SA2 DSC1105

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Contents

0.1 Introduction

This study focuses on identifying social and demographic predictors of pregnancy outcomes among women in the United States. The data used in this study come from the 2022–2023 Female Respondent Public Use File of the National Survey of Family Growth (NSFG), a nationally representative survey conducted by the National Center for Health Statistics (NCHS). The survey collects detailed information about family life, reproductive health, marriage, contraception, and related topics from women aged 15–49 in the U.S.

The primary objective of this analysis is to examine how a woman's background, education, marital status, and family structure relate to the total number of pregnancies a woman have. Using Poisson and negative binomial regression models, this study explores the associations between these predictors and pregnancy numbers. Additional statistical methods, including ordinal and multinomial logistic regression, chi-square tests, and data visualizations, are used to support a deeper understanding of patterns in the data.

```r
data <- read_csv("NSFG_2022_2023_FemRespPUFData.csv")
```

```
## Rows: 5586 Columns: 1912
## -- Column specification --------------------------------------------------------
## Delimiter: ","
## chr    (1): DEVICE_TYPE
## dbl (1817): CaseID, RSCRAGE, RSCRNINF, RSCRHISP, RSCRRACE, FTFMODE, AGE_R, A...
## lgl   (94): TRYADOPT_02, TRYADOPT_03, BIONUMHX_4, MARENDHX_4, ENDMARRX_Y_4, ...
##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```r
data
```

```
## # A tibble: 5,586 x 1,912
##    CaseID RSCRAGE RSCRNINF RSCRHISP RSCRRACE FTFMODE DEVICE_TYPE AGE_R AGESCRN
##     <dbl>   <dbl>    <dbl>    <dbl>    <dbl>   <dbl> <chr>       <dbl>   <dbl>
##  1  96064      29        5        5        3       2 Mobile         29      29
##  2  96066      18        5        1        4       2 PC             18      18
##  3  96068      37        1        5        2       2 Mobile         37      37
##  4  96071      40        1        5        3       2 PC             40      40
##  5  96072      49        1        5        2       2 PC             49      49
##  6  96074      30        1        5        2       2 Mobile         30      30
##  7  96075      25        5        5        2       2 Mobile         25      25
##  8  96080      37        1        5        3       2 Mobile         37      37
##  9  96081      44        5        5        3       2 Mobile         44      44
## 10  96082      44        1        5        3       2 Mobile         44      44
## # i 5,576 more rows
## # i 1,903 more variables: HISP <dbl>, HISPGRP <dbl>, ROSCNT <dbl>,
## #   NUMCHILD <dbl>, HHKIDS18 <dbl>, NONBIOKIDS <dbl>, MARSTAT <dbl>,
## #   LMARSTAT <dbl>, RMARIT <dbl>, EVRMARRY <dbl>, SSMARCOH <dbl>, MANREL <dbl>,
## #   EARNHS_Y <dbl>, MYSCHOL_Y <dbl>, EARNBA_Y <dbl>, WTHPARNW <dbl>,
## #   ONOWN <dbl>, ONOWN18 <dbl>, INTACT <dbl>, PARMARR <dbl>, INTACT18 <dbl>,
## #   LVSIT14F <dbl>, LVSIT14M <dbl>, WOMRASDU <dbl>, MOMWORKD <dbl>, ...
```

A subset of variables was selected for this analysis:

Variable	Description
PREGNUM	Total number of pregnancies reported by the respondent (response variable).
FMARITAL	Current formal marital status of the respondent (e.g., married, divorced, never married).
HISPRACE2	Respondent's race and Hispanic origin, categorized as White, Black, or Other.
HIEDUC	Highest level of education completed by the respondent, treated as an ordered categorical variable.
AGER	Age of the respondent at the time of the interview (continuous variable).
EDUCMOM	Education level of the respondent's mother or female caregiver, used as a proxy for childhood socioeconomic background.
INTCTFAM	Indicates whether the respondent grew up in an intact family (i.e., living with both biological or adoptive parents).

0.2 Variable Selection

0.2.0.1 *Dependent Variable (Y)* Count Variable

`PREGNUM` - Total Number of Pregnancies

This is the main outcome of the analysis. We want to understand what factors are are related to how many times a woman has been pregnant.

```r
summary(data$PREGNUM)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   0.000   0.000   1.000   1.476   2.000  16.000
```

0.2.0.2 *Independent Variable (X_i)* Categorical (nominal)

`FMARITAL` - Marital Status

Whether someone is married, divorced, or never married can influences their chances of getting pregnant. For example, married women might be more likely to plan for children.

```r
summary(data$FMARITAL)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   1.000   1.000   5.000   3.361   5.000   5.000
```

`HISPRACE2` - Race and Hispanic Origin

This can help see if pregnancy patterns are different across group, possibly due to things like culture or access to healthcare.

```r
summary(data$FMARITAL)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   1.000   1.000   5.000   3.361   5.000   5.000
```

Ordered Categorical

`HIEDUC` - Highest Educational Level

For example, women with more education might focus on school or work first and have fewer, later, or no plans of pregnancies.

```r
summary(data$HIEDUC)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   1.000   4.000   6.000   5.863   8.000  11.000
```

Demographics

`AGER` - Age

The older someone is, the more time they've had to potentially have pregnancies.

```r
summary(data$AGER)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   15.00   25.00   33.00   32.36   40.00   50.00
```

`EDUCMOM`- Mother's Education

Growing up with an educated mother might shape attitudes towards family planning.

```r
summary(data$EDUCMOM)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   1.000   2.000   3.000   3.926   4.000  95.000
```

`INTCTFAM` - Grew Up in an Intact Family or Not

This looks at whether women lived with both parents growing up. Family structure might affect emotional development and future life choices, including when or whether to have children.

```r
summary(data$INTCTFAM)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   1.000   1.000   1.000   1.309   2.000   2.000
```

0.3 Data Cleaning

Checking null values:

```r
vars <- c("PREGNUM", "FMARITAL", "HIEDUC", "HISPRACE2", "AGER", "EDUCMOM", "INTCTFAM")

sapply(data[vars], function(x) sum(is.na(x)))
```

```
##   PREGNUM  FMARITAL    HIEDUC HISPRACE2      AGER   EDUCMOM  INTCTFAM
##         0         0         0         0         0         0         0
```

Recoding categorical variables:

```r
data <- data %>%
  mutate(
    FMARITAL = factor(FMARITAL,
                      levels = c(1, 2, 3, 4, 5),
                      labels = c("Married", "Widowed", "Divorced", "Separated", "Never Married")),
    HISPRACE2 = factor(HISPRACE2,
                       levels = c(1, 2, 3, 4),
                       labels = c("Hispanic", "White", "Black", "Other")),
    HIEDUC = factor(HIEDUC, ordered = TRUE),
    EDUCMOM = factor(EDUCMOM, ordered = TRUE),
    INTCTFAM = factor(INTCTFAM, levels = c(1, 2), labels = c("Intact", "Not Intact"))
  )
```

0.4 Statistical Analyses

```r
poisson_model <- glm(PREGNUM ~ FMARITAL + HISPRACE2 + HIEDUC + AGER + EDUCMOM + INTCTFAM,
                     data = data)
```

```r
summary(poisson_model)
```

0.4.0.1 Poisson Regression

```
##
## Call:
## glm(formula = PREGNUM ~ FMARITAL + HISPRACE2 + HIEDUC + AGER +
##     EDUCMOM + INTCTFAM, family = poisson(link = "log"), data = data)
##
## Coefficients:
```

```
##                       Estimate Std. Error z value Pr(>|z|)
## (Intercept)          -0.892588   0.066881 -13.346  < 2e-16 ***
## FMARITALWidowed      -0.262698   0.127781  -2.056 0.039797 *
## FMARITALDivorced     -0.158446   0.037558  -4.219 2.46e-05 ***
## FMARITALSeparated    -0.049787   0.058604  -0.850 0.395579
## FMARITALNever Married -0.783609   0.028664 -27.338  < 2e-16 ***
## HISPRACE2White       -0.061340   0.031257  -1.962 0.049709 *
## HISPRACE2Black        0.266027   0.036959   7.198 6.12e-13 ***
## HISPRACE2Other       -0.150477   0.042451  -3.545 0.000393 ***
## HIEDUC.L             -0.584296   0.065571  -8.911  < 2e-16 ***
## HIEDUC.Q             -0.145761   0.056741  -2.569 0.010202 *
## HIEDUC.C              0.320143   0.051383   6.231 4.65e-10 ***
## HIEDUC^4             -0.005446   0.054696  -0.100 0.920690
## HIEDUC^5              0.060968   0.054196   1.125 0.260601
## HIEDUC^6             -0.098124   0.051321  -1.912 0.055878 .
## HIEDUC^7             -0.037738   0.047820  -0.789 0.430015
## HIEDUC^8             -0.012116   0.040001  -0.303 0.761971
## HIEDUC^9             -0.007563   0.034637  -0.218 0.827159
## HIEDUC^10             0.025773   0.036457   0.707 0.479595
## AGER                  0.045455   0.001477  30.771  < 2e-16 ***
## EDUCMOM.L            -0.117960   0.056100  -2.103 0.035496 *
## EDUCMOM.Q             0.173696   0.049688   3.496 0.000473 ***
## EDUCMOM.C             0.098009   0.034487   2.842 0.004485 **
## EDUCMOM^4             0.078696   0.024613   3.197 0.001387 **
## INTCTFAMNot Intact    0.229787   0.024145   9.517  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for poisson family taken to be 1)
##
##     Null deviance: 12582.0  on 5585  degrees of freedom
## Residual deviance:  8731.9  on 5562  degrees of freedom
## AIC: 17206
##
## Number of Fisher Scoring iterations: 6
```

