How Effective Are Reading Comprehension Interventions for Children with ASD? A Meta-Analysis of Single-Case Design Studies

Generalized Multilevel Modeling: Logitudinal Logistic Regression

Suplemental Materialss

October 01, 2020

Contents

List of Figures

List of Tables

1 Preparation

1.1 Packages

1.1.1 General

```
library(tidyverse)      # Easily Install and Load the 'Tidyverse'
library(broom)          # Convert Statistical Analysis Objects into Tidy Tibbles
library(purrr)          # Functional Programming Tools
library(readxl)         # Read Excel Files
library(glue)           # Interpreted String Literals
library(xtable)         # Export Tables to LaTeX or HTML
library(pander)         # Tables
library(texreg)         # Conversion of R Regression Output to LaTeX or HTML

# library(devtools)
# devtools::install_github("SarBearSchwartz/texreghelpr")
library(texreghelpr)    # Extract Generalized REgression Output for Use in `texreg` tables
```

```
options(xtable.comment = FALSE,
        caption.placement = "top")
```

1.1.2 Specific

```
library(lme4)           # Linear Mixed-Effects Models
library(lmerTest)       # Tests in Linear Mixed Effects Models
library(effects)        # Effect Displays for Linear, Generalized Linear, and Other Models
```

1.2 Dataset

1.2.1 Import

```
data_raw <- readxl::read_excel("Data Collection and Organization/SCD_MetaA_MLM_data (1).xlsx")
```

1.2.2 Wrangle

```
data_clean <- data_raw %>%
  tidyr::separate(person_id,
                  into = c("study", "id"),
                  remove = FALSE) %>%
  dplyr::mutate_at(vars(person_id, study, id,
                        status, outcome_type, race_ethnic, dx, wwc),
                   factor) %>%
  dplyr::mutate(score_per = score/max_poss) %>%
  dplyr::mutate(status = factor(status,
                                levels = c(0, 1, 2),
                                labels = c("baseline",
                                           "intervention",
                                           "maintenance"))) %>%
  dplyr::mutate(num_cor = score_per * max_poss,
                num_inc = max_poss - num_cor) %>%
  dplyr::mutate(age_cat = cut(age,
                              breaks = c(6, 12, 18),
                              include.lowest = TRUE)) %>%
  dplyr::mutate(cog_cat = cut(cog_ability,
                              breaks = c(50, 79, 110))) %>%
  dplyr::rename(personID = person_id) %>%
  dplyr::select(study, id, personID,
                age, age_cat, dx, race_ethnic, cog_ability, cog_cat,
                total_iv_sess, wwc, wwc, tau_u,
                session_day, status,
                score, max_poss, outcome_type, score_per, num_cor, num_inc)

tibble::glimpse(data_clean)
```

```
Rows: 967
Columns: 20
$ study         <fct> 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,...
$ id            <fct> 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2, 2,...
$ personID      <fct> 1_1, 1_1, 1_1, 1_1, 1_1, 1_1, 1_1, 1_1, 1_1, 1_1, 1_1...
$ age           <dbl> 8, 8, 8, 8, 8, 8, 8, 8, 8, 8, 8, 8, 8, 8, 8, 8, 10, 1...
$ age_cat       <fct> "[6,12]", "[6,12]", "[6,12]", "[6,12]", "[6,12]", "[6...
$ dx            <fct> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,...
$ race_ethnic   <fct> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1,...
$ cog_ability   <dbl> 94, 94, 94, 94, 94, 94, 94, 94, 94, 94, 94, 94, 94, 9...
$ cog_cat       <fct> "(79,110]", "(79,110]", "(79,110]", "(79,110]", "(79,...
$ total_iv_sess <dbl> 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5,...
$ wwc           <fct> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,...
$ tau_u         <dbl> 1.0000, 1.0000, 1.0000, 1.0000, 1.0000, 1.0000, 1.000...
$ session_day   <dbl> 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 13, 17, 22, 25, 28...
$ status        <fct> baseline, baseline, baseline, baseline, baseline, bas...
$ score         <dbl> 4, 1, 5, 4, 5, 4, 7, 7, 7, 8, 7, 8, 8, 7, 7, 8, 3, 3,...
$ max_poss      <dbl> 8, 8, 8, 8, 8, 8, 8, 8, 8, 8, 8, 8, 8, 8, 8, 8, 8, 8,...
$ outcome_type  <fct> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,...
$ score_per     <dbl> 0.500, 0.125, 0.625, 0.500, 0.625, 0.500, 0.875, 0.87...
$ num_cor       <dbl> 4, 1, 5, 4, 5, 4, 7, 7, 7, 8, 7, 8, 8, 7, 7, 8, 3, 3,...
$ num_inc       <dbl> 4, 7, 3, 4, 3, 4, 1, 1, 1, 0, 1, 0, 0, 1, 1, 0, 5, 5,...
```

1.2.3 Reduce

Excluded:

- Study 5: repeating A-B (excluded entirely)
- Study 7: A-B-A-B-C (use only first cycle)
- Study 11:
- Study 12: exclude participants without ASD

```
data_mod <- data_clean %>%
  dplyr::mutate(wwc = factor(wwc,
                             levels = c(0, 1),
                             labels = c("met with reservations",
                                        "met"))) %>%
  dplyr::filter(study != "5") %>%
  dplyr::filter(study != "7" | (study == "7" & session_day <=8)) %>%
  dplyr::filter(study != "11") %>%
  dplyr::filter(!personID %in% c("12_1", "12_2")) %>%
  dplyr::filter(status %in% c("baseline", "intervention")) %>%
  dplyr::group_by(personID) %>%
  dplyr::mutate(phaseA = ifelse(status == "baseline", session_day, 0)) %>%
  dplyr::mutate(lastA = max(phaseA)) %>%
  dplyr::ungroup() %>%
  dplyr::mutate(time = session_day - lastA) %>%
  dplyr::mutate(time1 = ifelse(time < 0, time, 0),
                time2 = ifelse(time > 0, time, 0))

tibble::glimpse(data_mod)
```

```
Rows: 694
Columns: 25
$ study         <fct> 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,...
$ id            <fct> 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2, 2, 2, 2, 2, 2, 2,...
$ personID      <fct> 1_1, 1_1, 1_1, 1_1, 1_1, 1_1, 1_1, 1_1, 1_1, 1_1, 1_1...
$ age           <dbl> 8, 8, 8, 8, 8, 8, 8, 8, 8, 8, 8, 10, 10, 10, 10, 10, ...
$ age_cat       <fct> "[6,12]", "[6,12]", "[6,12]", "[6,12]", "[6,12]", "[6...
$ dx            <fct> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,...
$ race_ethnic   <fct> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1,...
$ cog_ability   <dbl> 94, 94, 94, 94, 94, 94, 94, 94, 94, 94, 94, 67, 67, 6...
$ cog_cat       <fct> "(79,110]", "(79,110]", "(79,110]", "(79,110]", "(79,...
$ total_iv_sess <dbl> 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5,...
$ wwc           <fct> met with reservations, met with reservations, met wit...
$ tau_u         <dbl> 1.0000, 1.0000, 1.0000, 1.0000, 1.0000, 1.0000, 1.000...
$ session_day   <dbl> 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 3, 4, 5, 6, 7, 8, ...
$ status        <fct> baseline, baseline, baseline, baseline, baseline, bas...
$ score         <dbl> 4, 1, 5, 4, 5, 4, 7, 7, 7, 8, 7, 3, 3, 3, 2, 4, 2, 2,...
$ max_poss      <dbl> 8, 8, 8, 8, 8, 8, 8, 8, 8, 8, 8, 8, 8, 8, 8, 8, 8, 8,...
$ outcome_type  <fct> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,...
$ score_per     <dbl> 0.500, 0.125, 0.625, 0.500, 0.625, 0.500, 0.875, 0.87...
$ num_cor       <dbl> 4, 1, 5, 4, 5, 4, 7, 7, 7, 8, 7, 3, 3, 3, 2, 4, 2, 2,...
$ num_inc       <dbl> 4, 7, 3, 4, 3, 4, 1, 1, 1, 0, 1, 5, 5, 5, 6, 4, 6, 6,...
$ phaseA        <dbl> 1, 2, 3, 4, 5, 6, 0, 0, 0, 0, 0, 3, 4, 5, 6, 7, 8, 9,...
$ lastA         <dbl> 6, 6, 6, 6, 6, 6, 6, 6, 6, 6, 6, 9, 9, 9, 9, 9, 9, 9,...
$ time          <dbl> -5, -4, -3, -2, -1, 0, 1, 2, 3, 4, 5, -6, -5, -4, -3,...
$ time1         <dbl> -5, -4, -3, -2, -1, 0, 0, 0, 0, 0, 0, -6, -5, -4, -3,...
$ time2         <dbl> 0, 0, 0, 0, 0, 0, 1, 2, 3, 4, 5, 0, 0, 0, 0, 0, 0, 0,...
```

