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Self-regulated learning and self-directed study in a pre-college sample

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Abstract

Self-regulated learning (SRL) is a multi-dimensional construct that has been difficult to operationalize using traditional, variable-centered methodologies. The current paper takes a person-centered approach to the study of SRL in a sample of 205 high-school students. Using latent profile analysis on self-reports of seven aspects of SRL, three groups were identified: high SRL, low SRL, and average SRL. Student self-reports of goal orientation were used as validation for the profile solution, with the high academic self-regulation group reporting the highest levels of mastery orientation while the low self-regulation group reported highest levels of avoidant orientation. Profiles were also compared on independently collected, behavioral measures of study behaviors, with the highly self-regulated group tending to study more material and for a longer time than less self-regulated individuals.

Keywords

self-regulated learning; study behaviors; latent profile analysis; mixture models; high school

1. Introduction

Self-regulated learning (SRL) is a multi-dimensional construct that has traditionally been difficult to operationalize (Boekaerts, 1996; Boekaerts & Corno, 2005). In general, SRL involves activating and sustaining cognitions, behaviors, and emotions in a systematic way to attain learning goals (Pintrich, 2000). Self-regulated learners manage their behaviors and anxieties to facilitate learning, actively avoiding behaviors and cognitions detrimental to academic success (Byrnes, Miller, & Reynolds, 1999; Stallworth-Clark et al., 2000). They understand the strategies and environments necessary for learning to occur, and feel capable of performing to their personal standards (Chemers, Hu, & Garcia, 2001; Pintrich & DeGroot, 1990; Zimmerman & Schunk, 2008). When challenged, self-regulated learners understand when and how to utilize strategies that increase persistence and performance (Schunk & Zimmerman, 1994). They purposefully use meta-cognitive strategies that incorporate self-monitoring and evaluative components that allow for self-observation and self-reaction (Kauffman, 2004). SRL is constantly evolving, with students developing upon existing behaviors and strategies based on prior success and emerging challenges (Winne, 1997).

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Due to the difficulty in operationally defining the construct, many SRL researchers have examined only limited aspects of SRL, often relying exclusively on correlational methods (Braten & Olaussen, 2005; Rheinberg, Vollmeyer, & Rollet, 2002). Meta-cognitive and effort management aspects of SRL are predictive of college academic achievement (Chen, 2002; Vrugt & Oort, 2008; Yukselturk & Bulut, 2007). Appropriately structuring one's time and environment has been predictive of college performance (Chen, 2002; Lahmers & Zulauf, 2000), as have academic self-efficacy beliefs (Bong, 2001; Chemers et al., 2001). In addition, behaviors and cognitions indicative of poor SRL, such as high test anxiety (Ruthig, Perry, Hall, & Hladkyj, 2004), engaging in self-handicapping (Martin, Marsh, & Debus, 2003), and believing that academics are irrelevant for future success (Greene, Debacker, Ravindran, & Krows, 1999), are associated with poorer achievement.

Although correlational methods greatly contribute to understanding SRL, one limitation is that relatively few facets of SRL can be examined simultaneously. Specifically, little research has examined how these facets might cluster as potential subgroup profiles of SRL. The few studies that have examined SRL profiles have mostly used cluster analysis and incorporated other indicators from related constructs, such as motivation and task value (Braten & Olaussen, 2005; Salisbury-Glennon et al., 1999; Turner, Thorpe, & Mayer, 1998; Wang, 2007). Several studies focused on middle-school students (Salisbury-Glennon et al., 1999; Turner et al., 1998), while others examined college students (Braten & Olaussen, 2005; Wang, 2007).

A strength of these previous person-centered studies is the use of multiple indicators of self-regulation to find qualitatively different student types. The current study also illustrates a person-centered approach to SRL using a mixture model to examine a range of SRL characteristics. There has been a call for person-centered approaches in educational psychology (Braten & Olaussen, 2005), and Butler (2002) discussed the need for methodologies capable of simultaneously examining the multiple characteristics of SRL.

The current study builds on previous research by utilizing latent profile analysis (LPA) on a broader set of SRL indicators that might better represent the construct. Measures of academic goal-orientation provide validation support of the latent profiles, and independently gathered observational data on self-directed study behavior are also used to compare profiles. Research has shown goal orientations to be linked with SRL, such that a more mastery orientation tends to be associated with more optimal SRL (Boekaerts, de Koning, & Vedder, 2006; Kolic-Vehovec, Roncevic, & Bajanski, 2008; Wolters, Yu, & Pintrich, 1996).