To assess whether the Poisson regression model was appropriate, we checked for overdispersion, by examining the ratio of the residual deviance to its degrees of freedom.

```r
dispersion <- sum(residuals(poisson_model, type = "pearson")^2) / poisson_model$df.residual
dispersion
```

```
## [1] 1.63383
```

The Poisson regression model showed evidence of overdispersion (dispersion statistic > 1).

To address this, a Negative Binomial model was fitted to account for the extra-Poisson variation.

```r
nb_model <- glm.nb(PREGNUM ~ FMARITAL + HISPRACE2 + HIEDUC + AGER + EDUCMOM + INTCTFAM,
                     data = data)
summary(nb_model)
```

```
##
```

```
## Call:
## glm.nb(formula = PREGNUM ~ FMARITAL + HISPRACE2 + HIEDUC + AGER +
##     EDUCMOM + INTCTFAM, data = data, init.theta = 2.346770487,
##     link = log)
##
## Coefficients:
##                       Estimate Std. Error z value Pr(>|z|)
## (Intercept)          -1.171003   0.088576 -13.220  < 2e-16 ***
## FMARITALWidowed      -0.308018   0.184903  -1.666  0.09575 .
## FMARITALDivorced     -0.243232   0.054254  -4.483 7.35e-06 ***
## FMARITALSeparated    -0.083390   0.087683  -0.951  0.34158
## FMARITALNever Married -0.876554   0.037591 -23.318  < 2e-16 ***
## HISPRACE2White       -0.062713   0.042515  -1.475  0.14019
## HISPRACE2Black        0.323478   0.050895   6.356 2.07e-10 ***
## HISPRACE2Other       -0.165591   0.056771  -2.917  0.00354 **
## HIEDUC.L             -0.686856   0.089277  -7.694 1.43e-14 ***
## HIEDUC.Q             -0.218934   0.076444  -2.864  0.00418 **
## HIEDUC.C              0.415490   0.069475   5.980 2.23e-09 ***
## HIEDUC^4             -0.028068   0.074604  -0.376  0.70675
## HIEDUC^5              0.078777   0.073555   1.071  0.28417
## HIEDUC^6             -0.088840   0.070085  -1.268  0.20493
## HIEDUC^7             -0.071344   0.065955  -1.082  0.27938
## HIEDUC^8              0.019116   0.055448   0.345  0.73028
## HIEDUC^9             -0.016349   0.047437  -0.345  0.73036
## HIEDUC^10             0.042292   0.050256   0.842  0.40006
## AGER                  0.054487   0.001976  27.568  < 2e-16 ***
## EDUCMOM.L            -0.130601   0.079521  -1.642  0.10052
## EDUCMOM.Q             0.220303   0.070078   3.144  0.00167 **
## EDUCMOM.C             0.131053   0.047777   2.743  0.00609 **
## EDUCMOM^4             0.080844   0.033125   2.441  0.01466 *
## INTCTFAMNot Intact    0.259201   0.033146   7.820 5.28e-15 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for Negative Binomial(2.3468) family taken to be 1)
##
##     Null deviance: 8370.1  on 5585  degrees of freedom
## Residual deviance: 5709.3  on 5562  degrees of freedom
## AIC: 16496
##
## Number of Fisher Scoring iterations: 1
##
##
##               Theta:  2.347
##           Std. Err.:  0.131
##
##  2 x log-likelihood:  -16445.707
```

Model fit was compared using the Akaike Information Criterion (AIC).

```
AIC(poisson_model, nb_model)
```

```
##               df      AIC
```

```
## poisson_model 24 17206.42
## nb_model      25 16495.71
```

The Negative Binomial model provided a better fit to the data, with a lower AIC (X) compared to the Poisson model (Y). Based on these results, the Negative Binomial model was considered the more appropriate model for inference.

Summary of significant predictors:

```r
coefs <- coef(nb_model)

IRRs <- exp(coefs)

percent_change <- (IRRs - 1) * 100

pvalues <- summary(nb_model)$coefficients[, "Pr(>|z|)"]

table <- data.frame(
  Estimate = coefs,
  IRR = IRRs,
  Percent_Change = round(percent_change, 2),
  P_Value = pvalues
)

significant_predictors <- table %>% filter(P_Value < 0.05)

significant_predictors
```

```
##                          Estimate       IRR Percent_Change       P_Value
## (Intercept)           -1.17100274 0.3100559         -68.99  6.699006e-40
## FMARITALDivorced      -0.24323236 0.7840893         -21.59  7.352042e-06
## FMARITALNever Married -0.87655424 0.4162146         -58.38 2.918191e-120
## HISPRACE2Black         0.32347775 1.3819254          38.19  2.074282e-10
## HISPRACE2Other        -0.16559115 0.8473926         -15.26  3.536329e-03
## HIEDUC.L              -0.68685607 0.5031555         -49.68  1.431509e-14
## HIEDUC.Q              -0.21893403 0.8033747         -19.66  4.183537e-03
## HIEDUC.C               0.41549045 1.5151136          51.51  2.226064e-09
## AGER                   0.05448669 1.0559984           5.60 2.716662e-167
## EDUCMOM.Q              0.22030261 1.2464539          24.65  1.668472e-03
## EDUCMOM.C              0.13105287 1.1400280          14.00  6.088342e-03
## EDUCMOM^4              0.08084384 1.0842016           8.42  1.466484e-02
## INTCTFAMNot Intact     0.25920087 1.2958941          29.59  5.281576e-15
```

The negative binomial regression model revealed several important factors associated with the number of pregnancies among women. Compared to married women, those who were never married had 58% fewer pregnancies (IRR = 0.42), and those who were divorced had 22% fewer pregnancies (IRR = 0.78). Widowed women also had fewer pregnancies (IRR = 0.73).

In terms of race, Black women had 38% more pregnancies than Hispanic women (IRR = 1.38), while women classified as Other races had 15% fewer (IRR = 0.85). White women had slightly fewer pregnancies (IRR = 0.94).

Education showed a clear pattern: as education increased, the number of pregnancies generally decreased. For example, the main trend (HIEDUC.L) showed that each step up in education level was associated with a 50% decrease in the number of pregnancies (IRR = 0.50).

Age also had a strong positive effect: for each additional year of age, the expected number of pregnancies increased by about 5.6% (IRR = 1.06), as older women naturally have had more time to become pregnant.

