

Analysis of Obesity Prevalence and Influencing Factors in the 2013–2016 Scottish Health Surveys

Group 6

AUTHOR

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Introduction

Obesity has become a significant public health concern in Scotland, raising worries about the rising burden of chronic diseases and healthcare costs. The 2013–2016 Scottish Health Surveys provide valuable insights into socio-economic and lifestyle factors that may influence obesity prevalence, including age, sex, education, and survey year. This project seeks to determine whether the prevalence of obesity has changed over time and to explore how demographic and socio-economic factors relate to weight classification. By analyzing these trends, we can gain a deeper understanding of the drivers behind obesity and inform targeted public health interventions.

Exploratory data analysis

These statistics can be illustrated in [Figure 1](#) below. We can also see that there are no significant change in the proportion of obese individuals between 2013 and 2016.

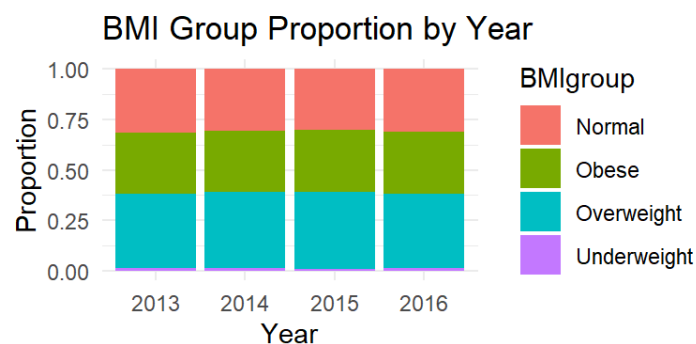


Figure 1: bar plot of BMIgroup by year

Next, we want to explore the relationship between Age and BMIgroup. In [Figure 2](#) shows that the age distribution varies significantly across different BMI groups. Generally, obese individuals tend to be older, whereas the underweight group is comparatively younger. This indicates age is an important factor associated with BMI categories.

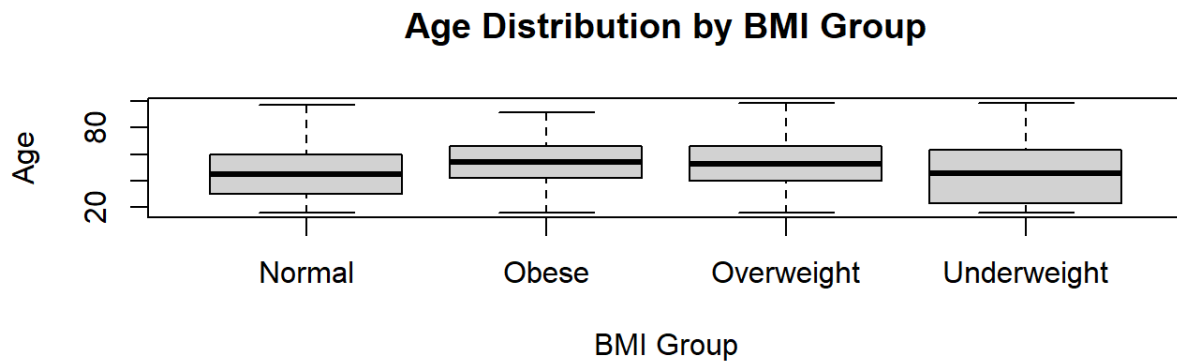


Figure 2: Box plot showing the relationship between Age and BMIgroup

Next, we analyse the relationship between BMI Group Proportion by Sex. In [Figure 3](#) we see there are noticeable differences in BMI group proportions between males and females. Males appear slightly more likely to be overweight, whereas females show relatively higher proportions in the normal and obese categories. Gender thus influences BMI distribution patterns.



Figure 3: Bar plot showing the relationship between Sex and BMIgroup

To assess the impact of socio-economic status, we look at BMI distributions across education levels. [Figure 4](#) shows that individuals with higher education levels (e.g., degrees) tend to have higher proportions of normal weight and lower obesity rates. In contrast, individuals with no qualifications show higher rates of obesity. This highlights how education - and by extension, socio-economic status - may influence obesity.

