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Diverse Engagement Profiles:

Demonstration and Implications of Test Preparation for High-Stakes Exams

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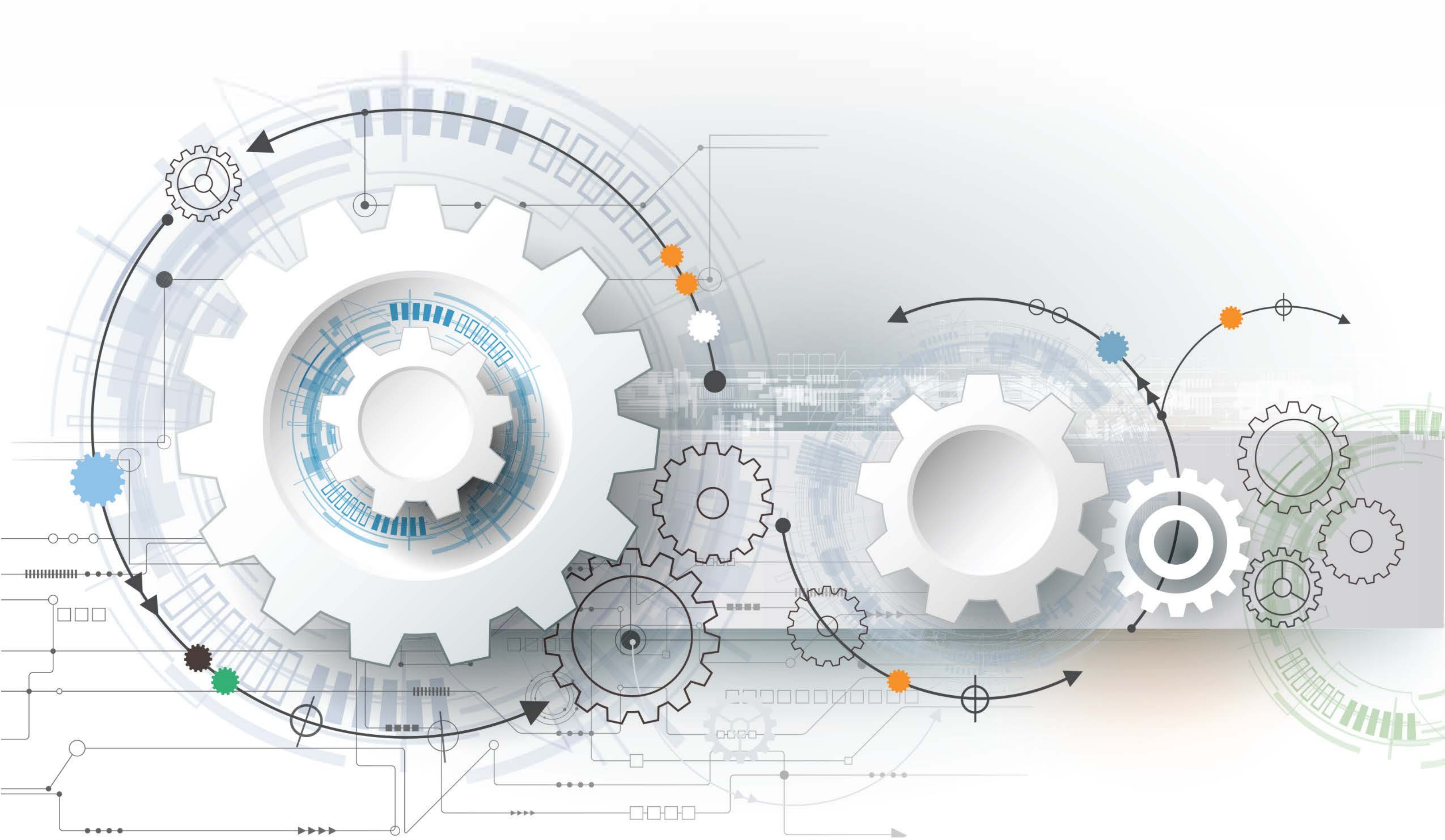

ABOUT THE AUTHORS

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Diverse Engagement Profiles: Demonstration and Implications of Test Preparation for High-Stakes Exams

Abstract

Students from different demographic and academic backgrounds use many different types of test preparation products. Understanding variations in test preparation usage can help inform product improvement efforts and can also help guide how test preparation developers advise new users to get the most from their preparation. In this study, we aim to characterize how students enrolled in a test preparation product, ACT® Online Test Prep (AOP), use that product. Following Geiser (2012), Masyn (2013), and Morin (2016), we use latent profile analysis (LPA) to identify students' engagement profiles using four engagement measures: activity, time, practice ACT score, and percent correct. Data collected from 9,017 students between December 2015 and June 2018 identified five student engagement profiles as Low-Usage/Low-Performance (24.1%), Low-Usage/High-Performance (7.2%), Low-Usage/Moderate-Performance (31.7%), Moderate-Usage/Low-Performance (16.8%), and High-Usage/Moderate-Performance (20.2%). We found that these engagement profiles were distinguished by activity, time, practice ACT score, and percent correct; they were also differentially predicted by gender in one profile. The heterogeneity of engagement profiles is discussed in relation to usage and performance as well as potential future research directions.

Word count 183

Keywords: ACT Online Test Prep, AOP, latent profile analysis, LPA, mixture models

Introduction

High-stakes standardized testing (e.g., ACT® and SAT) can play an important role in helping students attain their academic goals. As a result, students are motivated to improve their test scores to improve their readiness for college, meet admissions requirements, maximize scholarship opportunities, and avoid remediation. The use of these tests includes measuring college and career readiness, college admissions, scholarships, and course placement. In 2017, just over two million high school graduates, approximately 60% of high school graduates, took the ACT with an average ACT Composite score of 21.0 (ACT, 2017a; ACT, 2017b). Of those students, 27% met all four ACT College Readiness Benchmarks.