Looking at background factors, women whose mothers had some college education had 25% more pregnancies (IRR = 1.25), while those whose mothers had less than high school had slightly fewer (IRR = 0.88). Additionally, women who did not grow up in an intact family had 30% more pregnancies than those who did (IRR = 1.30),

0.4.0.2 Contingency Tables Distribution of Marital Status by Education Level:

```
ct <- table(na.omit(data[, c("FMARITAL", "HIEDUC")]))
ct
```

```
##                HIEDUC
## FMARITAL          1   2   3   4   5   6   7   8   9  10  11
##   Married        85  30  44 164 254 147 110 637 437  90  62
##   Widowed         5   0   1   1   1   5   2   6   3   0   1
##   Divorced       12   4  16  45  80  34  28  80  51   9   6
##   Separated      15   6   4  18  33  13   7  11   3   0   2
##   Never Married 506 129  88 579 588 154 135 533 258  36  18
```

Chi-Square Test

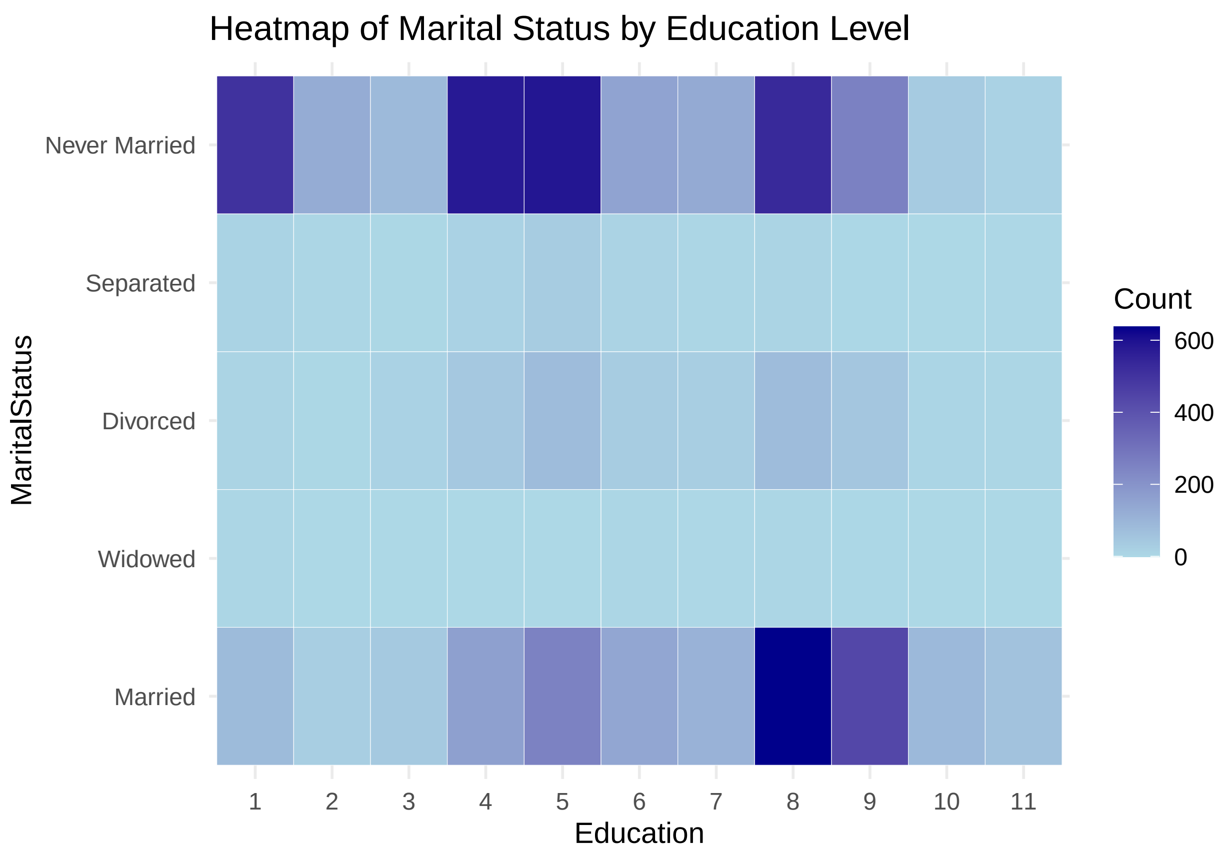
```
chi <- chisq.test(ct)
chi
```

```
##
##  Pearson's Chi-squared test
##
## data:  ct
## X-squared = 804.43, df = 40, p-value < 2.2e-16
```

The Pearson's Chi-squared test of independence indicated a statistically significant association between marital status and highest educational level. ($p < 2.2e-16$). This suggests that the distribution of education levels differs significantly across marital status categories.

Heatmap

```
library(ggplot2)

ct_df <- as.data.frame(ct)
names(ct_df) <- c("MaritalStatus", "Education", "Count")

ggplot(ct_df, aes(x = Education, y = MaritalStatus, fill = Count)) +
  geom_tile(color = "white") +
  scale_fill_gradient(low = "lightblue", high = "darkblue") +
  labs(title = "Heatmap of Marital Status by Education Level") +
  theme_minimal()
```



0.4.0.3 Categorical Response Modeling Ordinal Logistic Regression (HIEDUC)

```r
ord_model <- polr(HIEDUC ~ AGER + HISPRACE2 + INTCTFAM + EDUCMOM, data = data, Hess = TRUE)

summary(ord_model)
```

```
## Call:
## polr(formula = HIEDUC ~ AGER + HISPRACE2 + INTCTFAM + EDUCMOM,
##     data = data, Hess = TRUE)
##
## Coefficients:
##                         Value Std. Error t value
## AGER                  0.08940    0.00282  31.700
## HISPRACE2White        0.41712    0.06688   6.237
## HISPRACE2Black       -0.08701    0.08194  -1.062
## HISPRACE2Other        0.82256    0.08788   9.360
## INTCTFAMNot Intact -0.61583    0.05362 -11.486
## EDUCMOM.L             0.59627    0.14481   4.118
## EDUCMOM.Q            -0.99603    0.12586  -7.914
## EDUCMOM.C            -0.49350    0.08275  -5.963
## EDUCMOM^4            -0.23277    0.05267  -4.420
##
## Intercepts:
##        Value    Std. Error t value
## 1|2     0.6613   0.1095     6.0382
```

```
## 2|3      0.9830   0.1088      9.0329
## 3|4      1.2296   0.1085     11.3299
## 4|5      2.2246   0.1101     20.2030
## 5|6      3.1571   0.1143     27.6332
## 6|7      3.4809   0.1157     30.0755
## 7|8      3.7430   0.1169     32.0222
## 8|9      5.1388   0.1242     41.3677
## 9|10     6.9035   0.1406     49.1129
## 10|11    7.8775   0.1634     48.2170
##
## Residual Deviance: 21710.97
## AIC: 21748.97
```

Odd Ratios

```
exp(coef(ord_model))
```

```
##                AGER     HISPRACE2White     HISPRACE2Black     HISPRACE2Other
##           1.0935126          1.5175921          0.9166692          2.2763287
## INTCTFAMNot Intact          EDUCMOM.L          EDUCMOM.Q          EDUCMOM.C
##           0.5401950          1.8153335          0.3693430          0.6104877
##           EDUCMOM^4
##           0.7923370
```

An ordinal logistic regression revealed that age was positively associated with higher educational attainment (OR = 1.09, $p < .001$). Compared to the hispanics, White individuals (OR = 1.52, $p < .001$) and those of Other races (OR = 2.28, $p < .001$) had higher odds of achieving higher education levels. Coming from a non-intact family significantly reduced the odds of attaining higher education (OR = 0.54, $p < .001$). While maternal education showed a complex relationship, with both significant positive and negative coefficients.

