Daily Life Sampling Workshop

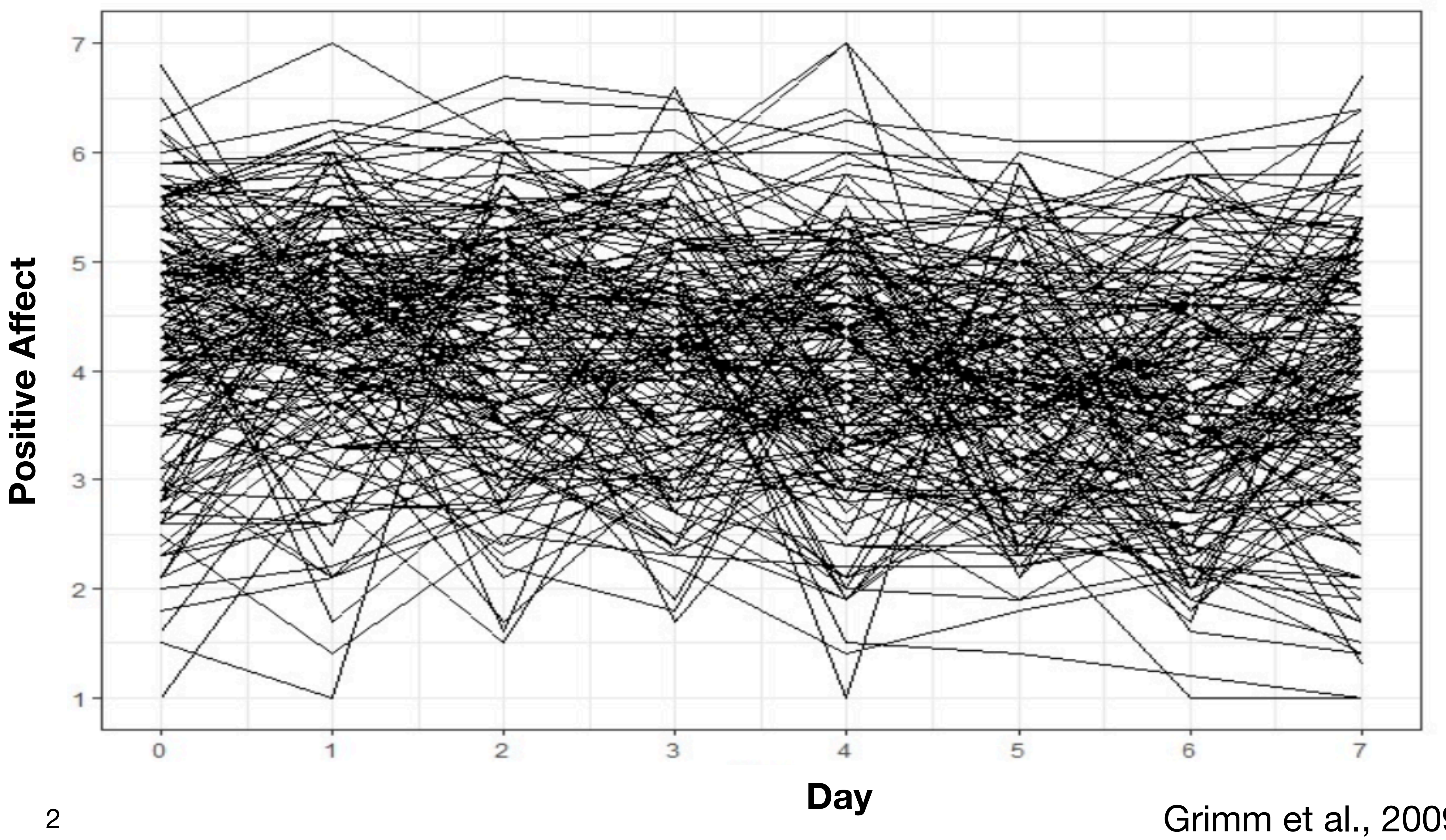
Analyzing Intensive Longitudinal Data — Multilevel Modeling

10.6.25

Structure of Intensive Longitudinal Data

- Repeated measurements within individuals across short time intervals (e.g., hours, days)

- Complex data structures and relationships



Grimm et al., 2009

Common Analytic Approaches

- Multilevel modeling (MLM)
  - Bayesian MLMs
- Structural Equation Modeling (SEM)
  - Growth curve modeling
- Dynamic modeling
- Group Iterative Multiple Model Estimation [GIMME]
- And more!