Students can use many different tools to prepare for the ACT test, including resources from ACT, which provide different types of supports and content review. Within the test preparation literature, research has demonstrated the positive impact of test preparation on test scores (e.g., Briggs, 2009; Messick & Jungeblut, 1981; Moore, Sanchez, & San Pedro, 2018; Sanchez & Harnisher, 2018). Some research has studied motivational factors that may affect student preparation (e.g., Appelrouth, Zabrucky, & Moore, 2015), while other research has investigated the causal evidence of the impact of test preparation on scores (Moore et al., 2018).

However, different usage patterns of test preparation products have not been studied. Therefore, we seek to identify the emergent profiles of users of ACT Online Prep (AOP). In this manuscript, we elaborate on key features of AOP, present the empirical data, discuss the results, and summarize recommendations for future researchers.

ACT Online Prep (AOP)

ACT[1] offers a variety of test preparation materials that feature real questions and sample materials from previous tests including: the Real ACT Prep Workbook; ACT® Academy™; ACT Online Prep (AOP); ACT Rapid Review; and a collaboration with Kaplan Test Prep to offer an interactive virtual classroom called ACT® Kaplan® Online Prep Live (OPL). In this paper, we limited our examination of test preparation to the AOP product.

AOP is a subscription-based online service with access to a dynamic, interactive test preparation course designed by ACT. It consists of six components that target skills in the four subjects (English, mathematics, reading, and science): practice sessions, instructional lessons, ACT practice tests, discussion boards, educational games, and flashcards. The program offers a personalized learning path, and students can choose from a variety of activities with comprehensive content review. Predicted scores and feedback are provided, and users can reset the activities, including tests.

Practice Sessions

Practice sessions consist of diagnostic and practice questions. This feature consists of more than 2,400 practice questions (items) that cover the four ACT subjects. The practice items facilitate learning through scaffolding with immediate feedback on student progress.

Instructional Lessons

Instructional lessons are extensive reviews of content covered within the four ACT subject tests. For example, the math lessons prepare students for math topics such as statistics and probability, Algebra, functions, number and quantity, and Geometry. At the end of each lesson, students are asked to report their confidence level in that topic (low, medium, high).

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[1] For more information about all ACT Test Prep products, visit https://www.act.org/content/act/en/products-and-services/the-act/test-preparation.html

ACT Practice Tests

When students practice the ACT test, they may pick a short or long form. A timed short ACT test is a limited number of retired ACT items in one of the four ACT subjects; once completed, students are provided with a predicted ACT subject test score range. The long form practice test consists of timed, retired ACT tests that mimic the official four-subject ACT test. At the end, students receive estimated ACT scores for each of the four individual subject tests as well as a Composite practice score. Students are able to reset and retake both forms of tests.

Discussion Boards, Educational Games, and Flashcards

These AOP components focus on peer/group interaction via a discussion board where students discuss test preparation or ask questions in order to learn from each other. Individual learning is also supported using educational games and flashcards, targeting specific concepts covered on the ACT.

Background: Test Preparation Efficacy Research

Students taking high-stakes exams come from different backgrounds and are exposed to different educational settings and instruction; therefore, personalized learning plans are an effective way to provide individualized opportunities (NACAC, 2015). The same holds true for test preparation strategies, which can provide students with individualized plans to navigate the complex requirements of assessments. Instead of following a common strategy, students may use many types of strategies to arrive at a final answer when taking standardized tests (Baleghizadeh & Yousefian, 2012). Further, applying different strategies toward understanding the construction of tests is a valid preparation approach (Baleghizadeh & Yousefian, 2012). Worthwhile preparation activities could include practicing different types of questions under time constraints, utilization of vocabulary knowledge, and ways to eliminate wrong answer choices.

Several factors that influence the effectiveness of test preparation, such as prior test score, school attendance, and preparation participation have been examined, and the results showed various contributions to improved test scores. For example, allotted time and type of test preparation were found to have positive influences on test scores. Messick and Jungeblut (1981) studied the impact of time and methods of test preparation on the improvement of students' SAT score by examining previously published studies. They emphasized that both amount of time and duration of test preparation positively impacted students' scores. They further noted that the effect of time was confounded with other aspects of test preparation (i.e., increasing curriculum emphases on content knowledge and skill development).

Appelrouth, Zabrucky, and Moore (2015) noted that factors such as gender, school type, homework completion, time allotted, and tutoring type, (i.e., individual versus groups) could impact the effect test preparation has on SAT scores. They collected data from 1,933 junior and senior students who participated in SAT test preparation programs in three large metropolitan areas. They also collected demographic information, prior SAT score, attendance, preparation participation, and post SAT score. Time allotted on practice tests and type of preparation (e.g., individual versus group tutoring) were significant factors in predicting score gain. They stated that each individual preparation hour contributed to a 2.34 point gain on the SAT (0.07 SD units).[2,3] Both time and type of test preparation were positively related to students' test scores.

For the ACT test, several studies have been conducted which examine the effect of test preparation. Sanchez and Harnisher (2018) investigated the effectiveness of test preparation on

[2] In 2014, the standard error of measurement of the SAT was approximately 32 points (College Board, 2015). This means that if a student retook the SAT with no additional learning they have a 68% chance of scoring within 32 points of their original test score.
[3] Effect size is based on the coefficient of 2.34, the standard deviation associated with individual tutoring hours (9.31), and the 2016 College Bound Seniors Report standard deviation of SAT total score (297.4).

ACT score gains for students that had taken the test more than once by comparing scores for a treatment group who enrolled in test preparation and a control group who did not. Using a quasi-experimental design, they found that the treatment group had higher retest scores (0.13 SD units) than their control group counterparts. They also found that this increase was greatest for low-income students.

Moore, Sanchez, and San Pedro (2018) examined the impact of 10 different ACT preparation tools on ACT retest scores. The findings indicated that students who participated in test preparation had higher ACT Composite scores compared to students who did not. The adjusted ACT Composite mean was 24.33 for the test preparation group verses 23.63 for the non-test preparation group (0.14 SD units). Moreover, the adjusted mean score varied based on time spent on test preparation (e.g., adjusted mean score of 24.91 when a student studied 11 hours or more with a private tutor or consultant).

