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Latent Profiles of Online Self-Regulated Learning: Relationships with Predicted and Final Course Grades

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Abstract

This study used a combined person- and variable-centered approach to identify self-regulated online learning latent profiles and examine their relationships with the predicted and earned course grades. College students (N=177) at a Southeastern U.S. university responded to the Online Self-Regulated Learning Questionnaire. Exploratory structural equation modeling revealed four self-regulation factors: goal setting, environment management, peer help-seeking, and task strategies. Latent profile analysis yielded four latent profiles: Below Average Self-Regulation (BASR), Average Self-Regulation (ASR), Above Average Self-Regulation (AASR), and Low Peer Help-Seeking (LPHS). Compared with the AASR group, when students anticipated obtaining a higher course grade, they were less likely to engage in peer help-seeking and task strategies and more likely to adopt the LPHS self-regulation profile. Relating to LPHS, membership to all other groups predicted significantly lower course grades. AASR and LPHS predicted their performance most accurately, with non-significant differences between the predicted and the final course grades.

Keywords: online self-regulated learning, latent profile analysis, person-centered approach, variable-centered approach, higher education

Introduction

With advances in technology, as well as the COVID-19 pandemic, online learning has become an essential component of the learning opportunities available to most students (Aristovnik et al., 2020; Kaplan, 2017) and will likely become mainstream by 2025 (Palvia et al., 2018. Online learning, defined as learning taking place on the Internet (Moore et al., 2011) implies learners' physical separation from their instructors and the institution. It requires students to engage more actively in regulating their learning as they decide where, when, and how to study (Gerjets et al., 2008; Wang et al., 2013). Therefore, students' self-regulating abilities are essential for their academic performance when taking online courses (Ally, 2004; Barnard et al., 2009; Sitzmann et al., 2009; Winters et al., 2008; Zimmerman, 2008).

Self-regulated learning (SRL) is essential in all learning environments, whether face-to-face, blended, or online (Greene, 2018; Zimmerman, 2008); it allows for the achievement of learning goals and serves as a valuable educational outcome in and of itself (Chen, 2012; Greene, 2018). However, students encounter more difficulties in online classes than in other environments when they do not employ effective SRL techniques (Azevedo, 2005). Understanding how individual students develop and deploy self-regulation strategies is essential in order to promote online SRL (OSRL) and provide differentiated support according to students' characteristics and needs (Guo & Reinecke, 2014; Hood et al., 2015; Kocdar et al., 2018; Schwam et al., 2021; Wong et al., 2019; Yeh et al., 2010; Zhang et al., 2015; Zheng, 2016;). Although research has acknowledged differences in students' SRL skills and strategies (Greene & Azevedo, 2007), there has been a lack of clarity on how to account for these differences (Barnard-Brak et al., 2010). The current study addressed this gap by classifying OSRL characteristics based on how individual students endorsed and employed self-regulated learning strategies in an online course. Identifying profiles based on attributes of SRL among online students, and determining how such profiles relate to academic performance, was intended to advance SRL theory and offer guidance to support OSRL through a more nuanced personal approach.

Most research studies on SRL have followed a variable-centered approach, examining relationships among variables and summarizing trends for an entire sample without investigating how such relationships may vary across subgroups (Howard & Hoffman, 2017). In contrast, person-oriented approaches have examined each person, identifying subgroups of individuals with similar profiles (Bergman & Anderson, 2010). Such profiles reflect individual differences in motivation, strategy use, communication, and relation to others (Hampson & Colman, 1995; Woolfolk et al., 2006). Identifying OSRL profiles helps reveal distinct OSRL strategies and provided valuable information for promoting self-regulatory strategies based on individual student needs (Woolfolk, 2001). Combining the variable-centered and the person-centered methods allows researchers to investigate generalities across entire samples as well as the profiles of distinct subgroups (Marsh et al., 2009; Raufelder et al., 2013). In the current study, we used the combined approach to:

1. Identify the OSRL factors underlying the data.
2. Distinguish OSRL latent profiles.
3. Estimate the relationship between predicted grades and OSRL latent profiles.

4. Estimate the relationship between OSRL latent profiles and final grades.

Theoretical Perspective

The term self-regulation has been used to refer to self-generated thoughts, feelings, and actions that learners activate and maintain to attain personal goals (Zimmerman, 1998; Zimmerman & Kitsantas, 2014). Self-regulated learners often displayed specific motivational beliefs or attitudes, cognitive strategies, and metacognitive abilities. They engaged in a cyclical process of planning, performing, evaluating, and reflecting, functioned as active agents in their learning (Schunk & Zimmerman, 2008; Winne, 1997; 2018), and obtained improved academic performance (Greene, 2018; Pintrich, 2004; Pintrich & DeGroot, 1990). Research has shown that SRL processes enabled learning in online environments (Azevedo & Hadwin, 2005; Lehmann et al., 2014; Winters et al., 2008). SRL strategies have led to increased academic achievement in online learning (e.g., Broadbent & Poon, 2015; Cuesta, 2010). "Individuals who are self-regulated in their learning appear to achieve more positive academic outcomes than individuals who do not exhibit self-regulated learning behaviors" (Barnard-Brak et al., 2010, p. 61).

Over the past four decades, SRL has been examined from various theoretical perspectives (Boekaerts, 1996, 1999; Boekaerts & Corno, 2005; Efklides, 2011; Paris & Paris, 2001; Pintrich & Zusho, 2002; Schunk & Greene, 2018; Zimmerman & Schunk, 1989). A common feature of these theoretical perspectives their description of SRL as an active cyclical process of three phases: (a) a preparatory phase of task analysis and goal setting; (b) a performance phase of strategy use and monitoring; and (c) an appraisal phrase of reflection on and evaluation of learning outcomes (Panadero, 2017; Peel, 2019; Puustinen & Pulkkinen, 2001). This broader view has highlighted SRL as a multi-dimensional process, driven by goal-directed learning of individual learners and mediated by contextual influences. By adopting this view, researchers have made continuous efforts to identify the personal and environmental factors that may influence SRL (Greene, 2018; Peel, 2019; Winne, 2018).

