Longitudinal Analysis of Academic Growth Patterns at Morningside Academy: A Five-Year Assessment Study

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Abstract

This study analyzed longitudinal assessment data from Morningside Academy. . .

1 Introduction

2 Methods

3 Results

Our analytic strategy first involved obtaining aggregate scores of different growth measure types across participants. Reading comprehension, letter-word identification, and reading fluency measures were coalesced into composite scores. Next, we repeated this process for writing, by combining writing fluency, writing samples, and word attack growth scores. Finally, we combined the two assessment measures from mathematics, CALC as well as math fluency, into averaged scores. We then obtained grand means for each of the three academic domains (`Reading` , `Writing` , and `Math`). Refer to table 1 for a breakdown of these means.

Table 1: Table 1: Average Growth by Academic Domain

	Academic Growth Averages		
Year	Mean Reading	Mean Writing	Mean Math
2008-2009	1.52	1.91	1.90
2015-2016	2.43	2.57	2.52
2016-2017	2.39	2.46	NaN
2023-2024	1.42	NaN	2.38

Note: Note: NaN indicates missing data for that academic year.

In addition to means analyses, we conducted statistical tests to observe mean comparisons of academic domains, on aggregate. These tests allowed us to account for non-unique participant identification numbers within the current data, and further enabled us to observe potential differences in growth patterns across various academic years.

3.0.1 Research Question 1

3.0.1.1 ***Analytic Strategy*** A repeated measures analysis of variance (ANOVA) was conducted via the `aov` function in R to quantify patterns of academic growth across different assessment measure types. Individual measure types were aggregated by domain across participants to create three, composite academic domains of math, reading, and writing.. The repeated measures approach was utilized because growth scores were measured several times for each student across several assessment types within a given year (as well as during multiple years). Thus, we treated `assessment_type` as a within-subject factor. Since the data included non-unique student IDs, the model accounted for repeated measures per student. Post-hoc pairwise comparisons with Bonferroni correction were conducted to determine specific differences between the three assessment types, to account for uneven sample sizes within `year`.

3.0.1.2 ***Results*** A repeated measures ANOVA was conducted to examine the effect of Assessment Type (reading, writing, and math) on academic growth scores. Results showed a significant main effect of `assessment_type` , $F(2, 259) = 5.81$, $p < 0.003$, indicating that growth scores varied across assessment types. Additionally, there was a significant main effect of `year` , $F(3, 259) = 9.27$, $p < 0.001$, suggesting that academic growth differed across academic years. However, the interaction between `assessment_type` and `year` was not significant, $F(1, 402) = 0.62$, $p < 0.43$, indicating that growth patterns across assessments were consistent over time.

Post-hoc pairwise comparison tests using a Bonferroni correction revealed that growth in `Reading` was significantly lower than in `Math` (*M*difference = -0.92, $p = 0.015$) and `Writing` (*M*difference = -1.10, $p = 0.003$). No significant differences emerged between `Math` and `Writing` ($p = 1.00$), however. These comparisons suggest that students experienced the least academic growth in reading, while growth in math and writing was statistically similar (refer to the ANOVA model output below for full transparency). Results are shown in Fig. 1.