The Current Study

Purposes and Research Questions

This study is exploratory as it is the first investigation to identify distinct profiles of test preparation usage and we were not able to find similar published research. This study examines the frequently occurring combinations of four engagement factors among students who enrolled in AOP. We apply latent profile analysis (LPA) techniques to identify profiles of AOP usage and performance. Once specific profiles are defined, a secondary purpose is to test for gender differences in profile frequency. While there are many variables of interest besides gender one could examine, we use gender to examine a key demographic characteristic as well as to illustrate the methodology. Specifically, we seek to answer these questions: Is there a profile structure that adequately represents the heterogeneity of AOP usage (i.e., are there patterns of engagement)? If so, what are they and what is their prevalence? Are male and female students equally represented across different profiles?

Addressing these questions will provide insight into how test preparation strategies for high-stakes exams can be refined to address the needs of different user profiles. We hypothesize that two or more AOP student profiles will emerge. We also expect to observe profile differences in usage of AOP components and levels of performance.

Methods

Study Population and Design

AOP data were collected from December 2015 to June 2018. We collected data from activities, practice tests, lessons, and software resets.[4] Sixteen different AOP variables were available; however, not all of these variables were used due to redundancy. For example, there was a variable for each category of ACT practice test, i.e., English, mathematics, reading, and science, as well as a variable for the composite test score. We used the composite ACT practice test: the mathematical mean of the English, mathematics, reading, and science practice tests.[5] As a result, we retained 10 variables from the AOP activities, practice tests, lesson, and reset data.[6] We excluded cases when there were no records for the students (the student did not use that particular AOP component), using ListWise deletion, (i.e., delete all observations from the analysis that have missing values on one or more of the analysis variables; Peugh and Enders, 2004), as an attempt to have a full set of valid values across all 10 variables, leaving 9,017 AOP students for the analysis. All data descriptive analyses are conducted using SAS Enterprise 7.1.

[4] Software resets allow a student to clear responses for practice items and/or tests and take them again.
[5] We used the Composite score rather than the subject tests both as an overall index of achievement on the subject tests and because it is typically the key marker of achievement for college admissions and scholarships.
[6] The six omitted variables included the four subject scores used to create the Composite score as well as two duration items that were redundant with other duration variables.

Student race/ethnicity, gender, and family income were retrieved from the students' official ACT test record and are included as covariates. A summary table of the sample characteristics is presented in Table 1. Just over half of the students did not provide their family income, and one-third of the students did not provide their gender; however, we are left with about equal numbers of male and female students. In addition, most students were White. We did not access student's use of additional test preparation material beyond AOP.

Table 1. Study Sample Characteristics (N= 9,017)

Characteristic	N	Percent
Family Income		
Low-Income	317	4
Middle-Income	1,485	16
High-Income	2,484	28
Missing	4,731	52
Gender		
Male	3,069	34
Female	2,958	33
Missing	2,990	33
Race/Ethnicity		
White	3,785	42
African-American	18	0
Hispanic/Latino	475	5
Asian	776	9
Other	973	11
Missing	2,990	33

Note. *Percentages may not sum to 100% due to rounding.*

Measures. Data for 9,017 AOP students were collected on students' usage and performance. We used data relating to practice sessions, practice tests, and lessons as well as students' number of practice and test component resets. For measuring students' activity, we used two summary measures: average number of activities and total number of hours spent on practice items and practice tests. We also included students' practice ACT scores and percent of correctly answered items in practice and test items to measure performance. Since the four activity variables are on different scales (i.e., average, sum, and percentage) these values were standardized to ensure that the scale of the variable did not have an undue influence after they were averaged together. The four summary measures were activity, time, practice ACT score, and percent correct (Table 2).

Table 2. Description of the AOP Summary Measures

AOP Summary Measures		Description
Usage	Activity	The arithmetic mean of the standardized number of practice sessions, practice tests taken, lessons viewed, and practice and test resets
Usage	Time	Total hours spent on practice sessions and taking practice tests (time spent on lessons was not available)
Performance	Practice ACT score	Student's score on retired ACT tests as the arithmetic mean of the four ACT subject test scores, (English, mathematics, reading, and science), and rounded to the nearest whole number and reported on a scaled score from 1 to 36
Performance	Percent correct	The average percentage of correctly completed items in practice and test sessions

Data Analysis Procedure

To answer the main research question, we used the M*plus* option "TYPE=MIXTURE" to fit a LPA model starting with a parsimonious one-profile LPA model without covariates and then increased the number of latent profiles to two, three, four and five profiles.[7,8] For iterative testing, we used different sets of random start values (i.e., 500, 50) to avoid local maxima in determining the likelihood parameters with the Robust Maximum Likelihood (MLR) estimator. Then, overall model evaluation was based on fit statistics alongside a careful inspection of the nature of the groups and the proportion of students in each profile (i.e., model results, estimated profile size, entropy value, classification reliability, and class-conditional parameters). To

[7] An illustration, guidelines, and syntax of the analysis approach are provided in the Appendix.
[8] For a detailed treatment of the LPA methodology prior works (e.g., Geiser, 2012; Nylund, Asparouhov, & Muthén, 2007; Masyn, 2013; Morin, 2016; Muthén & Muthén, 1998–2015). For an overview of using LPA see Appendix A.

compare across all profile models, the Log likelihood (LogL) and the Information Criteria (IC), Akaike Information Criterion (AIC; Akaike, 1973), Bayesian Information Criterion (BIC; Schwarz, 1978), and Sample-Size Adjusted BIC (SSABIC; Sclove, 1987) were used.

For comparisons of neighboring profile models (e.g., two-profile versus three-profile), we used both the Lo-Mendell-Rubin LMR (LRT) and Bootstrap LR Difference Test (BLRT) with 500 replications with $p < .05$ as indications of model significance. Based on the model selection process and class interpretability, we selected a suitable number of profiles. We named and interpreted the profiles based on the four engagement variables (activity, time, practice ACT score, and percent correct).

Finally, to test whether males and females were equally represented within profiles we assigned each individual to the latent profile for which her or his assignment probability was greatest, and then we used the "R3STEP" option in M*plus* and added gender (female=1 and male=0) as an auxiliary latent class predictor to the LPA model. Of note, only AOP users with known gender are included (N=6,027, missing=2,999). Using one of the profiles as a reference group, positive values indicate that female students are more likely to be in the corresponding latent profile relative to male students. All statistical tests were two-tailed, and significance was determined at the 0.05 level using the M*plus* statistical package version 7.4 (Muthén & Muthén, 1998–2015).

