Exploring Predictors of Achievement-Goal Profile Stability during Mathematics Learning in an Intelligent Tutoring System

Leigh Harrell-Williams[1], Christian Mueller[1], Stephen Fancsali[2], Steven Ritter[2], Xiaofei Zhang[1], Deepak Venugopal[1]

[1] University of Memphis
{leigh.williams, cemuellr, xzhang12, dvngopal}@memphis.edu

[2] Carnegie Learning
{sfancsali, sritter}@carnegielearning.com

ABSTRACT

Using archived student data for middle and high school students' mathematics-focused intelligent tutoring system (ITS) learning collected across a school year, this study explores situational, achievement-goal latent profile membership and the stability of these profiles with respect to student demographics and dispositional achievement goal scores. Over 65% of students changed situational profile membership at some time during the school year. Start-of-year dispositional motivation scores were not related to whether students remained in the same profile across all unit-level measurements. Grade level was predictive of profile stability. Findings from the present study should shed light on how in-the-moment student motivation fluctuates while students are engaged in ITS math learning. Present findings have potential to inform motivation interventions designed for ITS math learning.

Keywords

Achievement goals, intelligent tutoring systems, latent profile analysis, situational motivation, dispositional motivation

1. INTRODUCTION

1.1 Background

Motivation plays a critical role in all aspects of student learning, including during learning with intelligent tutoring systems (ITS). Specifically, achievements goals have been one motivational construct that has been studied during ITS learning. Achievement goals are defined as the reasons that students engage in achievement-related behaviors. Typically, they are defined using two dichotomies: mastery/performance (content) and approach/avoidance (valence), and result in four goal types: mastery-approach, mastery-avoid, performance-approach, and performance-avoid [10]. Of these, mastery-approach goals (i.e., learning for the sake of learning) are assumed to be most adaptive or related to positive learning outcomes, and performance-avoid (i.e., avoid looking stupid in front of others) are assumed to be most maladaptive or related to negative learning outcomes, although student adoption of multiple goals has been documented [19]. The other aspect of achievement goals that has relevance for the present study is that recent research has shown that there is a difference between dispositional motivation constructs (i.e., person-level) and that of situational motivation constructs (i.e., fluctuating).

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Achievement goals have proven to be robust predictors of educational outcomes across many contexts and populations (e.g. [9], [14],[22],[23]). However, there is an increasing call by researchers to explore motivation as it actually exists: both dynamically and dispositionally [18]. For the former, increasingly, fluctuating motivation processes can be tied to in-the-moment learning, such as when students are engaging with ITS. Furthermore, advancements in technology and measurement are making it increasingly possible to explore how motivation shifts across tasks and across time, further advancing beyond reliance on only self-report measures [10]. Additionally, the distinction and subsequent implications between dispositional and situational motivation for student learning are only recently being explored in greater detail [6],[7]. To date, much of this work has explored these processes mainly with expectancy-value theory [17], and not with achievement goal theory.

However, some researchers have addressed noted limitations in measuring motivation processes more precisely at the task or domain level within an intelligent tutoring system framework [3] and exploring the possibility of using behavioral data in place of self-report [12]. Specifically, in the context of mathematics learning within Carnegie Learning's Cognitive Tutor system (now MATHia), students' achievement goal scores were found to change across units [3]. Additionally, a study exploring the relationship of achievement goals and self-efficacy with ITS-behavioral indicators (i.e., hint and glossary usage) found these indicators to be more related to self-efficacy than achievement goals [12]. One limitation in these two studies is that they consider goal adoption singularly (i.e., either mastery or performance) in their analysis strategy. However, as increasingly it has been shown that students will often adopt multiple goals while engaged in academic tasks, an approach that takes this into account is preferrable [23].

