Profiles in Self-Regulated Learning and their correlates for online and blended learning students.

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Abstract

This study examines a person-centered approach to self-regulated learning among 606 University students (140 online, and 466 in blended learning mode). Latent profile analysis revealed five distinct profiles of self-regulated learning: minimal regulators, restrained regulators, calm self-reliant capable regulators, anxious capable collaborators, and super regulators. These profiles showed that: (1) differences in academic success are associated with a learner's capacity for motivational regulation and self-regulated learning strategy implementation; (2) online learners are more likely to belong to profiles that are more adaptive, and less reliant on collaborations with others; (3) for learners at the lower end of the self-regulation spectrum, an increase in both motivational regulation and adoption of self-regulated learning strategies may be academically beneficial; and (4) high motivational regulation and strategy adoption can be all for naught, if the student is also highly anxious with worry and concern regarding performance.

Key words: self-regulated learning strategies; motivated self-regulation; online learning; higher education; latent profile analysis (LPA);

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1. Introduction

Technological advances in recent decades have altered the higher education landscape for staff and students. Whereas face-to-face content delivery has traditionally been constrained by limitations of room and campus capacity, staff-to-student ratios, timing of lecture delivery, and access to teaching staff and support, technology-enabled synchronous and asynchronous modes of teaching offer potential solutions to many of these challenges (Cunningham & Billingsley, 2002; Means, Toyama, Murphy, Bakia & Jones, 2009). It is unsurprising then that the proportion of students undertaking these online forms of study (wholly or blended) has increased in recent years, with estimates that up to one in five students study wholly online, and more than one-quarter of students take at least one online subject within their degree (Allen, Seaman, Poulin & Taylor-Straut, 2016; Norton & Cherastidtham, 2014). Moreover, many courses and subjects that are taught on-campus are supported by an online learning management system for passive elements of the course (assignment submission, lecture slides, and recordings, etc.) and potentially more interactive components (such as quizzes, discussion boards, and intelligent agents to monitor progress). Despite this push towards online-enabled modes of learning, these varied study modes (online, traditional, and blended) may attract and/or produce distinct populations of students, distinguishable in their self-regulated approaches to learning. The remit of this paper is to identify different profiles of self-regulated learning, and to evaluate whether profile membership is associated with study mode (blended vs wholly online) or academic performance.

1.1 Theoretical Background

1.1.1 Characteristics of Self-Regulated Learning

The ability to self-regulate one's study-related behaviours and cognitions has been linked to important educational attainment outcomes, including academic achievement (Zimmerman, 1990; Zimmerman & Schunk, 2011). To be considered 'self-regulated', a learner must be motivated, metacognitively involved, and active in his or her own learning process (Zimmerman, 1986; 2015). From a social cognitive perspective, self-regulation is developed through a bi-directional interaction between three important qualities: (1) self-observation (monitoring one's actions), (2) self-judgment (evaluation of one's performance), and (3) self-reactions (one's response to performance outcomes; Zimmerman, 1989). As such, one's self-regulation develops over time through an interaction of personal, behavioural, and environmental factors. The evolving nature and feedback loops described by Zimmerman (e.g., Zimmerman, 2015; Zimmerman & Schunk, 2011) thus suggest that SRL is amenable to intervention. However, to enact change in learning approach, one must understand the key characteristics of SRL and, in particular, which of these characteristics are most strongly aligned with student performance.

Self-regulated learning strategies can be broadly grouped into one of three classifications: (1) cognitive, (2) metacognitive, and (3) resource management. Cognitive strategies such as elaboration enable the learner to fuse new and existing information, with the aim of remembering the new material (Richardson, Abraham & Bond, 2012). Metacognitive strategies refer to the awareness to set goals, and then monitor, plan, and regulate learning (Pintrich & DeGroot, 1990), and resource management strategies require learners to use resources around them (such as peers) or to persist when confronted with academic challenges (Richardson, Abraham, & Bond, 2012). Use of these strategies assist learners to acquire and retain knowledge, and such strategies have been found to predict academic achievement in both traditional (Richardson et al., 2012) and online learning environments (Broadbent & Poon, 2015).