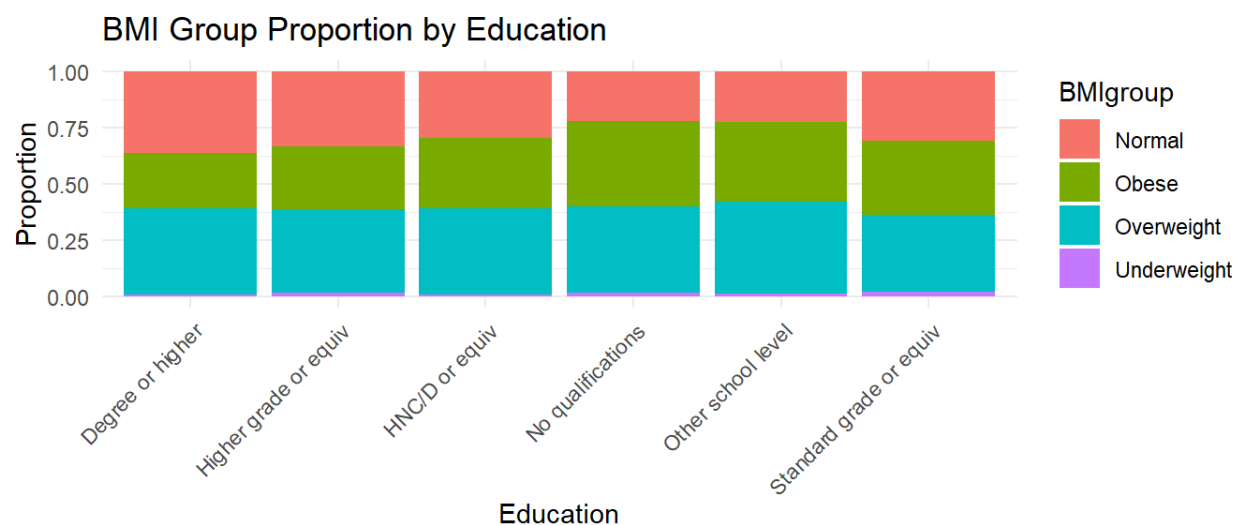


Figure 4: Bar plot showing the relationship between Education and BMIgroup

In summary, our exploratory analysis reveals that while overall BMI trends remained stable between 2013 and 2016, there are notable differences in BMI distributions based on age, gender, socio-

economic status, and lifestyle factors. Older age, lower education, and poor dietary habits are associated with higher obesity rates, while gender differences also influence BMI group proportions.

Formal data analysis

Table showing Chi-squared results

X-squared	df	p-value
0.11404	1	0.7356

Table showing Pearson’s Chi-squared results

X-squared	df	p-value
0.22577	3	0.9733

Output to check if obesity changes over year

obese binary			
Predictors	Odds Ratios	CI	p
(Intercept)	0.00	0.00 – 131922150951084279992224.00	0.717
Year	1.01	0.97 – 1.04	0.736

The formal analysis of obesity prevalence trends in Scotland, using data from the Scottish Health Survey, reveals no statistically significant change over the surveyed years (2013–2016). The Chi-squared Test for Trend in Proportions ($X^2=0.114$, $p=0.736$) and Pearson’s Chi-squared Test ($X^2=0.226$, $p=0.973$) both fail to reject the null hypothesis, indicating no evidence of a linear trend or overall difference in obesity proportions across the years. This conclusion is further supported by the logistic regression results, where the “Year” variable shows an odds ratio of 1.01 (95% CI: 0.97–1.04, $p=0.736$), suggesting that each passing year was associated with a non-significant change in obesity odds. The intercept (OR=0.43, $p<0.001$) reflects the baseline odds of obesity but does not inform temporal trends. Overall, these results demonstrate that obesity prevalence in Scotland remained stable during the study period, with no meaningful increase or decrease detected.

To answer the second question, we use linear regression to find out if age, gender, socio-economic status, or lifestyle factors are significant predictors for obesity.

We start by looking at if age is a significant predictor for a persons BMI group. We are fitting the following linear model:

$$\text{logit}(\pi) = \beta_0 + \beta_1 x_i + \epsilon_i, \quad \epsilon_i \sim N(0, \sigma^2), \quad i = 1, \dots, 14017$$

Here, π is the probability that the individual is obese, x_i is the age of the i th individual, and β_0, β_1 are regression coefficients. We are using the logit link function.

