# What is Multinomial Logistic Regression and how is it used in Mplus for data analysis?

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Multinomial Logistic Regression is a statistical technique used to model the relationship between a categorical dependent variable with three or more categories and one or more independent variables. It is an extension of the binary logistic regression model and allows for the prediction of multiple outcomes.

In Mplus, Multinomial Logistic Regression is used for data analysis by estimating the parameters of the model and providing information on the strength and direction of the relationship between the dependent and independent variables. This technique is commonly used in social sciences, education, and psychology to examine the influence of various factors on a categorical outcome. It is particularly useful in understanding the effects of multiple predictors on a categorical response and can provide valuable insights for decision-making and policy development. With its ability to handle complex data structures and non-linear relationships, Multinomial Logistic Regression is a powerful tool for analyzing categorical data in Mplus.

## Multinomial Logistic Regression | Mplus Data Analysis Examples

## Version info: Code for this page was tested in Mplus version 6.12.

## Multinomial logistic regression is used to model nominal
## outcome variables, in which the log odds of the outcomes are modeled as a linear
## combination of the predictor variables.

## Please note: The purpose of this page is to show how to use various data analysis commands.
## It does not cover all aspects of the research process which researchers are expected to do. In

**particular, it does not cover data cleaning and checking, verification of assumptions, model diagnostics and potential follow-up analyses.**

### Examples of multinomial logistic regression

**Example 1. People's occupational choices might be influenced by their parents' occupations and their own education level. We can study the relationship of one's occupation choice with education level and father's occupation. The occupational choices will be the outcome variable which consists of categories of occupations.**

**Example 2. A biologist may be interested in food choices that alligators make. Adult alligators might have different preferences from young ones. The outcome variable here will be the types of food, and the predictor variables might be size of the alligators and other environmental variables.**

**Example 3. Entering high school students make program choices among general program, vocational program and academic program. Their choice might be modeled using their writing score and their social economic status.**

**Description of the data**

**For our data analysis example, we will expand our third example with a hypothetical data set. The data set contains variables on 200 students. The outcome variable is prog, program type, where program type 1 is general, type 2 is academic, and type 3 is vocational. The predictor variables are social economic status, ses, a three-level categorical variable and writing score, write, a continuous variable. Let's start with getting some descriptive statistics of the variables of interest. You can download the data set here.**

