Interpret & Summarize Mixture Models with Auxiliary Variables: Distal Model & Moderation Model Examples

Adding Covariate and Distal Outcome Variables to Mixture Models

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What is included in this video tutorial?

> This tutorial covers the interpretation of the results of a mixture model with auxiliary variables. Specifically, an LCA model is specified with relations to covariate and distal outcomes in two examples. Auxiliary variable integration is specified using the 3-step ML auxiliary variable procedure using the `MplusAutomation` package (Hallquist & Wiley, 2018; Vermunt, 2010; Asparouhov & Muthén, 2014). In addition to running the models this tutorial covers plotting the results of distal outcome means and covariate relations in the context of moderation (see example; Nylund-Gibson et al., 2022).

Follow along! Link to `Github` repository:

https://github.com/immerse-ucsb/interpret-aux-vars

Data Source: Civil Rights Data Collection (CRDC)

> The CRDC is a federally mandated school and district level data collection effort that occurs every other year. This public data is currently available for selected variables across 4 years (2011, 2013, 2015, 2017) and all US states. In the following tutorial six focal variables are utilized as indicators of the latent class model; three variables which report on harassment/bullying in schools based on disability, race, or sex, and three variables on full-time equivalent school staff employees (counselor, psychologist, law enforcement). For this example, we utilize a sample of schools from the state of Arizona reported in 2017.

Information about CRCD: https://www2.ed.gov/about/offices/list/ocr/data.html

Data access (`R`): https://github.com/UrbanInstitute/education-data-package-r

LCA Indicators & Auxiliary Variables: Harassment & Staff Example[1]

Name	Description
LCA Indicator Variables	
report_dis	Number of students harassed or bullied on the basis of disability
report_race	Number of students harassed or bullied on the basis of race, color, or national origin
report_sex	Number of students harassed or bullied on the basis of sex
counselors_fte	Number of full time equivalent counselors hired as school staff
psych_fte	Number of full time equivalent psychologists hired as school staff
law_fte	Number of full time equivalent law enforcement officers hired as school staff
Auxiliary Variables	
lunch_program	School has a lunch program (0=No lunch program, 1=Lunch program at school).
read_test	Average reading test assessment score at school
math_test	Average math test assessment score at school

[1]Note. Data souce is from the public-use dataset, the Civil Rights Data Collection (CRDC; US Department of Education Office for Civil Rights, 2014)

Getting started: Load packages & Read in CSV data file from the `data` subfolder

```
library(MplusAutomation) # Conduit between R & Mplus
library(glue)            # Pasting R code into strings
library(here)            # Location, location, location
library(tidyverse)       # Tidyness
```

```
data_3step <- read_csv(here("data", "crdc_aux_data.csv"))
```

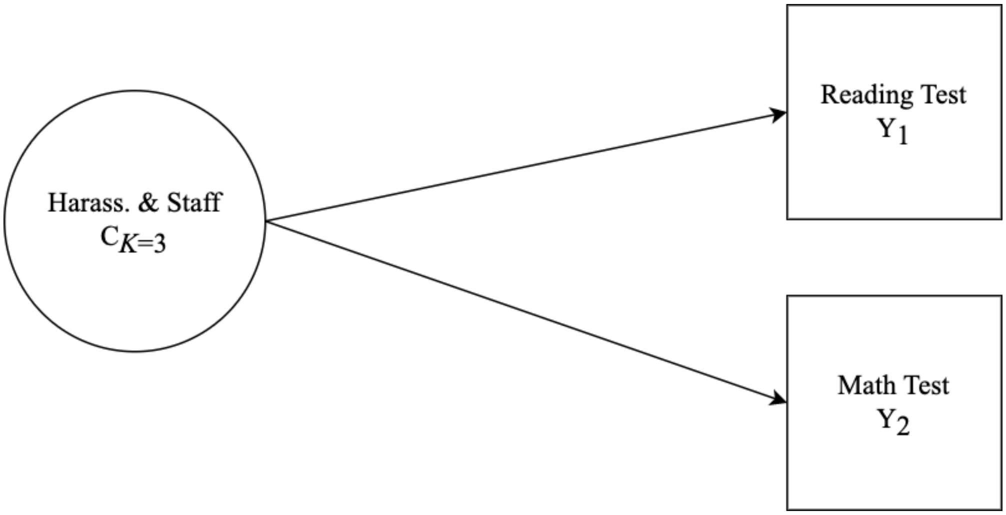
Auxiliary Variable Integration: Quickly Automate the "Manual 3-Step"!