Multilevel Modeling: Basics

- Standard regression model

$$Y_i = \beta_0 + \beta_1 X_1 + e_i$$

- This model assumes that all data points are independent of each other
  - Failing to distinguish observations that are non-independent violates the standard regression model
  - Intensive longitudinal data contains many observations nested within individuals — necessitates different modeling technique

Multilevel Modeling: Basics

- Multilevel models enable the estimation of processes at both the within- (level 1) and between-person levels (level 2)
- Level 1: most granular observation (e.g., sampling occasion in EMA protocol)

$$Y_{ij} = \beta_{0j} + e_{ij}$$

Residual error term

Observed variable at time (i) in individual (j)

Intercept for individual (j)

Multilevel Modeling: Basics

- Level 2: Between-person

$$\beta_{0j} = \gamma_{00} + U_{0j}$$

Intercept for individual (j)

Group average

Residual term specific to deviation around intercept [random effect]

- Putting it all together

$$Y_{ij} = \gamma_{00} + U_{0j} + e_{ij}$$

An Aside: Getting Acquainted with R

- In addition to lme4 (MLMs), we will use the tidyverse and easy stats ecosystems
  - Lme4 syntax: DV ~ IV + (1 + IV | Individual)

Modeling Daily Life Data: Unconditional Model

- Running an unconditional model enables the quantification of the amount of variance attributable to between vs. within person sources

```
#unconditional model of positive affect
m.pos.affect.null<- lmer(data = d.EMA, pos.affect ~ 1 + (1|subID))
summary(m.pos.affect.null)
```

- From this model, we extract the ICC (intraclass correlation coefficient)
- ICC = between-person variance/total variance
    - ICC = 0.6 => 60% of the variance is explained between-person, 40% within

Multilevel Modeling: Fixed Effects

- Adding in a time-varying predictor
- Level 1: $Y_{ij} = \beta_{0j} + \beta_{1j}X_{ij} + e_{ij}$
- Level 2: $\beta_{0j} = \boxed{\gamma_{00}} + \boxed{U_{0j}}$ **Random Effect**