Understanding how students developed and deployed an optimal combination of the SRL knowledge and skills for enhanced learning and achievement has gained attention in the recent research on OSRL. This research has often focused on identifying motivation factors (Puzziferro, 2008; Wang et al., 2013) and the most effective strategies to help students learn and achieve academic goals (Cleary & Callan, 2018; Greene, 2018; Hirt et al., 2021; Lynch & Dembo, 2004; Reimann & Bannert, 2018; Schunk & Greene, 2018). Such studies have been criticized for using predominantly self-reported measures of student satisfaction, feelings, or perceived value of the educational experience (Deimann & Bastiaens, 2010; Wang et al., 2013) and for their lack of accurate determinants of the effectiveness of SRL (Broadbent & Fuller-Tysiewicz, 2018; Reimann & Bannert, 2018; Schunk & Greene, 2018; Zimmerman, 1989, 1990). These authors did not compare survey results with academic performance as measured by the course grade; further, they did not investigate the impact of the students' prediction of their course grades on self-regulation strategies. The current study addressed this limitation by examining the relationships between predicted course grades (will), the selection and use of self-regulatory techniques (skill), and earned course grades (outcome).

Most researchers have used variable-centered approaches to examine SRL. Such methods focused on associations between variables and predictors' contributions to a response variable (Lausen & Hoff, 2006); they did not help explain how individuals selectively used combinations of self-regulatory techniques and how the selected strategies integrated into self-regulation profiles (Schwinger et al., 2012). Variable-centered approaches have relied upon "the assumption that relationships observed at this group level are representative of the whole sample; an assumption that will be false in cases where distinct subgroups exist" (Broadbent & Fuller-Tysiewicz, 2018, p. 1437).

Studies that used variable-centered approaches neglected individual differences and the existence of distinct subgroups. Such studies did not explain how individual students selected and implemented motivational and learning strategies, and how specific regulation profiles were formulated based on each learner's individualized strategy use (Broadbent & Fuller-Tysiewicz, 2018; Schwinger et al., 2012). In contrast, person-centered approaches to SRL adopted an idiographic perspective (Molenaar, 2004; Molenaar & Campbell, 2009). This perspective viewed individuals as organized entities who functioned and developed distinctively from other individuals (Bergman & Magnusson, 1997; Bergman et al., 2003). Person-centered approaches defined SRL as a dynamic, multi-dimensional process influenced by student characteristics, abilities, and personal experiences. Characterizing SRL as a multi-dimensional and individualized process provided a unique perspective and examined how "learners personally activate and sustain cognitions, affects, and behaviors that are systematically oriented toward the attainment of personal goals" (Zimmerman & Schunk, 2011, p. 1).

Variable-centered and person-centered approaches operated on disparate but complementary assumptions; therefore, a combinational method has emerged. The combined method offered the potential to minimize weaknesses and maximize each method's advantages (Bámaca-Colbert & Gayles, 2010; Raufelder et al., 2013) and provided an alternative way to explore individual differences in educational research. Building on different cases, Bergman (1998) and von Eye (2010) proposed the following sequence of combined analyses: (a) start with variable-centered procedures to identify operating factors (Feyerabend, 1975; von Eye & Bogat, 2006); (b) use exploratory, person-centered analyses to distinguish possibly existing subpopulations (von Eye & Bogat, 2006); (c) use confirmatory person-centered analyses of data from independent samples to test theoretical assumptions; and finally, (d) use variable-centered methods to link theories and results from the various research approaches (Feyerabend, 1975; Molenaar & Campbell, 2009).

Current Study

Following the recommended sequence (Bergman, 1998; von Eye, 2010), the current study used a combined variable-centered and person-centered approach and focused on the link between individualized use of SRL strategies and academic achievement (e.g., Schwinger et al., 2009, 2012; Wang et al., 2013). First, we employed the variable-centered method to operationalize the construct of SRL and its latent dimensions. We used survey variables to identify OSRL factors and estimate OSRL factor scores. Second, we used the person-centered approach to analyze and compare online learning self-regulation patterns and identify latent profiles. As Bergman and Magnusson (1997) suggested, variables included in the analyses were considered "only as components of the pattern under analysis and interpreted in relation to all the other variables considered simultaneously; the relevant aspect is the profile of scores" (p. 293). Third, we used

the variable-centered procedures to investigate the relationship between self-regulation profiles and academic performance.

The course grade served as an outcome variable for evaluating the overall effectiveness of online learning (Lim et al., 2006). Previous studies did not include critical predictors of academic performance. Such predictors include help-seeking, metacognition, effort regulation, elaboration, time management, and critical thinking (Schwinger et al., 2009, 2012). Examining the relatedness of profiles of SRL to student predicted and actual course grades addressed this limitation.

Including a broader range of OSRL techniques allowed us to determine whether high-performing students used all SRL strategies more than did other students or whether they employed only the most effective ones (Broadbent & Fuller-Tysiewicz, 2018; Hirt et al., 2021). The person-centered approach enabled us to (a) identify several distinct self-regulation profiles with unique characteristics, (b) determine whether the academic performance anticipated at the beginning of the course impacted the self-regulation profile employed by online learners, and (c) determine which of the identified profiles predicted increased academic performance. Establishing SRL profiles helped us better understand how motivations and strategies interacted in OSRL. Specifically, we investigated four hypotheses:

Hypothesis 1

Distinct latent factors of online learning self-regulation underlie the data (Barnard et al., 2009). We examined a broad range of motivational and SRL skills to identify the OSRL strategies most frequently employed by the students in our sample.

Hypothesis 2

Distinct latent profiles of self-regulation exist based on participants' endorsement of OSRL factors (Barnard et al., 2008). The OSRL profiles help educators facilitate the use and proficiency of the most effective self-regulation techniques (Bruso & Stefaniak, 2016; Panadero, 2017).

Hypothesis 3

Depending on the expected course grade, students adopt specific OSRL strategies as described by the online learning self-regulation latent profiles (Barnard et al., 2008). Including student-predicted course grades is a novel approach to explore how OSRL profiles differ based on the expected level of performance.