Richardson et al.'s (2012) meta-analysis found that the strategies of effort regulation, time management, metacognition, elaboration, critical thinking, help seeking, and concentration predicted (p<.05) academic achievement in traditional higher education settings. In comparison, a meta-analysis of online learners by Broadbent & Poon s (2015) found that the variety of relevant self-regulated learning strategies that were significantly related to academic performance and the predictive value of these significant SRL strategies for online learners' performance were lower than the effects reported by Richardson et al. (2012) for traditional learning environments. This latter review identified four learning strategies that were significantly associated with academic achievement for online learners: metacognition, time management, effort regulation, and critical thinking (Broadbent & Poon, 2015). Broadbent and Poon (2015) argue that some self-regulated learning strategies (e.g., peer learning) may be less effective for online learners, or that other factors may also have influence over online learning success. For instance, level of student motivation may serve to maintain use of self-regulated learning strategies, even under challenging learning conditions or periods of self-doubt. Similarly, availability of resources to help students improve their self-regulated learning may also facilitate adoption of these strategies.

Among identified factors for self-regulated learning, the strategies used to implement effective learning practices, as well as the motivation driving learning, appear crucial (Pintrich & De Groot, 1990). The Motivated Strategies for Learning Questionnaire (MSLQ; Pintrich, Smith, García & McKeachie, 1993) is the most frequently used self-report measure for SRL, and comprises the most comprehensive set of self-regulatory strategies and motivational factors related to SRL. Based on the MSLQ, the present study focuses on six motivated learning beliefs; most notable is the motivational belief of self-efficacy, which is the learner's confidence in their ability to perform a task, and is one of the strongest motivational predictors of academic achievement (Honicke & Broadbent, 2016; Richardson et al., 2012; Robbins, Lauver, Davis, Langley & Carlstrom, 2004; Wang, Shannon, & Ross, 2013). In Richardson et al.'s large meta-analysis, other influential motivational beliefs from the MSLQ included: (1) test anxiety - which includes both the negative thoughts and affective and physiological arousal experienced by the learner; (2) task value - the learner's evaluation of the task in terms interest, importance, and utility; (3) control - the belief that outcomes are contingent upon the learner's own effort, rather than external sources, such as a teacher; (4) intrinsic goal orientation - desire to acquire mastery and skill over learning for its own purpose; and (5) extrinsic goal orientation – the desire to participate in a task for reasons such as grades, rewards or to outperform others.

1.1.2 A Person-Centered Approach

While motivational and self-regulated learning strategies have been shown to influence academic outcomes, the vast majority of studies have adopted a variable-centred approach. Variable-centred approaches operate at the group-level (i.e., summarising trends across all participants in a sample), and focus on associations between variables as well as the contributions that predictor variables make to an outcome (Hoff & Laursen, 2006). This approach neither explains, however, how learners combine the various motivational and learning strategies effectively, nor how they are integrated into a learner's regulation profile (Schwinger, Steinmayr & Spinath, 2012). Moreover, variable-centered approaches are reliant 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. Person-centered approaches (typically in the form of latent class or profile analysis) address this assumption directly by identifying subgroups of individuals who share particular attributes, from which group differences in patterns of development may be identified (Hoff & Laursen, 2006). In so doing, person-centered approaches are able to empirically test whether: (1) there are distinct subgroups of learners, differentiated on the basis of breadth and/or strength of endorsement of various self-regulated learning strategies and motivation factors; (2) a particular type of learner is more likely to be drawn to one subgroup than another (e.g., mature age or online learners); and (3) these subgroups of learners differ in important external criteria (such as academic performance).

