Who Stays Single? Exploring the Factors Behind Non-Marriage in the United States in 2023*

Low Income and Education Levels Correlate with Higher Propensity to Remain Unmarried

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This study examines the socio-demographic determinants of non-marriage in the United States in 2023 using logistic regression analysis on individual-level data. The findings highlight that individuals with lower income and education levels, particularly below a bachelor's degree, are significantly more likely to remain unmarried. Additionally, gender and race also play critical roles, with men and certain racial groups, such as African Americans, showing higher unmarried rates. These results underscore structural inequities and socio-economic barriers shaping marital outcomes, offering insights into broader societal patterns and potential areas for intervention.

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*Code and data are available at: https://github.com/LilianS77/US_Marriage.

1 Introduction

Marriage is widely perceived as a fundamental element of both social cohesion and economic stability. It profoundly influences individual lives and the broader social fabric. In recent decades, however, marital patterns in the United States have shifted noticeably, with a growing proportion of individuals choosing to remain unmarried. This trend prompts important questions about the factors underlying these decisions and the broader societal impacts of such changes. Understanding these issues is essential for addressing wider socio-economic inequalities and cultural transformations.

This study investigates the determinants of non-marriage by utilizing a dataset from IPUMS USA (IPUMS 2024), which provides survey data encompassing demographic, social, and economic variables. While previous research has primarily examined individual factors like education or income in isolation, few studies have explored the interplay between multiple socio-demographic factors in shaping marital decisions. This research addresses this shortfall by analyzing these factors in combination.

The estimand of this study is the reason an individual remains unmarried, analyzed in the context of their socio-demographic characteristics, including education level, income, race, gender, and age. This approach enables a deeper understanding of how these attributes collectively influence marital behavior.

The findings, derived through logistic regression analysis, reveal significant patterns. Higher education levels are strongly linked to higher marriage rates, while economic stability, as indicated by higher income, positively correlates with marital status. Marked disparities are evident among racial and gender groups. African Americans, for instance, demonstrate higher rates of non-marriage, whereas males are slightly more likely to remain unmarried than females. These findings underscore persistent structural inequities and cultural complexities influencing marriage in contemporary American society. Recognizing these inequities equips policymakers and social institutions to design targeted interventions that address inequality, foster opportunities for stable relationships, and adapt to evolving family dynamics in modern society.

The structure of this paper is as follows: Section 2 explains the dataset, variable selection, and measurement strategies employed to study marital status. Section 3 discusses the logistic regression methodology, including model rationale, prior specifications, and validation processes. Section 4 presents the key findings with supporting visualizations, emphasizing the roles of education, income, race, gender, and age in predicting non-marriage. Finally, Section 5 delves into the implications of the findings, acknowledges study limitations, and outlines potential areas for future research.

2 Data

2.1 Data Tool

The dataset was analyzed using R (R Core Team 2023) and utilized several R packages for data manipulation, visualization, and analysis, including ggplot2 (Wickham 2016) for creating elegant graphics, dplyr (Wickham et al. 2023) for data wrangling, and here (Müller and Bryan 2023) for simplifying file management. The data was processed efficiently using Apache Arrow (Richardson, Dunnington, and Developers 2023), and visualizations were further enhanced with the scales package (Wickham, Seidel, et al. 2023). logistic regression modeling was implemented using rstanarm (Cepeda, Gabry, et al. 2023), while statistical results were tidied with broom (Robinson 2023) and broom.mixed (Bolker et al. 2023). Tables were constructed using kableExtra (Zhu 2023) for a polished presentation. Reproducibility was ensured with knitr (Xie 2014). The bayesplot package (Gabry et al. 2023) was utilized for visualizing Bayesian model diagnostics and posterior predictive checks. Data was extracted from IPUMS USA (IPUMS 2024), and guidance on storytelling with data was drawn from Telling Stories with Data (Alexander 2023).

2.2 Measurement

For this study, data was specifically drawn from the American Community Survey (ACS) (Bureau 2024), a critical subset of IPUMS. The ACS conducts ongoing data collection throughout the year, selecting approximately 250,000 addresses each month to ensure the population's most current representation. The survey employs several collection methods to maximize participation. Initially, respondents receive a request to complete the survey online or return a paper questionnaire via mail. If no response is received, follow-up contact is made through telephone, utilizing a computer-assisted interview system (CATI). For those who remain unresponsive, a portion—approximately one-third—is selected for an in-person, computer-assisted personal interview (CAPI). In addition, the survey covers a wide range of social, economic and demographic characteristics, such as the variables of marital status, age and education analyzed in this study.

2.3 Outcome Variables

The primary outcome variable for this study is **Marital Status**, which categorizes individuals based on their marital state. The proportion of marital status categories is displayed in Figure 1. This variable allows for a comparison between individuals who have never married (`Not_Married`) and those who have (`Married`). For this study, **Not_Married**: Includes individuals who have never been married. **Married**: Includes individuals who are married, as well as those who are divorced, widowed, or separated.

2.4 Predictor Variables

The distribution of predictor variables is displayed in Figure 2. These variables capture demographic, socioeconomic, and personal characteristics, providing a comprehensive framework for analyzing factors associated with marital status. Below are the key predictor variables:

1. **Age**: A continuous variable representing the respondent's age in years.
2. **Gender**: A categorical variable indicating whether the respondent is male or female. Gender differences often play a role in marital patterns.
3. **Race**: A categorical variable categorized into White, Black, Asian, American Indian, and Other racial groups. This variable examines potential racial disparities in marital behavior.
4. **Education Level**: An ordinal variable indicating the highest level of education attained by the respondent. It is grouped into five categories: Below High School, High School, Some College, Bachelor's Degree, and Above Bachelor.
5. **Income**: A continuous variable measuring the respondent's annual income in dollars. Income reflects economic resources and may be associated with marital stability and decisions.