Results

We aimed to identify subpopulations of students based on their engagement with AOP. Data were screened for outliers,[9] and the distribution for each measure was observed. Table 3 presents the descriptive statistics for each measure to help contextualize sample characteristics. We used normal probability plots and histograms to check for normality. Practice ACT score and percent correct were approximately normally distributed, whereas the activity data had a slight departure from normality. The probability plot visually shows a linear relationship with minor deviations. Skewness of the four measures ranged from -.60 to 1.64, with kurtosis ranging from -.21 to 2.50.

Table 3. Descriptive Statistics of AOP Engagement Summary Measures (N= 9,017)

AOP Engagement Measure	Mean	Standard Deviation	Skewness	Kurtosis
Activity	0.269	0.75	0.97	.45
Time	7.99	2.45	1.64	2.50
Practice ACT score	23.44	6.88	-0.60	-0.21
Percent correct	48.52	17.79	.43	-.10

Finally, correlations between the four AOP measures were positive: activity and time (r = .56); activity and practice ACT score (r =.11); activity and percent correct (r =.15); time and practice ACT score (r =.12); time and percent correct (r =.11); and practice ACT score and percent correct (r =.67).

[9] Outliers were identified by running SAS "Outlier Macro" to calculate the interquartile range (IQR) to set up a "fence" outside of Q1 and Q3. Then, any values that fall outside of this fence are deleted since they considered outliers.

AOP Latent Profile Analysis

The validity of inferences made from LPA is dependent upon having good model fit and meaningful interpretation of profiles. In this study, we found that the five-profile model was most appropriate. Relative to the one- through four-profile models, the five-profile model exhibited lowest LogL, AIC, BIC, and SSABIC values, high reliability and entropy, as well as non-significant LMR and BLRT values. In the five-profile model, the entropy is .81 suggesting clear profile separation as well as high values of precision (>.86) of correct profile assignment probabilities (.88, .91, .86, .89, and .92) for each profile. Table 4 provides a summary of the fit statistics for possible latent profile structures to each of the five extracted profiles.

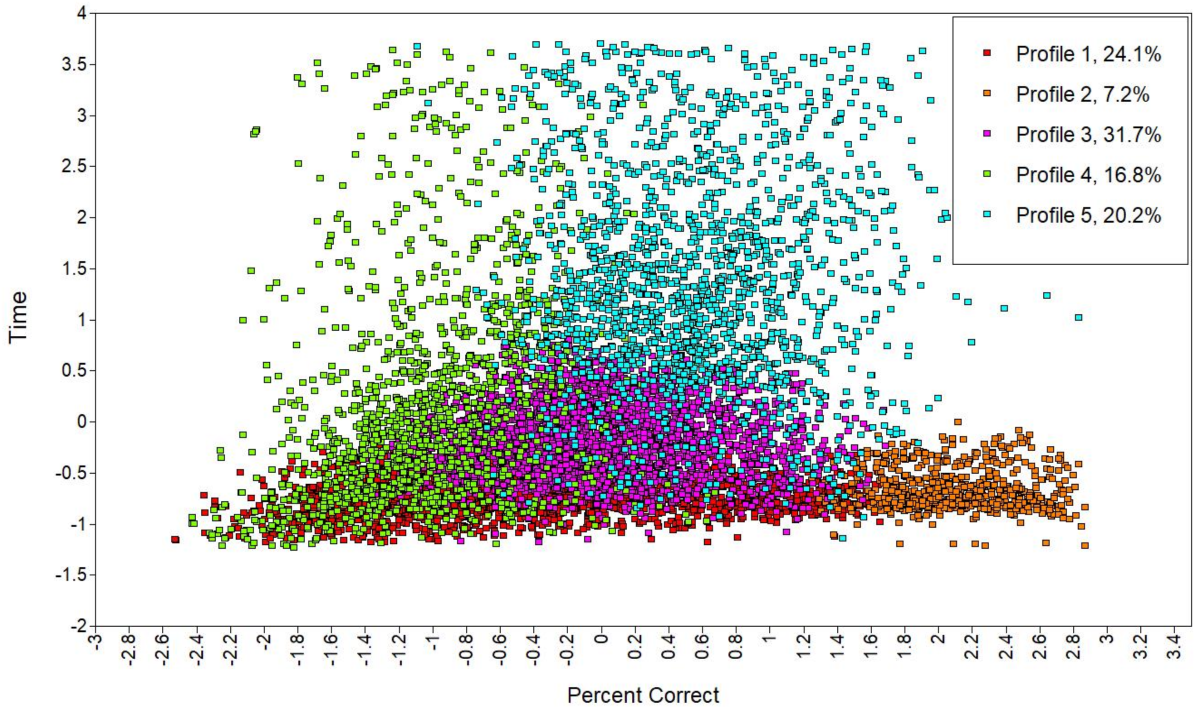
Table 4. Summary of the Fit Statistics for Possible Latent Profile Structures (N= 9,017)

Model	Profile Size	Entropy	Reliability	NP	LogL	AIC	BIC	SAABIC	BLRT k-1 profile versus k profile	LMR k-1 profile versus k profile
One-profile	100	-	-	8	-51178.275	102372.550	102429.405	102403.982	-	-
Two-profile	55.8	.75	.93	17	-45732.911	91499.821	91620.638	91566.615	p =.000	p =.000
	44.2		.94							
Three-profile	25.6	.76	.88	26	-44006.356	88064.712	88249.490	88166.866	p =.000	p =.000
	39.2		.94							
	35.2		.87							
Four-profile	20.2	.79	.87	35	-42040.697	84151.395	84400.135	84288.911	p =.000	p =.000
	31.3		.85							
	20.6		.89							
	27.9		.93							
Five-profile	24.1	.81	.88	44	-41327.162	82742.325	83055.027	82915.202	p =.000	p =.000
	07.2		.91							
	31.7		.86							
	16.8		.89							
	20.2		.92							

Note. Reliability= reliability of classification; NP= number of free parameters; LogL= Log likelihood; AIC= Akaike Information Criterion; BIC= Bayesian Information Criterion, SAABIC= Sample-Size Adjusted BIC; BLRT= Bootstrap Likelihood Test; LMR= Lo-Mendel Rubin Test; *k*= profile number.