2 Exploratory Data Analysis

2.1 Person-Profile Plots - Raw Data

2.1.1 Study 5: (Solis et. al., 2016) A-B-A-B-A-B-A-B-A

Exclude all time points

```
data_clean %>%
  dplyr::filter(study == "5") %>%
  ggplot(aes(x = session_day,
             y = score_per,
             group = personID)) +
  geom_point(aes(color = status),
             size = 2) +
  geom_line() +
  theme_bw()
```

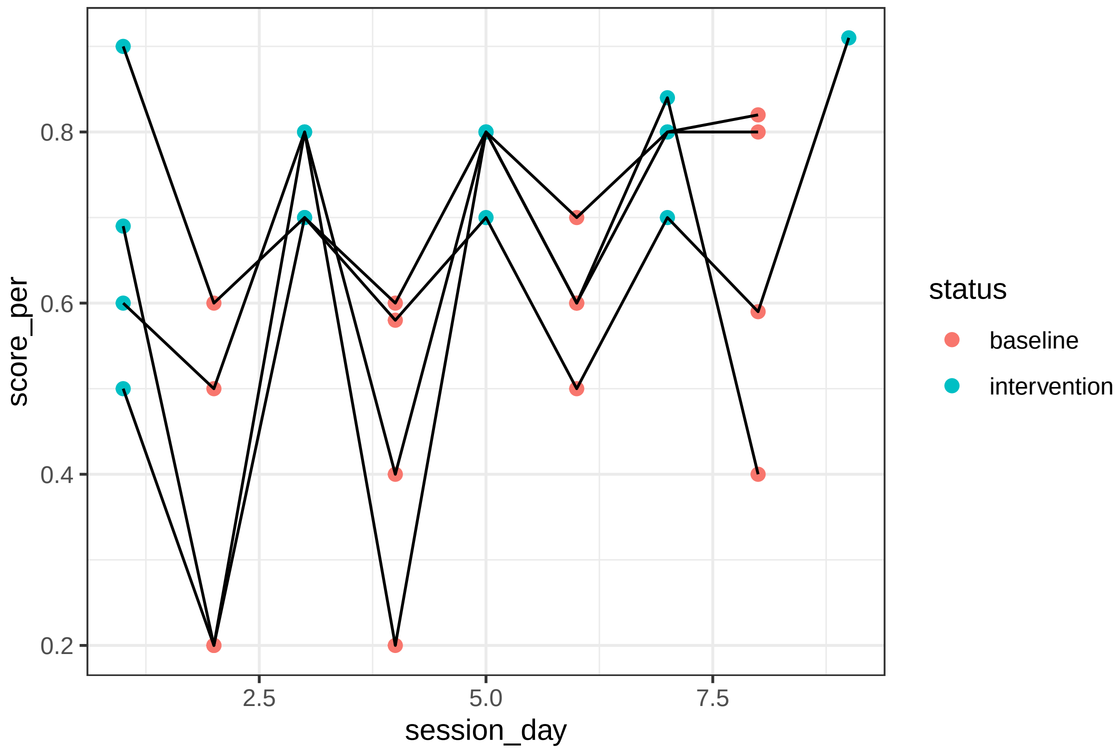

Figure 1: Raw Data: Study 5 only, repeating A-B (excluded entirely)

2.1.2 Study 7: (Carnahan and Williamson, 2014) A-B-A-B-C

Only inlcude the first set of A-B point points

```
data_clean %>%
  dplyr::filter(study == "7") %>%
  ggplot(aes(x = session_day,
             y = score_per,
             group = personID)) +
  geom_point(aes(color = status),
             size = 2) +
  geom_line() +
  theme_bw()
```

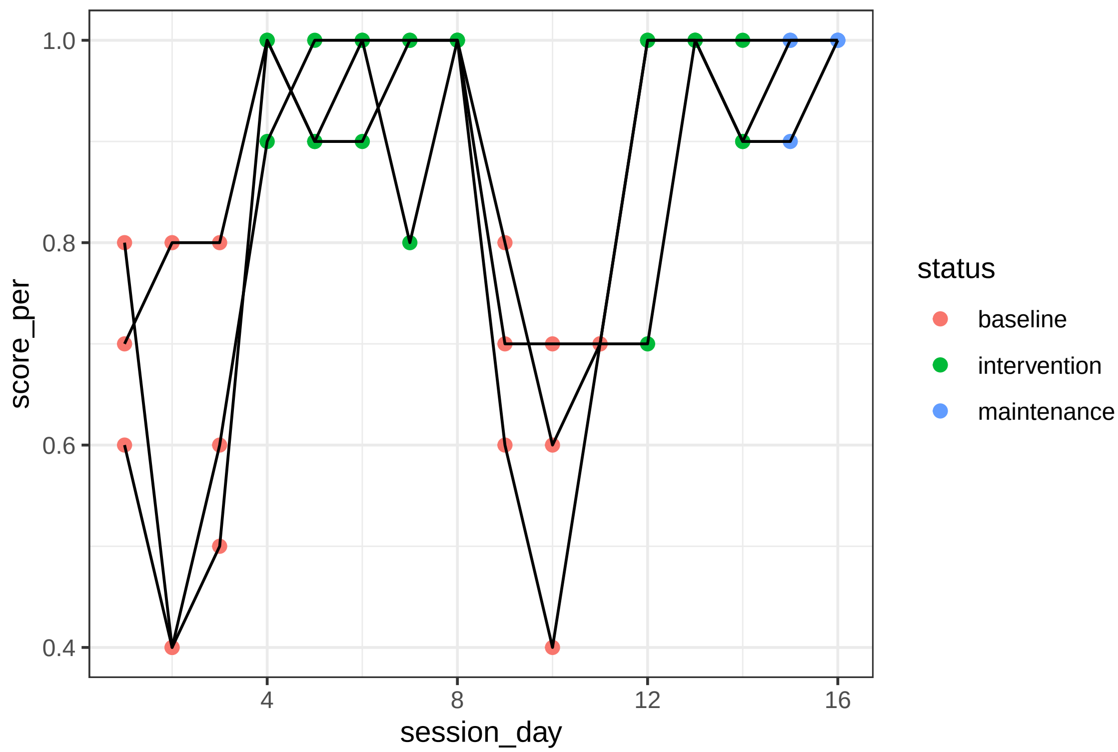

Figure 2: Raw Data: Study 7 only, A-B-A-B-C (use only first cycle)

2.1.3 Study 11: (Cadette, 2015)

Multiple baseline across the same subject

```
data_clean %>%
  dplyr::filter(study == "11") %>%
  ggplot(aes(x = session_day,
             y = score_per,
             group = personID)) +
  geom_point(aes(color = status),
             size = 2) +
  geom_line() +
  theme_bw()
```