Hypothesis 4

Students' final course grades vary across OSRL latent profiles. This hypothesis assumes that academic outcomes are significantly related to OSRL strategies (Greene, 2018). Unlike previous research, our study employed more complex modeling techniques that estimated the impact of variables measuring expected academic performance on the classification process. Based on previous research, our goal was to identify strategies of self-regulation and describe how such strategies may vary due to context, procedural factors, and individual differences. Based on previous research, our goal was to identify self-regulation strategies and describe how such strategies may vary due to context, procedural factors, and individual differences (Hampson & Colman, 1995; Händel et al., 2020; Schwam et al., 2021).

Method

Participants

Participants in the study (N = 177) were students enrolled in fully online graduate-level education courses at a southeastern US university. Most participants were females (n = 161, 91%,) and only 9% (n = 16) identified as males. Participants identified themselves as White (n = 133, 75.1%), African American (n = 33, 18.6%), Hispanic (n = 6, 3.4%), or as other ethnicities (n = 5, 2.9%).

Data Sources

Data for the study consisted of (a) demographic information, (b) predicted course grade, (c) final course grade, and (d) responses to an online learning self-regulation questionnaire. At the beginning of the semester, we collected demographic information and asked participants to predict their overall grade at the end of the course as a percent correct estimate (e.g., 84%). The course syllabus described the class letter grade scale as: A = 90%, B = 80%, C = 70%, and F = 69% or below. The final course grade was the sum of student performance scores on (a) six end-of-unit tests developed by the instructor based on the textbook (Alexander, 2016); (b) two theory-to-practice assignments; and (c) two online discussions.

The Online Self-Regulated Learning Questionnaire (OSLQ; Barnard et al., 2009) was adapted to examine student OSRL. The OSLQ was designed to measure students' ability to self-regulate their learning in online and traditional face-to-face learning environments. Our modified OSLQ included 24 items that measured 6 dimensions of self-regulation: (a) goal setting; (b) environment structuring; (c) task strategies; (d) time management; (e) help-seeking; and (f) self-evaluation on a Likert scale, ranging from 1 (*strongly disagree*) to 7 (*strongly agree*). Higher scores showed increased OSRL. According to Nunnally (1978), Cronbach α coefficient of .70 or better is acceptable when used in social science research such as this study. The values for Cronbach α ranged from .786 to .899 in the current study, indicating high levels of internal consistency.

Data Analysis

Data analyses consisted of (a) descriptive analysis, (b) exploratory factor analysis, (c) latent profile analysis with a covariate and a distal outcome, and (d) examining demographic and achievement variables by latent profile. We calculated item means and standard deviations to examine the distribution of survey responses. Then, we used exploratory factor analysis (EFA) within the exploratory structural equation modeling (ESEM) framework to identify the latent variables underlying the data (Marsh et al., 2014). The ESEM approach was beneficial because it allowed the estimation and rotation of common factors and yielded a realistic representation of the data by calculating cross-loadings and assessing model fit (Marsh et al., 2014; Morin & Maiano, 2011; Morin et al., 2013). ESEM was employed to overcome the limitations of confirmatory procedures. With confirmatory approaches, the strict requirement of zero cross-loadings may lead to distorted factors, overestimated factor correlations, and distorted structural coefficients (Asparouhov & Muthén, 2009). Especially in the early stages of theory development, items are rarely pure indicators of the corresponding constructs. Cross-loadings other than zero could inflate the associations between the factors and misspecified cross-loading items. Simulation studies have shown that researchers should estimate even small cross-loadings such as .100; otherwise, parameters could be inflated or biased (Asparouhov et al., 2015).

We used Mplus 8.2 statistical software as well as the mean- and variance-adjusted weighted least squares (WLSMV) estimation procedure with Geomin rotation. The WLSMV method does not rely on the assumption of multivariate normality and provides more accurate results with smaller samples and ordinal data than do other estimation procedures (Finney & DiStefano, 2006). The indices used to assess model fit were the (a) $\chi 2$ statistic and its *p*-value; (b) $\chi 2/df$ index; (c) root mean square error of approximation index (RMSEA) and its 95% confidence interval (CI); (d) comparative fit index (CFI); (e) Tucker-Lewis index (TLI); and (f) weighted root mean residual (WRMR). We sequentially removed cross-loading items until the model reached a simple structure. After obtaining an optimal solution, researchers computed scores for individual factors. These coefficients estimate the location of every person on the identified factors (DiStefano et al., 2009).

We then conducted latent profile analysis (LPA) to estimate a latent categorical variable (*C*) using a set of continuous observed indicators (Collins & Lanza, 2009). The LPA model specified the individual factor scores as observed indicators of the latent categorical variable of online learning self-regulation. The LPA model included the predicted course grade as a covariate of *C* and the final course grade as C's distal outcome. To estimate this model, we followed Asparouhov and Muthén's (2014) three-step approach. It corrects for classification error by (a) estimating the LPA model first, (b) creating a nominal most likely profile variable *N*, and (c) estimating the mixture model with covariates and a distal outcome where *N* is an indicator of *C* with measurement error at the misclassification rate estimated at step one.

Models with two (model 2), three (model 3), four (model 4), and five (model 5) latent profiles were estimated. We selected the optimal model based on the interpretability of the latent profiles and statistical measures. The statistical criteria consisted of goodness of fit indices and estimates of classification precision. The indices used to assess model fit were the Bayesian Information Criteria (BIC) and the Akaike Information Criteria (AIC). Models with lower AIC and BIC values are more parsimonious and better fit the data (DiStefano, 2012; Muthén, 2004; Vermunt & Magidson, 2002).

The classification precision measures were (a) the average latent profile probabilities for the most likely profile membership, (b) classification probabilities for the most likely latent profile membership, and (c) entropy. Average latent profile probabilities and classification probabilities for most likely profile membership represent the proportions of correctly classified cases in each latent profile. Entropy is an overall index of classification certainty and shows whether the estimated profiles have distinct characteristics. Entropy coefficients range from 0 to 1, and values closer to 1 show that a model has superior classification precision (Akaike, 1977; Ramaswamy et al., 1993; Vermunt & Magdison, 2002).