A search of the literature identifies very few studies that have taken a person-centered approach to motivated self-regulation and self-regulated learning strategies used by learners. However, from this limited pool of research, there is consensus that there are distinct subgroups of learners, differentiated on the basis of profile of motivation (Bråten & Olaussen, 2005; Kolić-Vehovec, Rončević & Bajšanski, 2008; Liu, Wang, Kee, Koh & Chua, 2014; Pintrich, 1989; Schwinger et al., 2012; Turner, Thorpe & Meyer, 1998), self-efficacy (Abar & Loken, 2010; Chen & Usher, 2013; Liu et al., 2014), and self-regulated learning strategy use (e.g. Banard-Brak, Paton & Lan, 2010; Heikkilä, Lonka, Nieminen & Niemivirta, 2012; Heikkilä, Niemivirta, Nieminen & Lonka, 2011). Moreover, the above noted studies demonstrated differences in academic performance across these subgroups, highlighting the practical importance of discerning subgroups. Typically, performance was higher for profiles that strongly endorsed: (1) the effective use of learning strategies, and/or (2) intrinsic / extrinsic motivation and self-efficacy. In contrast, learners who were unmotivated and did not engage in effective learning strategies had lower academic achievement. Collectively, the studies found that these profiles also differed on other important external criteria, including self-regulated learning strategies (Bråten & Olaussen, 2005; Kolić-Vehovec et al., 2008); stress and exhaustion (Heikkilä et al., 2011; 2012); epistemological beliefs (Bråten & Olaussen, 2005; Heikkilä et al., 2011; 2012); goal orientations and website usage (Abar & Locken, 2010); self-efficacy, implicit theory of ability, and year level (Chen & Usher, 2013); effort expenditure (Schwinger et al., 2012); and needs satisfaction, autonomy, enjoyment, effort, and value (Liu et al., 2014).

Person-centered studies have shifted our focus towards identifying different types of motivated self-regulated learners who share particular learning attributes, yet there are several key limitations with these prior studies. First, although self-regulation is a broad and multifaceted construct, the aforementioned studies tend to examine subcomponents of self-regulation rather than developing a comprehensive motivated self-regulation profile in higher education settings. In these studies, the have authors have tended to focus solely on motivational *or* learning strategies aspects of self-regulated learning, rather than both. Second, the few studies that incorporate both (e.g., Heikkilä & Lonka, 2006; Heikkilä et al., 2011; 2012; Liu et al., 2014; Pintrich, 1989; Turner et al., 1998) have included a reduced number of motivational and learning strategies and/or fail to test the predictive validity of these resulting profiles against achievement (e.g., Turner et al., 1998). Importantly, these studies failed to include key predictors of academic achievement identified from prior reviews, such as effort regulation, time management, metacognition, elaboration, critical thinking, and help seeking (Broadbent & Poon, 2015; Richardson et al., 2012). By incorporating the broader range of self-regulation components, researchers can better assess whether 'high achievers' are differentiated by endorsing all strategies more frequently than others, or whether they give preference to a small subset of strategies that produce maximal benefit.

1.1.3 Online vs Blended Learning

Few of the existing person-centered papers cited above included online learners (although see Banard-Brak et al., 2010), and none comprised a sample of both blended and online learners together. The lack of online learners is troubling given that the online environment may attract a particular type of student and influence the way students learn. For instance, the flexible learning arrangements afforded to online learning are likely to mean that the online learner needs to be highly autonomous, motivated, provide their own structure around learning, manage their time efficiently, and actively engage in the learning process to succeed (Schrum & Hong, 2002; Song, Singleton, Hill, & Koh, 2004). Online learning environments may also reduce opportunities for peer and staff interactions and communication (Bouhnik & Marcus, 2005), which may be off-putting for some potential students wanting a high level of interaction. Roblyer (1999) found that students who prefer face-to-face courses emphasize the importance of these forms of interaction, whereas those enrolled online instead value the ability to control timing and pace of their learning experiences. Roblyer's findings align with the findings of Broadbent (2017), who found that online university students were (1) less likely to engage in peer learning and help seeking strategies, whilst also being (2) more likely to use all other SRL strategies than their blended learning counterparts. In light of potential differences in SRL use by study mode, latent profile analyses derived from one population (e.g., students in traditional or blended learning modes) may fail to adequately represent SRL profiles of students from another population (e.g., online). A sample comprising a mixture of these student groups may thus help to uncover the breadth of SRL profiles of students.