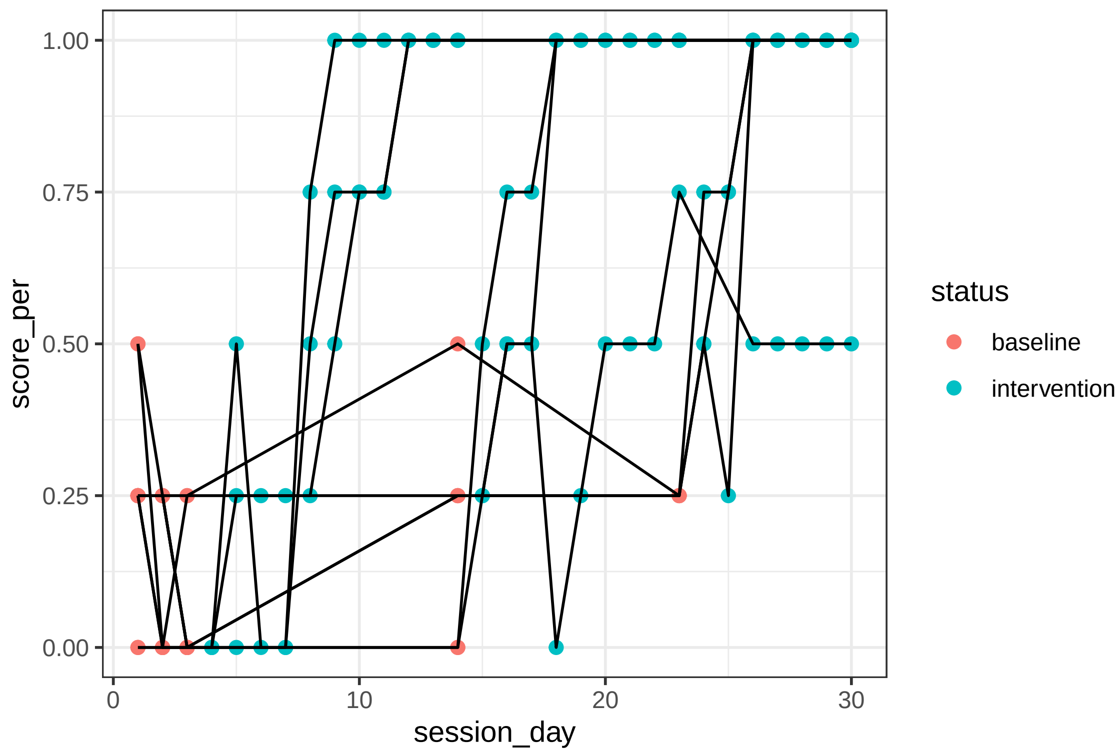

Figure 3: Raw Data: Study 11 only

2.1.4 Study 12: (Chovanes, 2018) only 1 of the 3 participants had an ASD diagnosis

Two of the participants did NOT have an ASD diagnosis.

- No ASD dx: 12_1 and 12_2 (data should not have been entered)
- Has ASD dx: 12_3

```
data_clean %>%
  dplyr::filter(study == "12") %>%
  ggplot(aes(x = session_day,
             y = score_per,
             linetype = personID,
             group = personID)) +
  geom_point(aes(color = status),
             size = 2) +
  geom_line() +
  theme_bw()
```

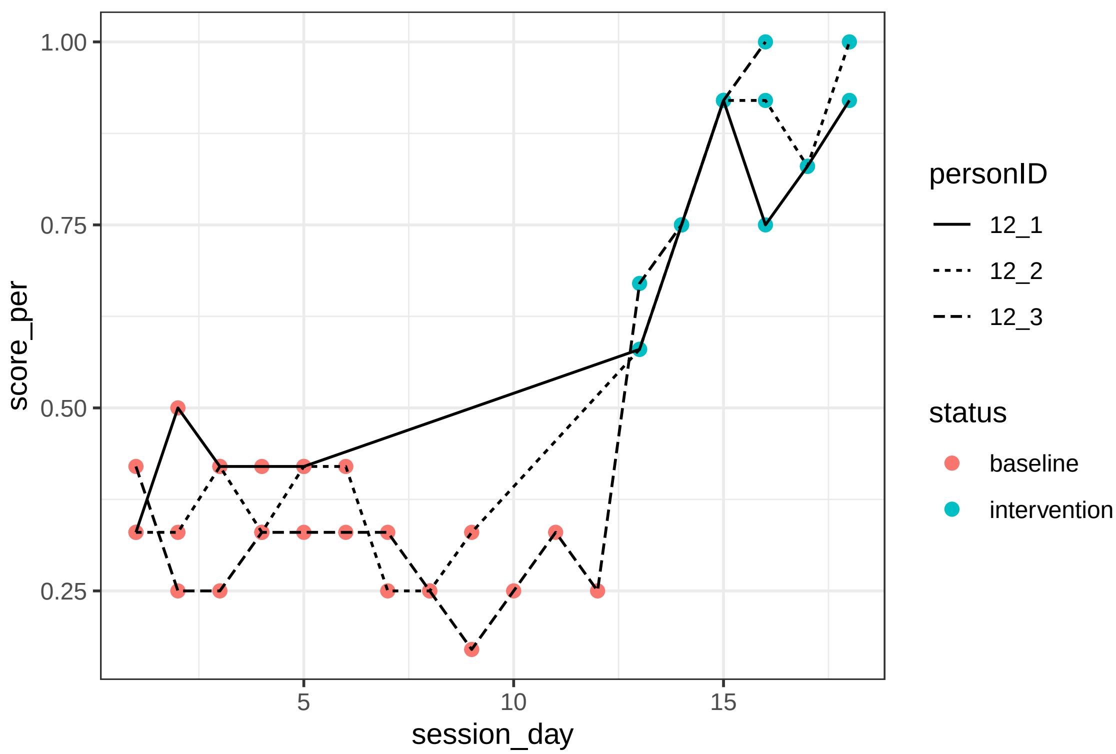

Figure 4: Raw Data: Study 12 only, only 1 of the 3 participants had an ASD diagnosis

2.1.5 All Observations for Modeling

Center time at the last day of baseline.

```
data_mod %>%
  ggplot(aes(x = time,
             y = score_per,
             group = personID)) +
  geom_point() +
  geom_line() +
  geom_vline(xintercept = 0,
             color = "red",
             linetype = "longdash") +
  theme_bw()
```

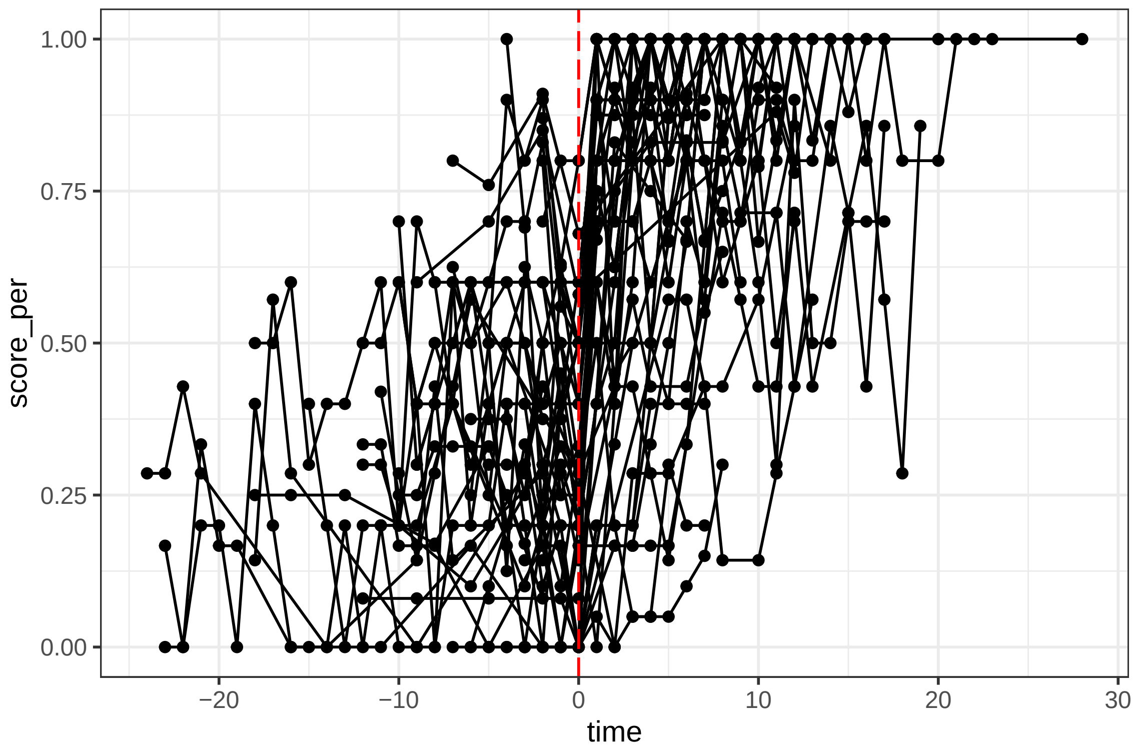

Figure 5: Raw Data: All Studies Baseline-Intervention, time centered at last baseline