Finally, latent profiles were further described by comparing factor scores, demographic information, student GPA, course grades, and predicted grades across groups. We compared continuous variables across groups using the Kruskal-Wallis *H* test. Similarly, we compared the distribution of categorical variables across profiles using the $\chi 2$ test. Using the Wilcoxon Signed Ranks Test, we examined differences between predicted grades and final course grades within each group.

Results

The survey item with the highest mean rating was from the environment structuring scale (Barnard et al., 2009); the item stated "I know where I can study most efficiently for online courses." The item with the lowest mean rating was from the help-seeking scale (Barnard et al., 2009) and stated "I am persistent in getting help from the instructor through e-mail." Table 1 reports the means and standards deviation of all survey items.

Table 1

Descriptive Statistics and Model Parameter Estimates

Factors	Cronbach's alpha	Survey item	*M* (*SD*)	Loading	Two-tailed *p*-value
F1: Goal setting	.826	I set goals to help me manage my studying time for my online courses.	5.20 (1.418)	0.886	0.000
		I set short-term (daily or weekly) goals as well as long-term goals (monthly or for the semester).	5.19 (1.590)	0.885	0.000
		I keep a high standard for my learning in my online courses.	5.59 (1.268)	0.478	0.000
		I try to schedule the same time every day or every week to study for my online courses, and I observe the schedule.	4.86 (1.691)	0.441	0.000
F2: Environment management	.899				
		I find a comfortable way to study.	5.62 (1.369)	0.922	0.000
		I choose the location where I want to study to avoid too much distraction.	5.58 (1.334)	0.914	0.000
		I know where I can study most efficiently for online courses.	5.66 (1.292)	0.727	0.000
		I choose a time with few distractions for studying for my online courses.	5.40 (1.419)	0.678	0.000
F3: Peer help-seeking	.893				
		I communicate with my classmates to find out how I am doing in my online classes.	4.51 (1.837)	0.998	0.000
		I share my problems with my classmates online, so we know what we are struggling with and how to solve our problems.	4.59 (1.817)	0.865	0.000
		I communicate with my classmates to find out what I am learning that is different from what they are learning.	4.37 (1.820)	0.86	0.000

Factors	Cronbach's alpha	Survey item	*M* (*SD*)	Loading	Two-tailed *p*-value
		I find someone knowledgeable in course content so that I can consult with him or her when I need help.	4.33 (1.817)	0.685	0.000
		If needed, I try to meet my classmates face-to-face.	4.54 (1.974)	0.574	0.000
F4: Task strategies	.786				
		I summarize my learning in online courses to examine my understanding of what I learned.	4.77 (1.476)	0.757	0.000
		I work extra problems in my online courses in addition to the assigned ones to master the course content.	3.75 (1.824)	0.702	0.000
		I prepare my questions before joining the chat room and discussion.	4.47 (1.758)	0.674	0.000
		I ask myself a lot of questions about the course material when studying for an online course.	4.67 (1.468)	0.623	0.000
		I am persistent in getting help from the instructor through email.	3.60 (1.800)	0.464	0.000
		I read aloud instructional materials posted online to fight against distractions.	4.56 (1.846)	0.37	0.000
F2 – F1				0.538	0.000
F3 – F1				0.221	0.001
F3 – F2				0.228	0.000
F4 – F1				0.620	0.000
F4 – F2				0.402	0.000
F4 – F3				0.441	0.000

Exploratory factor analysis (EFA) yielded a four-factor solution. We obtained a simple structure after sequentially removing five cross-loading items. Goodness of fit indices showed that the final solution had an overall good fit to the data ($\chi 2_{(101)} = 211.255$, $\chi 2/df = 2.091$, RMSEA = 0.079, CI = [0.064 - 0.093]; CFI = 0.983; TLI = 0.971). Table 1 lists the items included in each factor and their factor loading estimates, and *p* values. The first factor, F1, included four items referring to setting learning goals and study time. Cronbach's α index of internal consistency for this factor was .826. The second factor, F2, included four items referring to choosing a suitable environment for studying. F2 had an internal consistency of .899. The third factor, F3, included five items referring to communicating with peers for self-evaluation and help-seeking. This factor had an internal consistency of .893. Finally, the fourth factor, F4, included six items referring to task strategies and had an internal consistency of .786. As indicated in Table 1, all relationships

among factors were statistically significant. The strongest relationships were F1 - F4 and F1 - F2 (Table 1). Table 2 presents the factor covariances and correlations.

Table 2

Factor Covariances and Correlations

Factor	F1	F2	F3	F4
		Covariance		
F1	0.921			
F2	0.559	0.891		
F3	0.233	0.232	0.919	
F4	0.666	0.419	0.434	0.901
		Correlation		
F2	0.618**			
F3	0.254**	0.257**		
F4	0.731**	0.468**	0.477**	

Note. ** Significant at α = 0.01 (2-tailed). F1: goal setting; F2: environment management; F3: peer help-seeking; F4: task strategies.

We estimated LPA models with two (Model 2), three (Model 3), four (Model 4), and five (Model 5) latent profiles. Although Model 5 had a better fit to the data (Table 3), it included a group of only four individuals, which may indicate an overfitted model (DiStefano, 2012; Nylund et al., 2007). Typically, groups that include less than 5% of the sample are considered too small (Nasserinejad et al., 2017).

Table 3

Goodness of Fit and Classification Precision by Model

Index	Model 2	Model 3	Model 4	Model 5
Entropy	.864	.816	.841	.855
AIC	1817.507	1750.905	1724.390	1703.768
BIC	1861.973	1814.428	1806.969	1805.405
Sample-adjusted BIC	1817.638	1751.092	1724.632	1704.067

Note. AIC: Akaike Information Criterion; BIC: Bayesian Information Criterion.