Note: Models `step1_3step.out` & `step2_3step.out` are labeled differently than in the technical documentation for the 3-step procedure. For example, in Asparouhov & Muthén (2014) this syntax corresponds to **steps 1-3**.

```
m_step1  <- mplusObject(
  TITLE = "Step1  (MANUAL 3-STEP ML APPROACH)",
  VARIABLE =
   "categorical = report_dis report_race report_sex counselors_fte psych_fte law_fte;

    usevar = report_dis report_race report_sex counselors_fte psych_fte law_fte;

    classes = c(3);

    !!! All auxiliary variables to be considered in the final model should be listed here !!!
    auxiliary =
    lunch_program title1_e title1_s read_test math_test;",

  ANALYSIS =
   "estimator = mlr;
    type = mixture;
    starts = 500 100;

    !!! to replicate class order use, `optseed = 887580;` !!!",

  SAVEDATA =
   "!!! This saved dataset will contain class probabilities and modal assignment columns !!!
    File=3step_savedata.dat;
    Save=cprob;
    Missflag= 999;",

  PLOT =
    "type = plot3;
    series = report_dis report_race report_sex counselors_fte psych_fte law_fte(*);",

  usevariables = colnames(data_3step),
  rdata = data_3step)

m_step1_fit <- mplusModeler(m_step1,
                 dataout=here("3step_mplus", "Step1_3step.dat"),
                 modelout=here("3step_mplus", "Step1_3step.inp") ,
                 check=TRUE, run = TRUE, hashfilename = FALSE)

# ----------------------------------------------------------------------------------------
```

```r
# Step 2 - Extract logits & saved data from the step 1 unconditional model.
# -------------------------------------------------------------------------------------

logit_cprobs <- as.data.frame(m_step1_fit[["results"]]
                                         [["class_counts"]]
                                         [["logitProbs.mostLikely"]])

savedata <- as.data.frame(m_step1_fit[["results"]]
                                     [["savedata"]])

colnames(savedata)[colnames(savedata)=="C"] <- "N"

# -------------------------------------------------------------------------------------
# Step 2 (part 2) - Estimate the unconditional model with logits from step 2.
# -------------------------------------------------------------------------------------

m_step2  <- mplusObject(
  TITLE = "Step2  (MANUAL 3-STEP ML APPROACH)",

  VARIABLE =
 "nominal=N;
  USEVAR = n;
  missing are all (999);
  classes = c(3); ",

  ANALYSIS =
 "estimator = mlr;
  type = mixture;
  starts = 0;",

  MODEL =
    glue(
 "%C#1%
  [n#1@{logit_cprobs[1,1]}];
  [n#2@{logit_cprobs[1,2]}];

  %C#2%
  [n#1@{logit_cprobs[2,1]}];
  [n#2@{logit_cprobs[2,2]}];

  %C#3%
  [n#1@{logit_cprobs[3,1]}];
  [n#2@{logit_cprobs[3,2]}];"),

  usevariables = colnames(savedata),
  rdata = savedata)

m_step2_fit <- mplusModeler(m_step2,
                 dataout=here("3step_mplus", "Step2_3step.dat"),
                 modelout=here("3step_mplus", "Step2_3step.inp"),
                 check=TRUE, run = TRUE, hashfilename = FALSE)
```

EXAMPLE 0: Distal Outcome Model




```
m_step3  <- mplusObject(
  TITLE = "Distal Outcome Model (Step3)",

  VARIABLE =
 "nominal = N;
  usevar = n;
  missing are all (999);

  usevar = read_tes math_tes;
  classes = c(3); ",

  ANALYSIS =
 "estimator = mlr;
  type = mixture;
  starts = 0;",

  MODEL =
  glue(
 "!!! DISTAL OUTCOMES = read_tes math_tes !!!

  %OVERALL%

  read_tes;
  math_tes;

  %C#1%
  [n#1@{logit_cprobs[1,1]}];
  [n#2@{logit_cprobs[1,2]}];
```

```
  [read_tes](m01);                !!! estimate conditional intercept mean !!!
  read_tes;                       !!! estimate conditional intercept variance !!!

  [math_tes] (m1);
  math_tes;

  %C#2%
  [n#1@{logit_cprobs[2,1]}];
  [n#2@{logit_cprobs[2,2]}];

  [read_tes](m02);
  read_tes;

  [math_tes] (m2);
  math_tes;

  %C#3%
  [n#1@{logit_cprobs[3,1]}];
  [n#2@{logit_cprobs[3,2]}];

  [read_tes](m03);
  read_tes;

  [math_tes] (m3);
  math_tes;  "),

  MODELCONSTRAINT =
 "New (rdiff12 rdiff13
  rdiff23 mdiff12 mdiff13
  mdiff23);

  rdiff12 = m1-m2;   mdiff12 = m01-m02;
  rdiff13 = m1-m3;   mdiff13 = m01-m03;
  rdiff23 = m2-m3;   mdiff23 = m02-m03;",

  MODELTEST =
  ## NOTE: Only a single Wald test can be conducted per model run. Therefore,
  ## this example requires running separate models for each omnibus test (e.g.,
  ## 2 models for each outcome variable). This can be done by commenting out
  ## all but one test and then estimating multiple versions of the model.

 "!m01=m02;    !!! Distal outcome omnibus Wald test for `read_tes` !!!
  !m02=m03;

  m1=m2;       !!! Distal outcome omnibus Wald test for `math_tes` !!!
  m2=m3; ",

  usevariables = colnames(savedata),
  rdata = savedata)

m_step3_fit <- mplusModeler(m_step3,
                 dataout=here("3step_mplus", "EX0_Distal_Model.dat"),
                 modelout=here("3step_mplus", "EX0_Distal_Model.inp"),
```

```
                  check=TRUE, run = TRUE, hashfilename = FALSE)
```

EX0: Distal Outcome Plot

Note: The distal outcome means are estimated at the average of the covariate (`lunch_pr`). This is specified by centering lunch program as shown in the `Step-3` model syntax.

This syntax reads in the `Step3` model & extract model parameter estimates.