1.2 The Present Study

The present study builds on prior person-centered approaches to understanding SRL profiles (as covered in Section 1.1.2) in several important ways. First, SRL profiles will be derived using a more comprehensive combination of motivational and self-regulated learning strategies than in prior studies. This more comprehensive measurement will include all six motivational factors, and all nine self-regulated learning strategies mentioned earlier from the MSLQ, and also grade goals (i.e., the mark the student aims for). Second, we will expand the range of correlates, extending beyond academic achievement to also explore how profiles differ in terms of intention to study and study automaticity. Successful self-regulation relies on conscious intention to manage and implement regulatory process and behaviours, but with time and practice, some of these processes can become automatic to conserve energy (Carver & Scheier, 1998). Intention to study will be used as a proxy for the conscious intentional aspect of self-regulation, while study automaticity will be used as a proxy for the automatic aspect. Lastly, as it is likely that online learners self-regulate differently to their blended learning counterparts, the sample comprises both study modes, and study mode is included as a potential correlate of latent classes.

Using a person-centered approach, this study seeks to identify (1) how many and which different motivated self-regulated learning profiles can be distinguished; (2) which of these profiles are associated with greater academic achievement, intention to study, and study automaticity; and (3) whether online students are over-represented in any one profile or show different motivation and strategy use. A typology of motivated self-regulated learning may give researchers and instructors a better understanding of how motivations and strategies interact when an individual is self-regulating for learning. We hypothesise that: (1) the most adaptive motivated self-regulated learning profiles (high in motivational self-regulation, high in the use of self-regulated learning strategies) will have the highest academic achievement, and will have high intention to study and high automaticity; (2) that non-adaptive motivated self-regulated learning profiles (low in motivational self-regulation, low in the use of self-regulated learning strategies) will have lower academic achievement, intention to study, and automaticity; and (3) online learners will more likely to belong to profiles that are adaptive motivated self-regulators, but are less likely to be in profiles that rely on the use of peers and instructors as a source of self-regulation.

2. Method

2.1. Participants.

Participants were 606 undergraduate students attending a University in Australia during the period of 2014-2016. Participants had a mean age of 23.50 years (*SD* = 7.78, range 17-67 years). Participants were completing a range of courses, but majority studied in the

Faculty of Health. Most participants were female, in their first year, had a mean subject grade of 72.78 (*SD* = 12.45; range 10-90), and studied in a blended learning environment (traditional face-to-face learning but with access to resources through an online learning management system; *n* = 466). See Table 1for more details.

Table 1

Gender, course, year level and study mode information.

Variables	Percentage (%)
Gender	
Female	85.1
Male	14.9
Course	
Faculty of Health	67.0
Faculty of Arts and Education	13.5
Faculty of Arts and Education / Health	6.4
Faculty of Science, Engineering and Built Environment	5.6
Faculty of Business and Law	5.0
Faculty Business and Law / Arts and Education	1.3
Faculty Business and Law / Health	1.0
Faculty of Arts and Education / Science, Engineering and Built Environment	0.5
Year level	
First	50.5
Second	22.9
Third	16.7
Fourth	9.9
Study mode	
Blended learning	76.9
Online only learning	23.1

Online-only students (all learning occurred through an online learning management system; *n* = 140) were significantly older (M_{age} = 28.99 years, *SD* = 9.71, range 17-56 years) than blended learning students (M_{age} =21.85 years, *SD* = 6.23, range 17-67 years, $t_{(604)}$ = -

10.31, $p < .001$, $d = -.87$). There was no difference between online and blended students in terms of mean subject grade $t_{(604)} = -.72$, $p = .470$, $d = -.07$.

