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Projected Trends in Adult Obesity Prevalence in the United States through 2040: A Markov Chain Analysis

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Abstract: Obesity rates among adults have been increasing in the US to concerning levels. This poses a substantial public health risk because obese people have a higher chance of contracting multiple conditions, including cardiovascular disease, diabetes, and obstructive sleep apnea. Predictive modeling is needed because it can help develop mitigation policies. In this study, data from ten cycles of the NHANES survey were used to create a 10-year Markov transition matrix. The 10-year matrix was then decomposed into a 2-year matrix, which was used to project future obesity prevalence. Separate matrices were created for racial/ethnic and income categories. A bootstrap-based Monte Carlo simulation was utilized to determine uncertainty in the future obese adult population. By 2040, the obesity prevalence is projected to be 54.0% (51.4% to 55.6%), and the total obese population is forecasted to be 131.8 million (121.7 to 141.7 million). Additionally, the transition matrix demonstrates that obesity has a high level of persistence and that transitioning to a higher weight category is more likely than moving to a lower one. These projections are consistent with previous studies. Minority groups are disproportionately affected by obesity, and obesity rates among Black individuals are projected to be the highest in 2040. These results demonstrate the importance of public policy to address obesity as a persistent, population-level risk and to target disparities among different groups.

1. Introduction

Obesity is a significant public health problem in the United States. In recent years, the prevalence of obesity has been rising to alarming levels. According to NHANES data from the 2021 to 2023 cycle, 40.3% of US adults are obese, and 9.4% have severe obesity [1]. This is a rise from the 1999 to 2002 cycle, which found that 30.5% of US adults had obesity [2]. This data demonstrates that obesity is a widespread and worsening issue that can elevate one's risk for multiple chronic health conditions, including diabetes, heart disease, and obstructive sleep apnea [3]. Accurate models must be developed to predict future prevalence to best address it as a population-level risk. Predictions of the future burden can allow policymakers to prepare necessary interventions in advance and customize them for populations with higher rates of obesity. This can prevent the chronic diseases listed above, improve quality of life for many, and extend life expectancy [4,5]. In this study, a Markov chain with a transition matrix was used to project future trends in obesity. In this method, statistical models are created to use probability to explain how a system changes between different states. The states in this case are underweight, healthy weight, overweight, and obese. Using Markov chains to analyze the changes between these states over time offers important insights regarding the likelihood that people will move between weight categories [6]. This is a better method for prediction than using trends in the prevalence rate of obesity because it captures the way individuals gain or lose weight and possibly transition into an obese status, providing more detail about how people's weight is changing and why obesity levels are rising. However, Markov-chain models are not perfect, so some method is necessary to estimate the reliability of the results. We chose a Monte Carlo bootstrap simulation method, which randomly re-samples individuals to approximate the sampling distribution. This method was selected because it can effectively quantify uncertainty in reliability estimates without requiring strong distributional assumptions or a lot of extra computations [7]. Previous studies have projected obesity rates in the US [8,9]. Methodologies include multinomial regression and spatiotemporal Gaussian process regression. However, this study aims to estimate the future obesity prevalence more accurately by utilizing the Markov chain transition matrix methodology. Although our approach is based on Huang & Huang, who have already done a similar study using Markov chains and bootstrap methods to determine uncertainty, we use a larger dataset by pooling multiple NHANES cycles, a more rigorous filter for removing records that may make the results inaccurate, and four different weight statuses rather than three [6]. The goal of this study is to use a Markov transition model to analyze weight category changes and project future trends in obesity.

2. Methodology

We used data from the NHANES survey from 10 two-year cycles from 1999/2000 to 2017/2018 to develop the Markov transition matrix. Later datasets were not used because they may have been impacted by the COVID pandemic.

