How engagement during out-of-school time STEM programs predicts changes in motivation in STEM

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Abstract

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Introduction

Literature Review

Out-of-school time STEM programs

Out-of-school time (OST) STEM programs have started focusing on STEM content due to the lack of individuals choosing to focus on STEM careers. Although adaptive outcomes have been found while youth are attending OST STEM programs, little research has focused on outcomes after the program has ended. Often, the goal of OST STEM programs is to increase youth's long-term interest and competence in STEM. Therefore, examining youth interest and competence in STEM after spending time in the program is key. Framing the study around Emergent Motivation Theory (Csikszentmihalyi, 1990), we use a profile-oriented approach to investigate the relationship between youths' momentary engagement and their interest and perceived competence at program completion.

The Present Study

Research questions include: 1) What momentary profiles emerge? 2) What profiles are predictive of interest and perceived competence after attending an OST STEM program?

Method

We report how we determined our sample size, all data exclusions (if any), all manipulations, and all measures in the study.

Participants

Data were collected from 203 youth in nine OST programs, each lasting four weeks. Through an Experience Sampling Method (ESM) approach, youth were signaled through mobile phones, yielding 2,463 total ESM responses. Youth were asked to complete a survey before and after the program. A two-step cluster analysis was used to identity momentary profiles. Multilevel Modeling was used to account for the nesting of momentary responses within the nine OST STEM programs.

Material

Procedure

Data analysis

We used R (Version 3.4.3; R Core Team, 2017) and the R-package *papaja* (Version 0.1.0.9655; Aust & Barth, 2017) for all our analyses.

Results

Model 0

This model uses Maximum Likelihood (ML) estimation. Note that this model does not account for the error in the predictions for engagement when relating repeated measures engagement and post interest. The first (model 0a) does not include any covariates while the second (model 0b) adds gender, under-represented minority (URM) status, and pre-interest.

Model 0a.

```
## Linear mixed model fit by REML ['lmerMod']
## Formula: rm_engagement ~ 1 + (1 | participant_ID) + (1 | program_ID)
##    Data: d
##
## REML criterion at convergence: 6298.8
##
## Scaled residuals:
```

```
##     Min      1Q  Median      3Q     Max
## -4.4043 -0.5274  0.1040  0.5904  3.6900
##
## Random effects:
##  Groups         Name        Variance Std.Dev.
##  participant_ID (Intercept) 0.3244   0.5695
##  program_ID     (Intercept) 0.0130   0.1140
##  Residual                   0.4124   0.6422
## Number of obs: 2970, groups:  participant_ID, 203; program_ID, 9
##
## Fixed effects:
##             Estimate Std. Error t value
## (Intercept)   2.8566     0.0573   49.85
## Linear mixed model fit by REML ['lmerMod']
## Formula: post_interest ~ 1 + rm_engagement_BLUP + (1 | program_ID)
##    Data: d_for_m1
##
## REML criterion at convergence: 389.5
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -3.14505 -0.58832  0.07935  0.68551  2.28150
##
## Random effects:
##  Groups     Name        Variance Std.Dev.
##  program_ID (Intercept) 0.2028   0.4503
##  Residual               0.5999   0.7745
```

```
## Number of obs: 159, groups:  program_ID, 9
##
## Fixed effects:
##                    Estimate Std. Error t value
## (Intercept)          3.0744     0.1629  18.869
## rm_engagement_BLUP   0.4818     0.1160   4.152
##
## Correlation of Fixed Effects:
##             (Intr)
## rm_ngg_BLUP -0.012
```

```
##               Effect   Rsq upper.CL lower.CL
## 1              Model 0.089    0.186    0.024
## 2 rm_engagement_BLUP 0.089    0.186    0.024
## correlation between BLUP and interest 0.2983287
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula: rm_engagement ~ 1 + (1 | participant_ID) + (1 | program_ID)
##    Data: d
##
## REML criterion at convergence: 6298.8
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -4.4043 -0.5274  0.1040  0.5904  3.6900
##
## Random effects:
##  Groups         Name        Variance Std.Dev.
##  participant_ID (Intercept) 0.3244   0.5695
```

```
##  program_ID     (Intercept) 0.0130   0.1140
##  Residual                   0.4124   0.6422
## Number of obs: 2970, groups:  participant_ID, 203; program_ID, 9
##
## Fixed effects:
##             Estimate Std. Error t value
## (Intercept)   2.8566     0.0573   49.85
## Linear mixed model fit by REML ['lmerMod']
## Formula: post_interest ~ 1 + rm_engagement_BLUP + gender_female + urm +
##     pre_interest + (1 | program_ID)
##    Data: d_for_m2
##
## REML criterion at convergence: 307
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -4.2017 -0.4728  0.0722  0.5639  2.7381
##
## Random effects:
##  Groups     Name        Variance Std.Dev.
##  program_ID (Intercept) 0.0249   0.1578
##  Residual               0.4681   0.6842
## Number of obs: 141, groups:  program_ID, 9
##
## Fixed effects:
##                    Estimate Std. Error t value
## (Intercept)          1.6870     0.2782   6.064
```

```
## rm_engagement_BLUP   0.4669     0.1096   4.261
## gender_female       -0.0933     0.1208  -0.772
## urm                 -0.2056     0.1630  -1.262
## pre_interest         0.5309     0.0731   7.263
##
## Correlation of Fixed Effects:
##             (Intr) r__BLU gndr_f urm
## rm_ngg_BLUP  0.056
## gender_feml -0.210  0.158
## urm         -0.458 -0.028 -0.118
## pre_interst -0.809 -0.106  0.047 -0.005
```

```
##               Effect   Rsq upper.CL lower.CL
## 1              Model 0.392    0.510    0.288
## 5       pre_interest 0.296    0.415    0.184
## 2 rm_engagement_BLUP 0.112    0.221    0.034
## 4                urm 0.011    0.071    0.000
## 3      gender_female 0.004    0.052    0.000
## correlation between BLUP and interest 0.334664
```