2.1.5.1 All Studies Together

```r
data_mod %>%
  ggplot(aes(x = time,
             y = score_per,
             group = personID)) +
  geom_point() +
  geom_line() +
  geom_vline(xintercept = 0,
             color = "red",
             linetype = "longdash") +
  facet_wrap(~ study,
             labeller = label_both,
             nrow = 3) +
  theme_bw()
```

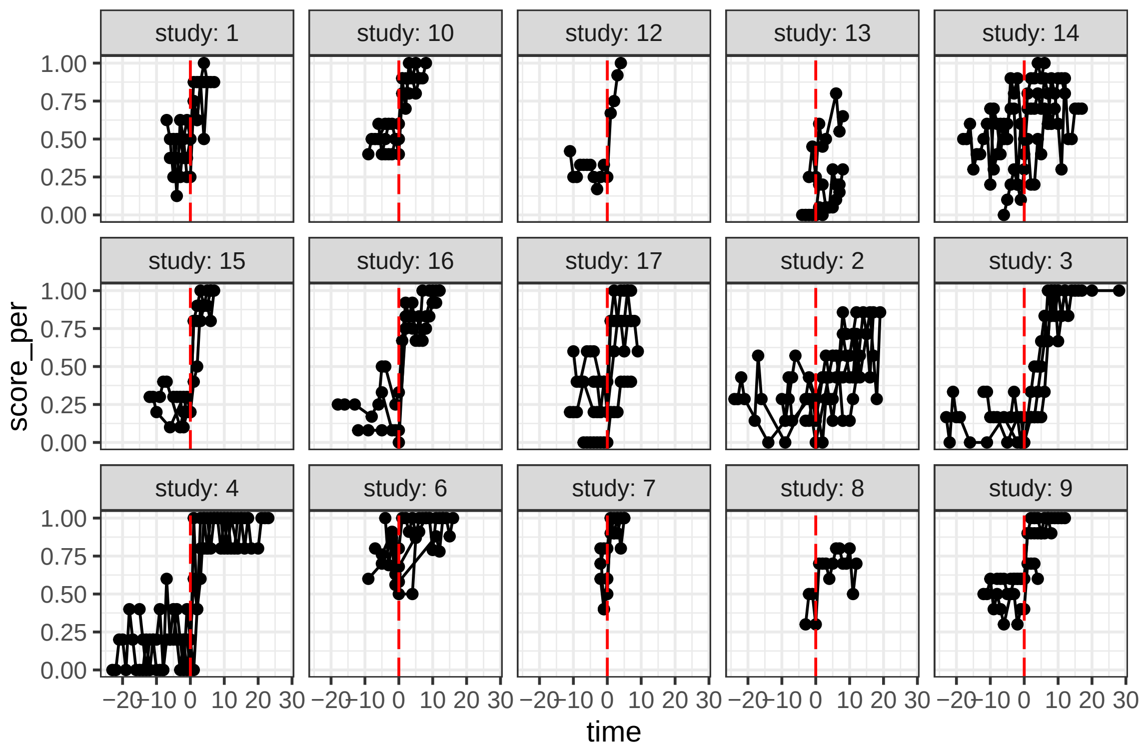

Figure 6: Raw Data: All Studies Baseline-Intervention, time centered at last baseline, BY STUDY

2.1.5.2 Panel by Study

2.2 Person-Profile Plots - Loess Smoothed

Loess = moving window smoothing function

Used to get an idea of what the pattern is like (wrap our brain aroudn the situation); not a true "statistical model"

2.2.1 All Observations for Modeling

```
data_mod %>%
  ggplot(aes(x = time,
             y = score_per,
             group = personID,
             color = id)) +
  geom_smooth(se = FALSE) +
  geom_vline(xintercept = 0,
             color = "red",
             linetype = "longdash") +
  facet_wrap(~ study,
             labeller = label_both,
             nrow = 3) +
  theme_bw()
```

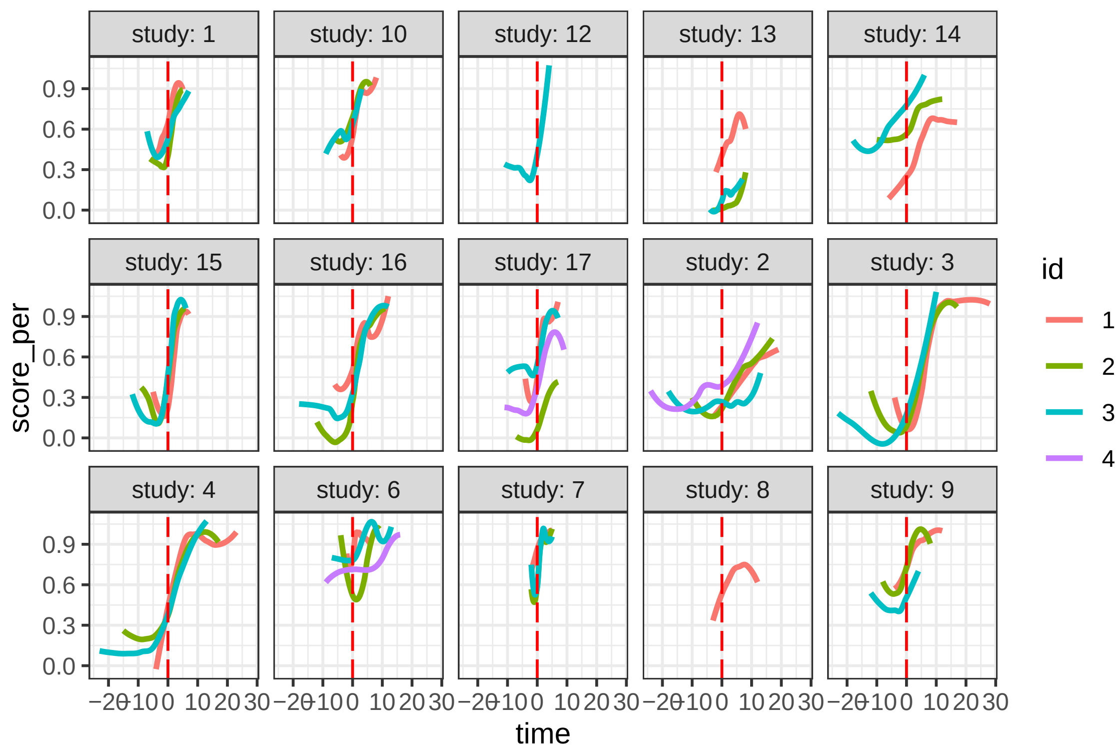

Figure 7: Loess Smoother: Baseline-Intervention, by Study

2.2.1.1 Panel by Study

```r
data_mod %>%
  ggplot(aes(x = time,
             y = score_per,
             group = personID,
             color = personID)) +
  geom_smooth(se = FALSE) +
  geom_vline(xintercept = 0,
             color = "red",
             linetype = "longdash") +
  theme_bw()
```