Given the gender imbalance in the present study, t-tests were also conducted to evaluate differences in indicator variables intended for the latent class analysis. Male students reported significantly lower scores on extrinsic motivation ($t = -2.48$, $p = .032$), test anxiety ($t = -3.74$, $p < .001$), elaboration ($t = -2.86$, $p = .004$), rehearsal ($t = -3.52$, $p < .001$), organization ($t = -4.17$, $p < .001$), and time management ($t = -2.98$, $p = .003$), but significantly higher scores on self-efficacy ($t = 2.30$, $p = .022$).

2.2. Materials.

2.2.1. Demographic survey.

Participants were asked their (1) age, (2) gender, (3) class level (e.g., year of study in a three or four-year undergraduate bachelor degree or equivalent), (4) Faculty of study, and (5) enrolment mode (blended or online). Blended study typically comprised of face-to-face instruction, which included weekly lectures and weekly tutorials and/or laboratory or other practical face-to-face time, as well as access to resources (lecture slides and recordings, readings, discussion boards, etc.) in an online learning management system. Online-only students had access to the resources provided online in the learning management system. These online-only students do not attend any face-to-face on-campus classes.

2.2.2. Academic achievement.

Academic achievement was measured by the official final grade for a subject taken from University records; the participant specified the subject. Grade included all the assessments for the specified subject and was scaled from 0 to a maximum of 100, with higher scores reflecting better performance. The subject specified by students for this question was used as a point of focus for all other scales in the questionnaire. Students were asked to answer all remaining questions within the context of this specified subject, which linked to their grade.

2.2.3. Motivational and Self-regulated learning strategies.

Motivational and self-regulated learning strategies were measured using the Motivated Strategies for Learning Questionnaire (MSLQ; Pintrich, 1991). The MSLQ is divided into motivational and self-regulated learning strategies. The motivational component comprises 30 questions, and focuses on six motivated learning beliefs: (1) intrinsic goal orientation, (2) extrinsic goal orientation, (3) task value, (4) control beliefs for learning, (5) self-efficacy for learning, and (6) test anxiety. The self-regulated learning strategies component of the MSLQ comprises of 50 questions, and is divided into three types of strategies: cognitive, resource management, and metacognitive strategies. Cognitive strategies consisted of four subscales: (1) rehearsal, (2) elaboration, (3) organisation, and (4) critical thinking. Metacognitive strategies consisted of one large scale: (1) metacognition. Lastly, resource management strategies consisted of four subscales: (1) time management, (2) effort regulation, (3) peer learning, and (4) help seeking.

When answering questions about their motivation and adopted learning strategies, participants were asked to think about the subject they specified at the start of the questionnaire. Items for each subscale are measured on a 7-point end point defined response scale with 1 representing ‘not at all true of me’ and 7 representing ‘very true of me’. Questionnaires were scored according to Pintrich’s (1991) scoring manual. High scores on subscales indicated greater levels of motivational and self-regulated strategy use. Each subscale was found to have an acceptable level of internal consistency ranging from $\alpha = .65$ to .84. See Table 2 for number of items and Cronbach’s alpha per scale.

2.2.4. Grade Goals.

Student’s grade goal was measured with one forced-choice question regarding the student’s goal grade for the subject they specified at the start of the questionnaire: “What is your goal level of academic achievement for this [subject name]”. There were six available responses: 0-49, 50-59, 60-69, 70-79, 80-89, and 90-100. This format follows a similar forced-choice format used by Zimmerman, Bandura and Martinez-Ponz (1992).

2.2.5. Study Automaticity.

Study automaticity was measured using the four-item Self-Report Behavioural Automaticity Index (SRBAI; Gradner, Abraham, Lally & de Bruijn, 2012). Questions began with the stem ‘Studying is something…’, followed by: (1) ‘I do automatically’, (2) ‘I do without having to consciously remember’, (3) ‘I do without thinking’, and (4) ‘I start doing before I realize I am doing it’. Each question is measured on a five-point Likert scale from strongly agree to strongly disagree. High scores indicated greater levels of automaticity. When answering questions about automaticity, participants were asked to think about the subject they specified at the start of the questionnaire. The scale was found to have an acceptable level of internal consistency (see Table 2).