We denoted students' engagement as low-usage/low-performance, low-usage/high-performance, low-usage/moderate-performance, moderate-usage/low-performance, high-usage/moderate-performance. Figure 1 demonstrates how the five-profile model helps illustrate the differences in engagement predictors (e.g., percent correct and time). Similar plots, not shown, demonstrate the differentiation of engagement by profiles on other predictors.

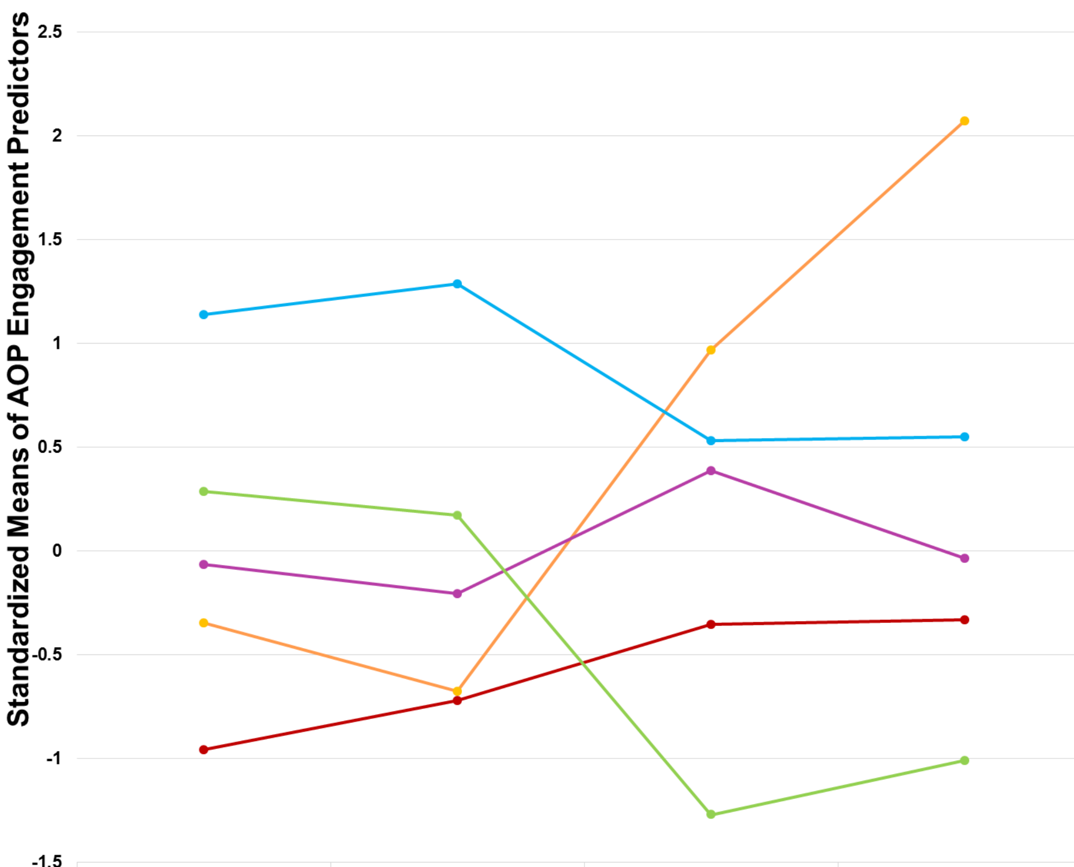
Figure 1. Time and Percent Correct Scatterplot for the Five-Profile Model Predictors (Total N=9,017; Red: Low-Usage/Low-Performance; 24.1%, N= 2,176, Orange: Low-Usage/High-Performance; 7.2%, N= 652 , Purple: Low-Usage/Moderate-Performance; 31.7%, N= 2,856 , Green: Moderate-Usage/Low-Performance; 16.8%, N= 1,511 , Blue: High-Usage/Moderate-Performance; 20.2%, N= 1821)



Interpretation of the Five Profiles of AOP Engagement

Figure 2 shows the standardized means for each profile across the four AOP engagement variables (i.e. activity, time, practice ACT score, and percent correct in each of the five latent profiles). High standardized means indicate higher values of that variable in the respective profile while lower standardized means indicate lower values of that variables. For example, students in the low-usage/high performance profile had below average number of activities and hours on practice items and tests, but had above average practice ACT scores and percent correct.

Figure 2. Five-Profile Model with Standardized Means of AOP Engagement Predictors (Total N=9,017; Red: Low-Usage/Low-Performance; 24.1%, N= 2,176 , Orange: Low-Usage/High-Performance; 7.2%, N= 652 , Purple: Low-Usage/Moderate-Performance; 31.7%, N= 2,856 , Green: Moderate-Usage/Low-Performance; 16.8%, N= 1,511 , Blue: High-Usage/Moderate-Performance; 20.2%, N= 1821)



	Activity	Time	Practice ACT score	Percent correct
Low-Usage/ Low-Performance	-0.959	-0.72	-0.354	-0.333
Low-Usage/High-Performance	-0.346	-0.675	0.967	2.072
Low-Usage/Moderate-performance	-0.067	-0.207	0.385	-0.034
Moderate-usage/Low-performance	0.286	0.17	-1.273	-1.012
High-Usage/Moderate-Performance	1.138	1.285	0.53	0.548

AOP Engagement Predictors

In addition to the profile size (Table 4), we used the 95% confident interval (CI) of means and standard deviations predictor values (Table 5) to enrich the engagement profile interpretation. In general, if the AOP engagement measure mean is less than zero, we treated it as low usage or low performance, and when it is greater than zero, we labeled it as moderate or high. Low-usage/low-performance students (N= 2,176) had a low number of activities, invested little time using AOP, and had the lowest ACT practice test score as well as the lowest percent correct on test and practice items. Low-usage/high-performance students (N=625) had a low number of activities and invested little time using AOP, but had the highest practice ACT scores and percent correct on test and practice items. In contrast, low-usage/moderate-performance students (N=2,856), the profile with the largest number of students, had a low number of activities and invested little time using AOP, but had moderate practice ACT scores and percent correct on test and practice items. Moderate-usage/low-performance (N=1,511) students had a good number of AOP activities and hours using practice items and tests but low practice ACT scores and percent correct on test and practice items. Finally, high-usage/moderate-performance students (N=1,821) had the highest number of AOP activities and hours using practice items and tests, but had moderate practice ACT scores and percent correct on test and practice items.