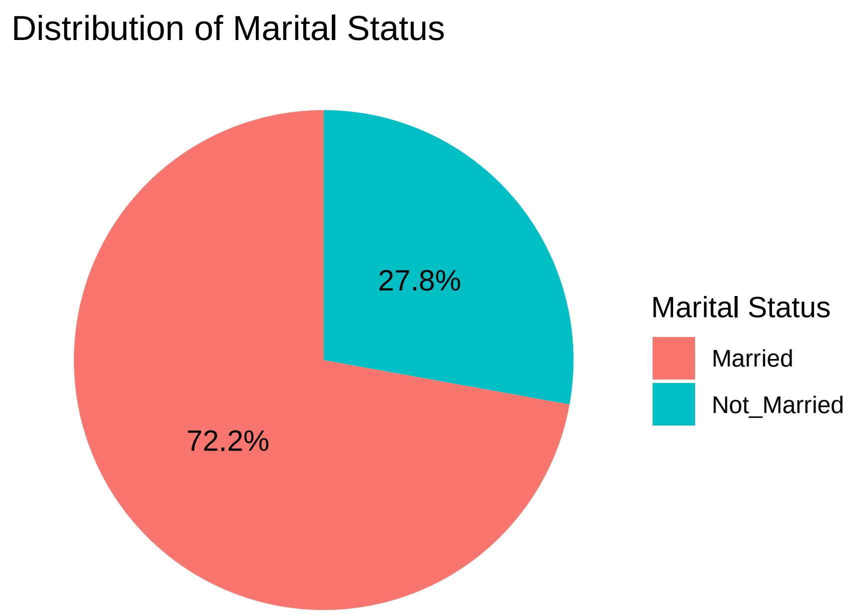


Figure 1: Proportion of Marital Status Categories

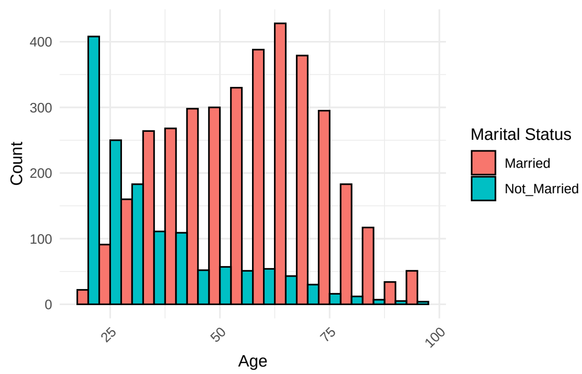
The unmarried results of the predictor variables are displayed in the Section 4.

2.5 Data Selection

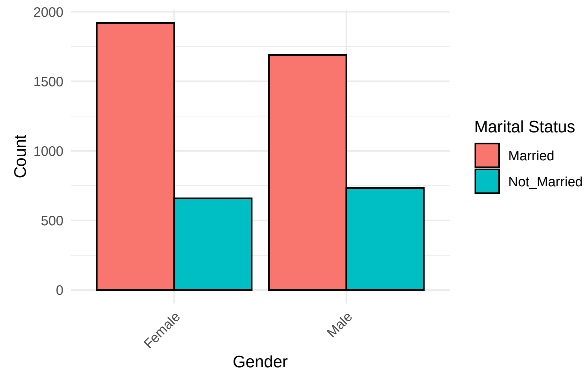
To examine the phenomenon of non-marriage in the United States, the IPUMS USA dataset was chosen as the primary data source, rather than IPUMS International. Although IPUMS International includes harmonized census data from 104 countries and encompasses over one billion individual records, its broad, global scope renders it less aligned with the objectives of this study. This research focuses specifically on societal patterns within the U.S. population. IPUMS USA, with its data derived from the American Community Surveys (ACS) and federal censuses, provides the precision and relevance needed to investigate non-marriage trends in the United States.

3 Model

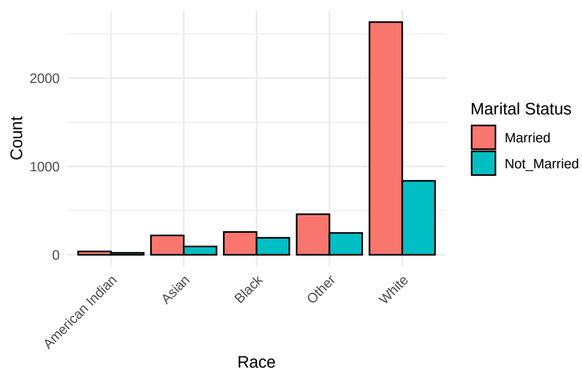
For this analysis, I apply a Logistic Regression Model to assess the likelihood of an individual not being married (outcome variable) based on several demographic and socioeconomic predictors (predictor variables). This model was chosen due to the binary nature of the outcome



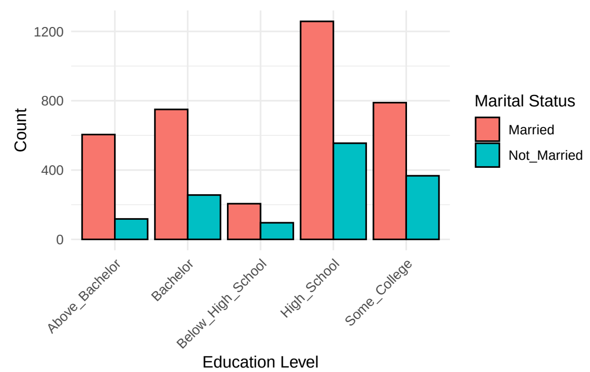
(a) Age Distribution by Marital Status



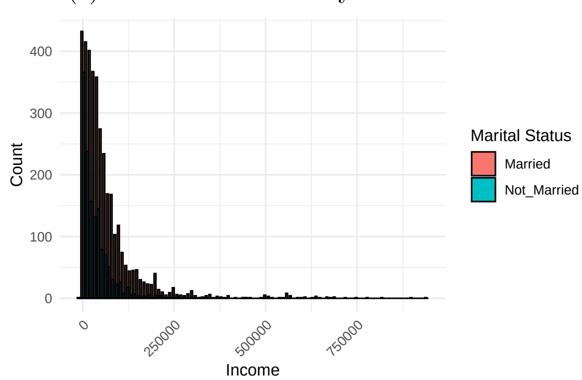
(b) Gender Distribution by Marital Status



(c) Race Distribution by Marital Status



(d) Education Level Distribution by Marital Status



(e) Income Distribution by Marital Status

Figure 2: Counts for Demographic Variables by Marital Status

variable, which distinguishes between individuals who are "Not Married" versus those who are married (including divorced, widowed, or separated).

3.1 Model Setup

3.1.1 Objective

The primary objective of the model is to analyze and predict the factors associated with individuals' marital status, focusing on identifying key predictors for individuals who have never been married (`Not_Married`).