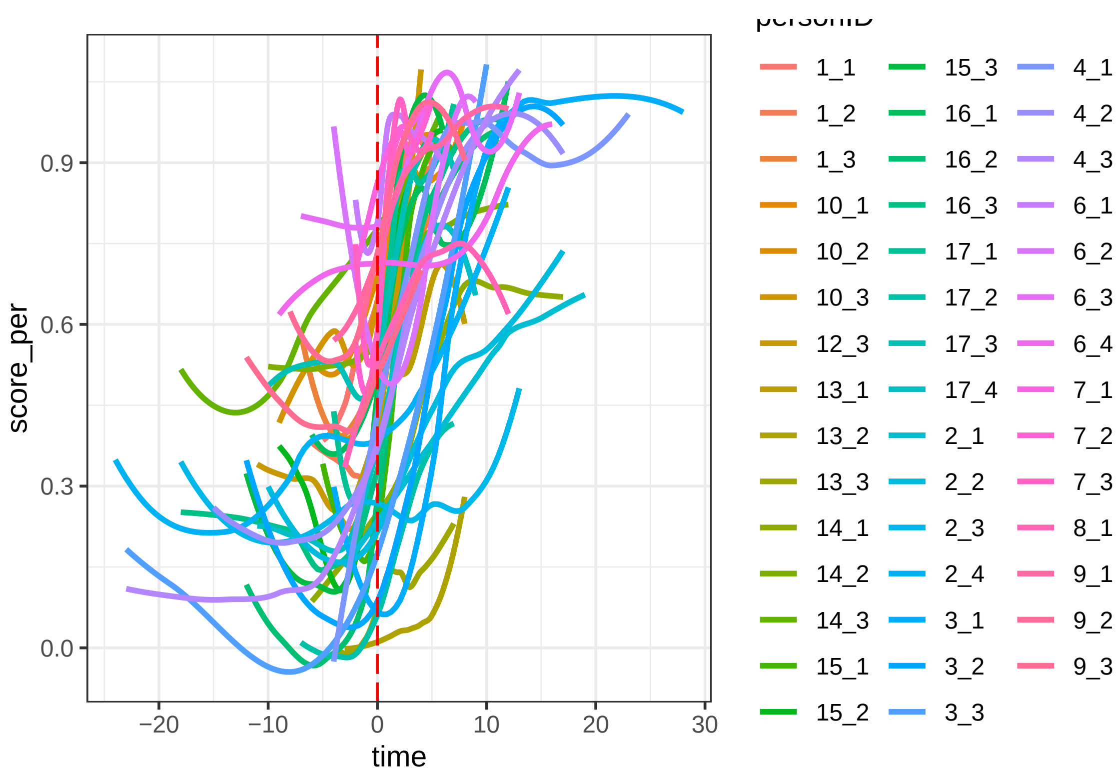

Figure 8: Loess Smoother: Person Profiles, Baseline-Intervention

2.2.1.2 Studies combined

2.3 Person-Profile Plots - Linear Model

This is conduction a linear regression for each participant, independently (ignoring all others), one at a time.

2.3.1 All Observations for Modeling

```r
data_mod %>%
  ggplot(aes(x = time,
             y = score_per,
             group = personID)) +
  geom_smooth(method = "lm",
              se = FALSE) +
  facet_wrap(~ study,
             labeller = label_both,
             nrow = 3) +
  theme_bw()
```

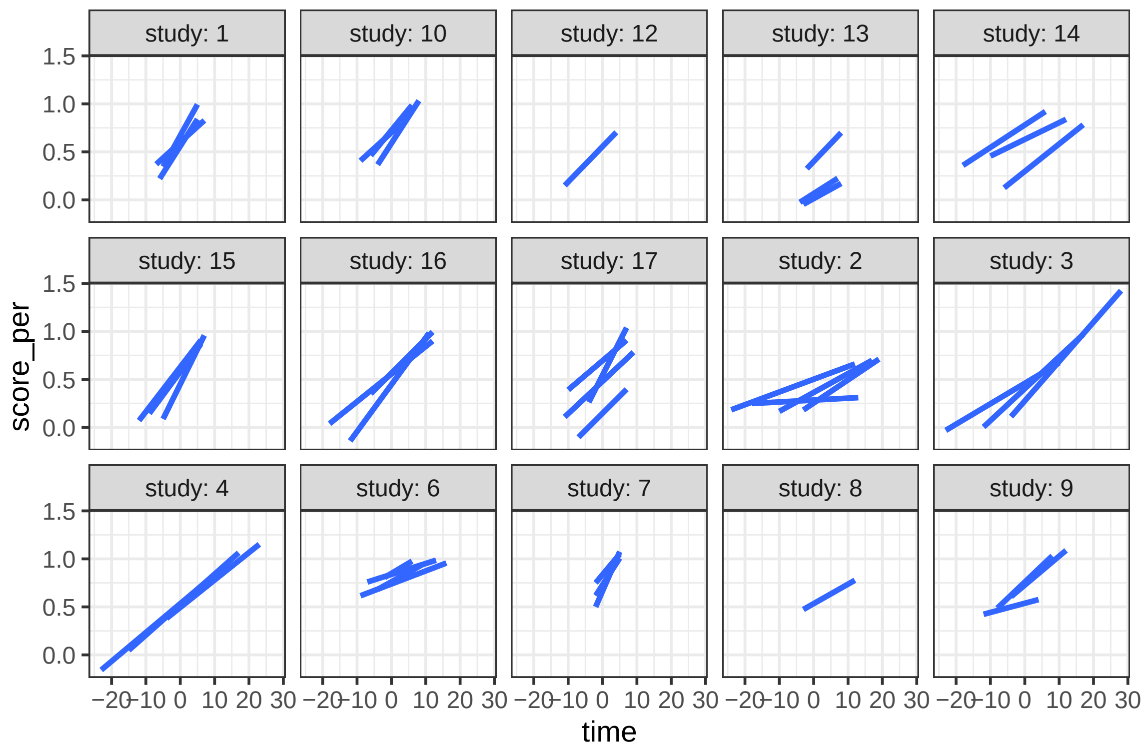

Figure 9: Linear Smoother: Baseline-Intervention, by Study

2.3.1.1 Panel by Study

```r
data_mod %>%
  ggplot(aes(x = time,
             y = score_per,
             group = personID)) +
  geom_smooth(method = "lm",
              se = FALSE) +
  theme_bw()
```

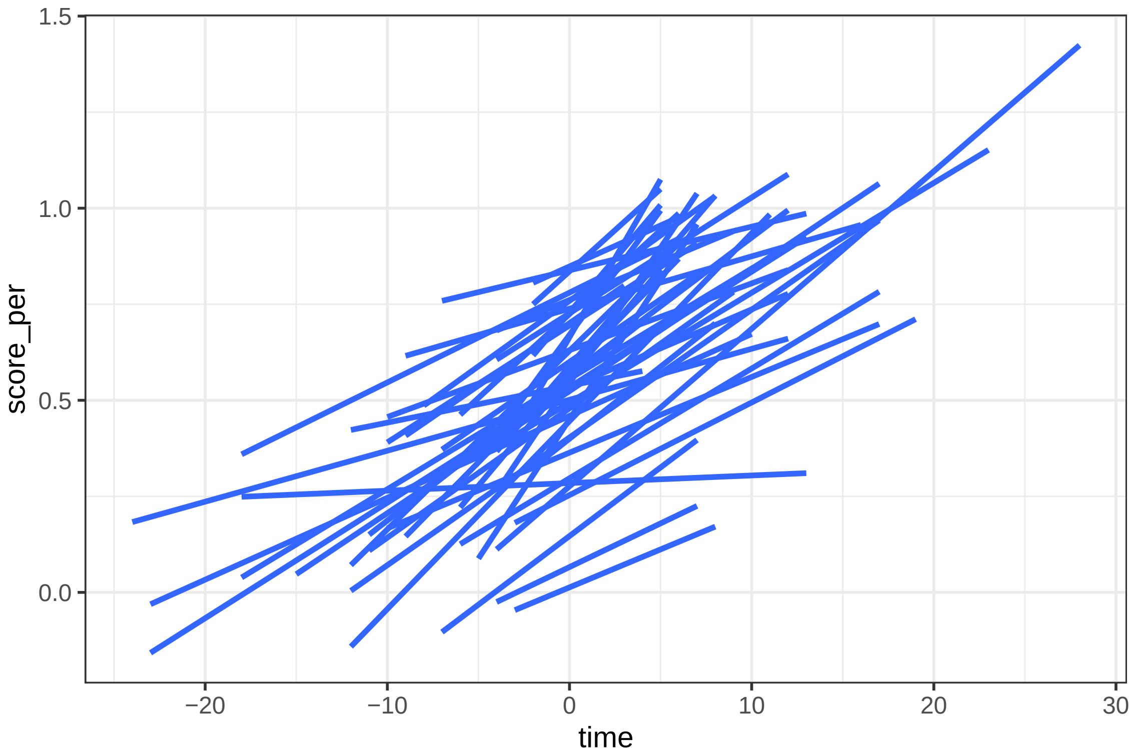

Figure 10: Linear Smoother: Baseline-Intervention

2.3.1.2 Studies combined

3 Genderalized Linear Mixed Effects Model (GLMM)

MULTILEVEL LOGISTIC REGRESSION

Correctly models the response, such that:

(a) each question is allowed to either be correct or incorrect only
(b) thus restraining the percent correct to be between 0% and 100%

by using a genderalization:

- binormial distribution for response, instead of the normal distribution
- link funtion = logit (log odds ratio), instead of the identity link

3.1 Model 1: Allow for differential slope pre/post intervention onset

Allow the baseline and intervention components to be seperate

3.1.1 Fit Model

```
fit_glmm_1 <- lme4::glmer(cbind(num_cor, num_inc) ~ time*I(time>0)  +
                                     (1| study/personID),
                          data = data_mod,
                          family = binomial(logit))
```

3.1.2 Parameter Esimates

```
texreg::texreg(list(fit_glmm_1),
               custom.model.names = "Beta (SE)",
               caption = "GLMM: Parameter Estimates - Model 1",
               caption.above = TRUE,
               single.row = TRUE,
               float.pos = "bh",
               digits = 4)
```

Table 1: GLMM: Parameter Estimates - Model 1

	Beta (SE)
(Intercept)	-0.8188 $(0.2846)^{**}$
time	0.0269 $(0.0037)^{***}$
time > 0TRUE	1.6959 $(0.0426)^{***}$
time:time > 0TRUE	0.0921 $(0.0063)^{***}$
AIC	8143.7521
BIC	8171.0070
Log Likelihood	-4065.8761
Num. obs.	694
Num. groups: personID:study	44
Num. groups: study	15
Var: personID:study (Intercept)	0.5925
Var: study (Intercept)	0.9728

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

3.1.3 Marginal Plot

```
effects::Effect(focal.predictors = c("time"),
                xlevels = list(time = c(seq(from = min(data_mod$time),
                                            to = 0,
                                            by = 0.5),
                                        seq(from = 1,
                                            to = max(data_mod$time),
                                            by = 0.5))),
                mod = fit_glmm_1) %>%
  data.frame() %>%
  ggplot(aes(x = time,
             y = fit)) +
  geom_line() +
  geom_ribbon(aes(ymin = lower,
                  ymax = upper),
              alpha = .2) +
  geom_ribbon(aes(ymin = fit - se,
                  ymax = fit + se),
              alpha = .2) +
  geom_hline(yintercept = 1, linetype = "dashed") +
  geom_hline(yintercept = .9, linetype = "dashed") +
  geom_vline(xintercept = 0,
             color = "red",
             linetype = "longdash") +
  theme_bw() +
  labs(x = "Number of Session Days (0 = Start of Intervention)",
       y = "Reading Comprehension\nPredicted Probability of Answering Correctly") +
  scale_y_continuous(breaks = c(seq(from = 0, to = 1, by = .25), .9))
```

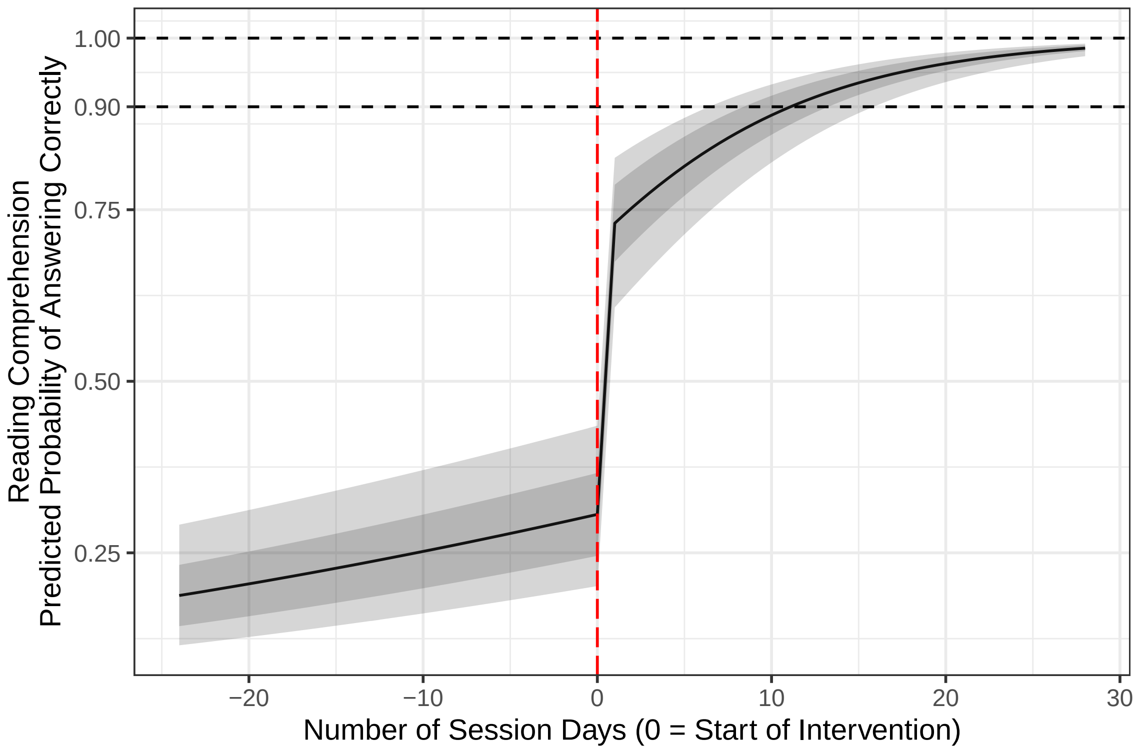

Figure 11: GLMM: Marginal Model - Model 1

3.2 Model 2: Examine Age

Age does in fact moderate slope over time.

3.2.1 Fit Model

```
fit_glmm_2 <- lme4::glmer(cbind(num_cor, num_inc) ~ time*I(time>0)*age_cat +
                                      (1| study/personID),
                          data = data_mod ,
                          family = binomial(logit))
```

3.2.2 Model Fit Comparison

Performed: Likelihood Ratio Test between nested models

Model 2 does in fact fit the data better than model 1.

```
anova(fit_glmm_1, fit_glmm_2)
```

```
Data: data_mod
Models:
fit_glmm_1: cbind(num_cor, num_inc) ~ time * I(time > 0) + (1 | study/personID)
fit_glmm_2: cbind(num_cor, num_inc) ~ time * I(time > 0) * age_cat + (1 |
fit_glmm_2:     study/personID)
           npar    AIC    BIC  logLik deviance Chisq Df Pr(>Chisq)
fit_glmm_1    6 8143.8 8171.0 -4065.9   8131.8
fit_glmm_2   10 7759.7 7805.1 -3869.8   7739.7 392.1  4  < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

3.2.3 Parameter Estimates