Model 4 included larger groups, had the most informative solution, and had a good fit to the data. This model was, therefore, selected as the optimal model. Model 4 had an adequate classification precision, with an entropy of 84.1%. As illustrated in Figure 1, the largest group (n = 92) had factor scores close to average on all factor scores and was labeled average self-regulation (ASR). The second largest group (n = 32) had scores that were significantly below the average on all factors and was labeled below average self-regulation (BASR). The third group (n = 30) had scores significantly above average on all factors, and we labeled it above average self-regulation (AASR). The fourth latent profile (n = 23) had scores higher than average on F1 and F2, lower than average on F3, and close to average on F4. We named this group low peer help-seeking (LPHS). Average latent profile probabilities and classification probabilities for most likely latent profile membership ranged between 75.7% and 95.5% (Table 4).

Figure 1

Mean Factor Scores by Latent Profile

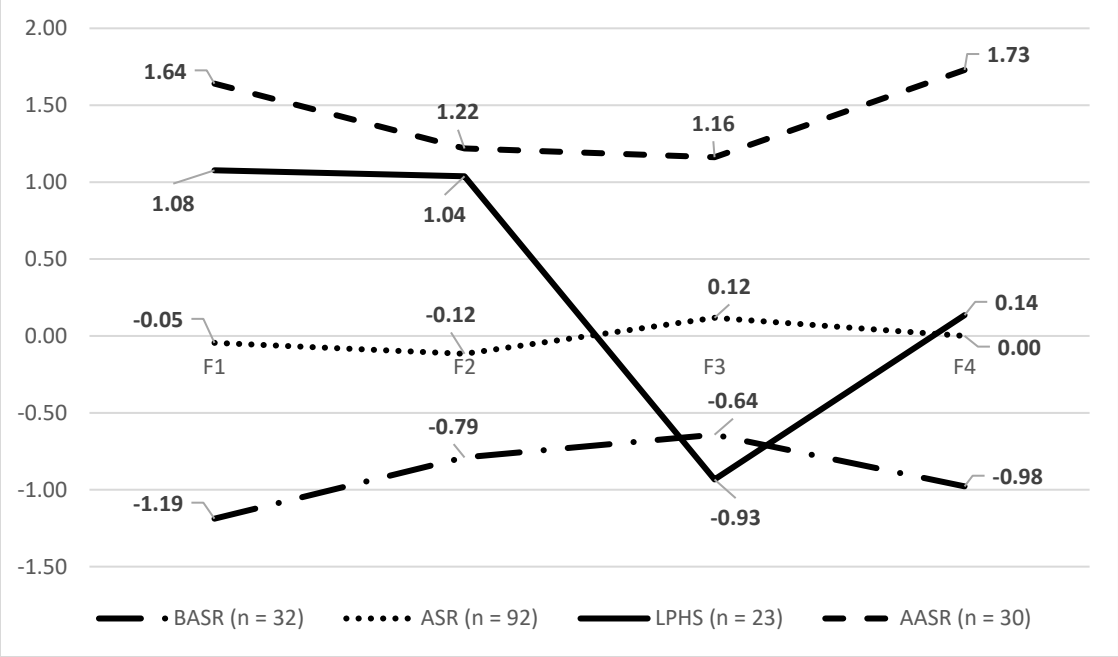


Table 4

Model 4: Average Latent Profile Probabilities and Classification Probabilities

Latent Profile Probability	BASR	ASR	LPHS	AASR
BASR: Average latent profile	.909	.091	.000	.000
BASR: Classification	.830	.170	.000	.000
ASR: Average latent profile	.053	.917	.024	.006
ASR: Classification	.027	.955	.012	.006
LPHS: Average latent profile	.000	.101	.878	.021
LPHS: Classification	.000	.178	.757	.064
AASR: Average latent profile	.000	.033	.049	.919
AASR: Classification	.000	.035	.014	.951

Note. Below average self-regulation (BASR), average self-regulation (ASR), above average self-regulation (AASR), low peer help-seeking (LPHS).

Table 5 reports the latent profile mean factor scores and two-tailed *p*-values. The Kruskal-Wallis test showed that scores on the four factors differed significantly across latent profiles (Table 6).

Table 5

Mean Factor Scores by Latent Profile

Profile	Factor	Estimate	Two-tailed *p* value
BASR (*n* = 32)			
	F1	-1.188	0.000
	F2	-0.790	0.000
	F3	-0.642	0.000
	F4	-0.978	0.000
ASR (*n* = 92)			
	F1	-0.045	0.693
	F2	-0.116	0.286
	F3	0.118	0.318
	F4	0.000	0.999
LPHS (*n* = 23)			
	F1	1.077	0.000
	F2	1.038	0.000
	F3	-0.933	0.007
	F4	0.135	0.695
AASR (*n* = 30)			
	F1	1.640	0.000
	F2	1.219	0.000
	F3	1.162	0.000
	F4	1.729	0.000

Note. Below average self-regulation (BASR), average self-regulation (ASR), above average self-regulation (AASR), low peer help-seeking (LPHS).

Table 6

Tests Factor Score Variation Across Latent Profiles

Statistic	F1	F2	F3	F4
Kruskal-Wallis *H*	123.542	78.267	60.300	89.833
df	3	3	3	3
p value	<.001	<.001	<.001	<.001

Note. F1: goal setting; F2: environment management; F3: peer help-seeking; F4: task strategies.

Table 7 reports, for each group, demographic distribution, average GPA, predicted grade, final course grade, and the difference between the expected and the final course grade. Results from significance tests showed that ethnicity ($\chi^2_{(12)} = 6.492$, $p = .889$), gender ($\chi^2_{(3)} = 1.402$, $p = .705$), age ($H_{(3)} = 5.874$, $p = .118$), GPA ($H_{(3)} = 5.614$, $p = .132$) , final course grade ($H_{(3)} = 7.500$, $p = .058$) , and the difference between the predicted and the final course grade ($H_{(3)} = .431$, $p = .934$) did not differ significantly across latent profiles. Only the predicted course grade ($H_{(3)} = 10.886$, $p = .012$) recorded statistically significant differences across groups, with higher values for the LPHS group, followed by AASR, ASR, and BASR.