**Data:**

**File is D:hsbdemo.dat ;**

**Variable:**

**Names are**

**id female ses schtyp prog read write math science socst honors awards**

**cid;**

**Missing are all (-9999) ;**

**Analysis:**

**Type = basic;**

**Plot:**

**type = plot1;**

**RESULTS FOR BASIC ANALYSIS**

**ESTIMATED SAMPLE STATISTICS**

**Means**

**ID FEMALE SES SCHTYP PROG**

**1 100.500 0.545 2.055 1.160 2.025**

**Means**

**READ WRITE MATH SCIENCE SOCST**

**1 52.230 52.775 52.645 51.850 52.405**

## Means

## HONORS AWARDS CID

________ ________ ________

## 1 0.265 1.670 10.430

## Covariances

## ID FEMALE SES SCHTYP PROG

________ ________ ________ ________ ________

## ID 3333.250

## FEMALE -2.507 0.248

## SES 8.797 -0.045 0.522

## SCHTYP 10.210 0.003 0.036 0.134

## PROG -2.308 0.001 0.009 -0.024 0.474

## READ 87.755 -0.270 2.167 0.323 -0.951

## WRITE 101.907 1.208 1.417 0.441 -1.179

## MATH 118.283 -0.137 1.840 0.337 -0.966

## SCIENCE 183.260 -0.628 2.018 0.234 -1.291

## SOCST 113.333 0.279 2.568 0.380 -1.440

## HONORS 1.148 0.031 0.060 -0.002 -0.012

## AWARDS 10.490 0.160 0.318 0.038 -0.152

## CID 89.335 0.031 1.336 0.236 -0.766

## Covariances

## READ WRITE MATH SCIENCE SOCST

____________ ____________ ____________ ____________ ____________

**READ 104.597**

**WRITE 57.707 89.394**

**MATH 63.297 54.555 87.329**

**SCIENCE 63.649 53.266 58.212 97.538**

**SOCST 68.067 61.236 54.489 49.191 114.681**

**HONORS 2.209 2.820 2.234 1.820 1.833**

**AWARDS 10.421 14.616 10.168 9.021 10.129**

**CID 50.576 44.807 46.073 47.645 40.461**

**Covariances**

**HONORS AWARDS CID**

____________ ____________ ____________

**HONORS 0.195**

**AWARDS 0.652 3.291**

**CID 1.611 7.832 33.485**

**Correlations**

**ID FEMALE SES SCHTYP PROG**

____________ ____________ ____________ ____________ ____________

**ID 1.000**

**FEMALE -0.087 1.000**

**SES 0.211 -0.125 1.000**

**SCHTYP 0.482 0.015 0.137 1.000**

**PROG -0.058 0.004 0.017 -0.095 1.000**

**READ 0.149 -0.053 0.293 0.086 -0.135**

**WRITE 0.187 0.256 0.207 0.127 -0.181**

**MATH 0.219 -0.029 0.272 0.098 -0.150**

**SCIENCE 0.321 -0.128 0.283 0.065 -0.190**

**SOCST 0.183 0.052 0.332 0.097 -0.195**

**HONORS 0.045 0.139 0.190 -0.015 -0.038**

**AWARDS 