The logistic regression model used in this study is:

$$\log\left(\frac{\hat{p}}{1-\hat{p}}\right) = \beta_0 + \beta_1 \cdot \text{age} + \beta_2 \cdot \text{gender} + \beta_3 \cdot \text{Race} + \beta_4 \cdot \text{Income} + \beta_5 \cdot \text{education\_level}$$

The priors for the coefficients are defined as:

$$\begin{aligned}
\beta_0 &\sim \text{Normal}(0, 2.5),\\
\beta_1 &\sim \text{Normal}(0, 2.5),\\
\beta_2 &\sim \text{Normal}(0, 2.5),\\
\beta_3 &\sim \text{Normal}(0, 2.5),\\
\beta_4 &\sim \text{Normal}(0, 2.5),\\
\beta_5 &\sim \text{Normal}(0, 2.5).
\end{aligned}$$

Where:

- $\hat{p}$: Represents the probability that an individual is classified as `Not_Married`.
- β_0: The intercept term, representing the log-odds of being `Not_Married` when all predictors are zero.
- β_1: The coefficient for the individual's age.
- β_2: The coefficient for gender.
- β_3: The coefficient for the race category.
- β_4: The coefficient for annual income.
- β_5: The coefficient for the education level.

3.1.2 Priors Explanation

In this model, normal priors with a mean of 0 and a standard deviation of 2.5 are assigned to all coefficients and the intercept. This choice reflects neutrality, implying no prior expectation of direction or magnitude for the coefficients.

The standard deviation of 2.5 reflects moderate uncertainty in prior beliefs, allowing the model to incorporate reasonable variability in predictor effects while avoiding overly restrictive priors.

3.2 Model Justification

The logistic regression model was chosen for this study due to its suitability in predicting binary outcomes. Specifically, it was employed to classify individuals as either "Not Married" or otherwise. This method is widely used in social science research to analyze the relationship between a binary dependent variable and several independent variables. It is therefore well-suited for examining patterns in marital status.

The decisions regarding model design were guided by the dataset's structure and the variables under analysis. For instance, age was treated as a continuous variable to preserve its detail and avoid arbitrary groupings. Gender was modeled as a categorical variable with two levels—male and female—to reflect its binary nature in the data. Each racial category was included as a distinct level to capture the unique effects associated with different racial groups. Similarly, education and income were retained in their granular forms to maximize the use of the dataset's available information.

While the method depends on certain assumptions, such as linearity in the log-odds and independence of observations, it allows for the inclusion of interaction terms and accommodates a wide range of predictors. This balance of clarity, flexibility, and alignment with the study's objectives makes logistic regression an effective choice for this research.

Posterior checks for the model and MCMC convergence check can be found in Section A.2.

4 Results

This study integrates multiple visualizations to provide a comprehensive understanding of the demographic, economic, and social dynamics associated with marital status. Below, we summarize the key findings derived from each visualization.

Figure 3 and Table 1 highlight the coefficients for RaceWhite, RaceOther, and RaceAsian are negative, indicating that individuals from these racial groups are less likely to remain unmarried compared to others. The coefficient for RaceBlack is positive, and its confidence interval does not include 0, suggesting that RaceBlack group are more likely to remain unmarried compared to other racial groups. Individuals with lower levels of education (e.g., below high school) have a higher likelihood of remaining unmarried. The coefficient for males is positive, indicating that men are slightly more likely to remain unmarried compared to female.

Table 1: Summary of the model

term	estimate	std.error	conf.low	conf.high
(Intercept)	3.26	0.37	2.65	3.87
age	-0.08	0.00	-0.09	-0.08
genderMale	0.37	0.08	0.24	0.51
RaceAsian	-0.67	0.37	-1.26	-0.07
RaceBlack	0.20	0.34	-0.38	0.77
RaceOther	-0.67	0.35	-1.22	-0.10
RaceWhite	-0.67	0.33	-1.21	-0.11
Income	0.00	0.00	0.00	0.00
education_levelBachelor	0.30	0.14	0.07	0.54
education_levelBelow_High_School	0.48	0.21	0.15	0.83
education_levelHigh_School	0.21	0.14	-0.02	0.46
education_levelSome_College	0.18	0.15	-0.06	0.43

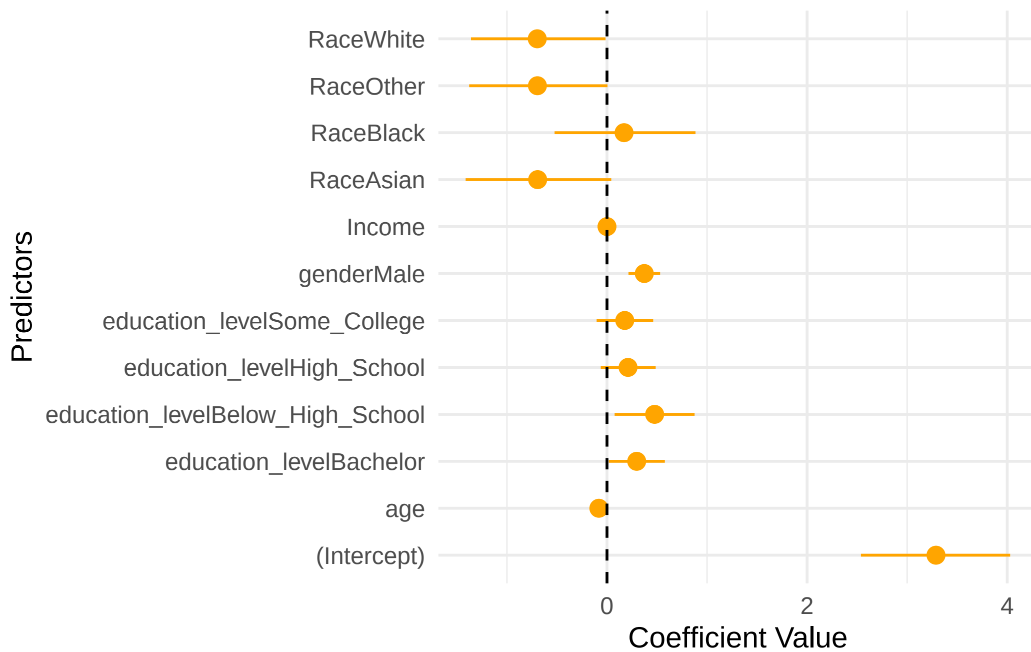


Figure 3: Coefficients of The Model

Figure 4 depicts the income distribution of unmarried individuals, revealing that the majority of unmarried individuals fall into lower income brackets. The distribution is heavily skewed, with a significant concentration of individuals earning below $50,000 annually. The density sharply declines for higher income levels, reflecting the economic constraints that may influence marital status. A small proportion of high-income individuals remain unmarried, as shown by the long right tail of the distribution.