Output from linear regression with age as the predictor

BM lgroup			
Predictors	Odds Ratios	CI	p

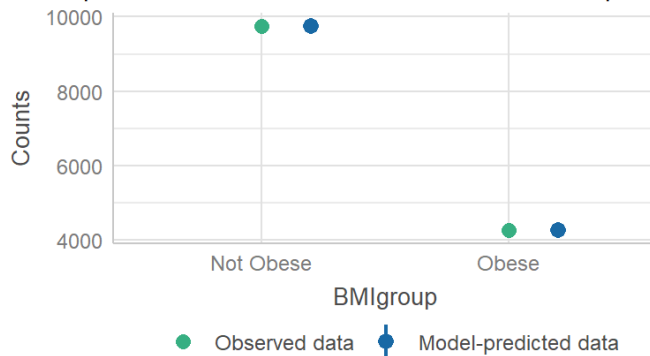
(Intercept)	4.33	3.86 – 4.86	<0.001
Age	0.99	0.99 – 0.99	<0.001

As seen the p-value from the above table, we can infer that age is a significant predictor for a persons BMI group. As someones age increases by one year, the odds of the person being obese increase by a factor of 0.99.

We now check the assumptions of our model, to find out if the model is valid.

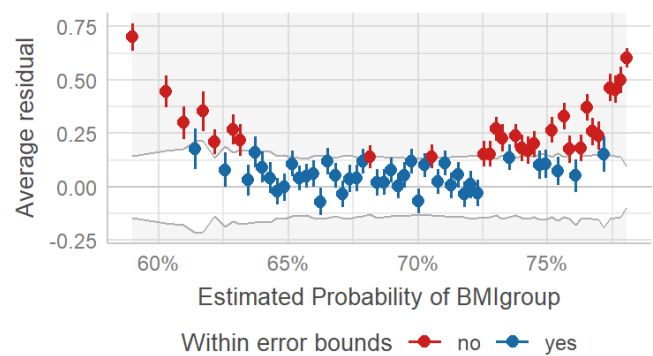
Posterior Predictive Check

Model-predicted intervals should include observed data points



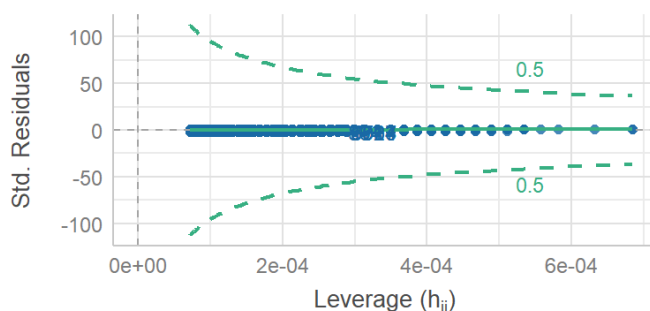
Binned Residuals

Points should be within error bounds



Influential Observations

Points should be inside the contour lines



Uniformity of Residuals

Dots should fall along the line

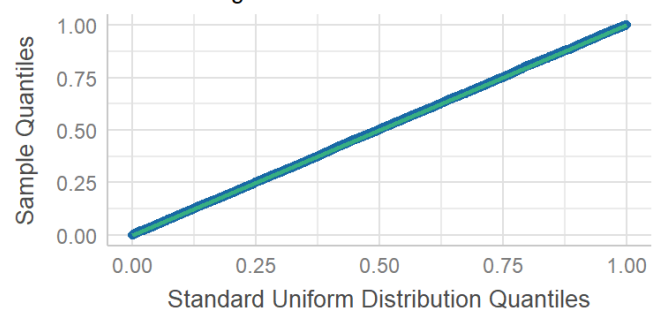


Figure 5: Diagnostic plots for the age model

There is no issues that can be seen in the posterior predictive check, influential observations graph, and the uniformity of residuals graph. There does appear to be a large amount of points falling outside the error bounds in the binned residuals graph. We would expect about 95% of points to fall within the error bounds if the model is true. As there is a large amount of points plotted it is hard to tell if there is 95% within the error bounds, as there may be overlap. However, it appears to be good enough.

We now look at sex to consider if it is significant through fitting the following model:

$$\text{logit}(\pi) = \beta_0 + \beta_1 x_i + \epsilon_i, \quad \epsilon_i \sim N(0, \sigma^2), \quad i = 1, \dots, 14017$$

Where x_i is an indicator variable taking the value 0 if the individual is a male and the value 1 if the individual is a female.

