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

Joshua Rosenberg[1], Patrick Beymer[1], & Jennifer Schmidt[1]

[1] Michigan State University

Author Note

This paper is to be presented at the 2018 Annual Meeting of the American Educational Research Association, New York, NY.

Correspondence concerning this article should be addressed to Joshua Rosenberg, Postal address. E-mail: jrosen@msu.edu

Abstract

Enter abstract.

Keywords: Engagement

Word count: X

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

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

Maximum Likelihood Estimation

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.

effect	group	term	estimate	std.error	statistic
fixed	fixed	(Intercept)	1.6870529	0.2782234	6.0636625
fixed	fixed	rm_engagement_BLUP	0.4668654	0.1095668	4.2610108
fixed	fixed	gender_female	-0.0932999	0.1207901	-0.7724133
fixed	fixed	urm	-0.2056539	0.1629742	-1.2618804
fixed	fixed	pre_interest	0.5309028	0.0730997	7.2627265
ran_pars	program_ID	sd_(Intercept)	0.1577843	NA	NA
ran_pars	Residual	sd_Observation	0.6841791	NA	NA

```
##               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
```

Markov Chain Monte Carlo Estimation

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.

```
##
##  Iterations = 3001:12991
##  Thinning interval  = 10
##  Sample size  = 1000
##
##  DIC: 9872.511
##
##  G-structure:  ~us(trait):participant_ID
##
##                                                        post.mean l-95% CI
## traitrm_engagement:traitrm_engagement.participant_ID     0.3375  0.26378
## traitpost_interest:traitrm_engagement.participant_ID     0.1078  0.03689
## traitrm_engagement:traitpost_interest.participant_ID     0.1078  0.03689
## traitpost_interest:traitpost_interest.participant_ID     0.6361  0.51238
##                                                        u-95% CI eff.samp
```

```
## traitrm_engagement:traitrm_engagement.participant_ID   0.4226    717.8
## traitpost_interest:traitrm_engagement.participant_ID   0.1847   1000.0
## traitrm_engagement:traitpost_interest.participant_ID   0.1847   1000.0
## traitpost_interest:traitpost_interest.participant_ID   0.7794   1000.0
##
##                ~us(trait):program_ID
##
##                                                    post.mean l-95% CI
## traitrm_engagement:traitrm_engagement.program_ID     5.775    1.496
## traitpost_interest:traitrm_engagement.program_ID     5.587    1.557
## traitrm_engagement:traitpost_interest.program_ID     5.587    1.557
## traitpost_interest:traitpost_interest.program_ID     5.965    1.218
##                                                    u-95% CI eff.samp
## traitrm_engagement:traitrm_engagement.program_ID    12.18     1093
## traitpost_interest:traitrm_engagement.program_ID    12.01     1000
## traitrm_engagement:traitpost_interest.program_ID    12.01     1000
## traitpost_interest:traitpost_interest.program_ID    12.81     1000
##
##  R-structure:  ~idh(trait):units
##
##                          post.mean l-95% CI u-95% CI eff.samp
## traitrm_engagement.units    0.4085   0.3864   0.4309     1000
## traitpost_interest.units    0.0001   0.0001   0.0001        0
##
##  Location effects: cbind(rm_engagement, post_interest) ~ -1 + trait:gender_female + t
##
##                                  post.mean l-95% CI u-95% CI eff.samp
```

```
## traitrm_engagement:gender_female  -0.05842 -0.23983  0.13108   1000.0
## traitpost_interest:gender_female  -0.20243 -0.46167  0.03909    896.5
## traitrm_engagement:urm             0.09985 -0.18320  0.35113    891.7
## traitpost_interest:urm            -0.11672 -0.45906  0.21206   1000.0
## traitrm_engagement:pre_interest    0.18050  0.06142  0.30424   1073.6
## traitpost_interest:pre_interest    0.35013  0.19166  0.51467    763.2
##                                   pMCMC
## traitrm_engagement:gender_female  0.510
## traitpost_interest:gender_female  0.112
## traitrm_engagement:urm            0.434
## traitpost_interest:urm            0.498
## traitrm_engagement:pre_interest   0.002 **
## traitpost_interest:pre_interest  <0.001 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##      var1
## 0.2410096
```

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/