Multinomial Logistic Regression (FMARITAL)

```
library(nnet)


multi_model <- multinom(FMARITAL ~ AGER + HIEDUC + HISPRACE2 + INTCTFAM + EDUCMOM, data = data)
```

```
## # weights:  105 (80 variable)
## initial  value 8990.320179
## iter  10 value 4788.946750
## iter  20 value 4570.514435
## iter  30 value 4329.546878
## iter  40 value 4307.172512
## iter  50 value 4294.564173
## iter  60 value 4288.023850
## iter  70 value 4285.055984
## iter  80 value 4284.876350
## iter  90 value 4284.793058
## final  value 4284.785665
## converged
```

```r
summary(multi_model)
```

```
## Call:
## multinom(formula = FMARITAL ~ AGER + HIEDUC + HISPRACE2 + INTCTFAM +
##     EDUCMOM, data = data)
##
## Coefficients:
##               (Intercept)         AGER  HIEDUC.L    HIEDUC.Q     HIEDUC.C
## Widowed        -13.847419  0.137375781 -1.137889 -3.73196753 -0.560036481
## Divorced        -3.876427  0.050830428 -0.673565 -0.85348318  0.508101102
## Separated       -3.910267  0.005557382 -6.890322 -2.37233086  2.144735718
## Never Married    4.250342 -0.122303787 -2.107126 -0.06123458  0.005483283
##                  HIEDUC^4    HIEDUC^5   HIEDUC^6   HIEDUC^7    HIEDUC^8
## Widowed        8.84971832  0.79895015 10.0186257 -0.9243043  5.03307640
## Divorced       0.24158043 -0.25925148  0.2446356 -0.2483576  0.12511021
## Separated      5.50734340  5.87235209  4.7724076  3.7886524  1.88801847
## Never Married -0.08568934 -0.03702391  0.1292377  0.1166894 -0.04385163
##                 HIEDUC^9  HIEDUC^10 HISPRACE2White HISPRACE2Black
## Widowed       0.13089716 -0.2711864     -0.3621942      1.2786401
## Divorced      0.01192105  0.2589399      0.1653316      0.6420555
## Separated     0.97614769  0.4730555     -0.8693778      0.7690865
## Never Married 0.03867706  0.1845408     -0.2263038      1.4364641
##               HISPRACE2Other INTCTFAMNot Intact  EDUCMOM.L   EDUCMOM.Q
## Widowed           0.30752855        -0.03306627 -5.5094246 -5.08976607
## Divorced         -0.44821199         0.27748924  0.1398526 -0.04459118
## Separated        -0.30105546         0.39735786  0.3038083  0.16505446
## Never Married     0.08609194         0.24118677  0.3141166 -0.25129469
##                 EDUCMOM.C   EDUCMOM^4
## Widowed       -3.16924676 -1.10716310
## Divorced       0.27030043  0.19048699
## Separated      0.33063935  0.20121662
## Never Married  0.07179422  0.06649254
##
## Std. Errors:
##               (Intercept)        AGER  HIEDUC.L  HIEDUC.Q  HIEDUC.C  HIEDUC^4
## Widowed         1.6533935 0.039176289 0.7593761 0.7681827 0.8031961 0.6727713
## Divorced        0.3772580 0.008358290 0.3908232 0.3281538 0.2898631 0.3310172
## Separated       0.5167518 0.012248673 0.5211894 0.4657348 0.4729608 0.4529131
## Never Married   0.1883858 0.004633564 0.2174254 0.1900274 0.1743171 0.1862932
##                HIEDUC^5  HIEDUC^6  HIEDUC^7  HIEDUC^8  HIEDUC^9 HIEDUC^10
## Widowed       0.6191645 0.5111762 0.7702012 0.7282115 0.8167772 0.7384899
## Divorced      0.3505231 0.3315506 0.2853504 0.2264372 0.1814630 0.1809561
## Separated     0.3253042 0.3561902 0.4391397 0.4089524 0.3433274 0.3061782
## Never Married 0.1807431 0.1736410 0.1639437 0.1388889 0.1136678 0.1193634
##               HISPRACE2White HISPRACE2Black HISPRACE2Other INTCTFAMNot Intact
## Widowed           0.61882097      0.6517044      0.7155492         0.47028848
## Divorced          0.17079271      0.2269126      0.2514625         0.13044949
## Separated         0.27071404      0.2931462      0.3577169         0.20950772
## Never Married     0.09604306      0.1355093      0.1228875         0.07935933
##               EDUCMOM.L EDUCMOM.Q EDUCMOM.C  EDUCMOM^4
## Widowed       0.4447710 0.4695173 0.4044752 0.43421156
## Divorced      0.3107417 0.2737883 0.1858717 0.12522205
## Separated     0.4427407 0.3976491 0.2953838 0.22584163
```

```
## Never Married 0.2128769 0.1861256 0.1214668 0.07773155
##
## Residual Deviance: 8569.571
## AIC: 8729.571
```

Odds-Ratios

```r
coefs <- summary(multi_model)$coefficients
se <- summary(multi_model)$standard.errors

zvals <- coefs / se
pvals <- 2 * (1 - pnorm(abs(zvals)))

multi_summary <- data.frame(
  Outcome = rep(rownames(coefs), each = ncol(coefs)),
  Predictor = rep(colnames(coefs), times = nrow(coefs)),
  OR = round(exp(c(coefs)), 3),
  p = round(c(pvals), 4)
)

multi_summary
```

```
##          Outcome          Predictor        OR      p
## 1        Widowed        (Intercept)     0.000 0.0000
## 2        Widowed               AGER     0.021 0.0000
## 3        Widowed           HIEDUC.L     0.020 0.0000
## 4        Widowed           HIEDUC.Q    70.129 0.0000
## 5        Widowed           HIEDUC.C     1.147 0.0005
## 6        Widowed           HIEDUC^4     1.052 0.0000
## 7        Widowed           HIEDUC^5     1.006 0.6500
## 8        Widowed           HIEDUC^6     0.885 0.0000
## 9        Widowed           HIEDUC^7     0.320 0.1340
## 10       Widowed           HIEDUC^8     0.510 0.0848
## 11       Widowed           HIEDUC^9     0.001 0.0000
## 12       Widowed          HIEDUC^10     0.122 0.0000
## 13       Widowed      HISPRACE2White     0.024 0.0000
## 14       Widowed      HISPRACE2Black     0.426 0.0093
## 15       Widowed      HISPRACE2Other     0.093 0.0000
## 16       Widowed INTCTFAMNot Intact     0.941 0.7473
## 17       Widowed          EDUCMOM.L     0.571 0.4856
## 18       Widowed          EDUCMOM.Q     1.662 0.0796
## 19       Widowed          EDUCMOM.C     8.540 0.0000
## 20       Widowed          EDUCMOM^4     1.005 0.9749
## 21      Divorced        (Intercept)  6972.425 0.0000
## 22      Divorced               AGER     1.273 0.4655
## 23      Divorced           HIEDUC.L   246.495 0.0000
## 24      Divorced           HIEDUC.Q     0.918 0.6455
## 25      Divorced           HIEDUC.C     2.223 0.1969
## 26      Divorced           HIEDUC^4     0.772 0.4595
## 27      Divorced           HIEDUC^5   355.083 0.0000
## 28      Divorced           HIEDUC^6     0.964 0.8377
## 29      Divorced           HIEDUC^7 22440.569 0.0000
## 30      Divorced           HIEDUC^8     1.277 0.4606
```

```
## 31      Divorced          HIEDUC^9   118.203 0.0000
## 32      Divorced         HIEDUC^10     1.138 0.4567
## 33      Divorced     HISPRACE2White     0.397 0.2301
## 34      Divorced     HISPRACE2Black     0.780 0.3841
## 35      Divorced     HISPRACE2Other    44.197 0.0000
## 36      Divorced INTCTFAMNot Intact     1.124 0.4766
## 37      Divorced          EDUCMOM.L   153.404 0.0000
## 38      Divorced          EDUCMOM.Q     1.133 0.5806
## 39      Divorced          EDUCMOM.C     6.606 0.0000
## 40      Divorced          EDUCMOM^4     0.957 0.7522
## 41     Separated        (Intercept)     1.140 0.8727
## 42     Separated               AGER     1.012 0.9476
## 43     Separated           HIEDUC.L     2.654 0.0045
## 44     Separated           HIEDUC.Q     1.039 0.7337
## 45     Separated           HIEDUC.C     0.762 0.7135
## 46     Separated           HIEDUC^4     1.296 0.1524
## 47     Separated           HIEDUC^5     1.605 0.1223
## 48     Separated           HIEDUC^6     1.203 0.1221
## 49     Separated           HIEDUC^7     0.696 0.5583
## 50     Separated           HIEDUC^8     1.180 0.3330
## 51     Separated           HIEDUC^9     0.419 0.0013
## 52     Separated          HIEDUC^10     0.797 0.0185
## 53     Separated     HISPRACE2White     3.592 0.0498
## 54     Separated     HISPRACE2Black     1.900 0.0047
## 55     Separated     HISPRACE2Other     2.158 0.0087
## 56     Separated INTCTFAMNot Intact     4.206 0.0000
## 57     Separated          EDUCMOM.L     1.360 0.6674
## 58     Separated          EDUCMOM.Q     0.639 0.0747
## 59     Separated          EDUCMOM.C     0.740 0.4000
## 60     Separated          EDUCMOM^4     1.090 0.4836
## 61 Never Married        (Intercept)     0.967 0.9439
## 62 Never Married               AGER     1.320 0.0334
## 63 Never Married           HIEDUC.L     1.488 0.0579
## 64 Never Married           HIEDUC.Q     1.273 0.0024
## 65 Never Married           HIEDUC.C     0.004 0.0000
## 66 Never Married           HIEDUC^4     1.150 0.6527
## 67 Never Married           HIEDUC^5     1.355 0.4926
## 68 Never Married           HIEDUC^6     1.369 0.1401
## 69 Never Married           HIEDUC^7     0.006 0.0000
## 70 Never Married           HIEDUC^8     0.956 0.8706
## 71 Never Married           HIEDUC^9     1.179 0.6781
## 72 Never Married          HIEDUC^10     0.778 0.1770
## 73 Never Married     HISPRACE2White     0.042 0.0000
## 74 Never Married     HISPRACE2Black     1.310 0.1459
## 75 Never Married     HISPRACE2Other     1.392 0.2630
## 76 Never Married INTCTFAMNot Intact     1.074 0.5545
## 77 Never Married          EDUCMOM.L     0.330 0.0108
## 78 Never Married          EDUCMOM.Q     1.210 0.1282
## 79 Never Married          EDUCMOM.C     1.223 0.3729
## 80 Never Married          EDUCMOM^4     1.069 0.3923
```

A multinomial logistic regression was used to examine how factors like age, education (both respondent's and mother's), race/ethnicity and family background affect marital status. The results showed that older age increases the chances of being widowed — for every additional year, the odds go up by 15% (OR =

1.15, $p < .001$). Black individuals were about 3.6 times more likely to be widowed (OR = 3.59, p = .009) compared to Hispanic individuals.