2.1. Dataset and Cleaning

The National Health and Nutrition Examination Survey (NHANES) is a nationwide survey that assesses the dietary habits and general health of people of all ages in the US. The data tables from NHANES used to create the Markov transition matrix were Demographic Variables and Sample Weights (DEMO), Body Measures (BMX) and Weight History (WHQ) [10]. Duplicate records, adults below the age of 30, pregnant people, and records without survey weight, stratum, and/or primary sampling unit were filtered out from DEMO. Data with no height or weight recorded or with illogical high or low records were removed from BMX. This was used to calculate BMI. Missing historical weight records in WHQ were removed. The final pooled Markov estimation sample included 35,726 respondents, with approximately 3,000–4,000 usable observations per cycle.

2.2. Transition Matrix Construction

Based on NHANES data, the current state was compared to the state from 10 years ago to determine transition likelihoods. There are 4 possible states: underweight, normal, overweight, and obese, producing a 4 x 4 matrix. Since the transition probabilities were around the same across different years (see Figure 1), one matrix was created using pooled data. A pooled matrix would result in greater accuracy due to the increased quantity of weight data.

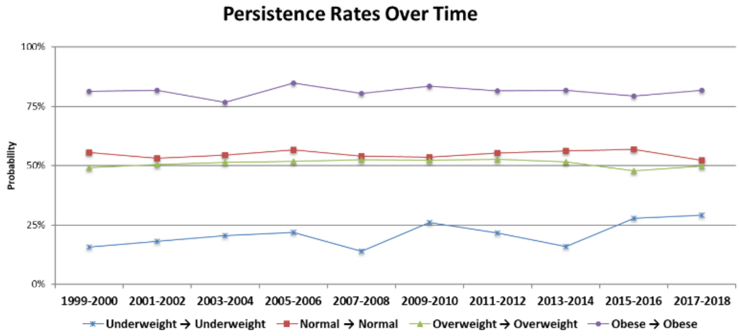


Figure 1: Persistence Rates by NHANES Survey Year.

The 10-year matrix was decomposed into a 2-year one using a fifth root calculation. Though it is advantageous to start with a 10-year matrix due to higher statistical reliability and decreased susceptibility to short-term shocks, a 2-year matrix can better show gradual change when making predictions regarding obesity rate. Additionally, separate transition matrices were created by race/ethnicity and by income to show variance between different demographic groups. The racial and ethnic groups included the following: Non-Hispanic White, Non-Hispanic Black, Mexican-American, Other Hispanic, and Other Race, which was composed of races and ethnicities not contained in the main analytical groups and may have multi-racial or multi-ethnic respondents. The three income groups were low, middle, and high, using the NHANES income variable INDFMPIR. This is the ratio of family income to poverty, where the poverty guidelines depend on family size, survey year, and state. In the dataset, low income was defined as below 130% of the federal poverty line; middle income was between 130% and 350%, and high income was above 350% of the poverty line. To project the prevalence percentages of the future population, the transition matrix was applied for each 2-year interval. Then, these rates were combined with population growth to determine the total population of individuals in each BMI category in the future. For the uncertainty analysis, two methods were used. The first was the sampling uncertainty, utilizing a bootstrap-based Monte Carlo simulation. The simulation changed the transition matrix according to the resampled survey data. Resampling was performed at the PSU-within-stratum level to maintain correlations among individuals who sampled together. The second was based on historical variation among each survey cycle's specific matrix. Each matrix was used to estimate the future prevalence and determine the upper and lower uncertainty bounds. The uncertainty for the total obese population was determined by combining the uncertainty from the Monte Carlo simulation with the uncertainty in the future population. The census projection has three possibilities: low, middle, and high. For each obese population draw, a rate value is calculated using the median prediction as an anchor point and the extreme outcomes as constraints. A population value was chosen from the census scenarios, and the estimated future obese population was computed. This was repeated to generate a distribution of possible populations by 2040. These calculations were conducted in Python 3.13.5.

3. Results

3.1. Ten-Year and Two-Year Transition Matrices

According to the matrix in Figure 2, obesity has a high level of persistence: 81.3% of obese individuals stay obese within a ten-year interval. Other weight categories also show some persistence, as people with normal weight remain in that category 54.9% of the time, and overweight individuals stay overweight in 51.0% of cases. It is easier to gain weight than to lose it. There is a 37.9% chance of an overweight person becoming obese, but only an 11.1% chance of reaching a healthy weight.