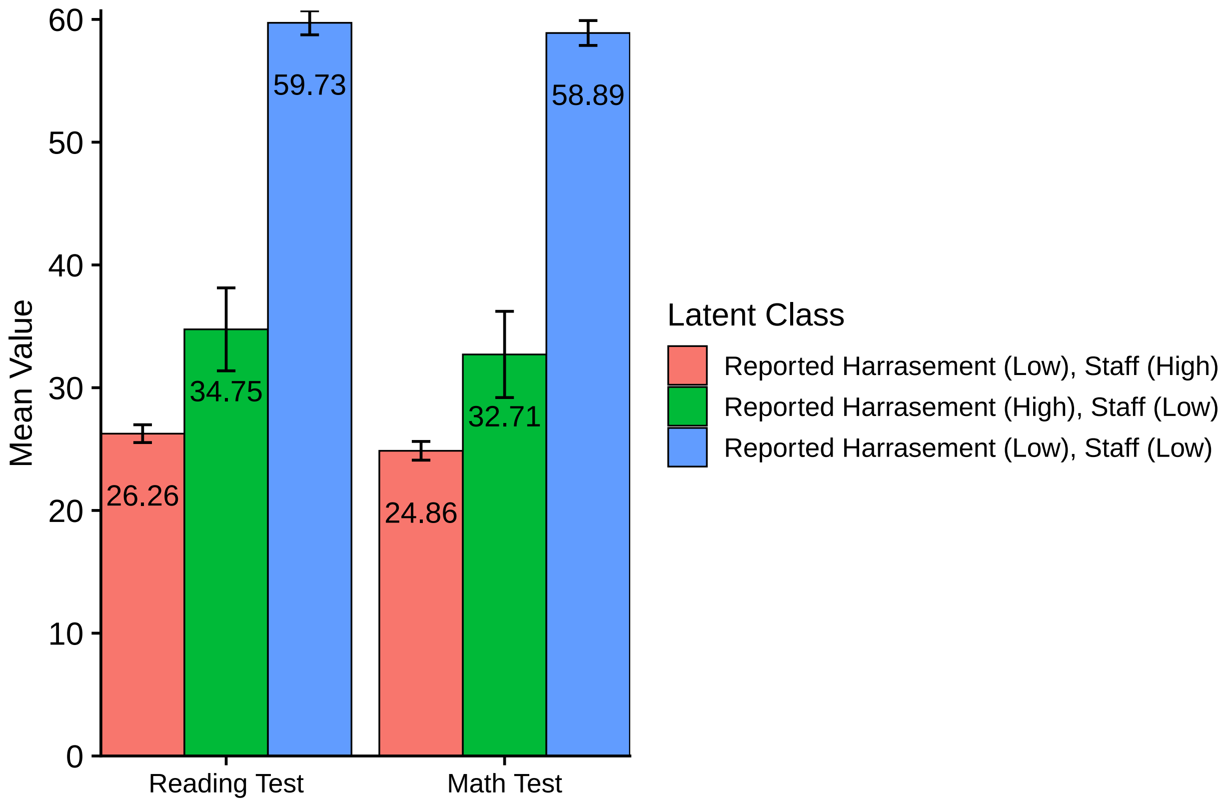
```
model_step3 <- readModels(here("3step_mplus", "EX0_Distal_Model.out"), quiet = TRUE)

model_step3 <- data.frame(model_step3$parameters$unstandardized)
```

This syntax is used to create the `data-frame` that produces the distal outcome bar plot.

```
distal_data <- model_step3 %>%
  filter(paramHeader == "Means") %>%
  filter(param == c("READ_TES","MATH_TES")) %>%
  mutate(param = case_when(
      param == "READ_TES" ~ "Reading Test",
      param == "MATH_TES" ~ "Math Test")) %>%
  mutate(LatentClass = factor(LatentClass,
      labels = c("Reported Harrasement (Low), Staff (High)",
                 "Reported Harrasement (High), Staff (Low)",
                 "Reported Harrasement (Low), Staff (Low)"))) %>%
  mutate(value_labels = round(est,2))
```

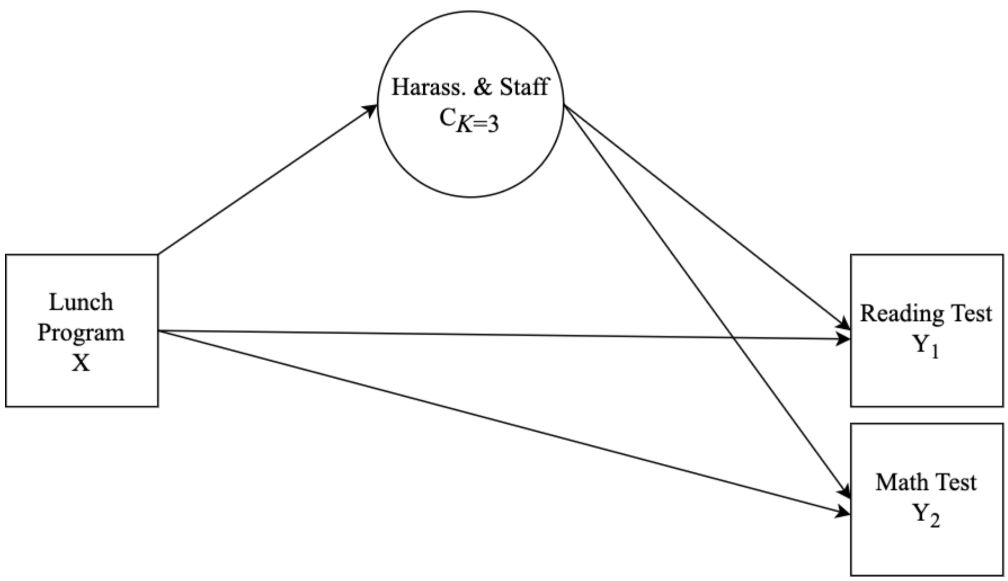
Plot distal outcomes grouped by class

```
library(cowplot)
library(reshape2)

ggplot(distal_data,
       aes(fill=LatentClass, y=est, x=fct_rev(param))) +
  geom_bar(position="dodge", stat="identity", color="black", size=.3) +
  geom_errorbar( aes(ymin=est-se, ymax=est+se),
                 width=.2, position=position_dodge(.9)) +
  geom_text(aes(y = est -5, label = value_labels),
            size=4, position=position_dodge(.9)) +
  theme_cowplot() +
  labs(x = "", y = "Mean Value", fill = "Latent Class") +
  theme(text=element_text(size=12),
        axis.text.x=element_text(size=10)) +
        coord_cartesian(expand = FALSE)
```




```
ggsave(here("figures","EX0_Distal_barplot.png"), dpi=300, height=3, width=6, units="in")
```

EXAMPLE 1: Distal Outcome Model with Covariate Control.