```
texreg::texreg(list(fit_glmm_1, fit_glmm_2),
               custom.model.names = c("Model 1", "Model 2"),
               caption = "GLMM: Parameter Estimates - Models 1 and 2",
               caption.above = TRUE,
               single.row = TRUE,
               float.pos = "bh",
               digits = 4)
```

Table 2: GLMM: Parameter Estimates - Models 1 and 2

	Model 1	Model 2
(Intercept)	-0.8188 $(0.2846)^{**}$	-1.2057 $(0.3306)^{***}$
time	0.0269 $(0.0037)^{***}$	0.0243 $(0.0042)^{***}$
time > 0TRUE	1.6959 $(0.0426)^{***}$	1.7819 $(0.0583)^{***}$
time:time > 0TRUE	0.0921 $(0.0063)^{***}$	0.1436 $(0.0084)^{***}$
age_cat(12,18]		0.7866 (0.4753)
time:age_cat(12,18]		-0.0370 $(0.0098)^{***}$
time > 0TRUE:age_cat(12,18]		-0.1347 (0.0874)
time:time > 0TRUE:age_cat(12,18]		-0.0867 $(0.0143)^{***}$
AIC	8143.7521	7759.6562
BIC	8171.0070	7805.0810
Log Likelihood	-4065.8761	-3869.8281
Num. obs.	694	694
Num. groups: personID:study	44	44
Num. groups: study	15	15
Var: personID:study (Intercept)	0.5925	0.6254
Var: study (Intercept)	0.9728	0.9282

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

3.2.4 Marginal Plot

```
effects::Effect(focal.predictors = c("time", "age_cat"),
                xlevels = list(time = seq(from = min(data_mod$time),
                                           to = max(data_mod$time),
                                           by = 0.5)),
                mod = fit_glmm_2) %>%
  data.frame() %>%
  dplyr::filter((age_cat == "(12,18]" & time < 17) |
                (age_cat == "[6,12]" )) %>%
  ggplot(aes(x = time,
             y = fit)) +
  geom_line(aes(color = age_cat),
            size = 0.75) +
  geom_ribbon(aes(ymin = lower,
                  ymax = upper,
                  fill = age_cat),
              alpha = .2) +
  geom_ribbon(aes(ymin = fit - se,
                  ymax = fit + se,
                  fill = age_cat),
              alpha = .3) +
  geom_hline(yintercept = 1, linetype = "dashed") +
  geom_hline(yintercept = .9, linetype = "dashed") +
  geom_vline(xintercept = 0,
             color = "red",
             linetype = "longdash") +
  theme_bw() +
  labs(x = "Number of Session Days (0 = Start of Intervention)",
       y = "Reading Comprehension\nPredicted Probability of Answering Correctly") +
  scale_y_continuous(breaks = c(seq(from = 0, to = 1, by = .25), .9)) +
  theme(legend.position = c(1, 0),
        legend.background = element_rect(color = "black"),
        legend.justification = c(1.1, -0.1))
```

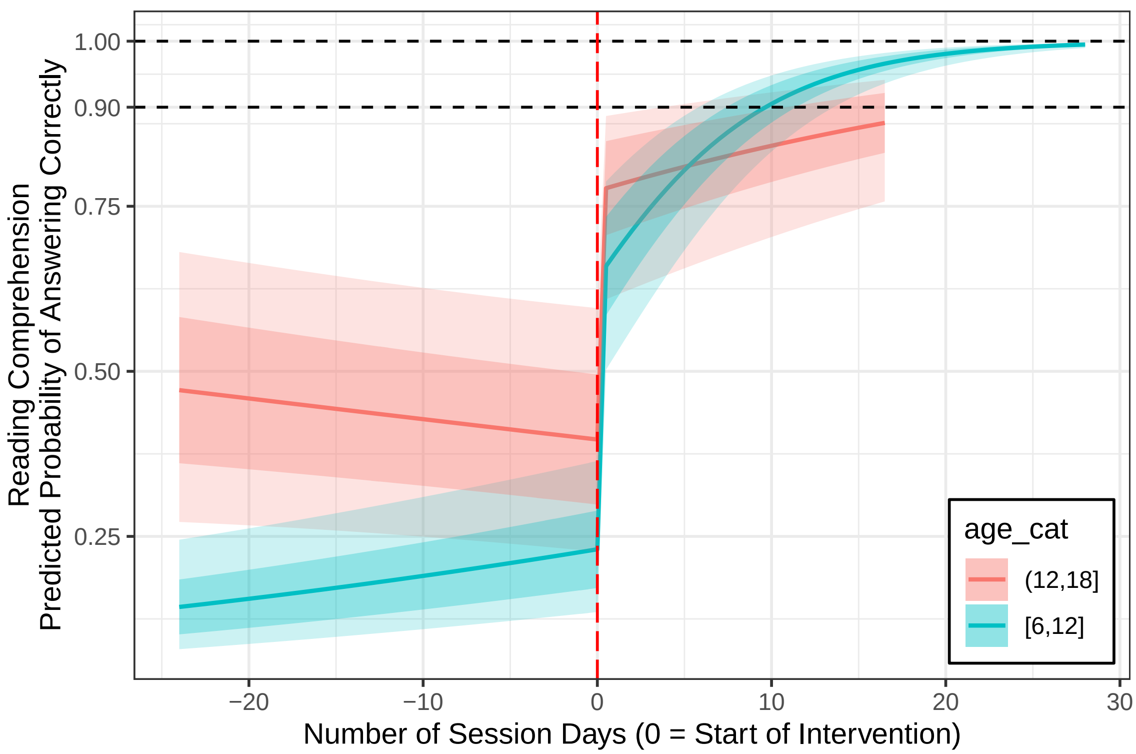

Figure 12: GLMM - Logistic Spline, Age Moderator: Marginal Model

3.3 Model 3: Examine "What Works Clearinghouse" (wwc)

This covariate is NOT significant.

3.3.1 Fit Model

Note: model 2 is re-run on the subset of participants for which the `wwc` variable is know.

```
fit_glmm_3 <- lme4::glmer(cbind(num_cor, num_inc) ~ time*I(time>0)*age_cat + wwc +
                                       (1| study/personID),
                          data = data_mod ,
                          family = binomial(logit))
```

3.3.2 Model Fit Comparison

Performed: Likelihood Ratio Test between nested models

Model 3 does NOT fit better than Model 2.

```
anova(fit_glmm_2, fit_glmm_3)
```

```
Data: data_mod
Models:
fit_glmm_2: cbind(num_cor, num_inc) ~ time * I(time > 0) * age_cat + (1 |
fit_glmm_2:     study/personID)
fit_glmm_3: cbind(num_cor, num_inc) ~ time * I(time > 0) * age_cat + wwc +
fit_glmm_3:     (1 | study/personID)
           npar    AIC    BIC  logLik deviance Chisq Df Pr(>Chisq)
fit_glmm_2   10 7759.7 7805.1 -3869.8   7739.7
fit_glmm_3   11 7759.2 7809.1 -3868.6   7737.2 2.482  1     0.1152
```

3.3.3 Parameter Estimates

```
texreg::texreg(list(fit_glmm_2, fit_glmm_3),
               custom.model.names = c("Model 2", "Model 3"),
               caption = "GLMM: Parameter Estimates - Models 2 and 3",
               caption.above = TRUE,
               single.row = TRUE,
               float.pos = "bh",
               digits = 4)
```

Table 3: GLMM: Parameter Estimates - Models 2 and 3

	Model 2	Model 3
(Intercept)	$-1.2057\ (0.3306)^{***}$	$-1.4942\ (0.3554)^{***}$
time	$0.0243\ (0.0042)^{***}$	$0.0243\ (0.0042)^{***}$
time > 0TRUE	$1.7819\ (0.0583)^{***}$	$1.7825\ (0.0583)^{***}$
age_cat(12,18]	0.7866 (0.4753)	0.5088 (0.4835)
time:time > 0TRUE	$0.1436\ (0.0084)^{***}$	$0.1434\ (0.0084)^{***}$
time:age_cat(12,18]	$-0.0370\ (0.0098)^{***}$	$-0.0372\ (0.0098)^{***}$
time > 0TRUE:age_cat(12,18]	−0.1347 (0.0874)	−0.1348 (0.0874)
time:time > 0TRUE:age_cat(12,18]	$-0.0867\ (0.0143)^{***}$	$-0.0863\ (0.0143)^{***}$
wwcmet		0.9360 (0.5790)
AIC	7759.6562	7759.1742
BIC	7805.0810	7809.1414
Log Likelihood	−3869.8281	−3868.5871
Num. obs.	694	694
Num. groups: personID:study	44	44
Num. groups: study	15	15
Var: personID:study (Intercept)	0.6254	0.6096
Var: study (Intercept)	0.9282	0.7948

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

3.4 Final Model = Model 2

3.4.1 Parameter Estimates