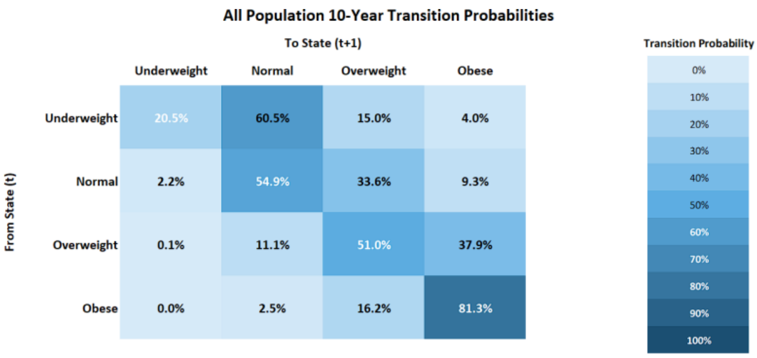


Figure 2: Markov 10-Year Transition Probability Matrix.

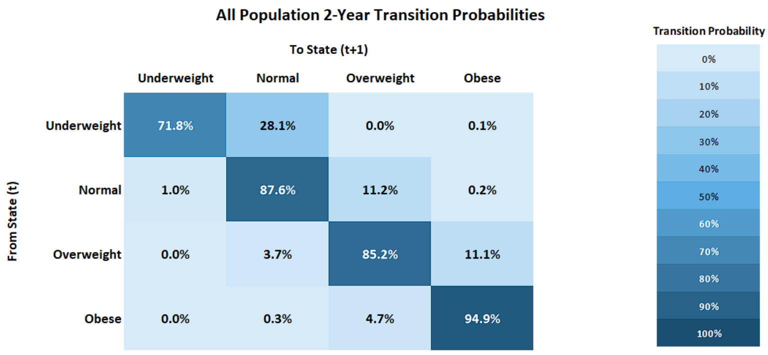


Figure 3: Markov 2-Year Transition Probability Matrix.

Since the 2-year matrix was derived from the 10-year one, it shows the same pattern: increasing BMI is more common than decreasing BMI, and people are most likely to remain in their current weight category, as shown in Figure 3. However, the shorter time interval in the matrix resulted in lower probabilities of transitioning between categories.

3.2. National Obesity Prevalence Projections

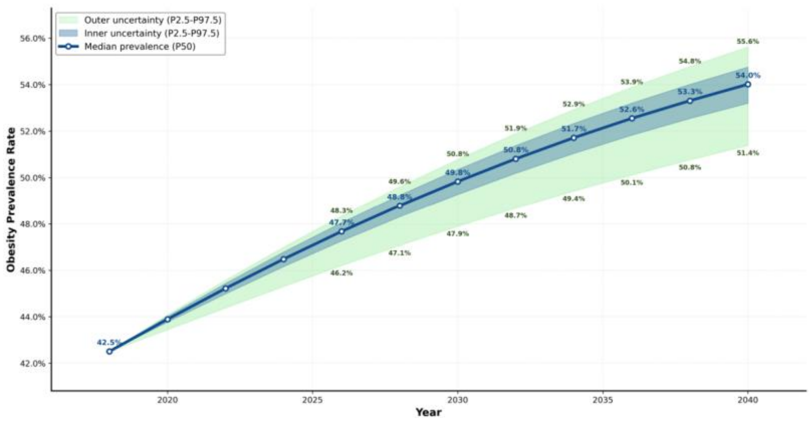


Figure 4: Projected Obesity Prevalence in the United States.

In Figure 4, the blue represents the sampling uncertainty, and the green shows matrix structural variation. The projected prevalence is around 50% by 2030 and continues to rise to 54.0% (between 51.4% and 55.6%, accounting for uncertainty) of the adult population by 2040. A majority of US adults are likely to be obese under all projected scenarios by 2040. Uncertainty increases over time, but the bands remain relatively narrow.