Specification details:

- This example contains two distal outcomes (`read_test` & `math_test`) and one binary covariate (`lunch_program`).
- Under each class-specific statement (e.g., `%C#1%`) the distal outcome means & variances are mentioned to allow these parameters to vary by class.
- Note that the binary covariate is centered so that reported distal means (intercepts) are estimated at the average of `lunch_program`.

```
m_step3  <- mplusObject(
  TITLE = "Distal Outcome Model with Control Covariate (Step3)",

  VARIABLE =
 "nominal = N;
  usevar = n;
  missing are all (999);

  usevar = lunch_pr read_tes math_tes;
  classes = c(3); ",

  DEFINE =
 "Center lunch_pr (Grandmean);",

  ANALYSIS =
 "estimator = mlr;
  type = mixture;
  starts = 0;",

  MODEL =
  glue(
 "!!! DISTAL OUTCOMES = read_tes math_tes !!!
  !!! COVARIATE = lunch_pr !!!

  %OVERALL%
  c on lunch_pr;                 !!! estimate covariate as predictor of latent class !!!

  read_tes on lunch_pr;          !!! estimate the direct effect of Y on X !!!
  math_tes on lunch_pr;

  read_tes;
  math_tes;

  %C#1%
  [n#1@{logit_cprobs[1,1]}];
  [n#2@{logit_cprobs[1,2]}];

  [read_tes](m01);               !!! estimate conditional intercept mean !!!
  read_tes;                      !!! estimate conditional intercept variance !!!

  [math_tes] (m1);
  math_tes;
```

```
  %C#2%
  [n#1@{logit_cprobs[2,1]}];
  [n#2@{logit_cprobs[2,2]}];

  [read_tes](m02);
  read_tes;

  [math_tes] (m2);
  math_tes;

  %C#3%
  [n#1@{logit_cprobs[3,1]}];
  [n#2@{logit_cprobs[3,2]}];

  [read_tes](m03);
  read_tes;

  [math_tes] (m3);
  math_tes;  "),

  MODELCONSTRAINT =
 "New (rdiff12 rdiff13
  rdiff23 mdiff12 mdiff13
  mdiff23);

  rdiff12 = m1-m2;   mdiff12 = m01-m02;
  rdiff13 = m1-m3;   mdiff13 = m01-m03;
  rdiff23 = m2-m3;   mdiff23 = m02-m03;",

  MODELTEST =
  ## NOTE: Only a single Wald test can be conducted per model run. Therefore,
  ## this example requires running separate models for each omnibus test (e.g.,
  ## 2 models for each outcome variable). This can be done by commenting out
  ## all but one test and then estimating multiple versions of the model.

 "!m01=m02;    !!! Distal outcome omnibus Wald test for `read_tes` !!!
  !m02=m03;

  m1=m2;       !!! Distal outcome omnibus Wald test for `math_tes` !!!
  m2=m3;

 ",

  usevariables = colnames(savedata),
  rdata = savedata)

m_step3_fit <- mplusModeler(m_step3,
                 dataout=here("3step_mplus", "EX1_Dist_Cov_Model.dat"),
                 modelout=here("3step_mplus", "EX1_Dist_Cov_Model.inp"),
                 check=TRUE, run = TRUE, hashfilename = FALSE)
```

EX1: Distal Outcome Plot

Note: The distal outcome means are estimated at the average of the covariate (`lunch_pr`). This is specified by centering lunch program as shown in the `Step-3` model syntax.

This syntax reads in the `Step3` model & extract model parameter estimates.

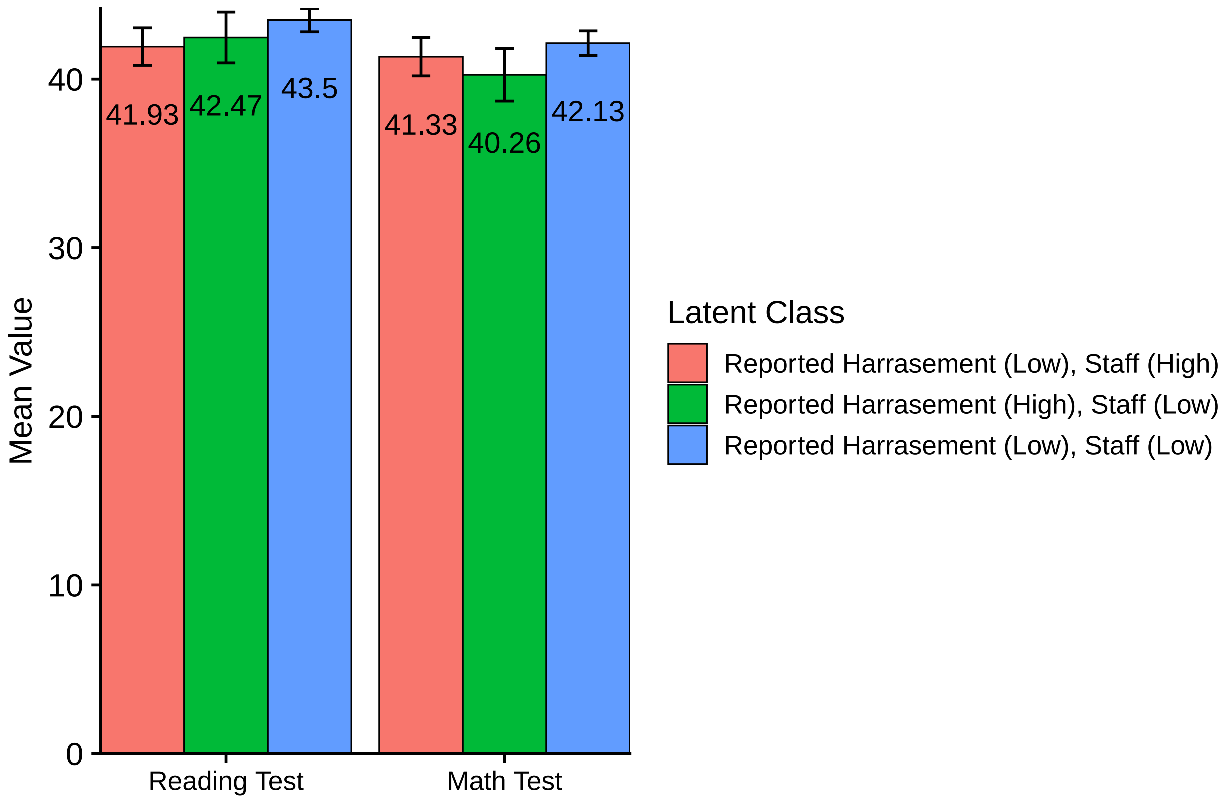
```
model_step3 <- readModels(here("3step_mplus", "EX1_Dist_Cov_Model.out"), quiet = TRUE)

model_step3 <- data.frame(model_step3$parameters$unstandardized)
```