When it comes to being separated, White respondents were 3.6 times more likely (OR = 3.59, p = .050) and Black respondents were 1.9 times more likely (OR = 1.90, p = .005) than Hispanics. Additionally, people from non-intact families were over 4 times more likely to be separated (OR = 4.21, $p < .001$).

For those never married, each year of age slightly decreased the odds (OR = 0.88, p = .033). White individuals were much less likely to be never married (OR = 0.042, $p < .001$) compared to Hispanics. Higher maternal education also reduced the chances of never marrying — for example, a one-unit increase in a specific measure of maternal education cut the odds by about 67% (OR = 0.33, p = .011).

Model Fit

```
library(pscl)

pR2(ord_model)
```

```
## fitting null model for pseudo-r2
```

```
##           llh       llhNull            G2      McFadden          r2ML
## -1.085549e+04 -1.183263e+04  1.954282e+03  8.258024e-02  2.952088e-01
##          r2CU
##  2.995394e-01
```

```
pR2(multi_model)
```

```
## fitting null model for pseudo-r2
## # weights:  10 (4 variable)
## initial  value 8990.320179
## iter  10 value 5486.601656
## final  value 5479.604946
## converged
```

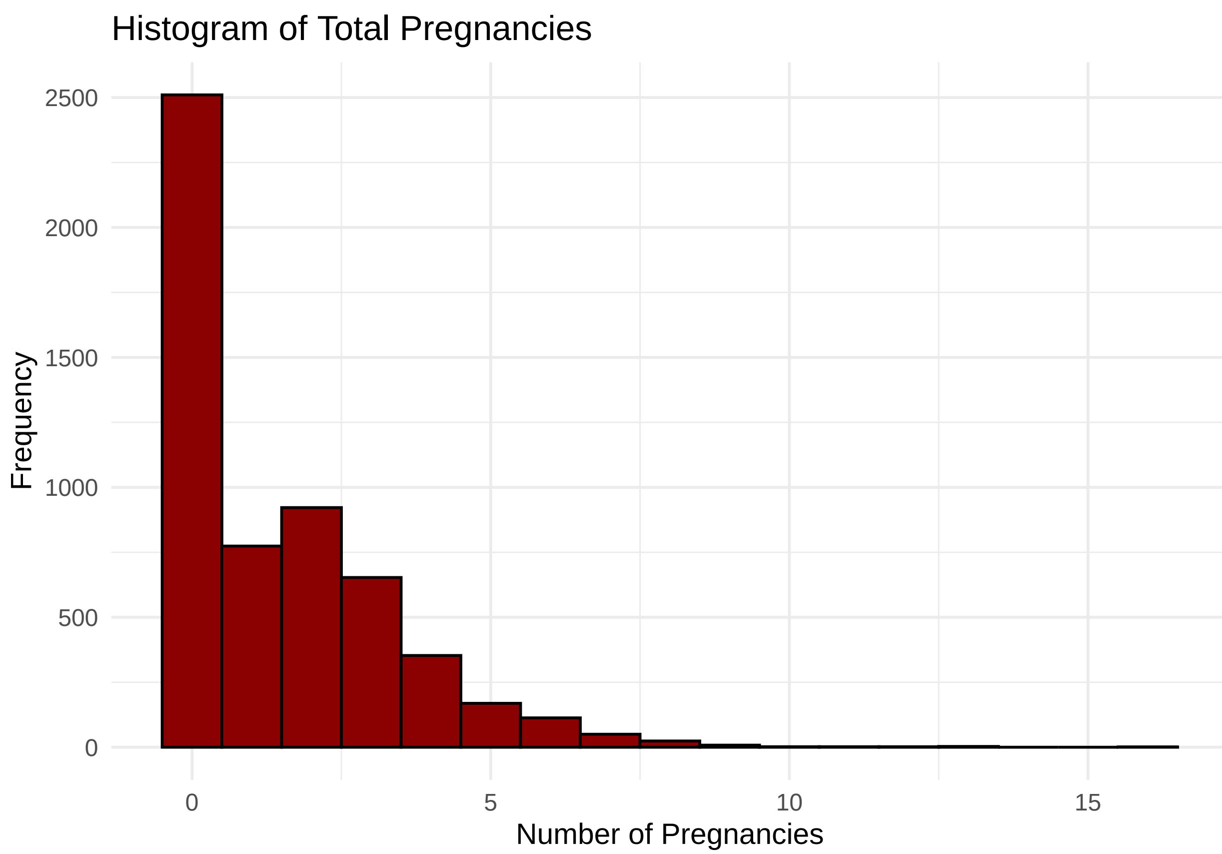
```
##           llh       llhNull            G2      McFadden          r2ML
## -4284.7856651 -5479.6049458  2389.6385614     0.2180484     0.3480521
##          r2CU
##     0.4049897
```

We assessed the model fit for both the ordinal and multinomial logistic regression models using pseudo-R^2 statistics. For the ordinal logistic regression model, the McFadden's R^2 was 0.083. The model explained approximately 29.5% (r2ML) to 30.0% (r2CU) of the variation in the outcome.

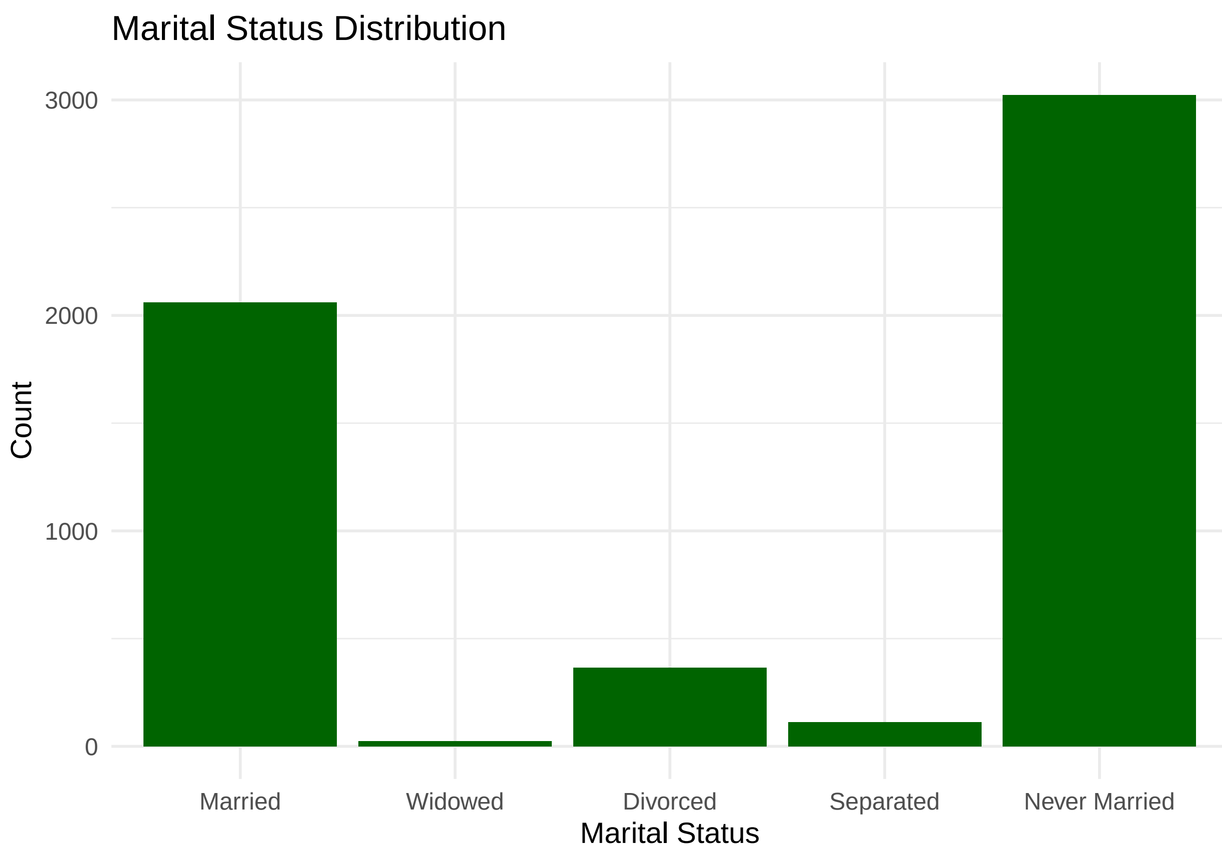
In comparison, the multinomial logistic regression model showed a better fit, with a McFadden's R^2 of 0.218. This model explained about 34.8% (r2ML) to 40.5% (r2CU) of the variance in the outcome.