Output from linear regression with sex as the predictor

BM lgroup			
Predictors	Odds Ratios	CI	p
(Intercept)	2.44	2.31 – 2.57	<0.001

Sex [Female]	0.89	0.83 – 0.96	0.002
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As seen from the above table, the p-value indicates that sex is a significant predictor at the 5% significance level. Furthermore, the odds ratio for being obese increase by 0.89 for females. Again, we check our model assumptions to find out if our results are valid.

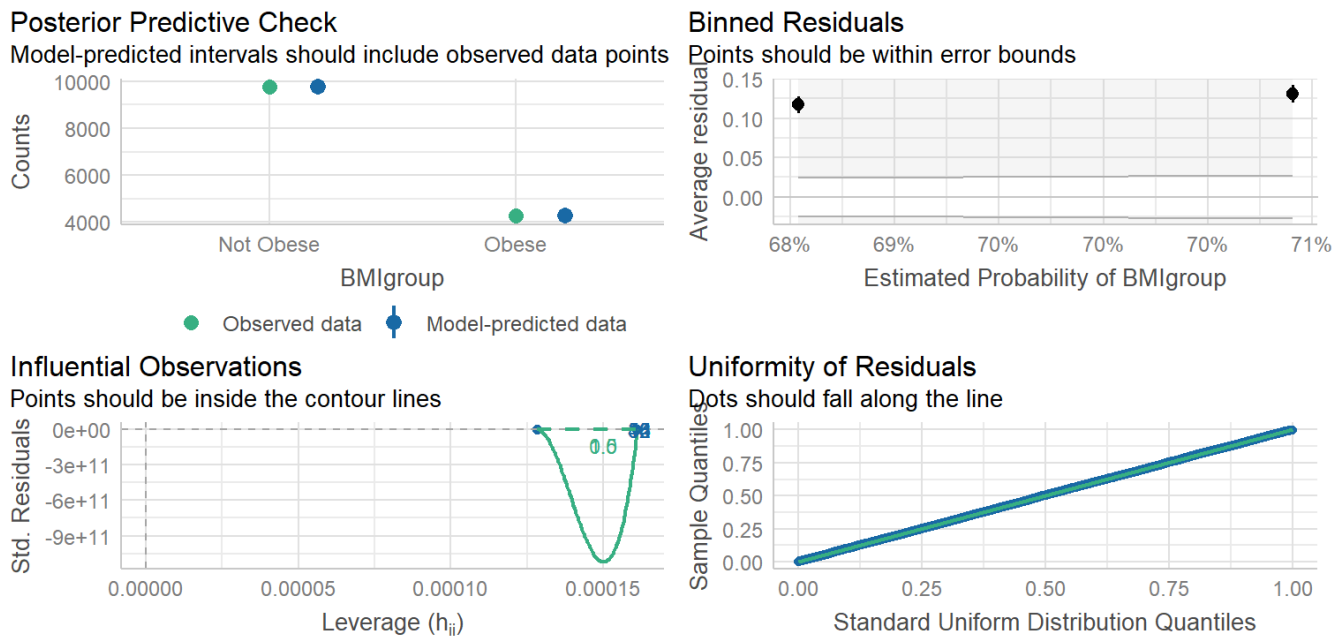


Figure 6: Diagnostic plots for the sex model

The plots in [Figure 6](#) look good enough. There may be issues with the binned residuals plot, however the issue likely stems from sex being a factor with 2 levels giving us only 2 points.

We now look at education to consider if there is a difference in obesity based on socio-economic factors. We fit the following model:

$$\text{logit}(\pi) = \beta_0 + \beta_1 x_i + \beta_2 x_j + \beta_3 x_k + \beta_4 x_l + \beta_5 x_m + \beta_6 x_n + \epsilon_i, \quad \epsilon_i \sim N(0, \sigma^2), \quad i = 1, \dots, 14017$$

Where x_i through x_n are indicator variables taking the value 1 if they have that level of education and 0 if they do not. The β_0 term refers to the reference level which is having a degree.