1.2 Current Study

The present study is part of a broader research effort designed to explore where how motivation patterns emerge during ITS mathematics learning, and how these patterns influence student choices during learning (e.g., strategy use). Furthermore, we were interested in exploring how these findings could influence development of teacher or tutor-delivered interventions. Building on work related to person-centered approaches for modeling multiple achievement goal adoption [24], we previously examined archived survey data recorded in an algebra-focused ITS to generate achievement-goal latent profiles using situational (i.e., end-of-unit) achievement goal scores, finding that 4 distinct profiles emerged [13]. In the present study, we explore situational profile membership and the stability of the profiles with respect to student demographics and dispositional (i.e., more global person-level) achievement goal scores. Our specific research questions were:

1. How stable are these student situational latent profile classifications across unit-level surveys?
2. How are student demographics (sex, free/reduced lunch status, grade level) related to student situational profile stability?
3. How are start-of-year dispositional achievement goal scores related to student situational profile stability?

2. METHOD

2.1 Data Source

The study employed a secondary analysis of a dataset retrieved from Carnegie Mellon University DataShop [5]. The students in the dataset were taking pre-algebra, algebra, and geometry courses and used Carnegie Learning's Cognitive Tutor (now MATHia) in the classroom as part of a blended instructional model for middle and high school math. Motivation survey data were collected within a mathematics-focused online intelligent tutoring system across an academic year from middle and high schoolers in a single school district.

2.2 Description of Students in Sample

The present sample consisted of 234 middle and high school students enrolled in a suburban school district in western Pennsylvania in the United States, which is a smaller subset of the larger available dataset. To be included in this study, students needed to have complete data for both the pre- and post-study dispositional motivation surveys as well as at least one situational motivation survey during the year. The student population within the district was primarily White (97%). The anonymized dataset available from DataShop contained district-provided data about each of the selected 234 students. Approximately 46% of students were classified as male, 2% of students in the sample were identified as "Non-white", 22% qualified for free/reduced lunch, 13% were classified as "special education", and less than 1% were classified as "gifted". There was no information about how the district defined or obtained these variables. Approximately 51% of students in the sample were in high schools (grades 9 to 12) and were taking classes classified as algebra (31%) or geometry (69%). For the middle school students with course enrollment data, 46% were identified as being enrolled in pre-algebra and 17% in 8th grade math (17%). Specific course names were not available for 37% of middle school students.

2.3 Measure

The original research study used an adapted subset of items from the Achievement Goals Questionnaire - Revised (AGQ-R; [10]). Only the three items from each of the mastery approach (MAP), performance approach (PAP), and performance avoidance (PAV) subscales were available in the dataset. As ours was a secondary analysis of publicly available data, we cannot state their exact reason for this decision. However, there has been some controversy and discussion around the MAV construct [19, 20], leading some authors to exclude it from their data collection or analysis.

Dispositional survey items, given at the start of the school year, were worded in terms of mathematics in general. For the end-of-unit surveys, the items were worded in terms of the algebra unit, such as "In this unit, my goal is to learn as much as possible". Students responded using a 7-point Likert-type scale from 1 (not at all true of me) to 7 (very true of me).

2.4 Analysis

Latent profile analysis (LPA) has become more commonly used in motivation research as a person-centered approach [24]. In our case, since we had multiple time points for each student, a multi-level profile analysis (MLPA) was most appropriate to account for both within-person and across-person differences. Whereas latent transitional analysis (LTA) is also popular in motivation research, that method assumes an equal number of timepoints across a study and that each student is completing the measure under the same conditions. Within the data in this study, students completed surveys at the end of units, meaning that had a varying number of timepoints (ranging from 1 to 20+), which is not accommodated by LTA. See [13] for in-depth detail of the MLPA results related to this project. The resulting exported latent class membership file, which indicated the most likely achievement profile (of the 4 identified profiles) that a student would be classified with at the end of the MATHia unit, was used in the analyses in this study.