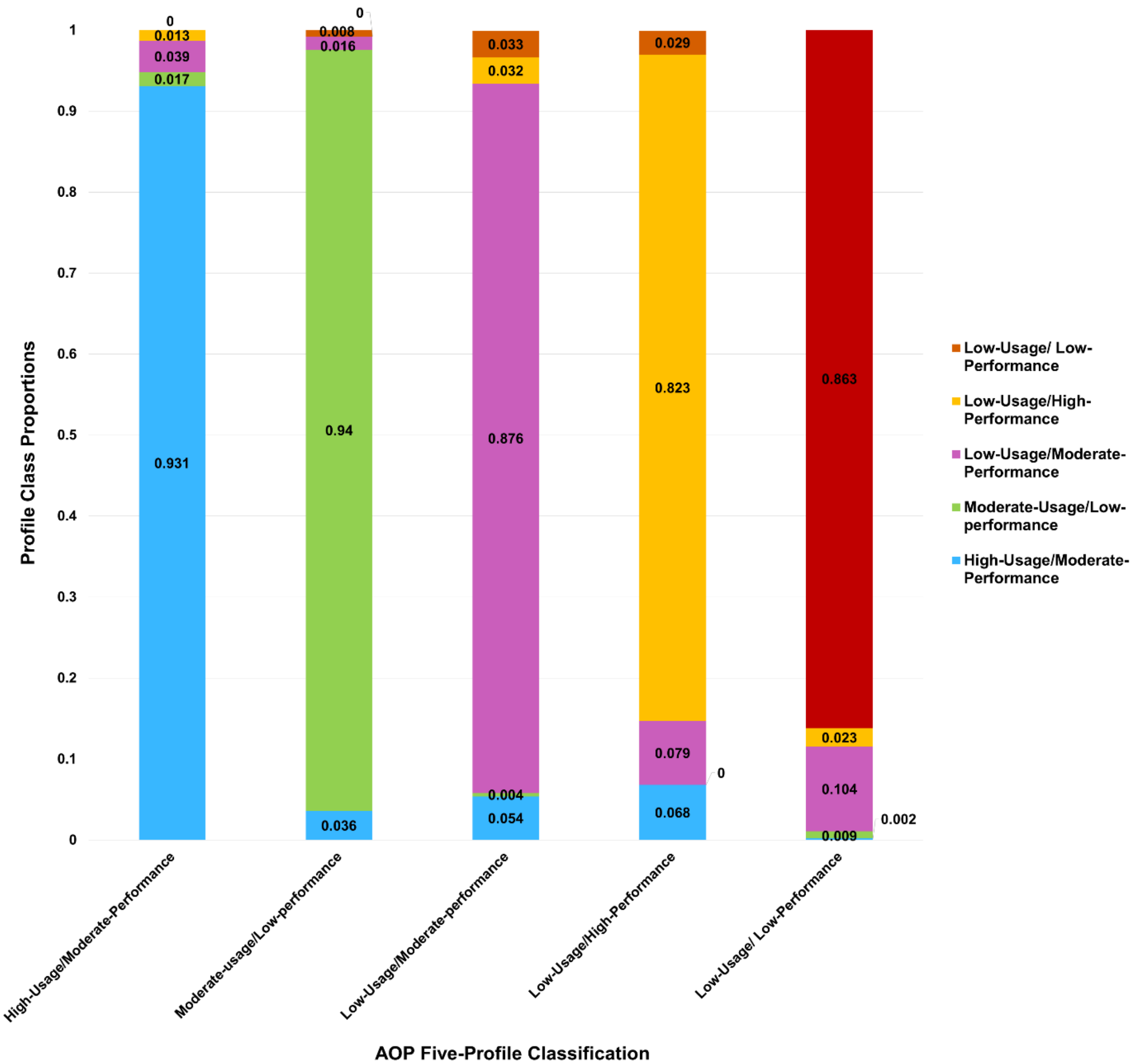
Table 5. 95% Confidence Intervals of the AOP Engagement Summary Measures by Profile (N= 9,017)

Profile and Parameter		**Activity**			**Time**			**Practice ACT Score**			**Percent Correct**		
		L 2.5%	**Est**	**U 2.5%**	**L 2.5%**	**Est**	**U 2.5%**	**L 2.5%**	**Est**	**U 2.5%**	**L 2.5%**	**Est**	**U 2.5%**
Low-usage/ low-performance	*M*	-0.98	-0.96	-0.94	-0.73	-0.72	-0.71	-0.44	-0.35	-0.27	-0.42	-0.33	-0.24
	SD	0.17	0.19	0.2	0.17	0.18	0.19	0.92	0.96	0.99	0.85	0.9	0.95
Low-usage/ low-performance	*M*	-0.46	-0.35	-0.23	-0.70	-0.68	-0.65	0.89	0.97	1.04	2.00	2.07	2.15
	SD	0.88	0.97	1.05	0.18	0.2	0.22	0.36	0.39	0.42	0.33	0.37	0.4
Low-usage/ moderate-performance	*M*	-0.11	-0.07	0.03	-0.24	-0.21	-0.17	0.34	0.39	0.43	-0.08	-0.03	0.01
	SD	0.49	0.51	0.52	0.34	0.36	0.38	0.62	0.65	0.68	0.54	0.57	0.59
Moderate-usage/low-performance	*M*	0.20	0.29	0.37	0.06	0.17	0.28	-1.35	-1.27	-1.19	-1.07	-1.01	-0.95
	SD	0.91	0.96	1	1.01	1.09	1.16	0.68	0.7	0.73	0.51	0.54	0.56
High-Usage/ moderate-Performance	*M*	1.07	1.14	1.20	1.20	1.29	1.37	0.48	0.53	0.58	0.50	0.55	0.60
	SD	0.92	0.95	0.98	1.06	1.09	1.12	0.59	0.62	0.65	0.57	0.6	0.62