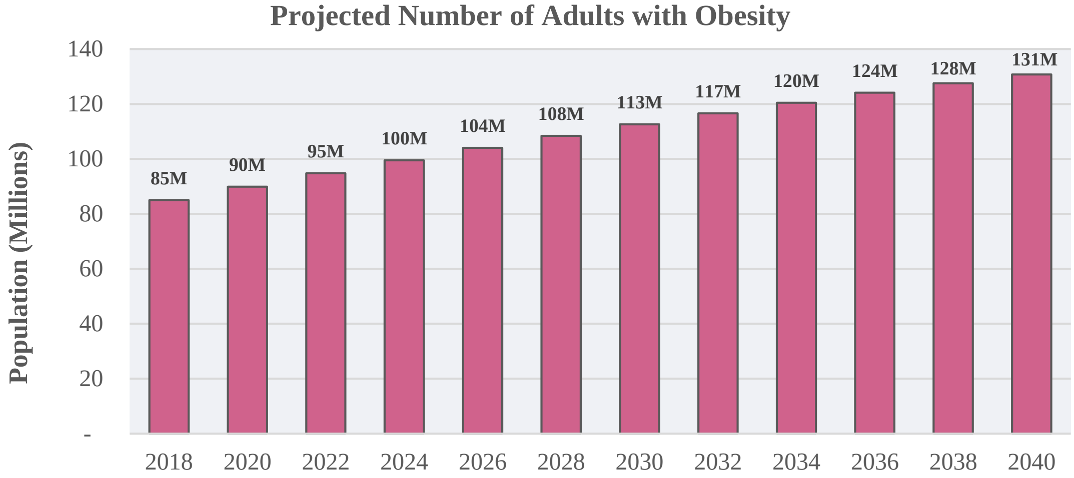


Figure 5: Projected Obese Population in the United States.

Based on the projected obesity percentages and population growth, the number of adults with obesity will continue to grow, reaching an estimated 131 million people by 2040 (see Figure 5). This demonstrates that obesity is and will be a significant and growing burden in the US.

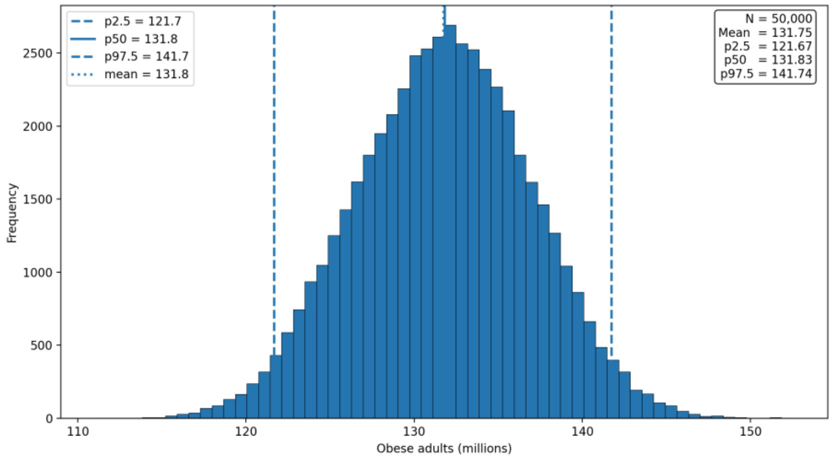
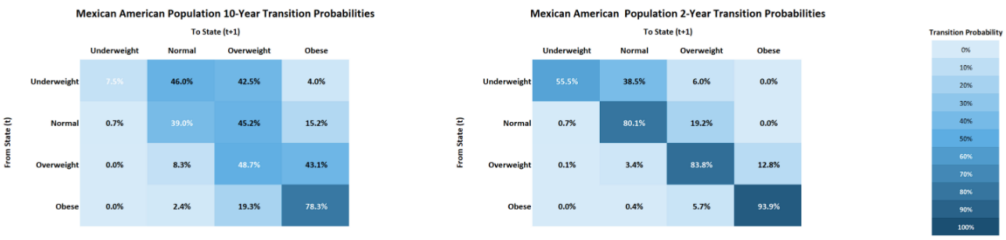


Figure 6: Obese Population in 2040 Uncertainty Analysis.