0.4.0.4 EDA and Multiple Comparison Charts

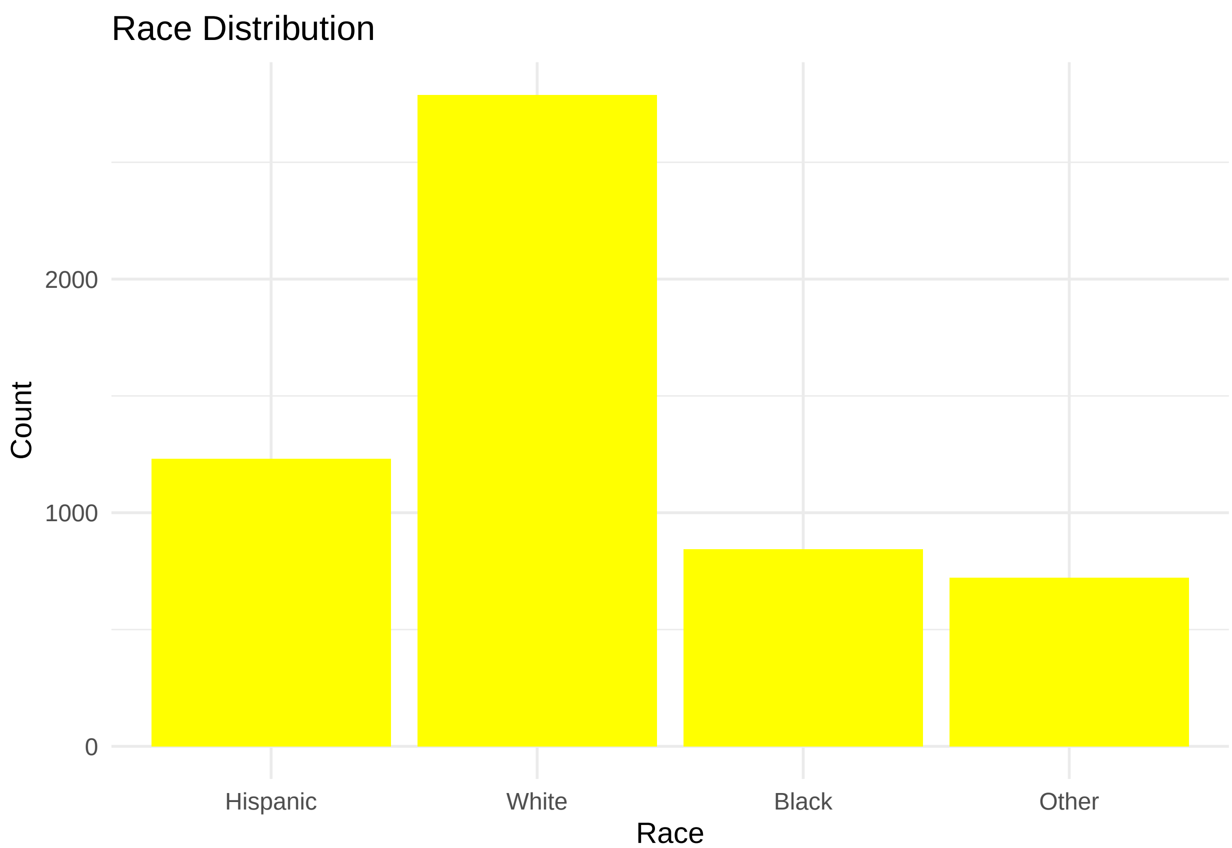
```
ggplot(data, aes(x = PREGNUM)) +
  geom_histogram(binwidth = 1, fill = "darkred", color = "black") +
  labs(title = "Histogram of Total Pregnancies", x = "Number of Pregnancies", y = "Frequency") +
  theme_minimal()
```



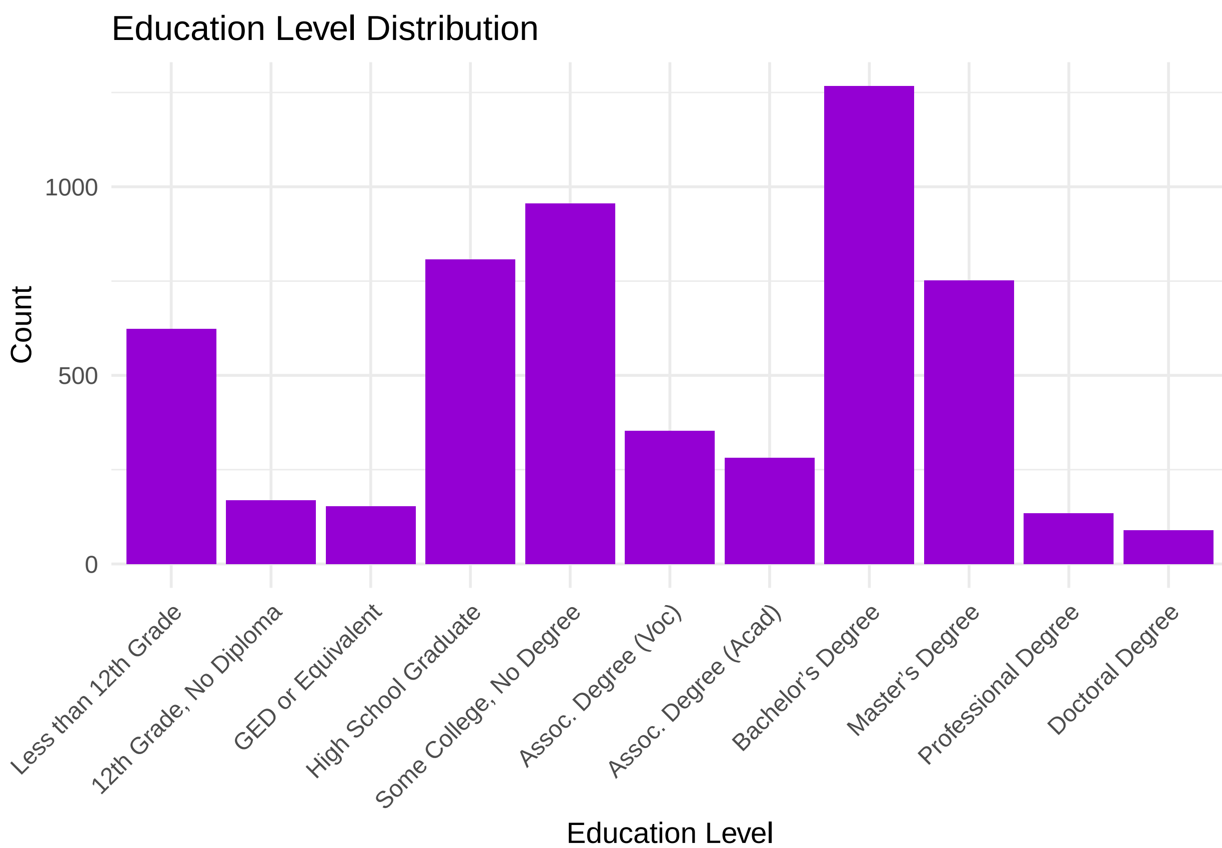

```r
ggplot(data, aes(x = FMARITAL)) +
  geom_bar(fill = "darkgreen") +
  labs(title = "Marital Status Distribution", x = "Marital Status", y = "Count") +
  theme_minimal()
```