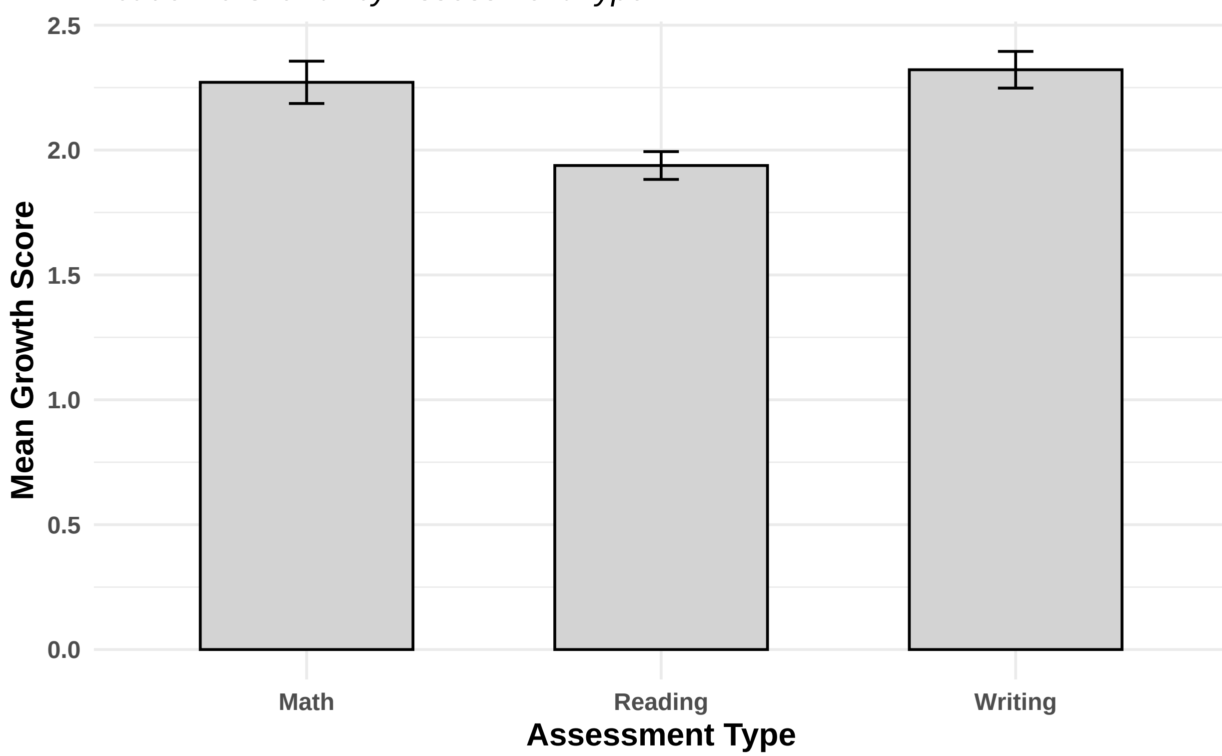
```
##
## Error: id
##                  Df Sum Sq Mean Sq F value   Pr(>F)
## Assessment_Type   2   24.5  12.275   5.806  0.00341 **
## year              3   58.8  19.603   9.273 7.59e-06 ***
## Residuals       259  547.5   2.114
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Error: id:Assessment_Type
##                  Df Sum Sq Mean Sq F value   Pr(>F)
## Assessment_Type   2   22.3  11.159   7.416 0.000687 ***
## year              1    0.9   0.927   0.616 0.432913
## Residuals       402  604.9   1.505
```

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Error: id:year
##           Df Sum Sq Mean Sq F value Pr(>F)
## year       1   0.92  0.9153    0.81  0.372
## Residuals 53  59.87  1.1296
##
## Error: id:Assessment_Type:year
##           Df Sum Sq Mean Sq F value Pr(>F)
## Residuals 33  35.64    1.08