The above uncertainty evaluation in Figure 6 shows the results of the Monte Carlo simulation. In all scenarios within the error bounds, the obese adult population in the US will be very high, with an average population projection of 131.8 million. Accounting for uncertainty, this number will be between 121.7 and 141.7 million.

3.3. Disparities by Demographic Group



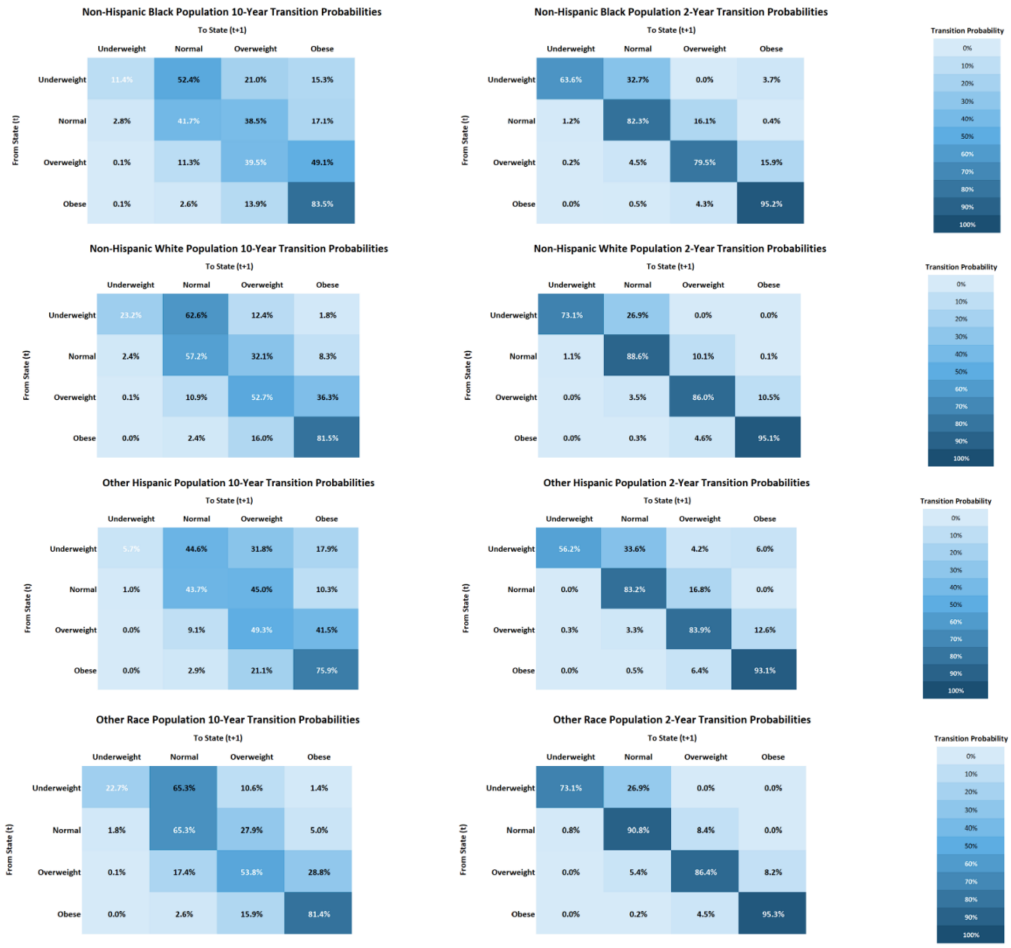


Figure 7: 10-year and 2-year Transition Matrices by Race.

According to Figure 7, although matrices for each race and ethnicity show the same general trends (for instance, high persistence of obesity), there are variations in transition rates across different populations. 83.5% of non-Hispanic Black individuals remain obese after an interval of ten years, a stronger persistence than any other group. Only 13.9% transition to an overweight state from obesity in a decade, compared to 16.0% of the non-Hispanic white population.