Table 7

Demographics and Student Achievement by Latent Profile

Variable	BASR *n* = 32 18%	ASR *n* = 92 52%	LPHS *n* = 23 13%	AASR *n* = 30 17%	Total *N* = 177 100%
Ethnicity					
White	75%	77%	66%	63%	73%
African American	22%	14%	30%	37%	21%
Hispanic	0%	5%	4%	0%	3%
Native American	0%	1%	0%	0%	1%
Other	3%	3%	0%	0%	2%
Gender					
Male	9%	12%	0%	7%	9%
Female	91%	88%	100%	93%	91%
Age					
M	24	25	30	23	25
(SD)	(6)	(8)	(11)	(6)	(8)
Kruskal-Wallis Test					
Mean rank	93.67	85.92	118.69	79.50	
GPA					
M	3.49	3.49	3.62	3.35	3.49
(SD)	(.41)	(.36)	(.49)	(.40)	(.39)
Kruskal-Wallis Test					
Mean rank	91.17	88.87	113.27	70.5	
Predicted grade					
M	86.52	88.12	91.85	88.56	88.12
(SD)	(5.01)	(5.62)	(3.24)	(5.13)	(5.42)
Kruskal-Wallis Test					
Mean rank	71.50	89.22	126.04	91.70	
Course grade					
M	89.44	90.32	94.47	90.43	90.48
(SD)	(6.11)	(6.33)	(3.88)	(7.73)	(6.39)
Kruskal-Wallis Test					
Mean rank	79.10	86.63	123.85	90.60	

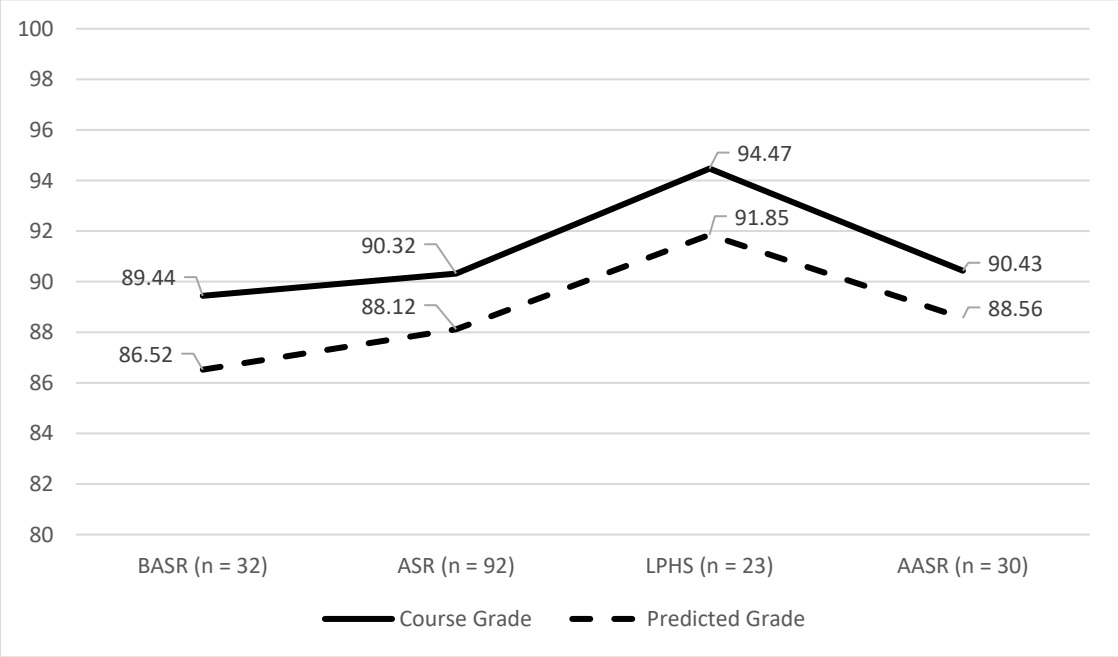
Variable	BASR *n* = 32 18%	ASR *n* = 92 52%	LPHS *n* = 23 13%	AASR *n* = 30 17%	Total *N* = 177 100%
Predicted grade - Course grade					
M	-2.92	-2.20	-2.62	-1.87	-2.32
(SD)	(5.48)	(6.16)	(4.72)	(8.31)	(6.19)
Kruskal-Wallis Test					
Mean rank	71.50	89.22	126.04	91.70	
Wilcoxon Signed Ranks Test					
Z	-2.704	-3.848	-1.853	-1.456	
P	.007**	.000**	.064	.145	

Note. *Statistically significant at α = .05. ** Statistically significant at α=.01. Below average self-regulation (BASR), average self-regulation (ASR), above average self-regulation (AASR), low peer help-seeking (LPHS).

The final course grade followed the same pattern (Figure 2), but differences across groups were not statistically significant. The LPHS profile had the highest average GPA, the highest final grade, and the highest predicted course grade. All groups underestimated their course grade by approximately two points. The Wilcoxon Signed Ranks test yielded differences statistically different from zero between the predicted course grades and final course grades for the ASR and the BASR latent profiles. These differences were not statistically significant for the LPHS and AASR latent profiles. Overall, the difference between the predicted grade and final course grade did not vary significantly across the four latent profiles (Table 7).

Figure 2

Average Course Grade and Predicted Grade by Latent Profile



Compared to AASR, the predicted grade had a significant relationship with the LPHS group, but not with the other latent profiles (Table 8). In other words, in the AASR group, individuals with higher predicted grades were 20.7% more likely to be members of the LPHS group. Compared to the LPHS group, membership in any other latent profile was a significant predictor of a lower final course grade. Conversely, members of the LPHS latent profile were more likely to have higher final grades than those of the BASR and the ASR latent profiles (Table 8).