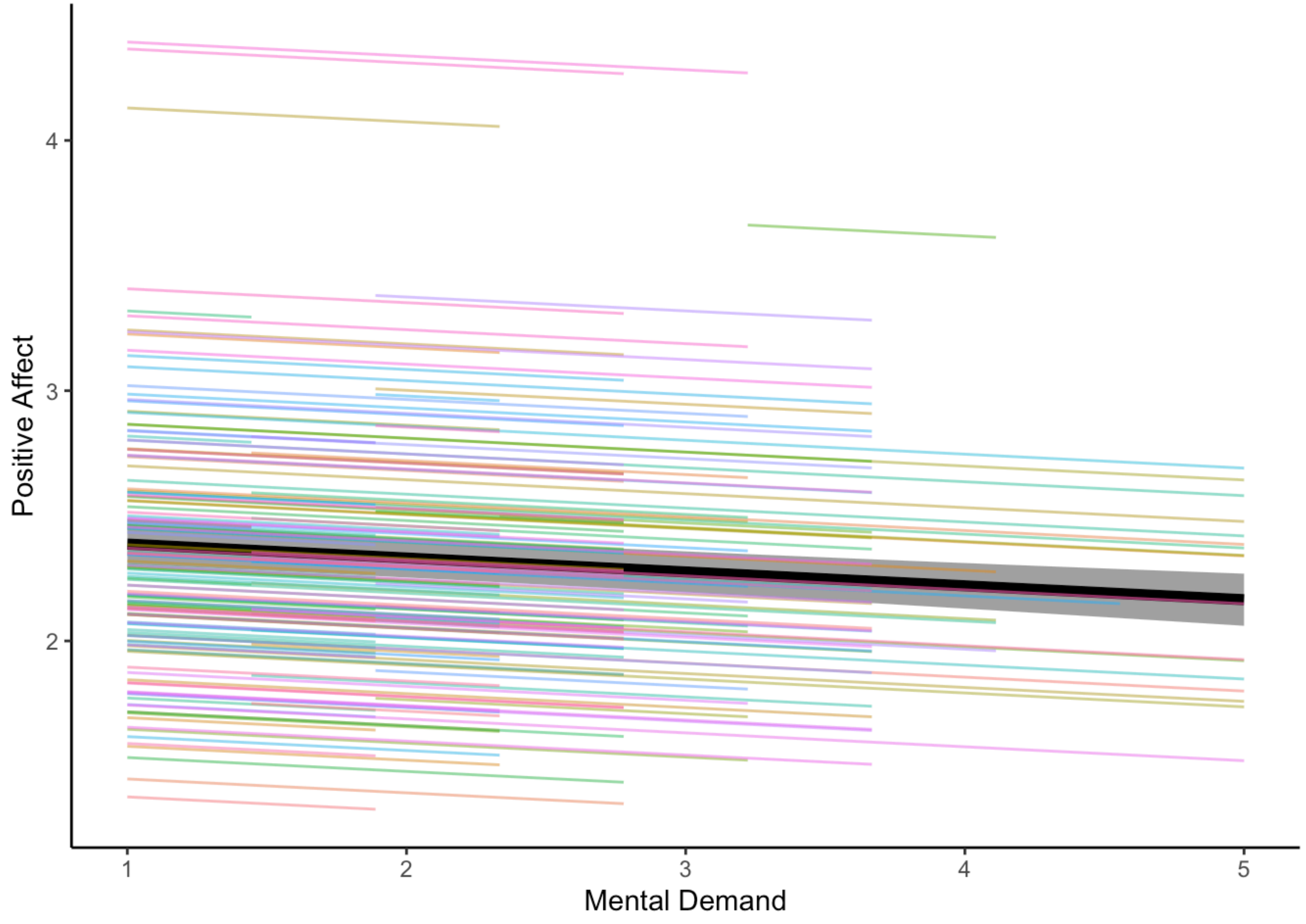
  $\beta_{1j} = \boxed{\gamma_{10}}$

  Fixed Effects

- Translated to lme4 syntax [tutorial]: pos.affect ~ **mean.demand** + (**1** | subID)

Multilevel Modeling: Fixed Effects

- What does this look like?



Multilevel Modeling: Fixed Effects

- Interpreting the model output

Intercept: Value of positive affect for a prototypical person on a prototypical day

Mental Demand: Positive affect decreased with a one-unit increase in mental demand in daily life

Intercept: Extent of inter-individual differences in the intercept

Residual: Residual error variance

```
## Linear mixed model fit by REML ['lmerMod']
## Formula: pos.affect ~ mean.demand + (1 | subID)
##    Data: d.EMA
##
## REML criterion at convergence: 4043.9
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -3.5945 -0.5743 -0.0061  0.5212  6.2847
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  subID    (Intercept) 0.2692   0.5188
##  Residual             0.1752   0.4185
## Number of obs: 3146, groups:  subID, 178
##
## Fixed effects:
##             Estimate Std. Error t value
## (Intercept)  2.44263    0.04488  54.427
## mean.demand -0.05558    0.01123  -4.947
##
## Correlation of Fixed Effects:
##             (Intr)
## mean.demand -0.466
```

Multilevel Modeling: Random Effects

- Adding in a time-varying predictor
- Level 1: $Y_{ij} = \beta_{0j} + \beta_{1j}X_{ij} + e_{ij}$
- Level 2: $$\beta_{0j} = \boxed{\gamma_{00}} + \boxed{U_{0j}}$$ $$\beta_{1j} = \boxed{\gamma_{10}} + \boxed{U_{1j}}$$