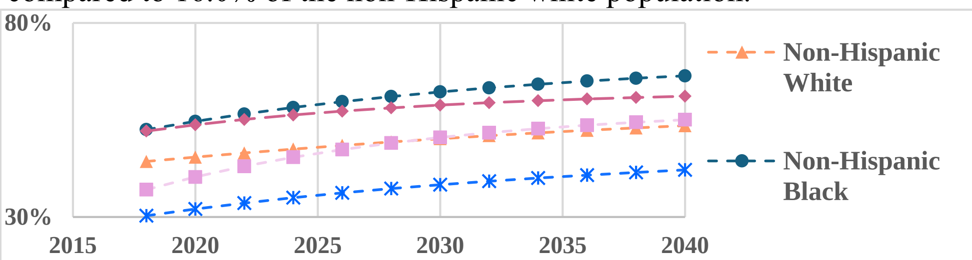


Figure 8: Prevalence Rate Projection by Race.

According to Figure 8, the prevalence of obesity is projected to vary by race and ethnicity, with different growth trends based on transition probabilities. Non-Hispanic Black people are expected to have the highest rate of obesity, at 66.4% in 2040. Also, by 2040, 61.1% of the Hispanic population of Mexican origin will be obese. The non-Hispanic Other Race group is projected to have the lowest prevalence of obesity, but this prediction is not useful for analysis because of the diverse groups that constitute the “Other Race” category.

Figure 9: 10-year and 2-year Transition Matrices by Income Level.

Similar to the matrices by race and ethnicity, the matrices by income level show the same general patterns but vary. Based on Figure 9, the high-income group has the highest persistence of obesity at 95.6% for 2 years, and the low-income group has the lowest persistence, with 93.4% of obese individuals staying obese after 2 years. Although this result may appear to be counterintuitive, transition rates are calculated from the initial BMI status; therefore, it is not incompatible with the lower obesity prevalence in the high-income population.

4. Discussion

This study used a Markov chain transition matrix model to project future obesity rates in US adults based on BMI transition probabilities. The model predicts that obesity prevalence will continue to increase in the future, reaching 49.8% by 2030 and rising to 54.0% by 2040, according to median estimates. The total obese adult population is projected to reach 131.8 million (p2.5 = 121.7 million, p97.5 = 141.7 million). The predicted increase in obesity prevalence is consistent with the transition probabilities. The population will gradually shift towards higher BMI categories over time, leading to an increase in obesity prevalence, due to two factors. Firstly, individuals are generally most likely to remain in their current weight category, with obesity exhibiting the most persistence. Once individuals become obese, they are unlikely to return to a lower weight category. Even after a decade, 81.3% of obese individuals will remain obese. Secondly, transitions to a higher weight category are more common than transitions to a lower one. For example, there is a higher chance of overweight individuals progressing to obesity than obese individuals losing weight to become overweight. As a result, as transitions occur each model cycle, projected obesity prevalence increases. Also, these probabilities suggest that avoiding weight gain could be more effective in preventing future increases in obesity prevalence than attempting weight loss after a person becomes obese. Furthermore, people are very unlikely to move more than one BMI category during each 10-year interval. Only 2.5% of individuals with obesity can reach a normal weight within 10 years. Although this study mainly focused on obesity prevalence, overweight can still increase the risk of conditions such as cardiovascular disease, diabetes, kidney disease, and musculoskeletal conditions [11]. Becoming overweight may reduce risks compared to staying obese, but the rarity of a transition to a normal-weight category poses health problems. These projections are consistent with previous studies that forecast continued increases in obesity rates in the US. According to a study by Ng et al., the obese and overweight combined adult population in the US will be 213 million in 2050 [9]. Similarly, DeCleene et al. project that the obese adult population will be 126 million in 2035, which is 46.9% of the total population [12]. Additionally, the transition matrix created in this study is similar to that of the study by Huang & Huang [6]. The same general patterns, including high persistence of obesity and the larger likelihood of weight gain, are shown in their matrix. However, small variations exist, likely due to the use of a larger dataset in this study, data cleaning, and the separation of the normal and underweight groups. The high projected obesity rates for minority groups, especially Black and Hispanic people, may worsen systemic disparities and healthcare access issues. It is already known that racial and ethnic minorities often face higher rates of obesity due to multiple factors, such as genetics, diet, stress, economic class, and discrimination [13]. Variations in the transition matrices appear consistent with these factors. For instance, non-Hispanic Black people are more likely to remain obese than their white counterparts and have lower rates of obese individuals becoming overweight. Difficulties in transitioning to a lower weight group may be attributed to the above obesity risk factors. Overall, if these projections are realized, obesity will place increasing demands on healthcare systems and resources. Co-morbidities associated with obesity, including cardiovascular disease and type 2 diabetes, will also increase. Therefore, it is necessary to implement public health policy to prevent further increases in obesity prevalence.