This syntax is used to create the `data-frame` that produces the distal outcome bar plot.

```
distal_data <- model_step3 %>%
  filter(paramHeader == "Intercepts") %>%
  filter(param == c("READ_TES","MATH_TES")) %>%
  mutate(param = case_when(
      param == "READ_TES" ~ "Reading Test",
      param == "MATH_TES" ~ "Math Test")) %>%
  mutate(LatentClass = factor(LatentClass,
      labels = c("Reported Harrasement (Low), Staff (High)",
                 "Reported Harrasement (High), Staff (Low)",
                 "Reported Harrasement (Low), Staff (Low)"))) %>%
  mutate(value_labels = round(est,2))
```

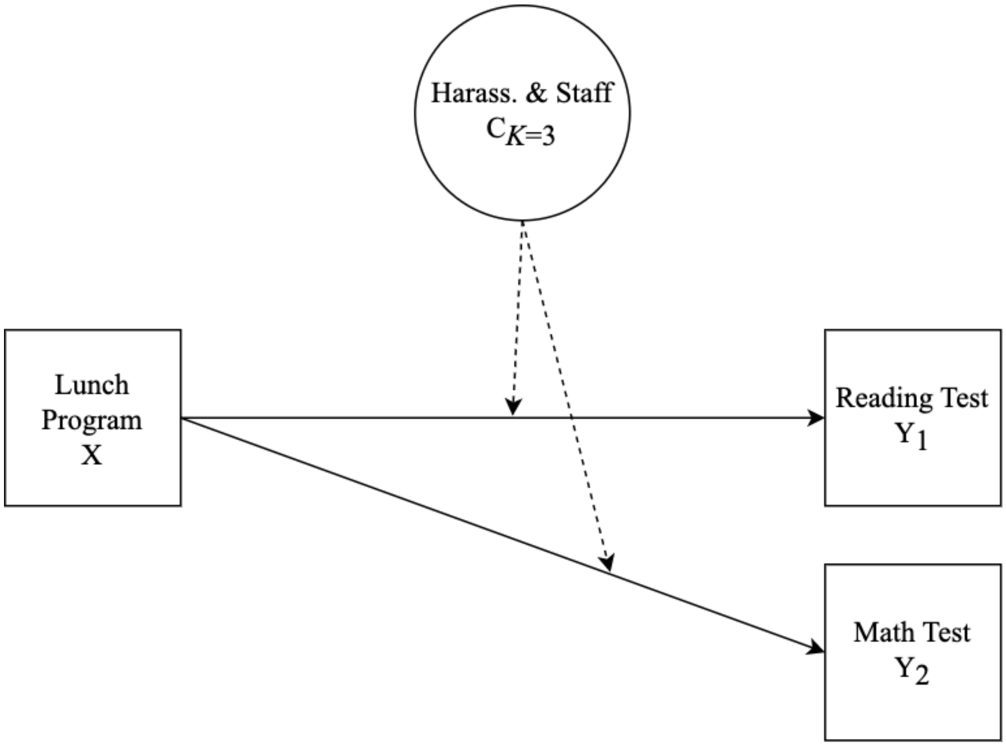
Plot distal outcomes grouped by class

```
ggplot(distal_data,
       aes(fill=LatentClass, y=est, x=fct_rev(param))) +
  geom_bar(position="dodge", stat="identity", color="black", size=.3) +
  geom_errorbar( aes(ymin=est-se, ymax=est+se),
                 width=.2, position=position_dodge(.9)) +
  geom_text(aes(y = est -4, label = value_labels),
            size=4, position=position_dodge(.9)) +
  theme_cowplot() +
  labs(x = "", y = "Mean Value", fill = "Latent Class") +
  theme(text=element_text(size=12),
        axis.text.x=element_text(size=10)) +
        coord_cartesian(expand = FALSE)
```




```
ggsave(here("figures","EX1_Distal_barplot.png"), dpi=300, height=3, width=6, units="in")
```

EXAMPLE 2: Moderation Model



Specification details:

- This example contains two distal outcomes (`read_test` & `math_test`) and one binary covariate (`lunch_program`).
- Under each class-specific statement (e.g., `%C#1%`) the distal outcome means & variances are mentioned to allow these parameters to vary by class.
- Moderation is specified by mentioning the `"outcome ON covariate;"` syntax under each of the class-specific statements.
- Note that the binary covariate is centered so that reported distal means (intercepts) are estimated at the average of `lunch_program`.

```
m_step3  <- mplusObject(
  TITLE = "Step3  (MANUAL 3-STEP ML APPROACH)",

  VARIABLE =
 "nominal = N;
  usevar = n;
  missing are all (999);

  usevar = lunch_pr read_tes math_tes;
  classes = c(3); ",

  DEFINE =
 "Center lunch_pr (Grandmean);",
```

```
 ANALYSIS =
"estimator = mlr;
 type = mixture;
 starts = 0;",

 MODEL =
 glue(
"!!! OUTCOMES = read_tes math_tes !!!
 !!! COVARIATE = lunch_pr !!!
 !!! MODERATOR = C !!!

 %OVERALL%
 read_tes on lunch_pr;
 read_tes;

 math_tes on lunch_pr;
 math_tes;

 %C#1%
 [n#1@{logit_cprobs[1,1]}];
 [n#2@{logit_cprobs[1,2]}];

 [read_tes](m01);
 read_tes;                    !!! estimate conditional intercept !!!
 read_tes on lunch_pr (s01);    !!! estimate conditional regression !!!

 [math_tes] (m1);
 math_tes;
 math_tes on lunch_pr (s1);

 %C#2%
 [n#1@{logit_cprobs[2,1]}];
 [n#2@{logit_cprobs[2,2]}];

 [read_tes](m02);
 read_tes;
 read_tes on lunch_pr (s02);

 [math_tes] (m2);
 math_tes;
 math_tes on lunch_pr (s2);

 %C#3%
 [n#1@{logit_cprobs[3,1]}];
 [n#2@{logit_cprobs[3,2]}];

 [read_tes](m03);
 read_tes;
 read_tes on lunch_pr (s03);

 [math_tes] (m3);
 math_tes;
 math_tes on lunch_pr (s3);"),
```

```
  MODELCONSTRAINT =
 "New (rdiff12 rdiff13
  rdiff23 rslope12 rslope13
  rslope23 mdiff12 mdiff13
  mdiff23 mslope12 mslope13
  mslope23);

  rdiff12 = m1-m2;   mdiff12 = m01-m02;
  rdiff13 = m1-m3;   mdiff13 = m01-m03;
  rdiff23 = m2-m3;   mdiff23 = m02-m03;
  rslope12 = s1-s2;  mslope12 = s01-s02;
  rslope13 = s1-s3;  mslope13 = s01-s03;
  rslope23 = s2-s3;  mslope23 = s02-s03;",

  MODELTEST =
  ## NOTE: Only a single Wald test can be conducted per model run. Therefore,
  ## this example requires running separate models for each omnibus test (e.g.,
  ## 4 models; 2 outcomes and 2 slope coefficients). This can be done by
  ## commenting out all but one test and then estimating multiple versions of the model.

 "!m01=m02;    !!! Distal outcome omnibus Wald test for `read_tes` !!!
  !m02=m03;

  !s01=s02;   !!! Slope difference omnibus Wald test for `read_tes on lunch_pr` !!!
  !s02=s03;

  m1=m2;       !!! Distal outcome omnibus Wald test for `math_tes` !!!
  m2=m3;

  !s1=s2;      !!! Slope difference omnibus Wald test `math_tes on lunch_pr` !!!
  !s2=s3; ",

  usevariables = colnames(savedata),
  rdata = savedata)

m_step3_fit <- mplusModeler(m_step3,
                 dataout=here("3step_mplus", "EX2_Moderation_Model.dat"),
                 modelout=here("3step_mplus", "EX2_Moderation_Model.inp"),
                 check=TRUE, run = TRUE, hashfilename = FALSE)
```

Estimate step 3 moderation model with covariate un-centered to produce simple-slopes plots

- Intercepts are estimated at the reference level of the covariate (i.e., `lunch_pr = 0`)

Note: Here the `update()` function is used to take the previous model and remove the Mplus syntax within the `DEFINE` statement that was used to center the covariate `Lunch Program`. Next, the updated model input syntax is used to estimate a new model. To learn more about the `update` function see the `MplusAutomation` tutorial article (https://www.tandfonline.com/doi/pdf/10.1080/10705511.2017.1402334).

```
m_uncen <- update(m_step3,
  DEFINE = ~" ") # This update removes the centering syntax from the model object `m_step3`

m_uncen_fit <- mplusModeler(m_uncen,
                            dataout=here("3step_mplus", "EX2_Uncentered.dat"),
                            modelout=here("3step_mplus", "EX2_Uncentered.inp"),
                            check=TRUE, run = TRUE, hashfilename = FALSE)
```

EX3: Distal Outcome Plot

This syntax reads in the `Step3` model & extract model parameter estimates.