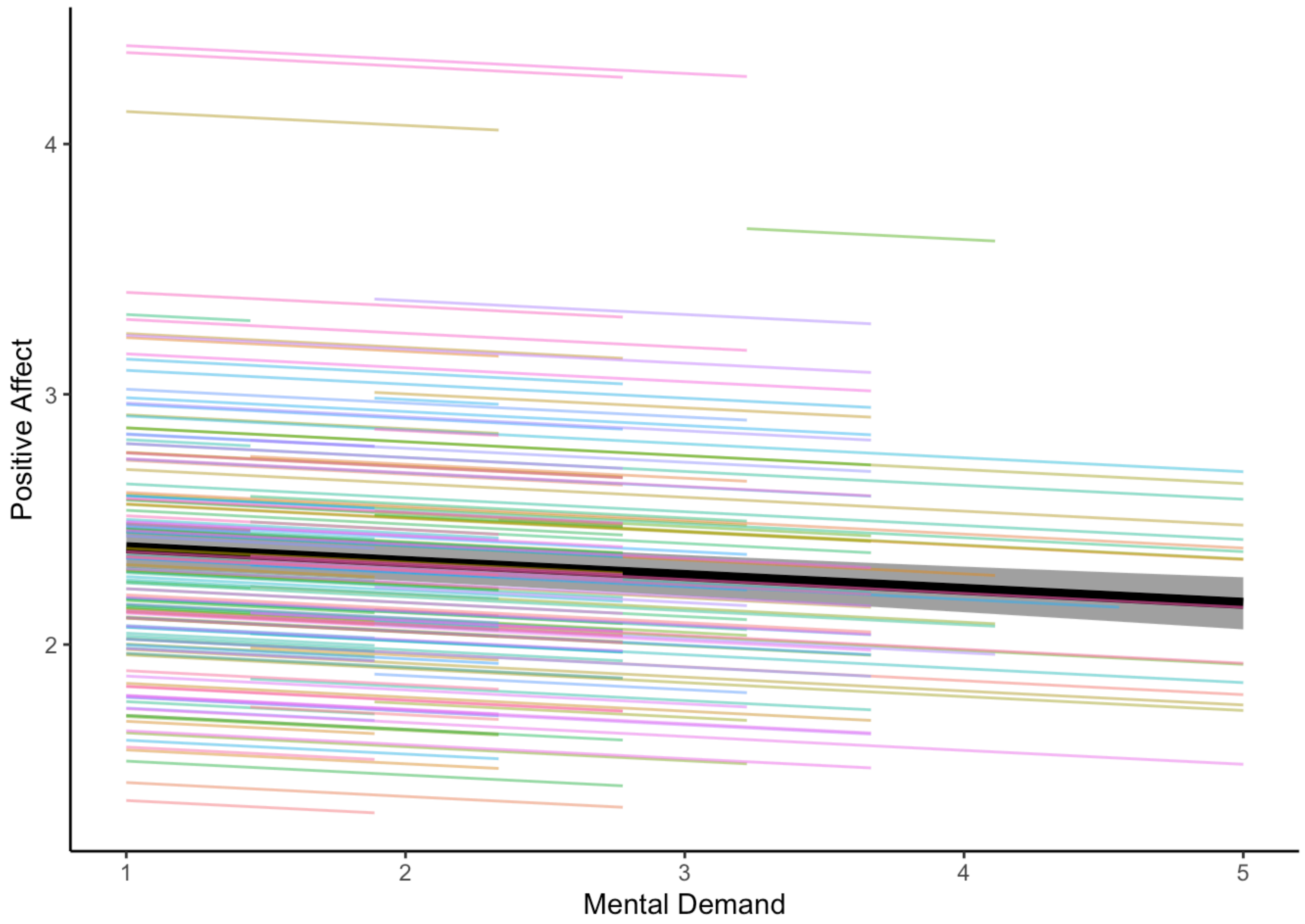
Random Effects

Fixed Effects

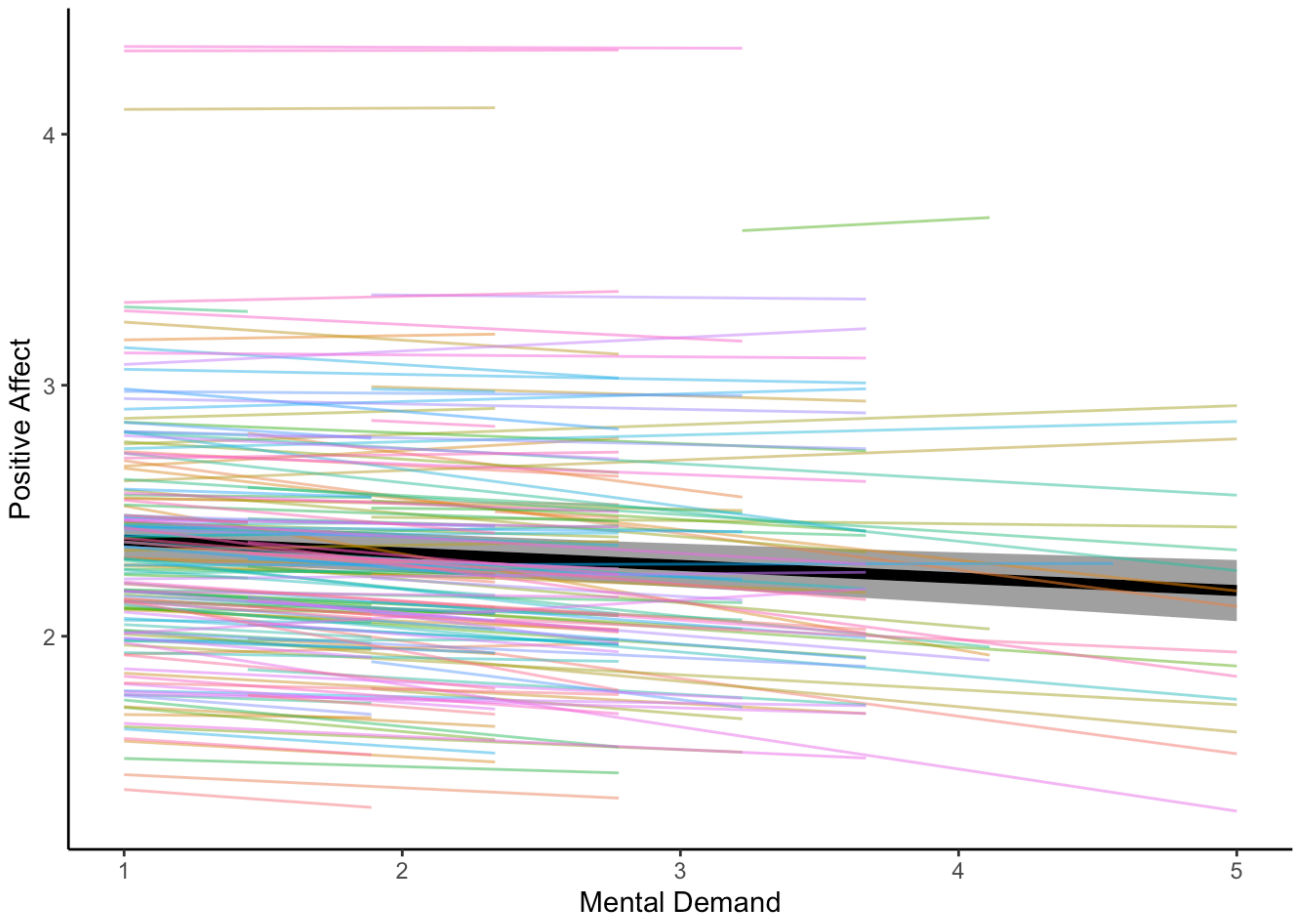
- Translated to lme4 syntax [tutorial]: pos.affect ~ **mean.demand** + (**mean.demand** | subID)