LPA may be considered an improvement upon cluster analysis because it offers statistical tests for the number of profiles (Pastor, Barron, Miller, & Davis, 2007), mitigating the problem of arbitrary and subjective stopping rules common in cluster analysis. Furthermore, existing LPA software utilizes full information maximum likelihood to accommodate missing data (Muthen & Muthen, 1998–2007), whereas traditional cluster analysis uses only cases with complete data. This provides additional statistical power given the presence of missing data. LPA also provides posterior probabilities of membership, allowing researchers to evaluate how well the solution classified individuals (McLachlan & Peel, 2000). Cluster analysis utilizes certain optimal fit criteria to place individuals within groups, providing no measure of how certain these placements were (Whiteman & Loken, 2006) (for more information on LPA, see Pastor et al., 2007).

The current study is also unique in having independently gathered observational data on actual self-directed study behaviors. Previous subtype analyses of SRL have relied exclusively on self-reports (Braten & Olaussen, 2005; Pastor et al., 2007; Rheinberg et al., 2002; Salisbury-Glennon et al., 1999; Wang, 2007). The current study estimates SRL profiles and compares these profiles on objective behavioral measures of self-directed learning. Self-directed

learning, in this case, represents the actual academic behaviors (e.g., studying, practice problems) that are associated with self-regulated cognitions and beliefs. Objective computer based measures provide evidence of behavior related to SRL outside of the classroom, offering convergent and predictive validity for the self-report measures. Independent observations are useful, as the validity of survey measures of SRL has been challenged due to concerns that students might respond in ways that they perceive teachers/researchers would desire (Boekaerts & Corno, 2005; Muis, Winne, & Jamieson-Noel, 2007; Patrick & Middleton, 2001).

There were 3 primary goals of the current study: (1) to describe profiles of self-regulated learners employing a broad range of indicators using a relatively novel analytic method; (2) to validate these groups using goal orientations, which have been used in previous cluster analytic studies (Braten & Olaussen, 2005; Pastor et al., 2007); (3) to examine the degree to which latent groups of self-regulated learners differ in their independently collected study behavior. We expect that the more optimal profiles of SRL will be associated with a more mastery orientation and better self-directed learning.

2. Method

2.1 Participants

The sample was 205 11th/12th grade students from an urban area in the Pacific Northwest enrolled in a voluntary non-profit college preparation program to enhance the likelihood of college attendance and retention. The majority of participants in this program are from economically disadvantaged families. The program had 10 classroom sessions providing math and English review, guidance in the college application process, and assistance in developing college study skills. The mean participant age was 16.5 years-old (S.D. = .78; 65% female).

2.2 Measures

2.2.1 Latent Profile Analysis Indicators—Seven indicators were used to form latent profiles. Four were from the Motivated Strategies for Learning Questionnaire (MSLQ) (Pintrich, Smith, Garcia, & McKeachie, 1991), which has been used on similar samples of students and has been associated with academic achievement (Pintrich & DeGroot, 1990; Vrugt & Oort, 2008). The *meta-cognition* subscale (12 items; $\alpha = .80$) measures how an individual activates and sustains cognitive processes of self-monitoring and evaluation during school work. The *effort management* subscale (4 items; $\alpha = .69$) measures persistence of academic exertion despite potential obstacles. The *time and study environment* subscale (8 items; $\alpha = .74$) measures the regulation of a personal environment necessary for learning to occur. The *test anxiety* subscale (5 items; $\alpha = .72$) measures nervousness during exams. All MSLQ items are on a 5 point scale (1 = not at all true, 5 = very true).

Three additional indicators were from the Patterns of Adaptive Learning Scales (PALS) (Midgley et al., 2000), also employed in studies of similar populations and shown to be associated with achievement (Abar et al., 2009). The *academic efficacy* scale (5 items; $\alpha = .84$) concerns how capable of academic performance students believe themselves to be. The *academic self-handicapping strategies* scale (6 items; $\alpha = .86$) measures intentional engagement in behaviors detrimental to academic success that could justify low achievement. The *academic skepticism* scale (6 items; $\alpha = .78$) measures beliefs that academics are unimportant to one's future.

2.2.2 Latent Profile Analysis Covariates—Three further subscales from the PALS (Midgley et al., 2000) were employed as covariates. The *mastery goal orientation* scale (5 items; $\alpha = .85$) measures intrinsic motivation to develop academic competence. The *performance-avoidance goal orientation* scale (6 items; $\alpha = .79$) measured motivation due to

fear of appearing academically incompetent. The *performance-approach goal orientation* scale (5 items; $\alpha = .81$) measures the motivation to appear competent in the eyes of others. The response set for the PALS is identical to the MSLQ.