5. Policy Implications

When developing public health policy, it is important to understand obesity as a persistent, population-level public health risk rather than a short-term health issue, as obese individuals are unlikely to transition to lower BMI categories. For the same reason, policies should also intervene earlier. Moreover, obesity mitigation strategies should address racial, ethnic, and socioeconomic disparities by targeting groups with a higher projected risk. Past interventions in multiple different forms have generally been effective. Vivamos Activos, a community-based program for adult Latinos with obesity, helped participants lose 2.1 kg on average within 6 months, but the weight loss was not sustained [14]. SHARE (Supporting Healthy Activity and Eating Right Every Day) was a program to help African American adults lose weight. After 24 months, people lost 2.4 kg on average [15]. Additionally, behavioral strategies have allowed low-income individuals in developed countries to lose a pooled mean difference of 1.56 kg. These methods include monetary incentives, caloric intake reduction, exercise, and social support [16]. Future interventions that are implemented could use similar approaches or develop novel strategies. The large and growing population of obese adults will incur high costs, as people with obesity spend more on healthcare than those at a healthy weight [17]. There are also indirect costs caused by disability, absence from work, and lower productivity [18]. Considering the high persistence of obesity and relative ease of weight gain compared to loss, measures to mitigate obesity risk may be financially worthwhile.

6. Limitations and Future Research Directions

This analysis was limited to people aged 30 and older because the study design uses weight information from 10 years earlier to create the transition matrix. Younger age groups are important for obesity research because increasing obesity prevalence in youth could impact future adult obesity rates. About 80% of obese adolescents will remain obese in adulthood, so not including the youth obesity population dynamics may have affected the results [19]. Furthermore, this study drew upon NHANES survey data from 1999 to 2018, so it does not include effects from the COVID-19 pandemic or recent increases in GLP-1 use. These factors could impact obesity rates in the near future. Additionally, future changes in population demographics can affect obesity outcomes. Future research should focus on age-specific models. The rate of obesity varies at different ages, peaking at age 50 to 64 for females and 50 to 54 for males [11]. As a result, transition matrices for different age groups may vary. Future studies could also try to apply transition matrices to younger populations. Additionally, as GLP-1 medications become more common and the composition of the population changes, new obesity studies may be needed. Thirdly, research should also investigate whether COVID-19 has any temporary or long-term impacts on obesity prevalence. If future NHANES datasets are not affected by the pandemic, they should be included in subsequent analyses, as more recent data may be more applicable to current obesity trends.

7. Conclusion

This study used a Markov transition model to project future obesity prevalence among US adults based on observed weight category transition rates and a Monte Carlo simulation to measure uncertainty. The results suggest that obesity is a persistent health condition that is becoming increasingly common among adults in the United States. By 2040, in all scenarios within the error bounds calculated through a Monte Carlo simulation, more than half of adults will be obese. The transition percentages demonstrate that obese individuals are likely to remain obese, and moving to a lower weight category is more difficult than transitioning to a higher one. These findings highlight the importance of effective responses in public health policy, which should intervene early and address demographic disparities and potential future increased healthcare costs.

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