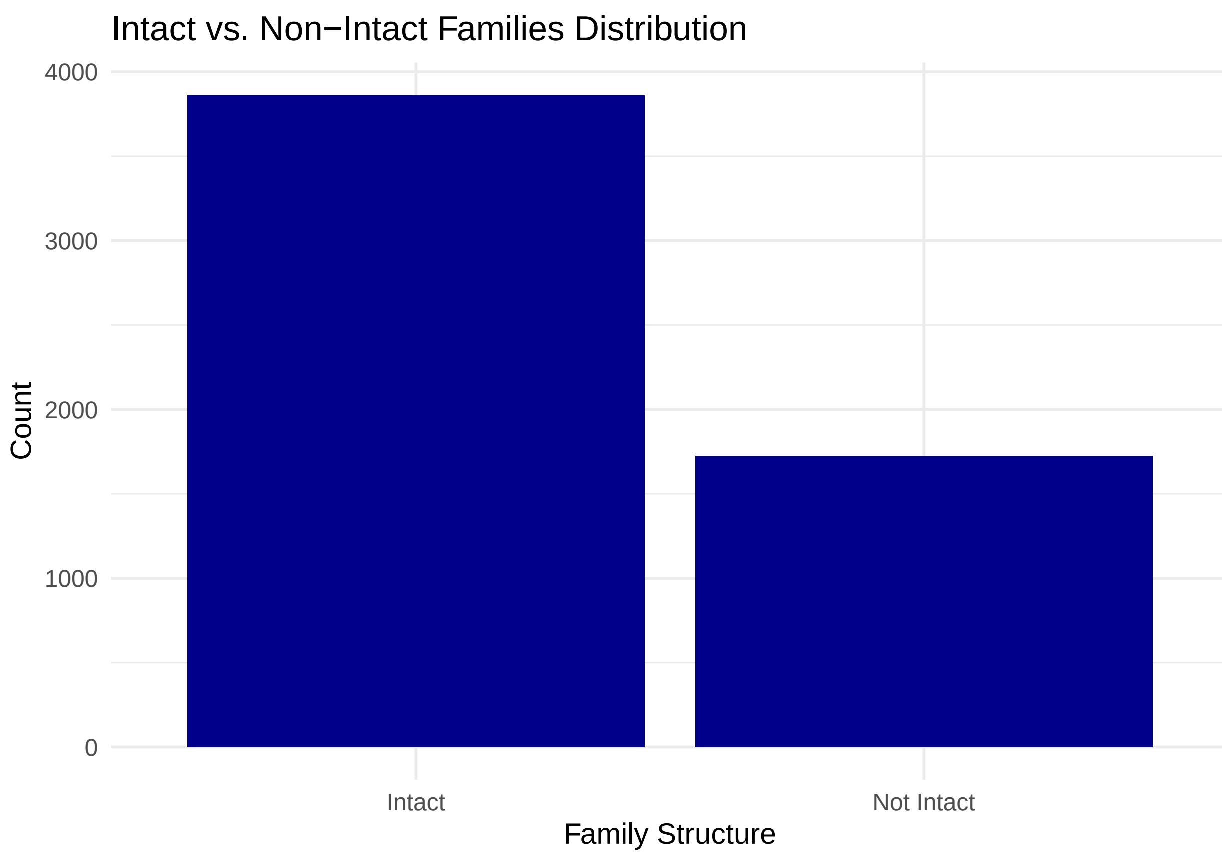

```r
ggplot(data, aes(x = HISPRACE2)) +
  geom_bar(fill = "yellow") +
    labs(title = "Race Distribution", x = "Race", y = "Count") +
  theme_minimal()
```



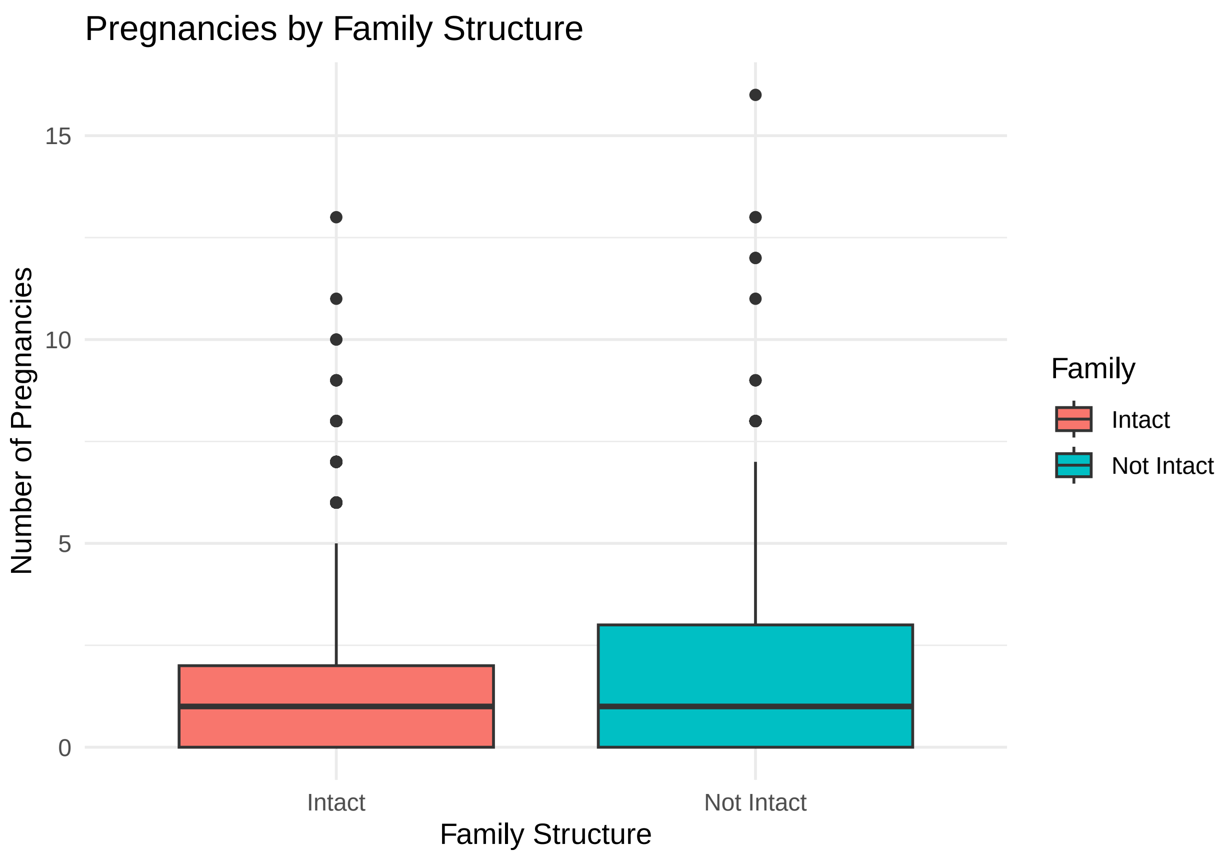

```r
data$HIEDUC_f <- factor(data$HIEDUC,
                        levels = 1:11,
                        labels = c("Less than 12th Grade",
                                   "12th Grade, No Diploma",
                                   "GED or Equivalent",
                                   "High School Graduate",
                                   "Some College, No Degree",
                                   "Assoc. Degree (Voc)",
                                   "Assoc. Degree (Acad)",
                                   "Bachelor's Degree",
                                   "Master's Degree",
                                   "Professional Degree",
                                   "Doctoral Degree"))


ggplot(data, aes(x = HIEDUC_f)) +
  geom_bar(fill = "darkviolet") +
  labs(title = "Education Level Distribution",
       x = "Education Level",
       y = "Count") +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))
```