2.2.3 Behavioral Measures of Self-Directed Learning—In addition to the classroom instruction, students were given accounts for a supplemental web-based study tool. Students preparing for the SAT could view tutorials and answer practice questions. The website provided practice questions in seven areas: algebra, geometry, arithmetic, data analysis, sentence completion, reading passages, and grammar. In addition, tutorials with content reviews and strategies are offered for each area. For example, the arithmetic tutorial consists of 32 pages reviewing numerical operations, fractions, and includes a lesson on how to fill in arithmetic SAT questions. Students could choose to skip to the practice questions. Practice questions were delivered computer adaptively; a running estimate of ability level, based on previous performance, was used to select the next most appropriate practice questions.

For the current study, measured variables included: whether a student used the site (operationalized as ever logging on for a total of more than 5 minutes), the length of time using the website, the number of questions attempted, and the proportion of the tutorials viewed in each section. The length of time using the website and the number of questions answered were log transformed, as is appropriate for positively skewed data (Tabachnick & Fidell, 2001). These behavioral measures represent aspects of self-directed study behavior that might differ across types of self-regulated learner.

2.2.4 Behavioral Ability Measure—Standardized estimates of student ability were available for students who answered at least 6 questions on the website. Although the website calculates ability estimates in each category (e.g., algebra), a weighted average of overall ability was used due to differential usage patterns.

2.3 Procedure

Students taking the college preparation program in 2007 and 2008 completed the self-report survey during either the first or second meeting. The website data represents total student usage across the duration of the program.

2.4 Plan of Analysis

To identify sub-populations of self-regulated learners, a series of LPAs were performed using MPlus (Muthén & Muthén, 1998–2007). The indicator variables were standardized for ease of interpretation. The choice of profile solution was guided by relative statistical fit (using the Akaike and Bayesian Information Criteria (AIC, BIC), the adjusted Likelihood Ratio Test (aLRT)) and interpretability of the profile structure. We then predicted profile membership using goal orientations. Finally, group membership was used to predict the independent computer based measures of self-directed learning and student ability.

3. Results

3.1 Latent Profile Solution

The three profile solution provided the best fit, according to the BIC and aLRT (see Table 1). The profiles were clearly defined, with significant mean differences across profiles on all indicators (see Table 2) and relatively high entropy (.84). Entropy approaching 1 indicates little profile overlap (Celeux & Soromenho, 1996)

The smallest profile (15%) was labeled the *high SRL group*, reporting high meta-cognition, effort management, time and environment skills, and academic efficacy, along with low test

anxiety, self-handicapping, and academic skepticism (see Table 2 for conditional means and SDs). Overall these students report appropriate regulatory behaviors and cognitions while avoiding behaviors and cognitions likely to detract from achievement. The second profile (37%), labeled the *low SRL group*, was characterized by low meta-cognition, effort management, time and environment skills, and academic efficacy, coupled with relatively high test anxiety, self-handicapping, and academic skepticism. These students tended toward academically self-destructive thoughts and behaviors. The final and largest profile (48%) was the *average SRL group*. This group was close to the population average across all aspects of SRL. Follow-up ANOVAs with Tukey post-hoc tests showed all profile comparisons to be significant across all indicators ($p < .05$) (see Table 2), with the exception of test anxiety where only the high SRL profile significantly differed from the low profile.

The profiles were clearly delineated, with the average posterior probability of profile membership over .90 for each profile (i.e., .94, .93, or .92). For the subsequent analyses, we classified students into their most likely classes. Due to the high probabilities of class membership, the bias due to classification error is likely small.

3.2 Connection to Academic Motivation – Concurrent Validity

Logistic regression predicted group membership with mastery, performance-avoidance, and performance-approach goal orientations to provide validation of the profiles. Goal orientations significantly distinguished between the latent profiles, Nagelkerke Pseudo $R^2 = .46$ (see Table 3 for goal orientation means and SDs). Mastery orientation significantly predicted membership in the low SRL versus the high or average SRL profiles, as did performance-avoidance. The low SRL group had the lowest mastery orientation, and highest performance-avoidance orientation.