Note. Est = Estimated parameter; M= Mean; SD= Standard Deviation; L 2.5%= lower 2.5%; U 2.5%= Upper 2.5%

Examining the estimated profile memberships and associated probabilities reveals that within each profile, each AOP user has a high probability of being in a specific profile and small to negligible probability of being in the other profiles. The classification probabilities for the most likely profile membership are presented in Figure 3 where each profile bar is depicted by five colors: red for low-usage/low-performance, orange for low-usage/high-performance, purple for low-usage/moderate-performance, green for moderate-usage/low-performance, and blue for high-usage/moderate-performance.

Figure 3. Profile Class Proportions for the Five-Profile Model (Total N=9,017; Red: Low-Usage/Low-Performance: 24.1%, N= 2,176 , Orange: Low-Usage/High-Performance: 7.2%, N= 652 , Purple: Low-Usage/Moderate-Performance: 31.7%, N= 2,856 , Green: Moderate-Usage/Low-Performance; 16.8%, N= 1,511 , Blue: High-Usage/Moderate-Performance; 20.2%, N= 1821)

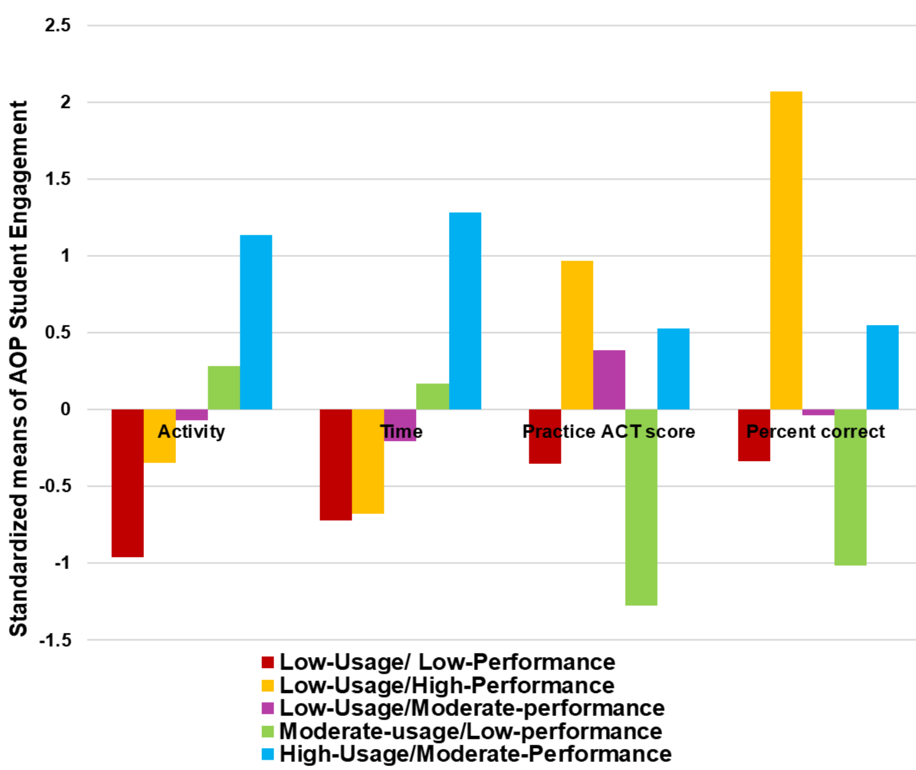


For example, within low-usage/low-performance profile memberships, most students are classified as low-usage/low-performance users (86.3%) with 10.4% being classified as low-usage/moderate-performance, 2.3 % as moderate-usage/low-performance, and less than 2%

being moderate-usage/low-performance and high-usage/moderate-performance. Within low-usage/high-performance profile memberships, most students are classified as being low-usage/high-performance users (82.3 %) with 2.3% being classifying as low-usage/low/performance, 7.9 % as low-usage/ moderate-performance, and 6.8 % as high-usage/moderate-performance users. The classes do not have perfect membership because the model does not fit the data perfectly.

Figure 4 shows the standardized mean of each AOP variable for the five profiles we identified. As shown, the standardized means for the four AOP measures (i.e., activity, time, practice ACT score, and percent correct) differ for each profile, which visually confirms the appropriateness of the five-profile model rather than the one-, two-, three-, or four-profile models.

Figure 4. Contribution of Each AOP Engagement Predictor to the Five-Profile Model



Each of the five profiles represents a distinct AOP profile. The correlation between practice ACT score and percent correct for the overall sample was high (.67). However, the correlation between the same two variables for low-usage/low-performance, low-usage/high-performance, low-usage/moderate-performance, moderate-usage/low-performance, and high-usage/moderate-performance profiles were .54, .81, .32, .28, and .51, respectively. Similarly, the correlation between the AOP time and practice ACT score variables across the five profiles varied. Overall, the correlation between activity and time was .56; however, only low-user/high-performance profile has a high correlation (.51) while other profiles correlations ranged between .02 and .13. This variation provides further demonstration of how the profiles help to differentiate users of AOP.

Gender as a predictor of profile. We investigated the relationship between the students' AOP engagement profiles and gender. Since we have about 33% of the AOP users with no gender data, the M*plu*s default for listwise deletion is applied to the auxiliary variable, gender, in the analysis. Of the 9,017 AOP users, 2,999 were excluded, and a total of 6,027 AOP users are used in the gender analysis. The gender analysis provides the statistics to compare each profile against a reference profile. The results showed that the AOP female users are underrepresented in the low-usage/high-performance profile only. Using any profile other than low-usage/high-performance profile as a reference group, the significant effect of gender (female) for the low-usage/high-performance profile ranged between - .49 and - .69 -, p =.000 (odds ratio ranged between .61 and .50) and was not statistically significant for other profiles. The other four profiles showed female overrepresentation against the low-usage/high-performance profile only if the low-usage/high-performance profile is used as a reference group. In other words, when compared to low-usage/high-performance profile, the probability of females being in one of the other four profiles significantly increases. Although females are less likely to be in the low-usage/high-performance profile, the gender analysis results demonstrate that females were a heterogeneous group of AOP users that were broadly distributed across the other four profiles.