##
##  Pairwise comparisons using t tests with pooled SD
##
## data:  analysis_long$Growth_Score and analysis_long$Assessment_Type
##
##         Math   Reading
## Reading 0.0147 -
## Writing 1.0000 0.0031
##
## P value adjustment method: bonferroni
```

Fig. 1

Academic Growth by Assessment Type



3.0.2 Research Question 2

3.0.2.1 ***Analytic Strategy*** To examine how academic growth varied across different academic years, a linear mixed-effects model (LMM) was conducted, using the `lmer` function within R, in addition to `car`, `lme4`, and `lmertest` for relevant statistics of significance in the output. Academic `year` was utilized as a fixed effect, with student ID included as a random effect to account for repeated measurements, due to certain students appearing in the data set multiple times across years. This method allowed us to model within-student variability while estimating the average effect of academic year on academic growth in reading, writing, and math. The LMM was fit using restricted maximum likelihood (REML) for unbiased estimates of fixed and random effects.

3.0.3 Results

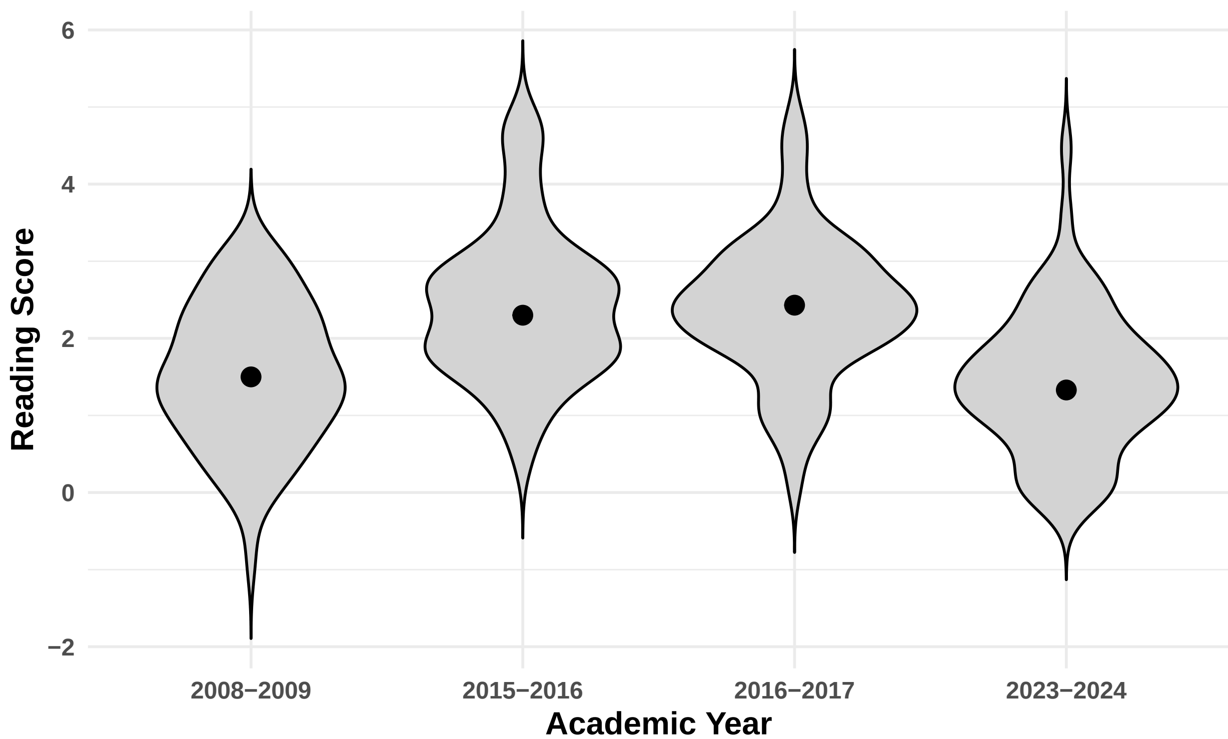
3.0.3.1 ***Reading*** A linear mixed-effects model (LMM) was conducted to assess the effect of academic year on reading growth scores, with year 2008-2009 serving as a reference or baseline year for comparisons. Academic year was treated as a fixed effect, and student ID was entered as a random intercept to account for repeated measurements. Results suggest that academic year significantly predicted reading scores, $F(3, 276) = 14.24$, $p < .001$. Students in the 2015-2016 academic year scored significantly higher than the reference year (2008-2009), $B = 0.91$, $SE = 0.15$, $t(276) = 6.04$, $p < .001$. Similarly, students in 2016-2017 also showed significant growth relative to the baseline, $B = 0.87$, $SE = 0.16$, t(276) = 5.53, $p < .001$. However, no significant difference was found between the 2023-2024 year and the reference year, $B = -0.10$, $SE = 0.16$, $t(276) = -0.62$, $p = .533$. Refer to the linear mixed model output (model is identical for reading, writing, and math) below for full transparency. Results for reading are shown in Fig. 2.