Model 1

These models use Markov Chain Monte Carlo (MCMC) estimation (via the **MCMCglmm** package). The first (model 1a) does not include any covariates while the second (model 1b) adds gender, under-represented minority (URM) status, and pre-interest.

Model 1a. This is a bivariate model predicting repeated measures engagement (`rm_engagement`) and post interest (`post_interest`). Two random effects are used, one for the participant random effect, and one for the program random effect. The correlation among the two outcomes is examined and appears to take on a positive, non-zero value with a 95% credible interval (slightly different from a confidence interval) that does not include zero.

```
##
##  Iterations = 3001:12991
##  Thinning interval  = 10
##  Sample size  = 1000
##
##  DIC: 10986.4
##
##  G-structure:  ~us(trait):participant_ID
##
##                                                    post.mean l-95% CI
## traitrm_engagement:traitrm_engagement.participant_ID    0.3304  0.26256
## traitpost_interest:traitrm_engagement.participant_ID    0.1258  0.05087
## traitrm_engagement:traitpost_interest.participant_ID    0.1258  0.05087
## traitpost_interest:traitpost_interest.participant_ID    0.7066  0.57165
##                                                    u-95% CI eff.samp
## traitrm_engagement:traitrm_engagement.participant_ID   0.4073   1000.0
## traitpost_interest:traitrm_engagement.participant_ID   0.1936    880.4
## traitrm_engagement:traitpost_interest.participant_ID   0.1936    880.4
## traitpost_interest:traitpost_interest.participant_ID   0.8548    283.1
##
##                ~us(trait):program_ID
##
##                                                post.mean   l-95% CI
## traitrm_engagement:traitrm_engagement.program_ID   0.02706  5.099e-11
## traitpost_interest:traitrm_engagement.program_ID   0.01136 -1.669e-01
```

```
## traitrm_engagement:traitpost_interest.program_ID   0.01136 -1.669e-01
## traitpost_interest:traitpost_interest.program_ID   1.58567  4.520e-01
##                                                  u-95% CI eff.samp
## traitrm_engagement:traitrm_engagement.program_ID  0.09114    301.5
## traitpost_interest:traitrm_engagement.program_ID  0.16929   1000.0
## traitrm_engagement:traitpost_interest.program_ID  0.16929   1000.0
## traitpost_interest:traitpost_interest.program_ID  3.50657   1000.0
##
##  R-structure:  ~idh(trait):units
##
##                           post.mean l-95% CI u-95% CI eff.samp
## traitrm_engagement.units    0.4132   0.3917   0.4336    887.7
## traitpost_interest.units    0.0001   0.0001   0.0001      0.0
##
##  Location effects: cbind(rm_engagement, post_interest) ~ -1 + trait
##
##                     post.mean l-95% CI u-95% CI eff.samp  pMCMC
## traitrm_engagement     2.861    2.722    3.007     1222 <0.001 ***
## traitpost_interest     3.088    2.226    3.998     1115 <0.001 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##      var1
## 0.2426489
```