0.100 0.177 0.243 0.057 -0.121**

**CID 0.267 0.011 0.320 0.111 -0.192**

**Correlations**

**READ WRITE MATH SCIENCE SOCST**

**________ ________ ________ ________ ________**

**READ 1.000**

**WRITE 0.597 1.000**

**MATH 0.662 0.617 1.000**

**SCIENCE 0.630 0.570 0.631 1.000**

**SOCST 0.621 0.605 0.544 0.465 1.000**

**HONORS 0.489 0.676 0.542 0.418 0.388**

**AWARDS 0.562 0.852 0.600 0.503 0.521**

**CID 0.855 0.819 0.852 0.834 0.653**

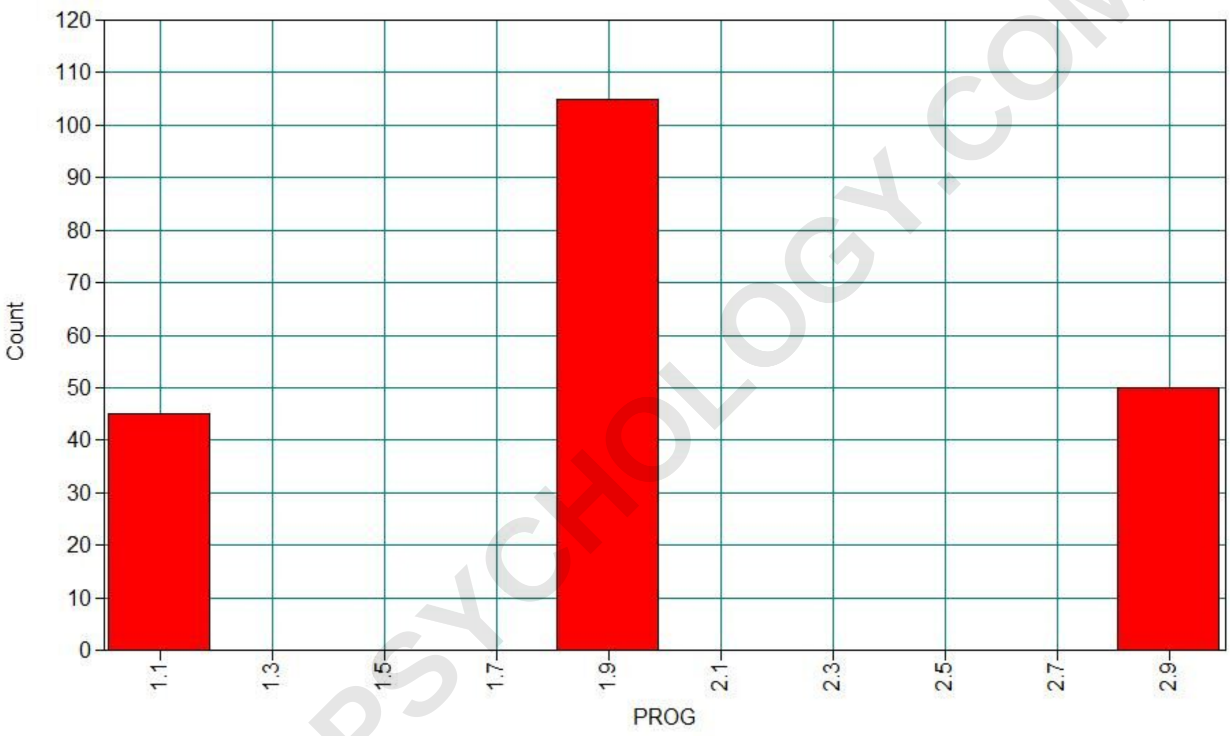
**Correlations**

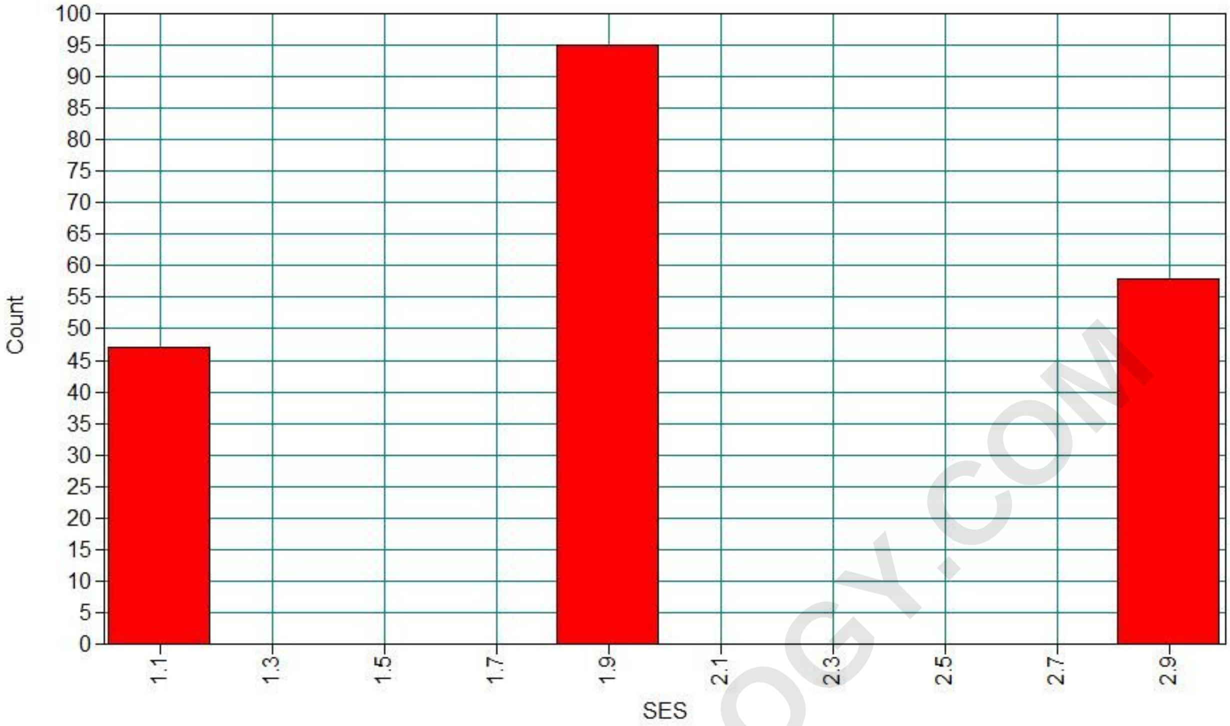
**HONORS AWARDS CID**

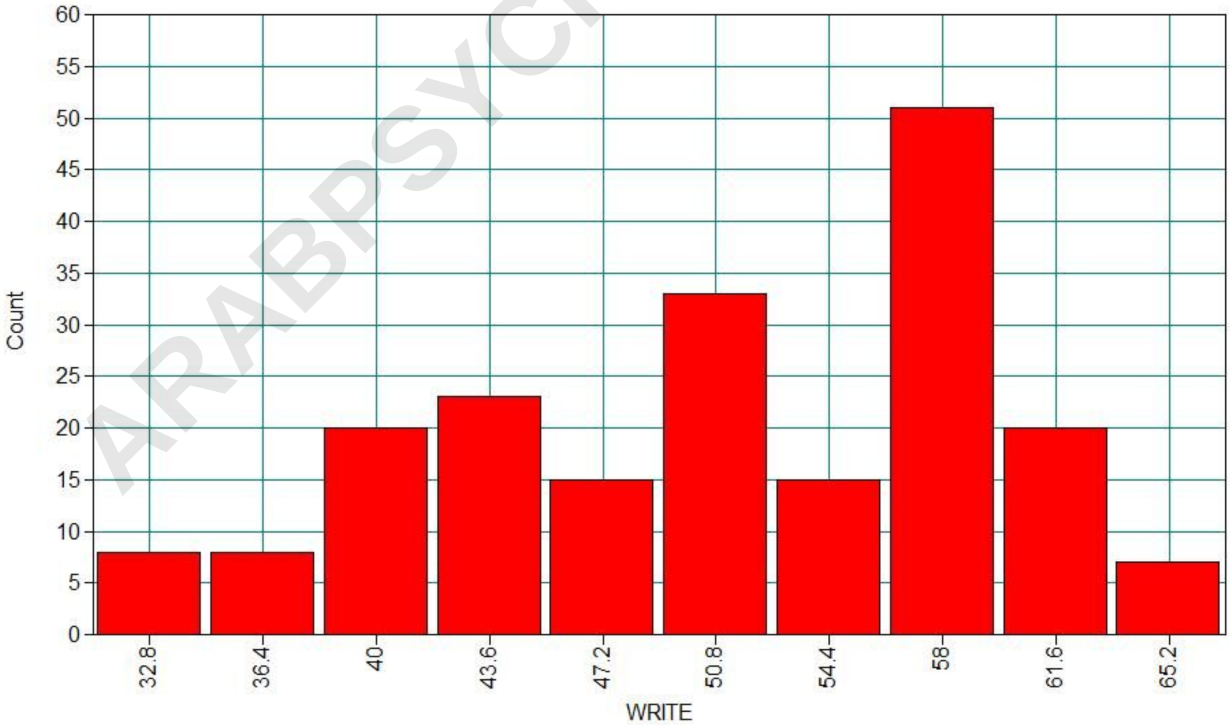
## HONORS 1.000

## AWARDS 0.815 1.000

## CID 0.631 0.746 1.000




Count
SES
100
95
90
85
80
75
70
65
60
55
50
45
40
35
30
25
20
15
10
5
0
1.1
1.3
1.5
1.7
1.9
2.1
2.3
2.5
2.7
2.9


Count
WRITE
60
55
50
45
40
35
30
25
20
15
10
5
0
32.8
36.4
40
43.6
47.2
50.8
54.4
58
61.6
65.2

## Analysis methods you might consider

## Multinomial logistic regression

**Below we show how to regress prog on ses and write in a multinomial logit model in Mplus. We specify that the dependent variable, prog, is an unordered categorical variable using the Nominal option. Mplus will not automatically dummy-code categorical variables for you, so in order to get separate coefficients for ses groups 1 and 2 relative to ses group 3, we must create dummy variables using the Define command. We include our newly created dummy variables, ses1 and ses2, in both the Usevariables option and the Model command. In the multinomial logit model, one outcome group is used as the "reference group" (also called a base category), and the coefficients for all other outcome groups describe how the independent variables are related to the probability of being in that outcome group versus the reference**

**group. Mplus automatically uses the last category of the dependent variable as the base category or comparison group, which in this case is the vocational category. Looking at the syntax below, in the model statement we have entered "prog#1 prog#2 on ses1 ses2 write." Mplus uses a variable name followed by a pound sign and a number to refer to the categories of the nominal dependent variable, except the final category, which is the reference