```r
texreg::texreg(list(fit_glmm_2),
               custom.model.names = c("Beta(SE)"),
               caption = "GLMM: Parameter Estimates - Models 2, raw betas",
               caption.above = TRUE,
               single.row = TRUE,
               float.pos = "bh",
               digits = 4)
```

Table 4: GLMM: Parameter Estimates - Models 2, raw betas

	Beta(SE)
(Intercept)	-1.2057 (0.3306)***
time	0.0243 (0.0042)***
time > 0TRUE	1.7819 (0.0583)***
age_cat(12,18]	0.7866 (0.4753)
time:time > 0TRUE	0.1436 (0.0084)***
time:age_cat(12,18]	-0.0370 (0.0098)***
time > 0TRUE:age_cat(12,18]	-0.1347 (0.0874)
time:time > 0TRUE:age_cat(12,18]	-0.0867 (0.0143)***
AIC	7759.6562
BIC	7805.0810
Log Likelihood	-3869.8281
Num. obs.	694
Num. groups: personID:study	44
Num. groups: study	15
Var: personID:study (Intercept)	0.6254
Var: study (Intercept)	0.9282

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

```r
texreg::texreg(list(extract_glmer_exp(fit_glmm_2)),
               custom.model.names = c("exp(Beta) = OR [95 CI]"),
               caption = "GLMM: Parameter Estimates - Models 2, exponentiated to ORs",
               caption.above = TRUE,
               ci.test = 1,
               single.row = TRUE,
               float.pos = "bh",
               digits = 4)
```

Table 5: GLMM: Parameter Estimates - Models 2, exponentiated to ORs

	exp(Beta) = OR [95 CI]
(Intercept)	0.2995 [0.1556; 0.5763]*
time	1.0246 [1.0162; 1.0332]*
time > 0TRUE	5.9413 [5.2938; 6.6680]*
age_cat(12,18]	2.1959 [0.8568; 5.6278]
time:time > 0TRUE	1.1544 [1.1353; 1.1739]*
time:age_cat(12,18]	0.9636 [0.9452; 0.9825]*
time > 0TRUE:age_cat(12,18]	0.8740 [0.7352; 1.0390]
time:time > 0TRUE:age_cat(12,18]	0.9170 [0.8915; 0.9432]*
AIC	7759.6562
BIC	7805.0810
Log Likelihood	−3869.8281
Num. obs.	694
Num. groups: personID:study	44
Num. groups: study	15
Var: personID:study (Intercept)	0.6254
Var: study (Intercept)	0.9282

* 1 outside the confidence interval.

3.4.2 Predicted Probablities

```
effects::Effect(focal.predictors = c("time", "age_cat"),
                xlevels = list(time = c(-15, -10, -5, 0, 5, 10, 15)),
                mod = fit_glmm_2) %>%
  data.frame() %>%
  dplyr::select(time, age_cat, fit) %>%
  tidyr::spread(key = time,
                value = fit) %>%
  pander::pander(caption = "GLMM: Estimated Marginal Probabilities - Model 2")
```

Table 6: GLMM: Estimated Marginal Probabilities - Model 2

age_cat	-15	-10	-5	0	5	10	15
(12,18]	0.4431	0.4275	0.412	0.3967	0.8099	0.8416	0.8689
[6,12]	0.1721	0.1902	0.2096	0.2305	0.8047	0.9051	0.9567

3.4.3 Marginal Plot

```
effects::Effect(focal.predictors = c("time", "age_cat"),
                xlevels = list(time = seq(from = min(data_mod$time),
                                           to = max(data_mod$time),
                                           by = 0.5)),
                mod = fit_glmm_2) %>%
  data.frame() %>%
  dplyr::mutate(age_cat = forcats::fct_rev(age_cat)) %>%
  dplyr::filter((age_cat == "(12,18]" & time < 17) |
                (age_cat == "[6,12]" )) %>%
  dplyr::mutate(age_cat = fct_recode(age_cat,
                                     "Age 12 and Under" = "[6,12]",
                                     "Over Age 12" = "(12,18]")) %>%
  ggplot(aes(x = time,
             y = fit)) +
  geom_ribbon(aes(ymin = lower,
                  ymax = upper),
              fill = "gray50",
              alpha = .4) +
  geom_line(size = .75) +
  geom_hline(yintercept = 1, linetype = "dashed") +
  geom_hline(yintercept = 0.9, linetype = "dashed") +
  geom_vline(xintercept = 0) +
  theme_bw() +
  labs(x = "Session Number (0 = End of Baseline)",
       y = "Reading Comprehension\nPredicted Proportion Answered Correctly",
       fill = NULL) +
  facet_grid(. ~ age_cat, scale = "free_x", space = "free_x") +
  scale_y_continuous(breaks = c(seq(from = 0, to = 1, by = .20))) +
  scale_x_continuous(breaks = c(seq(from = -30, to = +30, by = 10))) +
  annotate("text", x =  - 9, y = .075, label = "Baseline") +
  annotate("text", x =   10, y = .075, label = "Intervention")  +
  geom_text(data = data.frame(time = -20,
                              fit = .95,
                              age = "Age 12 and Under"),
            label = "Goal")
```

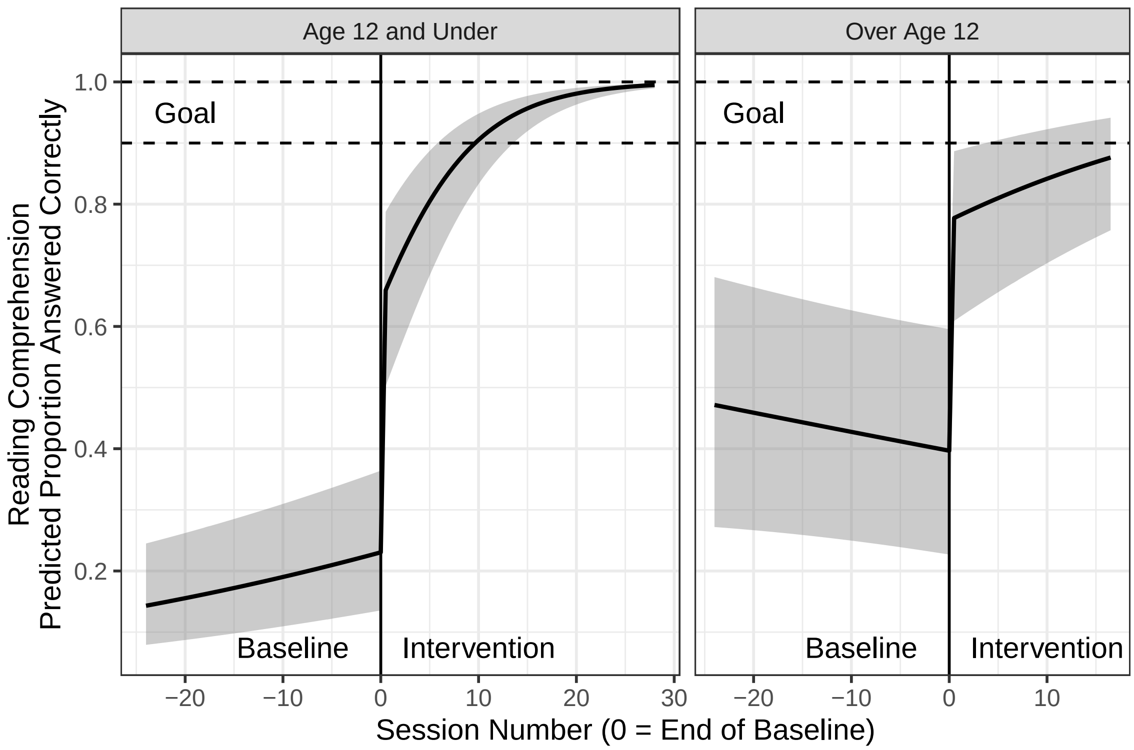

Figure 13: GLMM - Logistic Spline, Age Moderator: Marginal Model