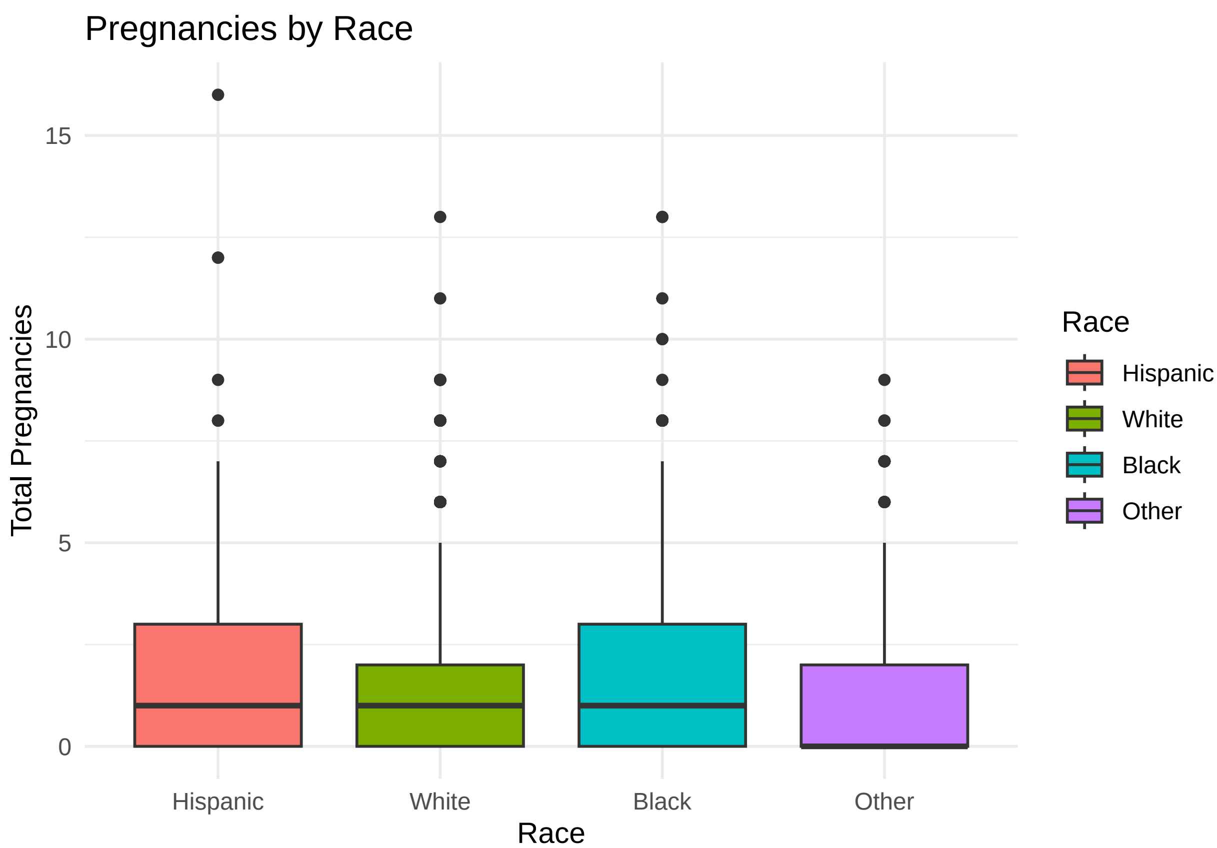

```r
ggplot(data, aes(x = INTCTFAM)) +
  geom_bar(fill="darkblue") +
  labs(title = "Intact vs. Non-Intact Families Distribution",
       x = "Family Structure",
       y = "Count") +
  theme_minimal()
```



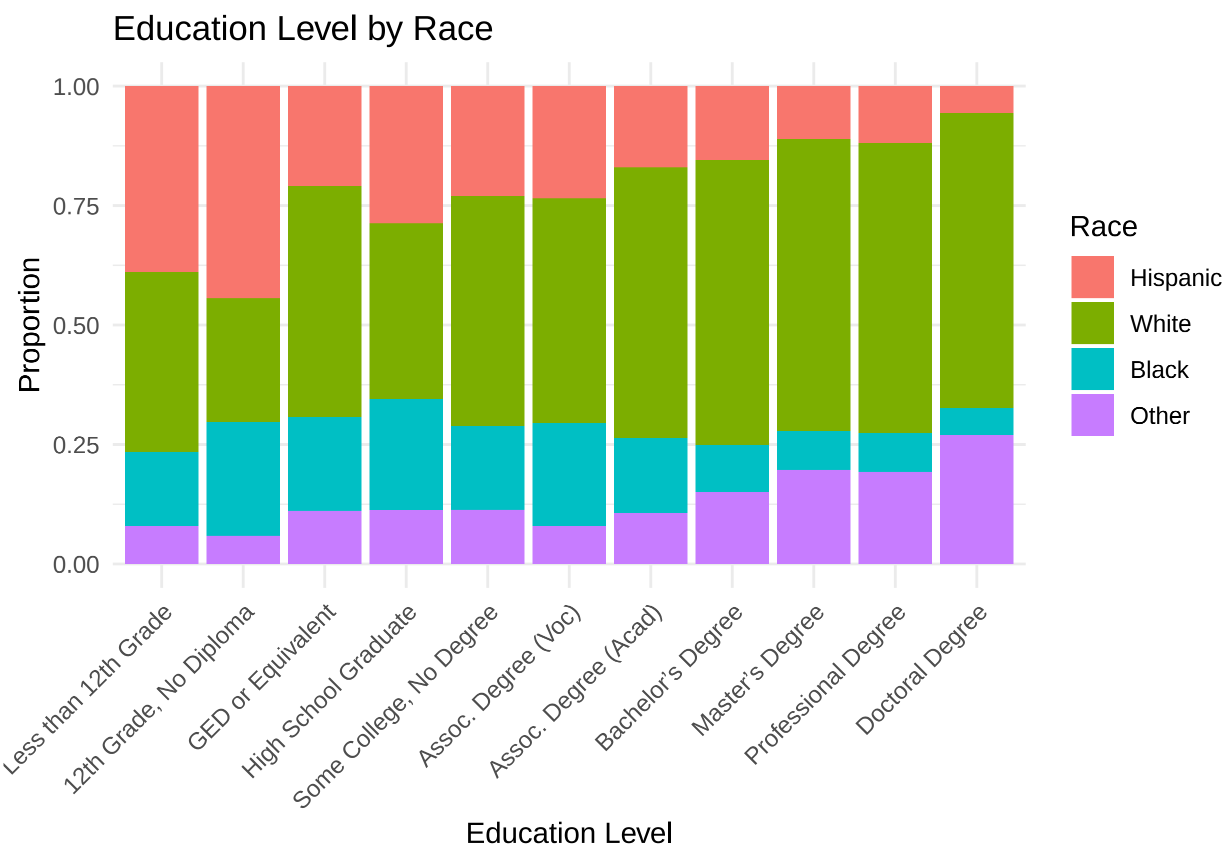

```r
ggplot(data, aes(x = INTCTFAM, y = PREGNUM, fill = INTCTFAM)) +
  geom_boxplot() +
  labs(title = "Pregnancies by Family Structure",
       x = "Family Structure",
       y = "Number of Pregnancies",
       fill = "Family") +
  theme_minimal()
```




```r
ggplot(data, aes(x = HISPRACE2, y = PREGNUM, fill = HISPRACE2)) +
  geom_boxplot() +
  labs(title = "Pregnancies by Race", x = "Race", y = "Total Pregnancies", fill = "Race") +
  theme_minimal()
```




```r
ggplot(data, aes(x = HIEDUC_f, fill = HISPRACE2)) +
  geom_bar(position = "fill") +
  labs(title = "Education Level by Race",
       x = "Education Level",
       y = "Proportion",
       fill = "Race") +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))
```



Multiple Tests

```
kruskal_test <- kruskal.test(PREGNUM ~ HISPRACE2, data = data)
kruskal_test
```

```
##
##  Kruskal-Wallis rank sum test
##
## data:  PREGNUM by HISPRACE2
## Kruskal-Wallis chi-squared = 38.536, df = 3, p-value = 2.177e-08
```

```
pairwise_result_fdr <- pairwise.wilcox.test(data$PREGNUM, data$HISPRACE2, p.adjust.method = "fdr")
pairwise_result_fdr
```

```
##
##  Pairwise comparisons using Wilcoxon rank sum test with continuity correction
##
## data:  data$PREGNUM and data$HISPRACE2
##
##       Hispanic White   Black
## White 0.05785  -       -
## Black 0.01322  1.4e-05 -
## Other 0.00022  0.00563 4.2e-08
##
## P value adjustment method: fdr
```

We compared the total number of pregnancies among different race groups using a Kruskal-Wallis test, which showed a significant difference ($^{2} = 38.54$, $p < 0.001$). To find out which of these groups differed, we did pairwise Wilcoxon tests with False Discovery Rate (FDR) adjustments to reduce false positives. Significant differences were found between Hispanic and Other ($p = 0.00022$), White and Black ($p = 0.00001$), Black and Other ($p < 0.00001$), and Hispanic and Black ($p = 0.01322$).

0.5 Limitations and Recommendations

One limitation of this study is that the data is cross-sectional. It captures information at a single point in time, so it cannot establish cause-and-effect relationships. Additionally, some variables like family structure and education levels are self-reported, which might introduce reporting bias. The sample also only includes women aged 15–49 in the United States, which limits the generalizability of the findings to other age groups or countries.

For future studies, it is recommended to use longitudinal data to better capture changes over time and establish causal relationships. Including more socio-economic and healthcare-related variables could help explain additional variability in pregnancy outcomes. Applying alternative modeling approaches such as machine learning algorithms may also improve predictive accuracy and uncover complex patterns not easily captured by traditional regression models.