Table 8

Relationships between Latent Profiles, Predicted Grade, and the Course Grade

Relationship	Estimate	*SE*	Estimate/*SE*	Two-tailed *p*-value	Odds ratio
Reference: AASR					
Predicted grade -> BASR	-0.059	0.064	-0.923	0.356	0.945
Predicted grade -> ASR	0.007	0.059	0.122	0.903	1.007
Predicted grade -> LPHS	0.188	0.079	2.373	0.018*	1.207
Reference: AASR					
BASR -> Final grade	-0.016	0.055	-0.286	0.775	
ASR -> Final grade	0.004	0.051	0.086	0.932	
LPHS -> Final grade	0.198	0.102	1.952	0.051	
Reference: BASR					
ASR -> Final grade	0.020	0.033	0.610	0.542	
LPHS -> Final grade	0.214	0.087	2.462	0.014*	
AASR -> Final grade	0.016	0.055	0.286	0.775	
Reference: ARS					
BASR -> Final grade	-0.020	0.033	-0.610	0.542	
LPHS -> Final grade	0.194	0.086	2.256	0.024*	
AASR -> Final grade	-0.004	0.051	-0.086	0.932	
Reference: LPHS					
BASR -> Final grade	-0.214	0.087	-2.462	0.014*	
ASR -> Final grade	-0.194	0.086	-2.256	0.024*	
AASR -> Final grade	-0.201	0.102	-1.970	0.049*	

Note: * Statistically significant at $\alpha = .05$. Below average self-regulation (BASR), average self-regulation (ASR), above average self-regulation (AASR), low peer help-seeking (LPHS).

Discussion

The current study combined person-centered and variable-centered perspectives (Bergman & Magnusson, 1997; Marsh et al., 2009; von Eye, 2010) and expanded the existing research on OSRL (e.g., Abar & Locken, 2010; Barnard-Brak et al., 2010; Broadbent & Poon, 2015; Cuesta, 2010; Schwinger et al., 2009, 2012). Our results helped clarify the complexity of self-regulation of learning in the online environment: particularly,

on what constitutes OSRL, how individual differences permeate through profiles of OSRL, and how the OSRL latent profiles are related to academic performance in the online learning environment.

Factors of Online Learning Self-Regulation

Our first objective was to ascertain the factors of OSRL. Exploratory factor analytic procedures within the ESEM framework yielded four OSRL factors: (a) goal-setting (F1); (b) environment management (F2); (c) peer help-seeking (F3); and (d) task strategies (F4). Items included in these four factors had high internal consistency levels, and the factor structure had a very good model fit. This evidence supported the four-factor solution as the optimal factor structure for our sample. Results were very similar to some of the factors of online self-regulated learning identified by Barnard et al. (2009): goal setting, environment structuring, task strategies, and help-seeking.

Nevertheless, our factor structure did not include two of the factors identified by Barnard et al. namely time management and self-evaluation. Items from these scales were either removed because of cross-loadings or loaded under a different factor. For example, two items from the original self-evaluation scale loaded under the task strategies factor (F4), whereas the other two loaded under the peer help-seeking factor (F3). The help-seeking factor was redefined as peer help-seeking (F3). This factor referred only to communicating with peers for self-evaluation and information on class progress and did not include seeking help from the instructor.

Similarly, the environment structuring factor became environment management. This factor referred primarily to selecting or manipulating the environment rather than making changes. All factor correlations and covariances were statistically significant. The most robust relationship was between goal-setting (F1) and task strategies (F4), followed by goal setting (F1) and environment management (F2). In contrast, the weakest relationships were between peer help-seeking (F3) and environment management (F2), and between peer help-seeking (F3) and goal setting (F1). However, the factor structure identified in this study varied from previous studies using the same instrument (Barnard et al., 2009). Further research should focus on examining the dimensions of OSRL with samples that are larger and reflect demographic distributions that are representative of the population. Such studies would provide evidence of external validity for the OSRL factor structure.

Latent Profiles of Online Self-Regulated Learning

The second objective was to identify latent profiles of OSRL. Results from LPA showed that students in our sample employed four types of self-regulation, as described by the BASR, ASR, LPHS, and AARS latent profiles. The BASR, ASR, and AASR latent profiles differed mainly quantitatively in the overall level of self-regulation. Nevertheless, the LPHS latent profile described a pattern of high levels of goal setting and environment management, average levels of task strategies, and reduced peer help-seeking levels. This model had good classification precision and was a good fit to the data. Scores on the four factors showed significant variations across latent profiles. These results constitute evidence that the four groups represent distinct profiles of online learning self-regulation.

The study conducted by Barnard-Brak et al. (2010) identified five profiles of online self-regulated learning identified as (a) super self-regulators, (b) competent self-regulators, (c) forethought-endorsing self-

regulators, (d) "performance-reflection self-regulators, and (e) non- or minimal self-regulators. Although the current study used the same data collection instrument, we found a four-profile model optimal for our sample. These four latent profiles were comparable to four of the groups identified by Barnard-Brak et al. The AASR, ASR, and BASR latent profiles identified in the current study described overall online learning self-regulation levels. These groups had profiles similar to the super self-regulators, competent self-regulators, and non- or minimal self-regulators. The LPHS latent profile corresponds to the forethought-endorsing self-regulators. Individuals assigned to this group more highly endorse goal setting and environment structuring as self-regulated learning skills while endorsing task strategies, time management, help-seeking, and self-evaluation to much lesser extents (Barnard-Brak et al., 2010). We did not identify a group of performance-reflection self-regulators in our sample. A critical difference between the two studies was that items measuring time management and self-evaluation did not load under distinct factors and were not, consequently, used as separate observed indicators for LPA. These survey items loaded under the task strategies factor (F4) and the peer help-seeking factor (F3).

While very informative and directly applicable to online learning, the OSRL latent profiles that we identified in the current study are sample-specific and based on a relatively small group of students. Future studies could continue examining OSRL using cross-sectional designs to determine whether the OSRL latent profiles differ across age groups, educational levels, subject areas, or geographical locations. Replicating the study with larger samples and samples with a more balanced demographic distribution would support the external validity of the OSRL latent profile model. Further, repeating the current study in other subject areas and learning environments would show the extent to which the learning context influences how students approach their learning (Severiens et al., 2001; Wong et al., 2019).