Multilevel Modeling: Random Effects

Slope is only fixed



Slope is fixed + random



Multilevel Modeling: Random Effects

- Interpreting the model output

Intercept: Extent of inter-individual differences in the intercept

Mental Demand: Extent of inter-individual differences in the slope for mental demand

Corr: The correlation between the random intercept and slope – people with higher intercepts for positive affect also tended to have shallower slopes

Residual: Residual error variance

```
## Linear mixed model fit by REML ['lmerMod']
## Formula: pos.affect ~ mean.demand + (mean.demand | subID)
##    Data: d.EMA
##
## REML criterion at convergence: 4030.2
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -3.7675 -0.5683 -0.0116  0.5199  6.4699
##
## Random effects:
##  Groups   Name        Variance Std.Dev. Corr
##  subID    (Intercept) 0.261876 0.51174
##           mean.demand 0.008271 0.09094  -0.14
##  Residual             0.171558 0.41420
## Number of obs: 3146, groups:  subID, 178
##
## Fixed effects:
##             Estimate Std. Error t value
## (Intercept)  2.43253    0.04502  54.034
## mean.demand -0.05014    0.01399  -3.585
##
## Correlation of Fixed Effects:
##             (Intr)
## mean.demand -0.486
```

Modeling Daily Life Data: Within-Person Centering

- Partition the predictors into between- and within-person parts

```
#creating a data frame with person-means of daily life mental demand
d.m.demand.sub <- d.EMA %>% select(subID, mean.demand) %>% group_by(subID) %>%
  summarise(mean.demand.avg = mean(mean.demand, na.rm = T))

#merging the person-mean data frame with the EMA data frame
d.EMA.merged <- d.EMA %>% inner_join(d.m.demand.sub, by = "subID") %>%
  mutate(mean.demand.pc = mean.demand - mean.demand.avg) #creating a person-centered variable
```

```
#both within- and between-person effects of mental demand entered into the model
m.pos.affect.demand.pc <- lmer(data = d.EMA.merged, pos.affect ~ mean.demand.pc + mean.demand.avg + (mean.deman
d.pc |subID))
summary(m.pos.affect.demand.pc)
```

Modeling Daily Life Data: Generalized MLM

- An assumption on the MLM is that the dependent variable is normally distributed
  - With easystats, you can use the check_model function to determine if your model violates critical assumptions
- Some data types (e.g., binary outcomes, count variables) are non-normal and necessitate an extension of the MLM — generalized MLM
  - Need to specify a link function when setting up your model in lme4
- For binary outcome data: **glmer**(pos.affect ~ mean.demand + (mean.demand | subID), data=d.frame, **family = "binomial"**)
- For count data: **glmer**(pos.affect ~ mean.demand + (mean.demand | subID), data=d.frame, **family = "poisson"**)