group and cannot be referred to in the model statement (if you try, Mplus will issue an error message). Thus the line included in our model statement indicates that we want to regress both levels of prog on ses(as dummy variables) and write. Additionally, by default for multinomial logistic regression, Mplus calculates robust standard errors.**

**Data:**

**File is C:UsersalinDocumentsmplus_andyhsbdemo.dat ;**

**Variable:**

**Names are**

**id female ses schtyp prog read write math science socst honors awards**

**cid;**

**Missing are all (-9999) ;**

**Usevariables are prog write ses1 ses2;**

**Nominal is prog;**

**Define:**

**ses1 = ses == 1;**

**ses2 = ses == 2;**

**Model:**

**prog#1 prog#2 on ses1 ses2 write;**

**MODEL FIT INFORMATION**

**Number of Free Parameters 8**

**Loglikelihood**

**H0 Value -179.982**

**H0 Scaling Correction Factor 1.016**

**for MLR**

**Information Criteria**

**Akaike (AIC) 375.963**

**Bayesian (BIC) 402.350**

**Sample-Size Adjusted BIC 377.005**

**(n* = (n + 2) / 24)**

**MODEL RESULTS**

**Two-Tailed**

**Estimate S.E. Est./S.E. P-Value**

**PROG#1 ON**

**SES1 0.180 0.651 0.277 0.782**

**SES2 -0.645 0.602 -1.071 0.284**

**WRITE 0.056 0.024 2.276 0.023**

**PROG#2 ON**

**SES1 -0.983 0.612 -1.604 0.109**

**SES2 -1.274 0.524 -2.430 0.015**

**WRITE 0.114 0.022 5.208 0.000**

**Intercepts**

**PROG#1 -2.546 1.331 -1.914 0.056**

**PROG#2 -4.236 1.206 -3.511 0.000**

**LOGISTIC REGRESSION ODDS RATIO RESULTS**

**PROG#1 ON**

**SES1 1.197**

**SES2 0.525**

**WRITE 1.057**

**PROG#2 ON**

**SES1 0.374**

**SES2 0.280**

**WRITE 1.120**

**The ratio of the probability of choosing one outcome category over the
probability of choosing the baseline category is often referred to as relative risk
(and it is also sometimes referred to as odds as we have just used to described the
regression parameters above). Relative risk can be obtained by
exponentiating the linear equations above, yielding regression coefficients that
are relative risk ratios for a unit change in the predictor variable. These
relative risk ratios can be found in the Logistic Regression Odds Ratio Results**

section of the output.

## Things to consider

## See also

## References