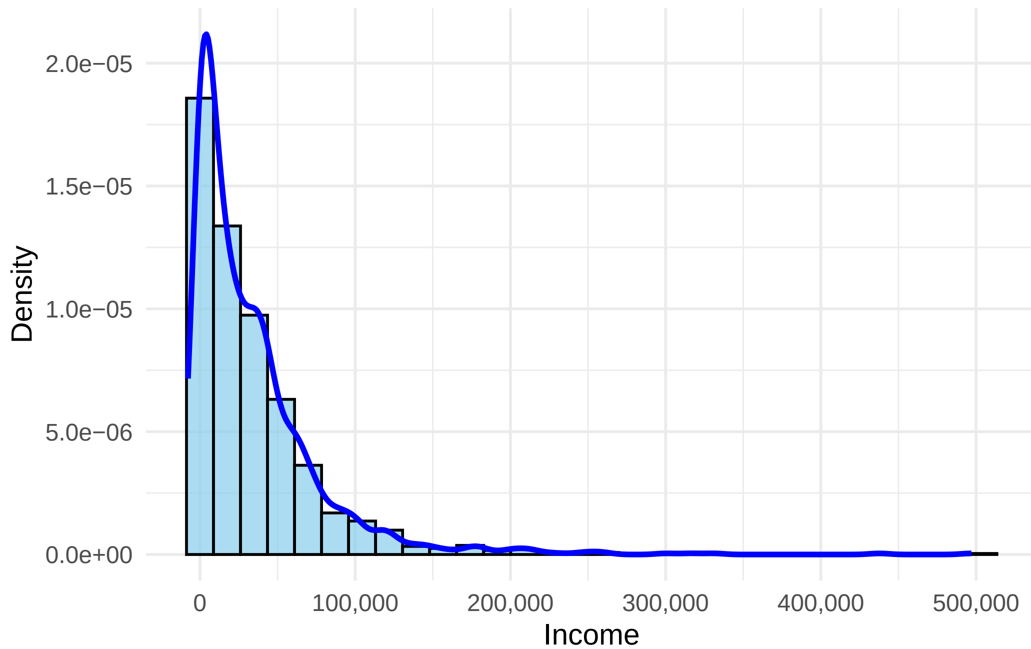


Figure 4: Income Distribution for Unmarried Individuals

Figure 5 shows the age distribution for unmarried individuals, which is dominated by younger age groups, particularly those in their 20s and early 30s. The density decreases substantially as age increases, illustrating that as individuals age, the likelihood of remaining unmarried diminishes.

The proportions of marital status by education level are presented in Figure 6. Individuals with higher education levels show significantly lower proportions of unmarried individuals, with 25% for those holding a bachelor's degree and 16% for those with education above a bachelor's degree. In contrast, individuals with lower educational attainment exhibit higher proportions of unmarried individuals, with 32%, 31%, and 32% for those with below high school, high school, and some college education, respectively.

Figure 7 and Figure 8 highlight the proportions of marital status by race and gender. Race disparities are evident, with “American Indian” and “Black” populations showing higher proportions of unmarried individuals, at 37% and 43%, respectively. In contrast, “White” and “Asian” groups exhibit the lowest proportions of unmarried individuals, at 24% and 30%,