For Questions 1-3, students were classified by the authors as being stationary across all unit surveys in terms of profile membership or having changed profiles at least once across unit surveys. For Question 1, descriptive statistics are reported. For Questions 2 and 3, single-level logistic regression was used to explore student demographics and dispositional AGQ-R scores as predictors of likelihood of whether students remained in the same profile across all unit-level measurements. As there was almost no variability in the student race (coded in the dataset as "NonWhite"), we focused on other available demographics that have been shown to be related to mathematics achievement, such as sex and free/reduced lunch status, and grade level (middle school or high school).

3. RESULTS

3.1 Summary of Situational Achievement Goal Profiles from Previous Work

To provide context for the latent profiles used within this study, Figure 1 illustrates the previously obtained profile means for the AGQ-R subscale scores within each of the four identified achievement goal profiles, taken from the previously published multilevel profile analysis [13].

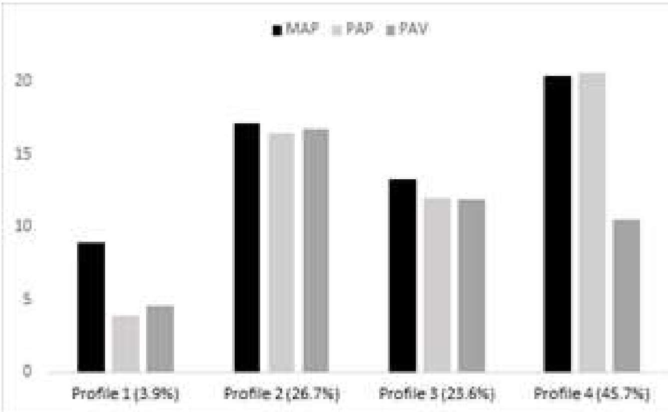

Figure 1. AGQ-R Subscale Score Means by Latent Profile

Note: MAP = mastery approach. PAP = performance approach. PAV = performance avoidance.

3.2 RQ1: Stability of Profile Classification

Across their unit-level survey responses, of the 329 students who had more than 1 unit-level survey completed, approximately 32.9% of students were always classified within the same profile (4.6% in Profile 1 only; 9.3.0%, Profile 2 only; 32.4%, Profile 3 only; 53.7%, Profile 4 only.). Of the students who transitioned across profiles at some point during the academic year, 71.8% had been classified in two different profiles, 27.3% had been classified in three different profiles, and 0.9% had been classified in all four profiles.

3.3 RQ2: Relationship of Student Demographics with Profile Stability

Results from the single-level logistic regression analysis indicated that only grade level was significant. In this case, it related to whether a student remained in the same profile across all unit. Specifically, high school students were more than twice as likely (OR = 2.287) to stay in the same achievement goal profile across units as compared to middle school students.

Table 2. Logistic regression results for demographic variables

Variable	Regression Coefficient	Std. Error	Odds Ratio 95% CI
Constant	-1.559	.291	-
Male (sex)	.243	.295	[.715, 2.271]
High School (grade level)	.827	.307	[1.268, 4.124]
Free/Reduced Lunch	.465	.372	[.815, 3.112]

3.4 RQ3: Relationship of Dispositional AGQ-R Scores with Profile Stability

Results from the single-level logistic regression analysis indicated that none of the three start-of-year dispositional AGQ-R scores were related to whether a student remained in the same profile across all unit-level (i.e., situational motivation) surveys.

Table 3. Logistic regression results for dispositional AGQ-R

Variable	Regression Coefficient	Std. Error	Odds Ratio 95% CI
Constant	-1.343	.687	-
MAP	.075	.060	[.959, 1.212]
PAP	-.063	.058	[.837, 1.053]
PAV	.016	.036	[.946, 1.090]

4. DISCUSSION

4.1 Implications

Our findings regarding stability parallel previous research conducted within the context of ITS learning. As with Bernacki and colleagues [2], there was significant variability in in-the-moment achievement goal adoption within the ITS, with nearly 65% of students' having their unit-level scores classified across different profiles at some point across the academic year. However, our stability findings are somewhat at odds with higher stability percentages for mathematics-specific dispositional achievement goal profiles, in the range of 60 to 70%, explored in other educational settings [21]. Hence, there seems to be more variation in achievement goals during mathematics learning than in comparisons of start and end-of year achievement goals. Some of this variation is likely due to unit content and/or difficulty, which we did not explore due to incomplete course information.