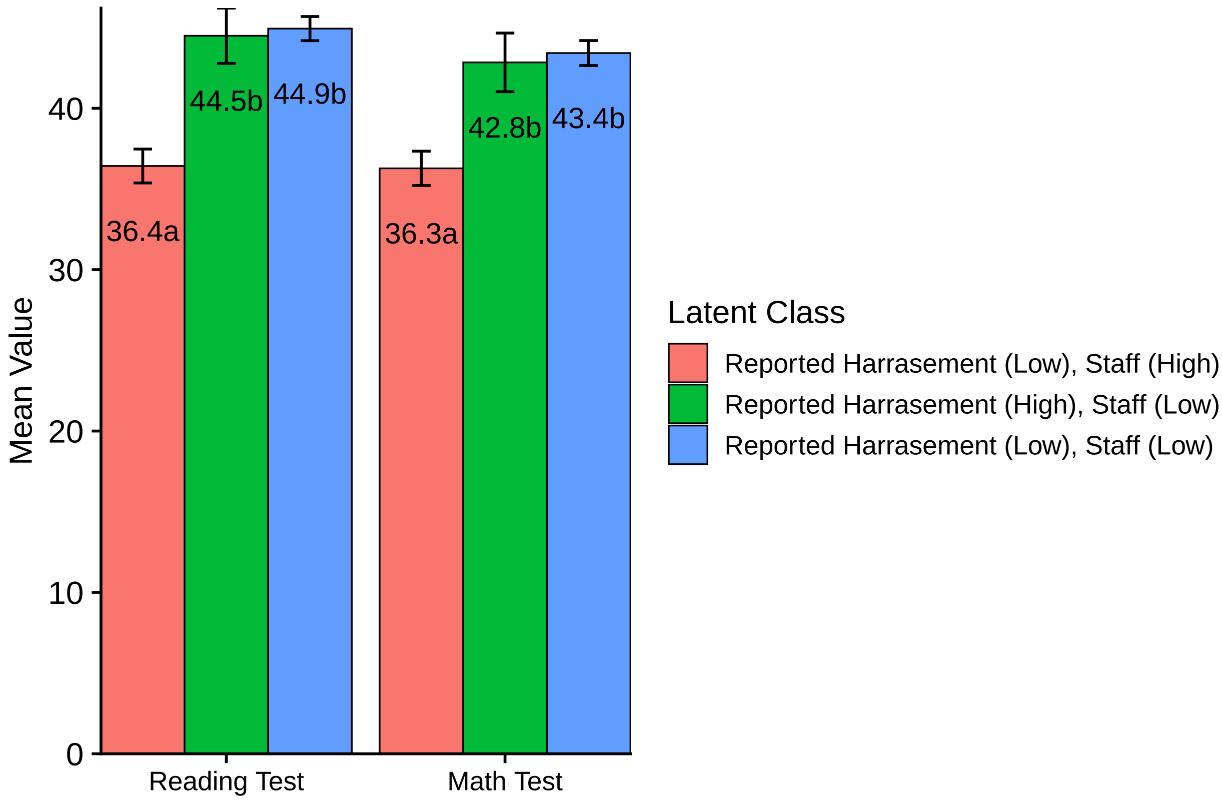
```
model_step3 <- readModels(here("3step_mplus", "EX2_Moderation_Model.out"), quiet = TRUE)

model_step3 <- data.frame(model_step3$parameters$unstandardized)
```

This syntax is used to create the `data-frame` that produces the distal outcome bar plot.

```
distal_data <- model_step3 %>%
  filter(paramHeader == "Intercepts") %>%
  mutate(param = case_when(
      param == "READ_TES" ~ "Reading Test",
      param == "MATH_TES" ~ "Math Test")) %>%
  mutate(LatentClass = factor(LatentClass,
      labels = c("Reported Harrasement (Low), Staff (High)",
                 "Reported Harrasement (High), Staff (Low)",
                 "Reported Harrasement (Low), Staff (Low)"))) %>%
  mutate(value_labels = c("36.4a", "36.3a", "44.5b", "42.8b", "44.9b", "43.4b"))
```

Plot distal outcomes grouped by class

```
ggplot(distal_data,
       aes(fill=LatentClass, y=est, x=fct_rev(param))) +
  geom_bar(position="dodge", stat="identity", color="black", size=.3) +
  geom_errorbar( aes(ymin=est-se, ymax=est+se),
                 width=.2, position=position_dodge(.9)) +
  geom_text(aes(y = est -4, label = value_labels),
            size=4, position=position_dodge(.9)) +
  #scale_fill_grey(start = 0.6, end = 1.0) +
  theme_cowplot() +
  labs(x = "", y = "Mean Value", fill = "Latent Class") +
  theme(text=element_text(size=12),
        axis.text.x=element_text(size=10)) +
        coord_cartesian(expand = FALSE)
```




```
ggsave(here("figures","EX2_Distal_barplot.png"), dpi=300, height=3, width=6, units="in")
```

EX2: Simple Slope Plots

Note: The un-centered distal intercepts represent the conditional means when the binary covariate is at its first level `lunch_pr = 0` (i.e., school does not have a lunch program). Therefore, the conditional mean for `lunch_pr = 1` (i.e., school has lunch program) can be calculated by adding the associated slope coefficient to the intercept.

Read in the un-centered model & extract relevant parameters

```
model_uncen <- readModels(here("3step_mplus", "EX2_Uncentered.out"), quiet = TRUE)

model_uncen <- data.frame(model_uncen$parameters$unstandardized)

slope_data <- model_uncen %>%
  filter(str_detect(paramHeader, 'ON|Inter'))%>%
  unite("param", paramHeader:param, remove = TRUE) %>%
  mutate(param = str_replace(param, "TES.ON_LUNCH_PR", "COEF")) %>%
  mutate(param = str_remove_all(param, "Intercepts_|_TES")) %>%
```

```
  mutate(LatentClass = factor(LatentClass,
    labels = c("Rep. Harrasement (Low), Staff (High)",
               "Rep. Harrasement (High), Staff (Low)",
               "Rep. Harrasement (Low), Staff (Low)")))
```

Reading test simple slope graph

Prepare `data-frame` for plotting

```
read_data <- slope_data %>%
  filter(str_detect(param, 'READ'))

read_wide <- read_data %>%
  select(param,est, LatentClass) %>%
  pivot_wider(names_from = param, values_from = est) %>%
  rename("No.Lunch.Program" = 'READ') %>%
  mutate(Lunch.Program = No.Lunch.Program + READ_COEF) %>% # calc. condit. means `LUNCH_PR = 1`
  select(-READ_COEF)

read_pos <- melt(read_wide, id.vars = "LatentClass") %>%
  mutate(variable = factor(variable,
                      levels = c("No.Lunch.Program","Lunch.Program"),
                      labels = c("No Lunch Program","Lunch Program")))
```