```
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: reading ~ year + (1 | id)
##    Data: analysis_avgs
##
## REML criterion at convergence: 759.4
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -2.5706 -0.6456 -0.0186  0.5856  3.2849
##
## Random effects:
##  Groups   Name        Variance  Std.Dev.
##  id       (Intercept) 7.725e-16 2.779e-08
##  Residual             8.624e-01 9.287e-01
## Number of obs: 280, groups:  id, 246
##
## Fixed effects:
##                Estimate Std. Error        df t value Pr(>|t|)
## (Intercept)     1.51724    0.10653 276.00000  14.243  < 2e-16 ***
## year2015-2016   0.91236    0.15115 276.00000   6.036 5.08e-09 ***
## year2016-2017   0.87120    0.15756 276.00000   5.529 7.45e-08 ***
```

```
## year2023-2024  -0.09785    0.15690 276.00000  -0.624    0.533
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) y2015- y2016-
## yr2015-2016 -0.705
## yr2016-2017 -0.676  0.477
## yr2023-2024 -0.679  0.479  0.459
## optimizer (nloptwrap) convergence code: 0 (OK)
## boundary (singular) fit: see help('isSingular')
```

Fig. 2

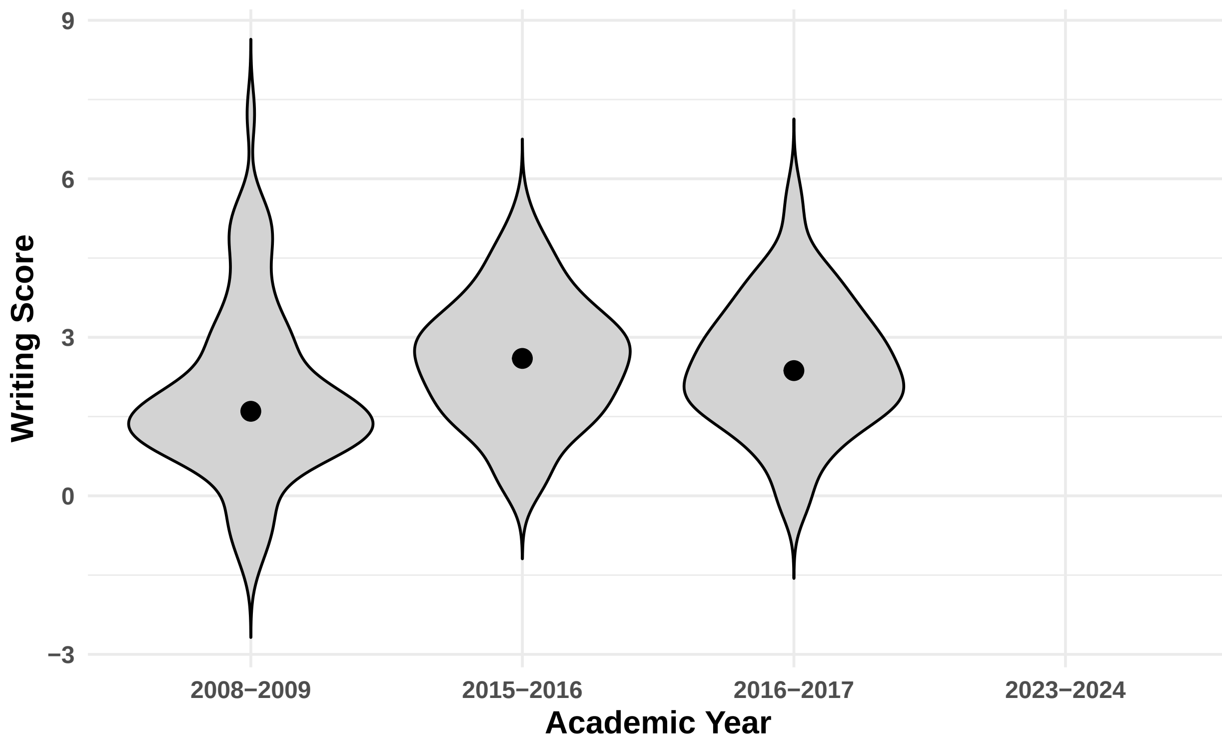
Reading Score Distribution by Academic Year



3.0.3.2 ***Writing*** A second, identical linear mixed-effects model was applied to examine writing growth scores. Academic year significantly predicted writing scores, F (3, 276) = 14.24, p < .001. Writing scores improved significantly in 2015-2016, B = 0.91, SE = 0.15, t (276) = 6.04, p < .001 and 2016-2017, B = 0.87, SE = 0.16, t (276) = 5.53, p < .001 compared to 2008-2009. The difference between 2023-2024 and the reference year was not significant, B = -0.10, SE = 0.16, t (276) = -0.62, p = .533. Results for writing are shown in Fig. 3.

Fig. 3

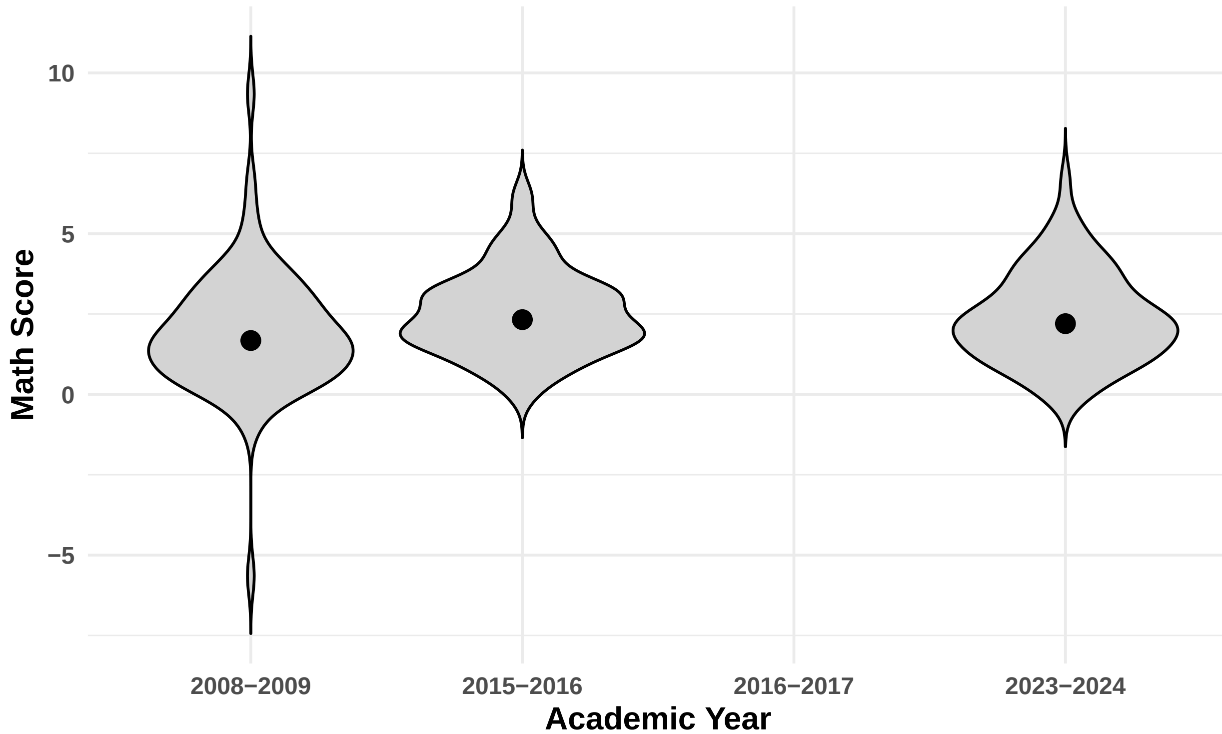
Writing Score Distribution by Academic Year



3.0.3.3 ***Math*** A third, identical linear mixed-effects model was conducted to examine the effect of academic year on math growth scores. Academic year significantly predicted math scores, F (3, 276) = 14.24, p < .001. Math scores were significantly higher in the 2015-2016 academic year compared to the reference year (2008-2009), B = 0.91, SE = 0.15, t (276) = 6.04, p < .001. Similarly, students in 2016-2017 scored significantly higher than those in the baseline year, B = 0.87, SE = 0.16, t (276) = 5.53, p < .001. In contrast, students' math scores in 2023-2024 did not significantly differ from the reference year, B = -0.10, SE = 0.16, t (276) = -0.62, p = .533. The low variance value was essentially zero (7.725e-16), between reading, writing, and math for the model which suggests that most of the variability in domain scores can be attributed to the effects of year, rather than between-student effects. Results for math are shown in Fig. 4.

Fig. 4

Math Score Distribution by Academic Year



4 Discussion

5 Conclusion

6 References