The finding that profile stability was more likely for high school students than middle school students suggests that studies exploring learning in mathematics ITS context might need to explore motivation within each of the grade levels instead of being jointly modeling. The lack of significance for our proxy for socio-economic status (free/reduced lunch) with regards to profile stability is encouraging from an equity standpoint as students from lower-income families are just as likely as other students to be in the more adaptive profiles at any time point.

Lastly, the lack of relationship between individual start-of-year dispositional achievement goal scores (i.e. students goals for the math course) and the stability of the situational profiles based on end-of-unit surveys potentially has implications for our larger research project. Specifically, these start-of-year scores might not be a useful catalyst for an early intervention, either inside or outside of the ITS.

4.2 Limitations

Some limitations are noted with regards to the classroom setting. The first is that the order and pace of content was teacher-dependent, potentially confounding any conclusions about the impact of specific unit content and time of year the measurement was taken. Secondly, students would ideally be nested within teachers, in addition to having multiple timepoints nested within students in the analyses used in our study to capture some variability in student responses possibly attributed to teacher or classroom attributes. However, there was missing data with regards to teacher and course information, preventing this modeling approach without a reduction in sample size.

Additionally, there are limitations related to the existing dataset. The sample had little diversity in terms of race or ethnicity as the data came from a single suburban district. While the sample size was reasonable for the procedures used in our analyses, the sample size did not allow for separate analyses for middle school and high school students or by type of course (algebra or geometry). Whereas the AGQR-R is a popular measure of achievement goals, the mastery avoidance (MAV) construct was not captured in the original study that generated the data. Nonetheless, the decision of the authors of the original study precluded us from making better comparisons about profile results to studies using all four AGQ-R subscales.

4.3 Ethical Considerations

Despite careful considerations, increasingly, use of student-level data poses several ethical issues that should be considered. In the present study, these ethical considerations pertained to the use of a convenience sample and ongoing issues related to data sharing and privacy. With respect to use of a convenience sample, potentially only districts (with students) who have adequate resources to purchase the ITS software could be included and thus, potentially leave out under-resourced schools and districts.

4.4 Future Research

Future research with the existing dataset should include the incorporation of student behavior captured by Carnegie Learning's Cognitive Tutor (now MATHia), such as hint usage, as well as researcher-constructed variables from student process data, such as percent of percent of steps correct on the first attempt per unit to explore how student behavior and performance is related to end-of-unit achievement goal profile membership and/or transition to another profile. Additionally, Elliot and colleagues [11] recently extended their achievement goal framework, which is "rooted in the definition and valence components of competence" (p. 632) and resulted in six goal types: task-approach, task-avoidance, self-approach, self-avoidance, other-approach, and other-avoidance. Although use of this new 3x2 framework is not as widespread as the AGQ-R yet, it could yield different results than those found in this paper. Future studies conducted should possibly include other motivation constructs (e.g., self-efficacy; [4]) and achievement emotions [1, 16], which could yield more robust learner profiles, which in turn lead to better understanding of students' overall choices and behavior during mathematics learning in an ITS.

4.5 Conclusion

While the lack of profile stability across various grade levels and educational contexts has been demonstrated [20], the present results are important as a review of the literature yielded no studies utilizing latent profile analysis while students were engaged within ITS-supported mathematics learning. In the scope of our larger project, the results support further work related to exploring where adaptive and maladaptive motivational patterns emerge during in-the-moment mathematics learning, how these patterns influence student choices during learning, and perhaps most importantly, to trigger teacher or tutor-delivered interventions before problems arise.

5. ACKNOWLEDGEMENTS

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