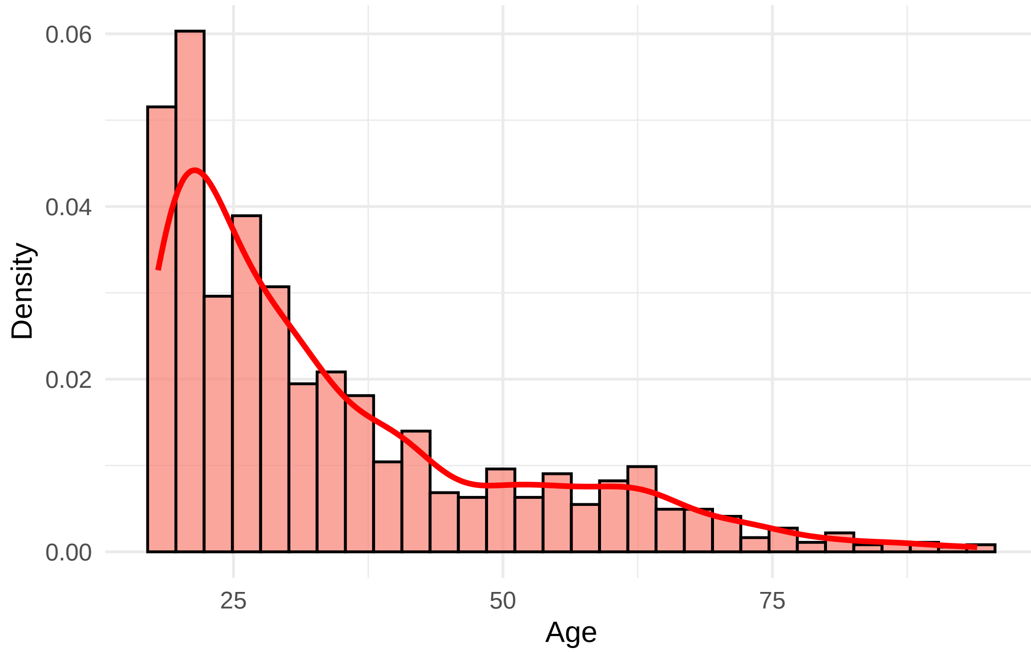


Figure 5: Age Distribution for Unmarried Individua

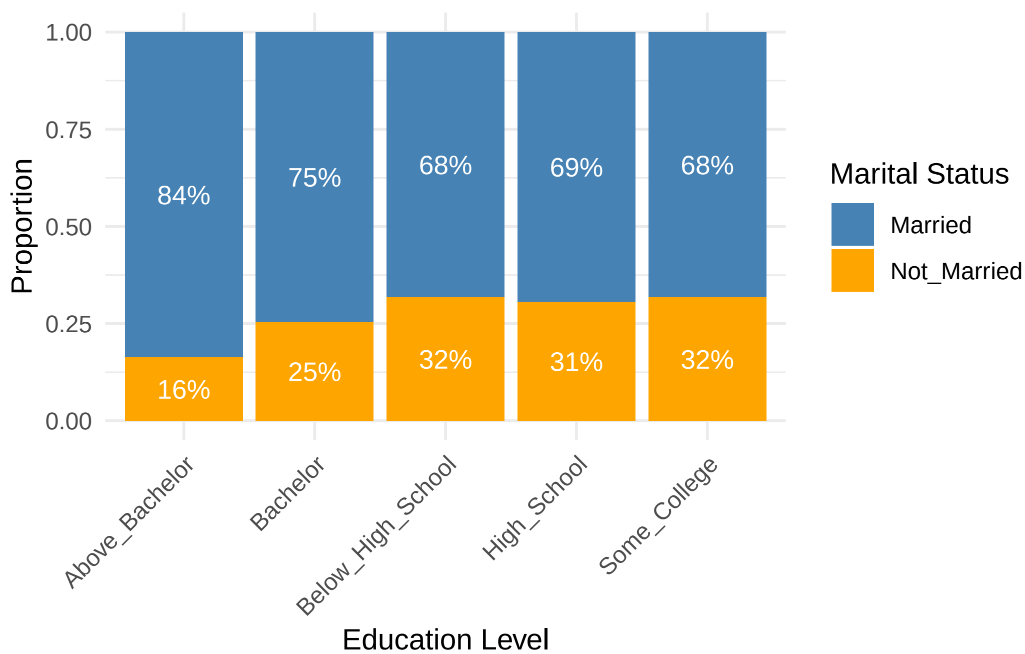


Figure 6: Proportions of Marital Status by Education Level

respectively. Gender analysis reveals that males are more likely to remain unmarried than females, with 30% of males unmarried compared to 26% of females.

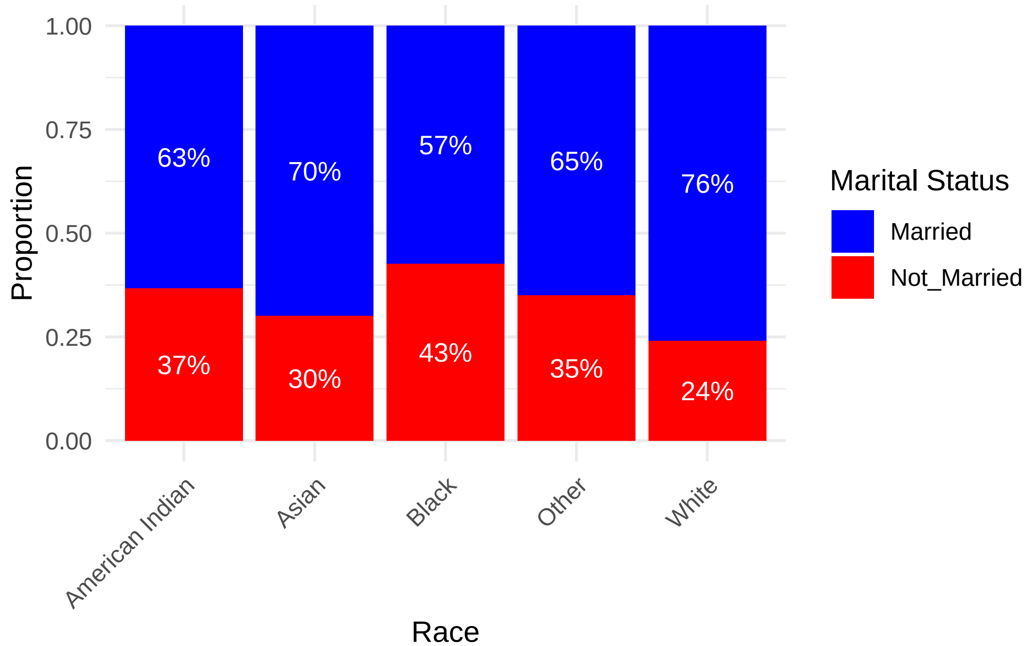


Figure 7: Proportions of Marital Status by Race

5 Discussion

5.1 Determinants of Non-Marriage and Societal Implications

This study delves into the socio-demographic factors that influence marital status, with a specific focus on the probability of remaining unmarried in the United States. By analyzing individual-level microdata through logistic regression, we identified significant predictors such as education, income, race, gender, and age.

For instance, the logistic regression model revealed that individuals with higher education levels, particularly those with a bachelor's degree or above, were significantly less likely to remain unmarried compared to those with lower education levels. Education, therefore, serves as a strong stabilizer in marital outcomes, providing individuals with economic resources and social capital that facilitate marriage. Simultaneously, the analysis underscored the heightened likelihood of remaining unmarried among African Americans, reflecting deeper structural inequities that impact marital patterns. Gender also emerged as a significant factor, with males exhibiting a slightly higher probability of being unmarried compared to females.

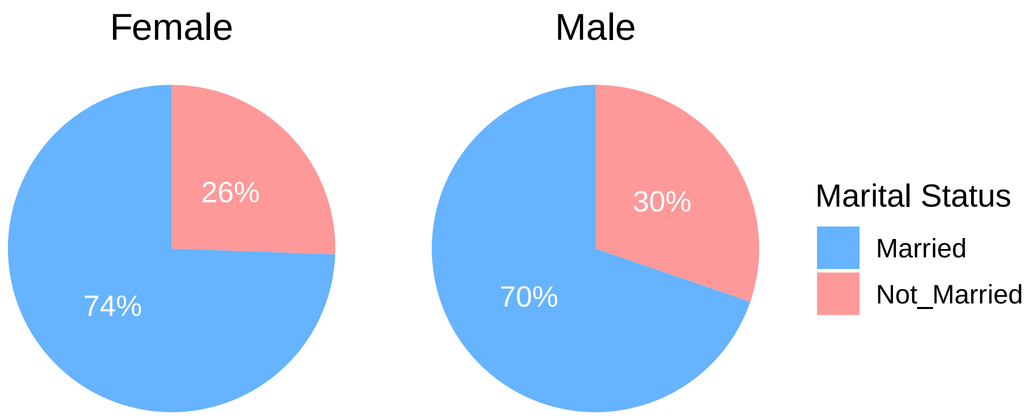


Figure 8: Marital Status Proportions by Gender

These findings, grounded in data and supported by statistical rigor, affirm prior literature while adding layers of nuance. They emphasize how individual socio-demographic traits intersect with broader societal structures to shape marital outcomes.