3.3 Prediction of Observed Self-Directed Study Behavior

We next examined differences in self-directed learning as measured by activity on the website. Since use of the website was voluntary, only a subset of students were observed to have logged on for more than 5 minutes ($n = 111$). A χ^2 test of independence revealed no significant differences in whether individuals used the website (coded yes/no) by group membership. There were also no significant differences between the users and non-users on any of the self-regulation and goal orientation composites.

The high SRL group used the website significantly more than the low SRL group (see Table 4 for usage means and SD's). There were also significant differences in the total number of math and English questions attempted. The high SRL profile attempted more questions than the combination of the average and low profiles.

The high SRL group also viewed a greater proportion of the subject specific tutorials than the combination of the average and low SRL profiles across all domains (see Table 5). The high SRL profile had a mean tutorial viewing of 66% across all sections, whereas the average and low profiles had means of 32% and 34%, respectively, $F(2,108) = 7.13$, $p < .001$. Lastly, the high SRL group exhibited a marginally higher ability estimate than the combination of the average and low SRL groups (see Table 4).

4. Discussion

The purpose of the current study was to examine potential subgroups of self-regulated learners within the population. This study expanded upon previous research (Braten & Olaussen, 2005; Butler, 2002; Chemers et al., 2001; Rheinberg et al., 2002) by using a parametric clustering method capable of taking into account a larger set of SRL indicator variables.

Three distinct subpopulations of college aspiring students were identified. The largest profile had conditional means that were roughly average across all indicators. The low SRL group was the next largest, and the high SRL group was the least prevalent profile observed. The solution in the current study was relatively similar, in terms of number of groups and interpretation, to several of the cluster solutions found in previous work that illustrated between 2 and 4 groups distinguished along a high/low ordering of SRL (Braten & Olaussen, 2005; Turner et al., 1998; Salisbury-Glennon et al., 1999; Wang 2007). Two advantages of the current study over these previous works were the use of LPA and the use of a broader set of SRL indicators. Using LPA provided researchers with clear statistical support for the 3 profile model, and the incorporation of a more representative set of SRL indicators provided for a more thorough depiction of the construct at the level of the individual. Pastor and colleagues (2007) also used LPA, but the indicators of their student profiles were limited to goal orientation.

Academic goal orientations were shown to differ across SRL profiles. As was hypothesized, the most optimal SRL profile was associated with the highest levels of mastery goal orientation. In addition, those individuals exhibiting the least optimal SRL tended to be most oriented toward avoiding academic embarrassment. These findings are in accordance with previous work on SRL and goal orientations (Boekaerts et al., 2006; Kolic-Vehovec et al., 2008).

The three profile solution was also shown to predict actual study behavior. The low SRL group spent the least amount of time using the supplemental online material, both in hours spent and questions attempted. This difference may be due to these students being least able to regulate meta-cognitive focus and behavioral effort. While previous research on the same online preparation site has shown students tend to spend less time on math than on verbal preparation (Loken, Radlinski, Crespi, Millet, & Cushing, 2004), in the current study, this pattern is only observable for the average and low SRL profiles. The high SRL profile attempted nearly identical numbers of math and verbal questions, exhibiting high levels of effort regulation and meta-cognition by preparing for all phases of their expected test. A person-centered approach, like LPA, allowed researchers to observe these differential patterns of study behaviors that would not otherwise be readily visible.

It is also possible that meta-cognitive difficulties and self-handicapping tendencies were evidenced by the average and low SRL profiles in terms of attending to the section specific tutorials provided by the website. The high SRL students tended to utilize these resources to a much greater extent. Taken as a whole, these differences in study behavior support the utility in academic research of the theoretical Self-Regulation Model of Decision Making (Byrnes et al., 1999), whereby self-regulated individuals set specific goals and utilize all appropriate and available resources to achieve these goals.

Several limitations must be addressed regarding the current study. First, the sample is relatively small, moderately skewed toward women, and includes only college aspiring high-school students. Future replication should examine a more representative sample, including students with limited desire for post-secondary education. Second, a substantial number of students did not choose to use the online supplemental materials. It is important to consider that website usage might be influenced by student SRL, as well as characteristics like prior academic achievement, scheduling restrictions, and prior online experience. Future work might examine individual and social influences on online resource use. Finally, the current study examined SRL at a single time point. Work should also examine potential transitions in SRL through late high-school and college, as SRL is a dynamic process (Winne, 1997).

The present study illustrates a person-centered approach to thinking about SRL among high-school students. Viewing this multi-dimensional construct as a discrete latent variable may

provide researchers and practitioners an alternative lens by which to conceptualize self-regulated learning.