Model 2a. This model is identical to model 1a, except it adds fixed effects for a) pre-interest (the same measure as for post-interest, but given to youth before, rather than after).

```
##
```

```
##  Iterations = 3001:12991
##  Thinning interval  = 10
##  Sample size  = 1000
##
##  DIC: 9874.073
##
##  G-structure:  ~us(trait):participant_ID
##
##                                                          post.mean l-95% CI
## traitrm_engagement:traitrm_engagement.participant_ID    0.3366  0.26372
## traitpost_interest:traitrm_engagement.participant_ID    0.1186  0.04197
## traitrm_engagement:traitpost_interest.participant_ID    0.1186  0.04197
## traitpost_interest:traitpost_interest.participant_ID    0.6796  0.55075
##                                                          u-95% CI eff.samp
## traitrm_engagement:traitrm_engagement.participant_ID   0.4172    832.9
## traitpost_interest:traitrm_engagement.participant_ID   0.1935    803.3
## traitrm_engagement:traitpost_interest.participant_ID   0.1935    803.3
## traitpost_interest:traitpost_interest.participant_ID   0.8232    759.7
##
##                ~us(trait):program_ID
##
##                                                      post.mean   l-95% CI
## traitrm_engagement:traitrm_engagement.program_ID  0.026367  4.113e-08
## traitpost_interest:traitrm_engagement.program_ID -0.009697 -1.804e-01
## traitrm_engagement:traitpost_interest.program_ID -0.009697 -1.804e-01
## traitpost_interest:traitpost_interest.program_ID  1.659889  4.548e-01
##                                                      u-95% CI eff.samp
```

```
## traitrm_engagement:traitrm_engagement.program_ID  0.08497    165.0
## traitpost_interest:traitrm_engagement.program_ID  0.15101    855.6
## traitrm_engagement:traitpost_interest.program_ID  0.15101    855.6
## traitpost_interest:traitpost_interest.program_ID  3.37140   1000.0
##
##  R-structure:  ~idh(trait):units
##
##                            post.mean l-95% CI u-95% CI eff.samp
## traitrm_engagement.units    0.4092   0.3881   0.4326     1000
## traitpost_interest.units    0.0001   0.0001   0.0001        0
##
##  Location effects: cbind(rm_engagement, post_interest) ~ -1 + trait + gender_female +
##
##                      post.mean l-95% CI u-95% CI eff.samp  pMCMC
## traitrm_engagement   2.39713  1.93197  2.75575    902.7 <0.001 ***
## traitpost_interest   2.63481  1.73029  3.60087   1000.0  0.002 **
## gender_female       -0.09363 -0.25923  0.06394    824.3  0.254
## urm                 -0.03994 -0.26898  0.18817   1227.2  0.734
## pre_interest         0.17536  0.08269  0.27574    690.3 <0.001 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##     var1
## 0.234083
```

Summary of findings

To calculate these correlations, I calculated the partial R^2 (i.e., the change in R-squared when adding the predictor) for the BLUPs for engagement, which I think helps to compare the results with the two approaches.

- BLUPs / lme4 model
  - Correlation between BLUPs for engagement and post-interest without covariates: .298
  - Correlation between BLUPs for engagement and post-interest with covariates (pre-interest, gender, and URM status): .334
- MCMC / mcmcGLMM model
  - Correlation between engagement and post-interest without covariates: .248
  - Correlation between engagement and post-interest with covariates (pre-interest, gender, and URM status): .280

However, I'm not sure this is correct. In the **lme4** models, we used the BLUPs in a separate linear model and obtained a regression coefficient relating repeated measures engagement to post interest, whereas in the **MCMCglmm** models we modeled the correlation of the random effects for repeated measures engagement and interest. One way to compare them is to use correlations instead of a linear model to examine the relations between the predictions (BLUPs) for repeated measures engagement and interest, but this does not allow us to account for covariates. To address this, could a partial correlation be examined (possibly using the **r2glmm** package or a manual approach)? Or, is there another way to transform the beta coefficient into a partial correlation coefficient? Or, is there a way to interpret the correlation between repeated measures engagement and post interest in the **MCMCglmm** models as a regression coefficient?

Discussion

References

Aust, F., & Barth, M. (2017). *papaja: Create APA manuscripts with R Markdown.* Retrieved from https://github.com/crsh/papaja

R Core Team. (2017). *R: A language and environment for statistical computing.* Vienna, Austria: R Foundation for Statistical Computing. Retrieved from https://www.R-project.org/