5.2 Insights into Education, Income, and Marriage Patterns

One of the most compelling findings of this study is the pronounced impact of education on marital status. Individuals with higher education levels—those with bachelor's degrees or above—demonstrated significantly lower rates of non-marriage. This is evident from the analysis showing that only 16% of individuals with education above a bachelor's degree were unmarried, compared to 32% of those with "Some College" education. The logistic regression coefficients also reinforced this relationship, with those holding higher degrees being far less likely to remain unmarried (e.g., coefficient for "Below High School" = 0.48).

This finding aligns with existing theories that higher education fosters economic stability, enhances social capital, and provides a greater sense of agency in life decisions, all of which are conducive to marriage. However, the results also highlighted that income, while less strongly predictive, plays a complementary role. The income distribution plot for unmarried individuals revealed clustering at lower income brackets, with the majority earning below $40,000 annually. This suggests that financial security continues to be an essential consideration in marital decisions, albeit to a lesser extent than education.

These patterns point to the interplay between socio-economic resources and marital outcomes, emphasizing how disparities in access to education and income perpetuate inequalities in family formation.

5.3 Gender and Race in Marital Trends

The analysis revealed striking disparities in marital trends across gender and racial lines. Gender-wise, men exhibited a higher likelihood of remaining unmarried compared to women, with 30% of men being unmarried versus 26% of women. This aligns with cultural norms and gendered expectations, where women are often perceived as more closely tied to family roles and marriage. Moreover, women may face greater societal pressure to marry, which could explain their lower rates of remaining unmarried.

Racial disparities in marital status were even more pronounced. For example, African Americans exhibited the highest rates of non-marriage (43%), significantly higher than those for Asian Americans (30%) and White individuals (24%). These patterns likely reflect a combination of structural inequalities, cultural factors, and historical contexts. Economic disparities, higher unemployment rates, and systemic barriers to wealth accumulation among African Americans may contribute to these higher non-marriage rates. Conversely, Asian Americans, who exhibited the lowest rates of remaining unmarried, may benefit from cultural norms that strongly prioritize marriage and family cohesion.

These findings underscore how structural inequities and cultural norms interact to shape marital trends. They also highlight the need for policies aimed at addressing systemic barriers and promoting equality in socio-economic outcomes to reduce disparities in family formation.

5.4 Weaknesses and Next Steps

While this study provides critical insights into the predictors of marital status, it is not without limitations. The reliance on cross-sectional data, for example, restricts the ability to establish causal relationships. While the findings suggest strong associations between education, income, race, gender, and marital outcomes, longitudinal data could better capture how these factors interact over time to influence marriage decisions.

Another limitation lies in the dataset itself, which does not include qualitative factors such as cultural attitudes, personal preferences, or psychological traits. These dimensions are critical for understanding the broader context of marital decisions. For instance, while income and education are robust predictors, societal expectations and individual life goals may play equally important roles that remain unquantified in this analysis.

Future research should aim to integrate mixed-method approaches, combining quantitative rigor with qualitative depth, to provide a holistic view of marital trends. Additionally, while this study focused exclusively on the United States, extending the analysis to include international data could uncover global patterns and cultural nuances. For example, exploring how marriage trends differ in countries with varying economic systems, religious practices, and gender norms would provide valuable comparative insights.

5.5 Conclusion

This study contributes to the understanding of non-marriage determinants by highlighting the interplay between education, income, race, gender, and age. Education emerged as the most significant predictor, with higher levels strongly associated with lower non-marriage rates. Income, while secondary, still played a notable role, emphasizing the importance of economic stability in marital decisions. Gendered expectations and racial disparities further revealed how societal structures and cultural norms influence marriage patterns.

The findings highlight the socio-economic inequities that shape family formation and underscore the importance of addressing structural barriers to promote marital stability. Future research should continue to explore these dynamics, leveraging longitudinal data and integrating qualitative perspectives to deepen our understanding of marriage and its evolving role in contemporary society.

A Appendix

A.1 Data Details

A.1.1 Cleaned Data

The table Table 2 shows the analysis data after data cleaning.

Table 2: Sample of cleaned data

Marital Status	Age	Gender	Race	Income	Education Level
Not_Married	73	Male	White	33900	Above_Bachelor
Married	43	Female	Asian	40000	High_School
Married	80	Female	White	13000	High_School
Married	66	Male	White	48000	Some_College
Married	52	Female	White	38100	Bachelor
Married	45	Female	American Indian	65000	High_School

A.2 Model Details

A.2.1 Posterior predictive check

Figure 9 provides an illustration of the posterior predictive check, showing the alignment between the observed outcome variable and the simulations derived from the posterior distribution. In a similar vein, Figure 10 depicts a comparison between the prior and posterior distributions, highlighting the degree to which the data informs and updates our estimates. Together, these figures offer strong evidence that the model achieves a reliable and accurate fit to the observed data.

A.2.2 Diagnostics

Figure 11 and Figure 12 provide insights into the MCMC diagnostics for the logistic regression model. Figure 11 show stable and well-mixed chains for all parameters, indicating convergence. fig-rhat shows $\hat{R}$ diagnostics are all close to 1, further confirming that the MCMC sampling has successfully converged to the posterior distribution.