In addition to a cross-sectional design, future research should also investigate OSRL longitudinally, as OSRL entails a dynamic personal process that continually evolves with students' development of existing behaviors and strategies based on prior success and emerging challenges (Abar & Loken, 2010; Greene, 2018; Severiens et al., 2001; Winne, 1995, 1996, 1997, 2018). Such studies would clarify whether increases in students' OSRL are associated with gains in academic achievement over time (Barnard et al., 2009). Further, longitudinal studies using latent transition analysis may help determine whether students' OSRL latent profiles change across time.

Predicted Grades and OSRL Latent Profiles

Our third objective focused on the relationship between the predicted course grades and the adoption of specific latent profiles of online learning self-regulation. Predicted course grades showed significant differences across groups, with the highest values for the LPHS latent profile, followed by the AASR, ASR, and BASR latent profiles. Results from LPA showed that, in reference to AASR, a higher predicted grade was a significant predictor of adopting the LPHS self-regulation strategy. In other words, compared with the AASR group, when students anticipated obtaining a higher course grade, they were less likely to engage in peer help-seeking and task strategies and, therefore, were more likely to adopt the LPHS self-regulation profile. This finding partially confirmed the initial hypothesis that the predicted course grade is a significant predictor of adopting a specific type of online learning self-regulation as described by the online learning self-regulation latent profiles (Barnard-Brak et al., 2010; Stan, 2012; Wang et al., 2013). Our study also examined the differences between students' predicted course grades and their final course grades. All

students underestimated their final course grades; however, the two groups with higher levels of OSRL (AASR and LPHS) had better prediction accuracy. These were the only groups with non-significant differences between the predicted grade and the final course grade.

Examining the relationship between expected outcomes and OSRL latent profiles is a unique contribution of our study. As far as we know, this has not been investigated previously. Therefore, further research is needed to determine whether the current results are sample-specific or replicate with other samples. Also, future research should investigate whether the relationship between predicted grades and OSRL strategies varies across age groups and subject areas. Additional covariates, representing human factors or individual differences, could be included in the latent profile model to examine how they predict OSRL latent profile memberships. Such covariates may be self-efficacy, goal orientations, educational level, prior academic performance, and so on.

OSRL Latent Profiles and Final Grades

Our fourth objective was to examine the relationship between latent profiles of online learning self-regulation and student academic performance by including the final course grade as a distal outcome of the self-regulation latent categorical variable. Descriptive statistics showed that groups with higher self-regulation levels had slightly higher final course grades, but variations across groups did not reach statistical significance. Specifically, the LPHS group had the highest course grades, followed by the AASR, ASR, and BASR groups. LPA results showed that, compared to the LPHS latent profile, membership in any of the other latent profiles predicted a lower final course grade. However, some relationships between latent profile memberships and final course grades did not vary significantly across all latent profiles.

These findings partially support the hypothesis that academic outcomes differ across self-regulation latent profiles (Broadbent & Poon, 2015; Greene, 2018; Wang et al., 2013). Further, our study did not replicate the significant differences in student GPA across online learning self-regulation latent profiles recorded by Barnard-Brak et al. (2010). Therefore, further research is needed to determine whether OSRL latent profiles are course-specific and how they relate to students' GPAs. Investigating the predictive power of the OSRL latent profiles on course grades across age groups and subject areas would contribute to a better understanding of how individualized OSRL impacts outcomes of online learning.

The current study expanded the research on establishing profiles of online SRL from undergraduate students (e.g., Barnard et al., 2009; Barnard-Brak, et al., 2010; Broadbent & Fuller-Tyszkiewicz, 2018; Broadbent & Poon, 2015) to graduate students. These findings can help online instructors design interventions and instructional techniques that support those strategies of self-regulation that have a positive impact on student achievement and thus avoid the practices that are not productive (Bruso & Stefaniak, 2016; Greene, 2018; Panadero, 2017; Wang et al., 2013; Winne & Nesbit, 2010). This information is critical in the online learning environment, which may require increased levels of self-regulation to achieve academic success (Barnard et al., 2009). For instance, (a) providing increased opportunities for interaction, (b) including a self-monitoring system, (c) supporting self-efficacy beliefs and optimistic attributions, (d) creating opportunities for cognitive apprenticeship such as coaching, and (e) providing feedback have been shown to help self-regulation when using technology-enhanced learning environments (Abar & Loken, 2010; Steffens, 2006; Wong et al., 2019).

Conclusion

The current study aimed to better understand how individual students used self-regulation strategies in the online learning environment. Using both variable-centered and person-centered approaches, we ascertained four dimensions of OSRL, identified four latent profiles of OSRL strategies employed by the students, and examined how the OSRL latent profiles relate to the predicted and the final course grades. Our results showed that the latent self-regulation variable did not necessarily have a continuous distribution. Students employed the various dimensions of self-regulation to a different extent based on their predicted performance in the course. The majority of high-performing students used all self-regulating strategies at the highest level (AARS). Nevertheless, a smaller group of high-performing students (LHPS) sought less help from their peers than the other groups and employed fewer task strategies than did the AASR group. Our results also showed that high-performing students predicted their course grades with more accuracy than did low-performing groups.

Together with other emerging studies (Abar & Loken, 2010; Barnard-Brak et al., 2010; Broadbent & Poon, 2015; Broadbent & Fuller-Tyszkiewicz, 2018; Hirt et al., 2021; Schwinger et al., 2009, 2012), the current research demonstrated the advantages of using a combined person-centered and variable-centered approach in the research of SRL in the online environment. Our results showed that viewing SRL as a multi-dimensional construct, and particularly as a discrete latent variable, could help us better understand the self-regulation of online learning. Addressing individual difference factors in the study of OSRL would enable us to account for the wide range of personal and contextual factors (Schwam et al., 2021; Wong et al., 2019). More importantly, such studies will shed light on developing online learning environments with adaptive support to optimize learning for individual students.

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