Discussion

AOP is a learning tool designed to improve the knowledge and skills assessed on the ACT that ultimately will help students succeed in college and in their careers. Understanding the patterns of engagement in test preparation resources is necessary for developing and improving test preparation tools and interventions. Within the context of test preparation for high-stake exams, prior studies have not examined patterns of engagement. Results of our study revealed five profiles that exemplify AOP students' engagement behaviors as low-usage/low-performance, low-usage/high-performance, low-usage/moderate-performance, moderate-usage/low-performance, and high-usage/moderate-performance. We found greater numbers of students in the low-usage/moderate-performance, the low-usage/low-performance, and the high-usage/moderate performance profiles. Moreover, female students were underrepresented in the low-usage/high-performance profile.

These student profiles may help developers target specific interventions and inform the degree to which interventions may be effective. This information is particularly salient in the context of test preparation for high-stakes exams since students' engagement patterns with test preparation products has not been studied. The results revealed three noteworthy findings.

1. The identification of five engagement profiles of AOP engagement. The results provide greater clarity about factors that characterize student experiences. It allows further understanding of test preparation users and how their engagement behaviors, including usage and performance, could be associated with gender.

Sanchez and Harnisher propose two types of students who may use test preparation: high achievers seeking exceptional scores and lower achievers seeking supplementary instruction. In our study, we identified low-usage/high-performance students who may be aligned with the type of students proposed by Sanchez and Harnisher (2018) while adding two additional types: high-usage/moderate-performance students who are highly engaged with test preparation materials in terms of activity and time while they have a moderate performance level based on their practice ACT score and percent correct and low-usage/low-performance students who make little use of test preparation and have lower achievement. While these results cannot provide insights into the motivations of and preparation strategies employed by students, it does raise questions about why students used AOP in the manner illustrated by their profile.

2. Although females were less likely to be in one of the AOP profiles, namely low-usage/high-performance profile, results demonstrated that female students were a heterogeneous group of test preparation users that were broadly distributed across the other four profiles.
3. It is important to consider students' strategies of how to utilize the features of the program. It is of particular note that while low-usage/high-performance students had limited usage of AOP, they are among the highest achievers in terms of their practice ACT test scores and in having the highest average of correctly completed practice and test items. It is possible that these students use their preparation time for practice items and tests rather than reviewing content because they feel they have mastery of the content. Alternatively, they may be higher achieving students who do not see an advantage to using AOP.

On the other hand, high-usage/moderate-performance students performed a high number of AOP activities, spent higher numbers of hours using practice items and tests, and had practice ACT score and percent correct around the average. Since these students are moderate achievers based on their practice test scores and percent correct, they need to be more efficient with their AOP time and engage in different types of activities that fulfil their academic needs.

There are a few limitations to this research worth discussing. First, while we made use of the AOP data we had available, there is a wealth of additional usage data that could be attained from the AOP platform. Future research will need to examine this more detailed data to better understand how students are using AOP. Second, this exploratory study did not make use of students' demographic information such as race/ethnicity, family income, coursework taken, high school GPA, or parent's education. Each of these may serve to illuminate our understanding of why test preparation products are being used.

Additionally, because our analysis approach requires a complete data set for each student, we used ListWise deletion for missing data (i.e. not using an AOP section). This mean that in this analysis we are focusing on students who are very active in the system. The focus on high usage students reduces our generalizability to students who purchase but make poor use of the product but allows us to learn about students who purchase and make good use of the product. This decision is supported by the fact that the vast majority of AOP users make relatively little use of the product as a whole and of its components individually. While this study looks at students who are using the product in a model consistent with intended use, it does not include other models of use. Finally, in this study we did not collect data on other forms of test preparation students may be using, and future studies should explicitly control for this effect.

Practical Implications of the Study and Recommendations for Future Research

The objective of this study was to better understand the different usage profiles of AOP users. Understanding how users engage with test preparation helps inform improvement efforts and can help guide how we advise new users to get the most from their preparation. If test preparatory intervention was implemented at a community level, for example at a school, this study suggests that more than 31.7% of the students, on average, may have high usage coupled with moderate performance. However, to support this claim, students' usage information and factors driving their preparation are needed, which can be gained through direct observation or think-aloud interviews.

This study demonstrates the use of LPA and may serve as a useful approach for examining learning behavior patterns with other programs. To our knowledge, no research has systematically investigated test preparation usage profiles by gender. Showing how this can be accomplished makes this process more transparent. In addition, tools like the M*plus* mixture analysis that simplify this process are beneficial for researchers seeking to investigate latent profile properties associated with test preparation.

Future research could expand on the current study in a number of ways. First, researchers may include additional measures of engagement when estimating user profiles. For example, more research is needed to investigate the AOP discussion board activity regarding peer influence on student engagement. Second, a study could investigate patterns of test preparation for only females or males and determine the most beneficial activities. In addition to gender, there are many other covariates that may be of interest in regards to test preparation. Third, regarding statistical models, since there is usually a general or second-order factor that affects the identification of individuals' pattern (e.g., computer literacy or Internet reliability), using a bi-factor model or second-order model may enrich the profile results.

Also, a multilevel LPA model may detect different patterns based on student, school, or community characteristics. Additionally, a propensity score analysis could be conducted to match AOP students with students who use other test preparation products, such as OPL (ACT Kaplan Online Prep Live) in order to compare test preparation product users' profiles on other factors such as achievement. Finally, examining a combination of different test preparation products for the same student could provide in-depth identification of student profiles and their test preparation behaviors. Furthermore, qualitative studies could target some of the AOP profile members to recognize students' response processes using probes, think-aloud, or focus group procedures.

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