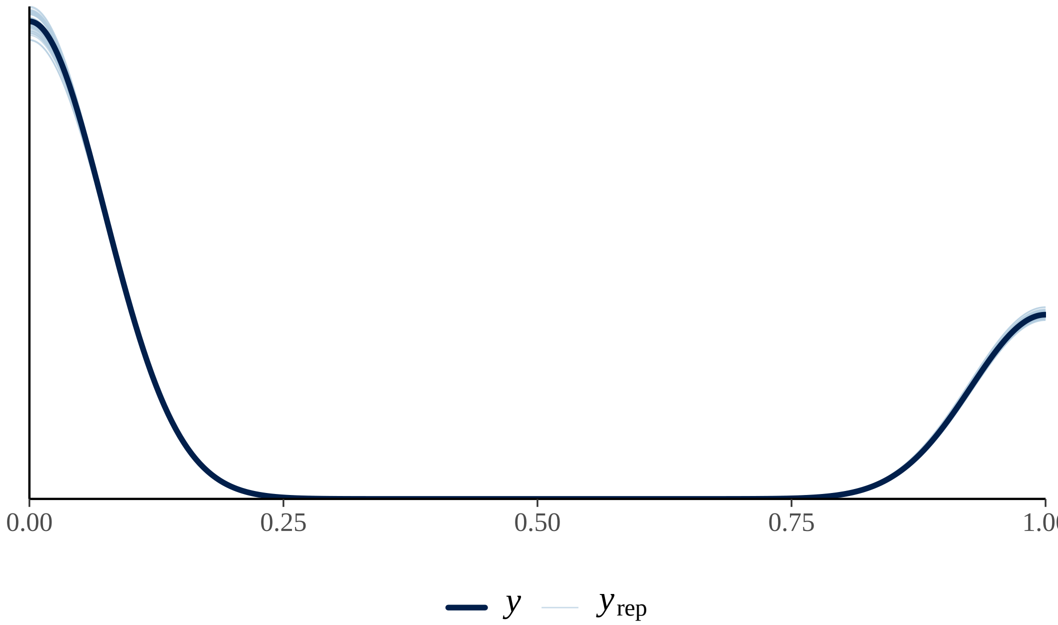


Figure 9: Posterior distribution for logistic regression model

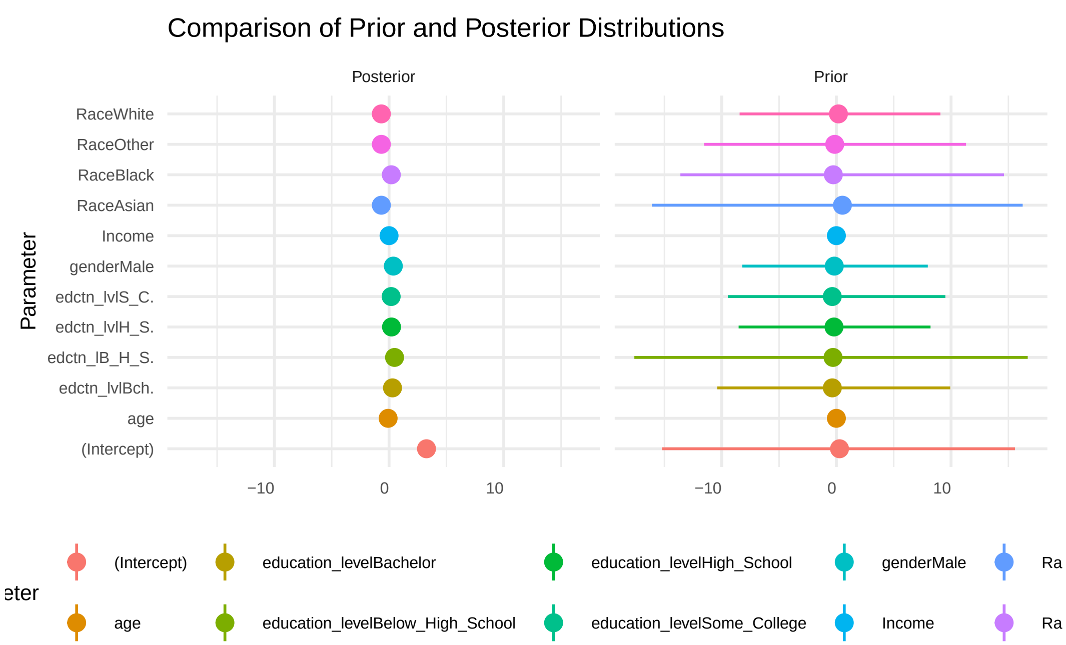
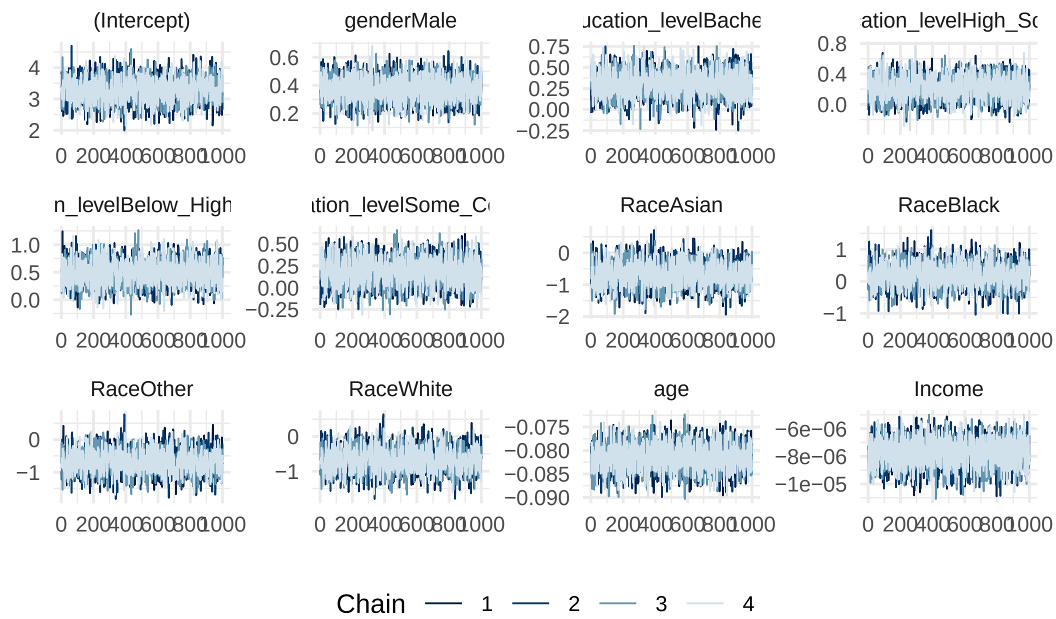