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Table 1

Latent profile analysis fit indices

	Log-likelihood	AIC	BIC	aLRT
1 Class	-2040.8	4109.7	4156.2	--
2 Class	-1870.5	3799.1	3895.4	$p < .001$
3 Class	-1798.5	3685.0	3831.2	$p < .05$
4 Class	-1761.1	3640.2	3836.3	$p = .18$

Note: Minimal AIC and BIC indicates best relative fit.

Significant aLRT denotes an improvement of fit given the additional class (i.e., 2 class model fits significantly better than the 1 class).

Table 2

Self-Regulated Learning Standardized Group Means and SDs

	<i>Self-Regulated Learning Group</i>		
	High (15%; n = 32)	Low (37%; n = 76)	Average (48%; n = 97)
<i>Aspects of Self-Regulation</i>			
Meta-Cognition	1.17 ^{a b} (.45)	-.74 ^{b c} (.79)	.21 ^{a c} (.80)
Effort Management	1.17 ^{a b} (.47)	-.83 ^{b c} (.79)	.32 ^{a c} (.71)
Time & Environment	1.37 ^{a b} (.55)	-.88 ^{b c} (.70)	.24 ^{a c} (.60)
Academic Efficacy	.85 ^{a b} (.58)	-.71 ^{b c} (.97)	.24 ^{a c} (.80)
Test Anxiety	-.38 ^b (1.12)	.21 ^b (.97)	-.06 (.93)
Self-handicapping	-1.13 ^{a b} (.10)	.65 ^{b c} (1.06)	-.14 ^{a c} (.71)
Academic Skepticism	-.59 ^b (.66)	.66 ^{b c} (1.06)	-.34 ^c (.73)

Note: Values in the table represent standardized within group means.

^a High significantly different from Average, $p < .05$

^b High significantly different from Low, $p < .05$

^c Average significantly different from Low, $p < .05$

Table 3

Goal Orientation Means and SDs by Self-Regulated Learning Group

	<i>Self-Regulated Learning Group</i>		
	High (n = 32)	Low (n = 76)	Average (n = 97)
<i>Goal Orientations</i>			
Mastery	24.50 (1.22)	20.16 (3.53)	23.05 (1.96)
Performance-Approach	16.78 (4.77)	16.07 (4.44)	17.68 (4.11)
Performance-Avoidance	12.59 (4.91)	15.13 (5.13)	13.13 (4.31)

Note: Values in the table represent within group scale means

Table 4

Website Usage and Ability Estimate Means and SDs by Self-Regulated Learning Group

	<i>Self-Regulated Learning Group</i>		
	High (n = 20)	Low (n = 42)	Average (n = 49)
<i>Website Usage Variables</i>			
Hours on Website	2.02 ^a (.77)	1.37 ^a (.91)	1.54 (.85)
Math Questions	3.44 ^{ab} (1.43)	2.08 ^{ab} (1.90)	2.48 ^b (1.91)
English Questions	3.75 ^b (.99)	2.91 ^b (1.61)	3.03 ^b (1.46)
<i>Student Ability</i>			
Ability (Z-score)	.18 (.57)	-.35 (.87)	-.07 (.92)

Note: Hours using the website, math questions, and English questions were log-transformed.

^aHigh significantly different from Low, $p < .05$

^bsignificant contrast: High vs. Average and Low $p < .05$

Table 5

Subject Specific Tutorial Viewing Means and SDs by Self-Regulated Learning Group

	<i>Self-Regulated Learning Group</i>		
	High (n = 20)	Low (n = 42)	Average (n = 49)
<i>Tutorial Subjects</i>			
Algebra	60 ^c (50)	35 ^c (46)	31 ^c (44)
Geometry	57 ^{a c} (49)	25 ^c (40)	23 ^{a c} (40)
Arithmetic	80 ^{a b c} (41)	33 ^{b c} (46)	36 ^{a c} (44)
Data Analysis	50 ^{a c} (51)	25 ^c (42)	22 ^{a c} (41)
Sentence Completion	80 ^c (41)	54 ^c (45)	55 ^c (46)
Reading Passages	65 ^{a c} (49)	36 ^c (44)	33 ^{a c} (46)
Grammar	70 ^{a b c} (47)	29 ^{b c} (44)	26 ^{a c} (43)

Note: Values represent the within group mean proportion of the tutorial that was viewed.

^a High significantly different from Average, $p < .05$

^b High significantly different from Low, $p < .05$

^c significant contrast: High vs. Average and Low $p < .05$