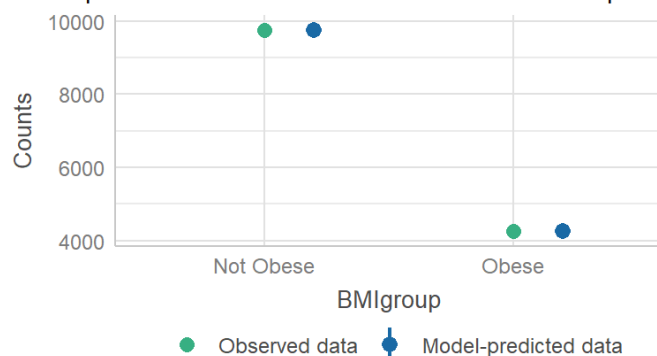
Output from linear regression with education as the predictor

BM lgroup			
Predictors	Odds Ratios	CI	p
(Intercept)	3.05	2.85 – 3.26	<0.001
Education [Higher grade or equiv]	0.84	0.75 – 0.94	0.003
Education [HNC/D or equiv]	0.72	0.64 – 0.82	<0.001
Education [No qualifications]	0.53	0.48 – 0.59	<0.001
Education [Other school level]	0.60	0.51 – 0.70	<0.001

As seen from the table above, all the levels of education are considered significant predictors of the persons BMI group. The odds of a person being obese is 3.05 for a person with a degree, then increases by 0.53-0.84 depending on qualification level. Again, we have to check the model assumptions.

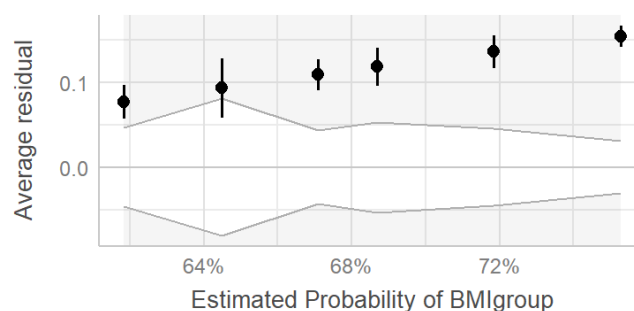
Posterior Predictive Check

Model-predicted intervals should include observed data points



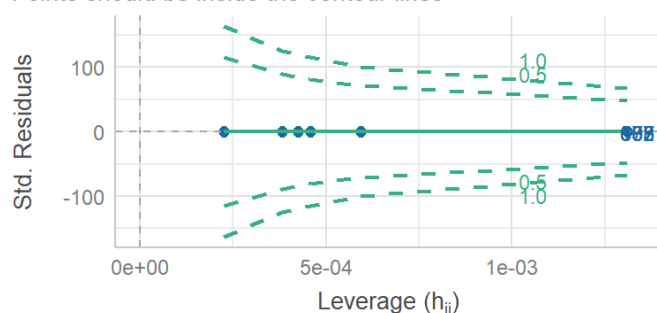
Binned Residuals

Points should be within error bounds



Influential Observations

Points should be inside the contour lines



Uniformity of Residuals

Dots should fall along the line

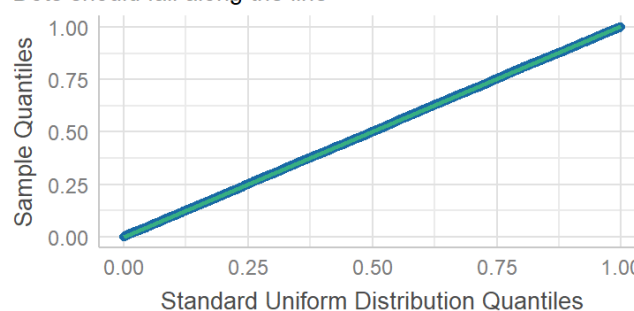


Figure 7: Diagnostic plots for the education model

The interpretation of [Figure 7](#) is much like the previous figures. The only graph that leaves cause for concern is the binned residuals graph, but again, because it is a factor, it is always going to not work as well as a continuous variable. Thus, the model is appropriate.

Conclusions

This analysis confirms that obesity prevalence in Scotland remained stable from 2013 to 2016, with no statistically significant trends over time. However, the study identifies strong and valid associations between obesity and several demographic and socio-economic variables. Age, gender, and education level all significantly affect obesity status. These conclusions are supported by consistent results from both exploratory data analysis and formal statistical models, which met key diagnostic assumptions, strengthening the validity of our findings. Future research could expand on this study by incorporating additional lifestyle factors such as physical activity levels, diet quality, and income. Longitudinal studies would also help determine causal relationships over time. Furthermore, spatial analysis of regional obesity patterns across Scotland may provide deeper insights for targeted public health interventions.