Plot positive mood simple slope graph

```
p_plot <- ggplot(read_pos,
            aes(y=value, x=variable,
                color=LatentClass,
                group=LatentClass,
                shape=LatentClass,
                lty=LatentClass)) +
  geom_point(size = 4) + geom_line() +
  xlab("") + ylab("Reading Test")  +
  theme_classic() +
  theme(text=element_text(size=12),
        axis.text.x=element_text(size=12),
        legend.text = element_text(size=8),
        legend.position = "right", legend.title = element_blank())
```

Negative mood simple slope graph

Prepare data-frame for plotting

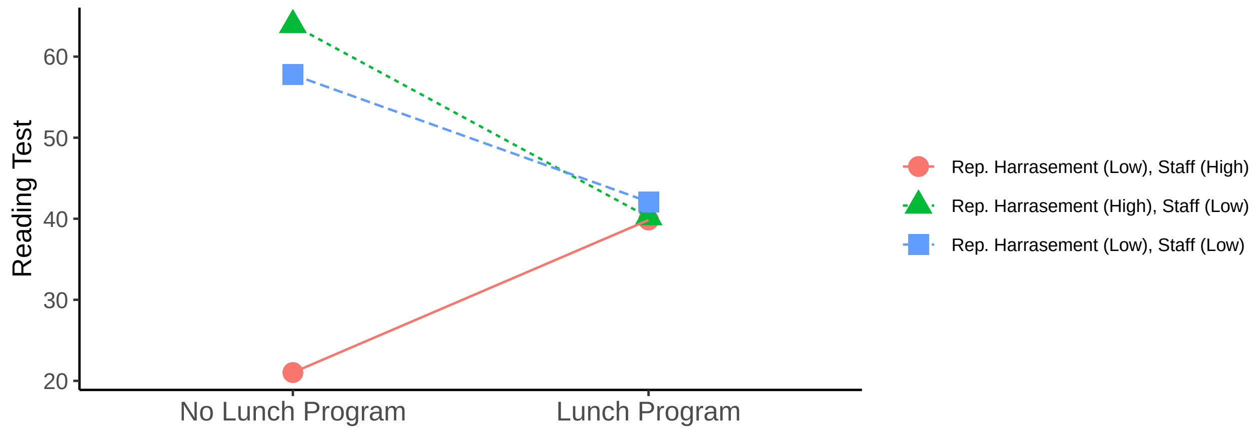
```
math_data <- slope_data %>%
  filter(str_detect(param, 'MATH'))

math_wide <- math_data %>%
  select(param,est, LatentClass) %>%
  pivot_wider(names_from = param, values_from = est) %>%
  rename("No.Lunch.Program" = 'MATH') %>%
  mutate(Lunch.Program = No.Lunch.Program + MATH_COEF) %>%   # calculate means for `Lunch.Program = 1`
  select(-MATH_COEF)

plot_math <- melt(math_wide, id.vars = "LatentClass") %>%
  mutate(variable = factor(variable,
                      levels = c("No.Lunch.Program","Lunch.Program"),
                      labels = c("No Lunch Program","Lunch Program")))
```

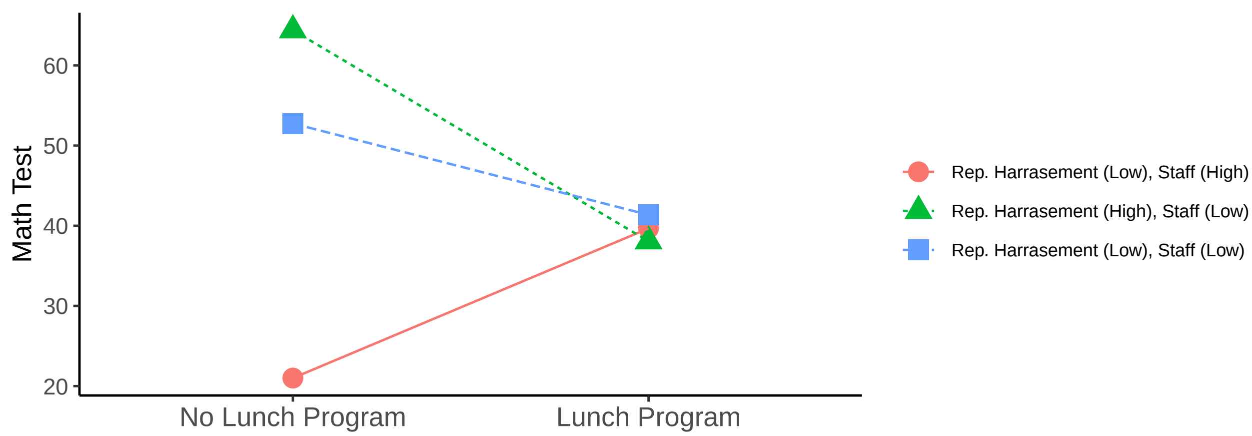
Plot negative mood simple slope graph

```
n_plot <- ggplot(plot_math,
            aes(y=value, x=variable,
            color=LatentClass,
            group=LatentClass,
            shape=LatentClass,
            lty=LatentClass)) +
  geom_point(size=4) + geom_line() +
  xlab("") + ylab("Math Test") +
  theme_classic() +
  theme(text=element_text(color = "black", size=12),
        axis.text.x=element_text(size=12),
        legend.text = element_text(size=8),
        legend.position = "right", legend.title = element_blank())
```

Combine the two simple slopes graphs for distal outcomes positive & negative mood

```
library(patchwork)

p_plot / n_plot # combines plots using the {patchwork} package
```






```
ggsave(here("figures", "EX2_Simple_slopes.png"), dpi=300, height=8.5, width=6.5, units="in")
```

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