Figure 10: Comparing prior distribution with posterior distribution



(a) Intercept

Figure 11: MCMC Convergence Check: Trace Plots for Key Parameters

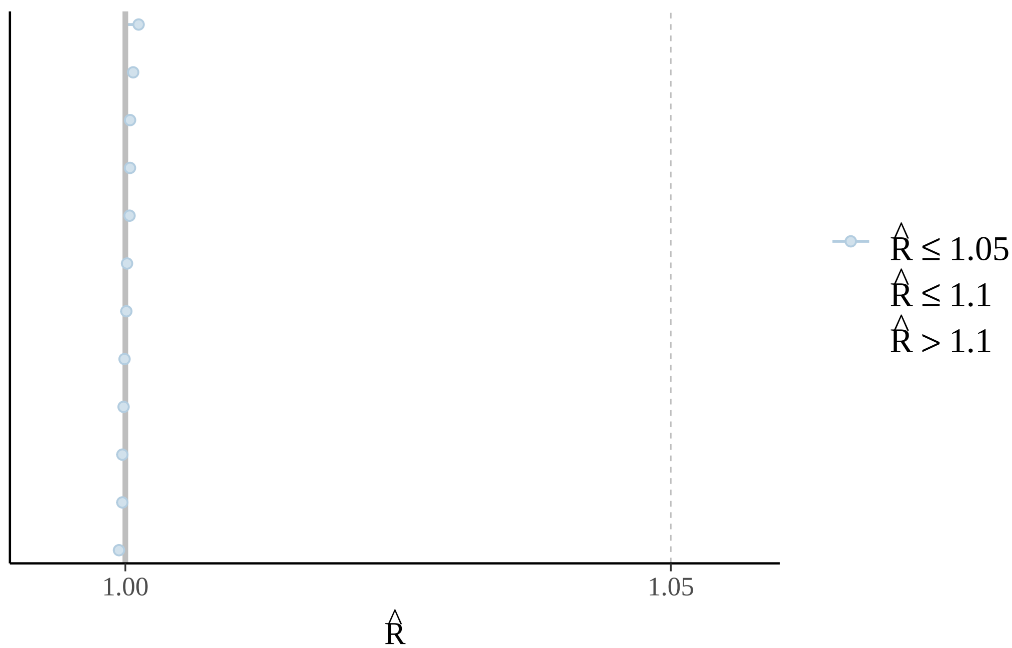


Figure 12: Rhat plot

A.3 Surveys, sampling, and observational data

A.3.1 Idealized Methodology

A.3.1.1 Overview

The objective of this survey is to explore the socio-demographic determinants of non-marriage in the United States. The study aims to understand factors influencing decisions to remain unmarried, including education, income, race, age, and cultural attitudes. A budget of $50,000 is allocated to collect diverse and representative data from individuals aged 18 and above. The methodology is designed to maximize the accuracy.

A.3.1.2 Sampling Approach

A stratified sampling approach is adopted to ensure the representation of key demographic and socio-economic groups. Stratification variables include:

- Age: 18–29, 30–44, 45–64, 65+
- Gender: Male, Female, Non-binary
- Race/Ethnicity: White, Black, Hispanic, Asian, American Indian, Other
- Income: <$20,000, $20,000–$59,999, $60,000–$99,999, >$100,000
- Education: Under High School, High School, Some College, Bachelor's Degree, Above Bachelor's Degree *Geographic Region: Northeast, Midwest, South, West The target sample size is 5,000 respondents, yielding a margin of error of ±2.5% at a 95% confidence level.

A.3.1.3 Recruitment Strategy

- Online Surveys: Partner with established survey platforms like Prolific or Qualtrics, which offer access to diverse and validated panels.
- Community Engagement: Partnerships with community organizations for in-person recruitment.
- Mail Invitations: Surveys sent by mail, accompanied by pre-paid return envelopes or online access codes for respondents to complete the survey.
- Telephone Interviews: Random-digit dialing (RDD) to reach both landlines and mobile phones, ensuring coverage of participants without internet access.

A.3.1.4 Data Collection

Data collection will utilize platforms like Google Forms, with telephone and mail surveys structured to mirror the design and flow of the Google Form questionnaire. To reduce the likelihood of participants abandoning the survey, it has been tailored to take approximately five to ten minutes to complete.

A.3.1.5 Data Validation and Quality Control

- Pre-Survey Validation: Pilot testing with diverse focus groups to refine question phrasing and structure.
- Ongoing Quality Checks: Automated checks for inconsistent or incomplete responses during the survey.
- Post-Survey Weighting: Application of population weights to correct for sample imbalances across demographic strata.

A.3.1.6 Budget Allocation

- Survey Recruitment: $30,000
- Incentives: $10,000
- Data Cleaning and Analysis: $5,000
- Miscellaneous (software, outreach): $5,000

A.3.2 Idealized Survey Questions

Welcome Message
Welcome! Thank you for participating in this survey on marital status and the factors influencing people's decision to remain unmarried. Your responses are anonymous and will only be used for research purposes. This survey will take approximately 5–10 minutes to complete.

Screening Questions
Q1: Are you currently residing in the United States?
- Yes
- No *(If "No," terminate the survey with a thank-you message.)*

Q2: What is your age?
- Under 18 *(Terminate the survey with a thank-you message.)*
- 18 or older

Consent to Participate
Before proceeding, please read the following:
- Your participation in this survey is voluntary.
- You may skip any question or withdraw at any time.
- All responses are anonymous and will be aggregated for research purposes.

Do you agree to participate in this survey?
- Yes, I agree to participate.
- No, I do not agree to participate. *(If "No," terminate the survey with a thank-you message.)*

Survey Questions

Q3: What is your gender?
- Male
- Female
- Non-binary
- Prefer not to say

Q4: What is your race/ethnicity?
- White
- Black or African American
- Asian
- Hispanic or Latino
- Native American or Alaska Native
- Other

Q5: What is your highest level of education?
- Less than high school
- High school diploma or equivalent
- Some college
- Bachelor's degree
- Postgraduate degree

Q6: What is your total annual income?
- Less than $20,000
- $20,000–$49,999
- $50,000–$79,999
- $80,000–$99,999
- $100,000 or more

Q7: What is your age group?
- 18–29
- 30–44
- 45–59
- 60 or older

Q8: What is your current marital status?
- Never married
- Married
- Divorced
- Widowed
- Separated

Q9: If never married, have you ever been in a serious relationship (e.g., cohabitation, long-term dating)?
- Yes
- No

Q10: How important do you consider marriage in your life?
- Very important
- Somewhat important
- Not very important
- Not at all important

Q11: What are the main reasons for not being married? *(Select all that apply)*
- Financial concerns
- Lack of a suitable partner
- Personal choice
- Career priorities
- Family or cultural pressures
- Other (please specify)

Q12: Do you feel societal pressure to get married?
- Strongly agree
- Agree
- Neutral
- Disagree
- Strongly disagree

Q13: Do you plan to get married in the future?
- Yes
- No
- Unsure

Q14: If unsure or no, what factors might influence your decision?
- Improved financial stability

- Finding the right partner
- Change in personal values
- Other (please specify)

Closing Message

Thank you for completing this survey! Your responses have been recorded. If you have any questions about this survey or its purpose, please contact xizi.sun@mail.utoronto.ca. Have a great day!

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