of significance possibly indicated a uniform vulnerability to nutritional challenges. By 2019, the significant positive correlation suggests potential improvements in rural areas, possibly due to increased access to amenities, healthcare, and public health initiatives.

- **Amenities and Lifestyle:** Access to amenities such as electricity, communication tools, and media significantly affected both underweight and overweight conditions. This highlights the role of technology and communication in shaping dietary and lifestyle choices.

9. Conclusion

This study aimed to investigate the factors influencing underweight and overweight conditions in the years 1999 and 2019. Through a comparative analysis of logistic regression models, we gained valuable insights into the changing dynamics of these conditions over two decades. The findings shed light on the evolving role of education, occupation, residency, and access to amenities in shaping individuals' nutritional status. This indicates a shifting terrain in the influence of education on health outcomes, likely influenced by a range of socio-economic factors.

The persistent influence of age on both underweight and overweight conditions reinforces the importance of targeted interventions across different age groups. The consistent negative impact of physical work on overweight status underscores the significance of promoting physical activity and well-designed workplace policies.

The changing effect of rural residency on overweight status highlights the complex interplay between urbanization, access to resources, and changing lifestyles. The significance of amenities like electricity, media access, and communication tools in both years underscores their role in influencing dietary habits and health-related behaviors.

Government of India emphasized girls education that resulted in significant reduction of illiteracy rates in two decades, between 1999 and 2019, because of "Sarva Siksha

Abhiyan", the government of India's flagship program for universal elementary education for children between the age of 6 and 14 years old, that was launched in 2001. [30] However, the same did not translate into reduction of malnutrition among women. Although, with rapid economic development, people have better access to services and amenities. Yet, this is not reflected in improvement of women's nutrition in India.[31] This poses the Double Burden of Malnutrition (DBM) and related risk of increase in Non Communicable Disease (NCD) [32], [33]

Limitations and Cultural Nuances

While the study contributes valuable insights, it's vital to acknowledge its limitations within the Indian context. Cultural norms around body image, dietary habits, and healthcare-seeking behaviors can significantly impact the results. Additionally, regional and cultural variations within India could influence the study's generalizability.

In conclusion, this research contributes to our understanding of the shifting factors influencing underweight and overweight conditions in different time periods. It

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highlights the intricate interplay of cultural, socio-economic, and healthcare factors in shaping underweight and overweight conditions among Indian women aged 15 to 49. These findings underscore the need for holistic interventions and policies that address the diverse dynamics within the Indian context to foster better health outcomes for women across different life stages. The insights gained can guide policymakers, healthcare practitioners, and researchers in tailoring strategies to address these public health challenges effectively. As we continue to witness societal changes, ongoing research is vital to ensure that interventions remain relevant and impactful in combating underweight and overweight conditions.

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