2.2.6. Intention to study.

Behavioural intention to study was adapted from Ajzen (2002) Theory of Planned Behaviour questionnaire, and included three questions: ‘I intend to study [X] many hours for this subject a week’, ‘I will try to study [X] many hours for this subject a week’, and ‘I plan to study [X] many hours for this subject a week’. Each question is measured on a seven-point response scale ranging from extremely likely to extremely unlikely. When answering questions about intention, participants were first asked to think about the subject they specified at the start of the questionnaire as well as how many hours they intended to study for this subject. High scores indicated greater levels of study intention. The scale was found to have an acceptable level of internal consistency (see Table 2).

Table 2

Number of items and Cronbach’s alpha for each scale

	No. of items	**α**
MSLQ Motivational Subscales		
Intrinsic goal orientation	4	.64
Extrinsic goal orientation	4	.70
Task value	6	.84
Control beliefs for learning	4	.63
Self-efficacy for learning	8	.92
Test anxiety	5	.82
MSLQ Learning Strategies Subscales		
Rehearsal	4	.66
Elaboration	6	.78
Organisation	4	.69
Critical thinking	5	.79
Metacognition	12	.76
Time management	8	.79
Effort regulation	4	.77
Peer learning	3	.69
Help seeking	4	.69
Study Automaticity	4	.88
Study Intentions	3	.83

2.3. Procedure

The University’s ethics committee approved this study. Students were recruited through University Facebook groups, in lectures, through word of mouth, and flyers placed on University noticeboards and on subject homepages of the University’s Learning Management System (LMS). Any University student could participate in the study, however the majority of students were from the same Faculty as the authors (Faculty of Health; see participant section) due to more concentrated recruiting from this Faculty. Students needed to be currently enrolled at the time of participation, and within the first four years of their undergraduate degree (or part-time equivalent), as the demands of a course can differ once a student enters a post-graduate level program. Recruitment was conducted over six semesters from April 2014 until October 2016. Students could participate anytime during the semester up until week 14. After reading the Plain Language Statement regarding the study and giving consent, participants undertook an online questionnaire, which took approximately 30 minutes to complete. At the start of the questionnaire, participants were asked to think about one specific subject when answering all the questions. Participants granted permission for the research team to access official grades from their specified subject at the end of the trimester.

2.4 Statistical Analyses

An initial series of analyses were undertaken to compare online and blended learning students across all SRL variables intended for the latent profile analysis. ANCOVAs (controlling for age) were conducted to evaluate univariate differences across these variables. Cohen's d values were calculated from adjusted group means to evaluate practical difference in magnitude of mean differences in SRLs across groups. Following Cohen's (1988) guidelines, d values less than .2 were considered trivial, .2 to .5 small, .5 to .8 moderate, and .8 or greater were considered a large effect.

Subsequently, latent profile analysis (LPA) was conducted using Mplus Version 7.1 (Muthén & Muthén, 1998-2011), followed by evaluation of correlates of latent profiles using SPSS Version 22.0 (IBM Corp., 2013). The final number of latent profiles was determined: (1) on the basis of comparing model fit between successive models (e.g., 2-class vs 3-class models), and also (2) by consideration of interpretability of the solution. The bootstrapped likelihood ratio test (BLRT; McLachlan & Peel, 2000) was used to evaluate whether a more complex model significantly ($p < .05$) improved fit over its less complex rival model (e.g., 2 classes vs 1). As this significance test approach tends to preference more complex models (i.e., those with more classes), the Bayesian Information Criterion (BIC; Schwarz, 1978) was included as a parsimony-adjusted measure of model fit. Lower BIC values indicate better model fit. Raftery's (1995) guidelines were applied for interpreting relative fit among competing models; BIC differences between models of 0-2 indicate weak support, BIC differences of 2-4 indicate positive support, >6 reflect strong support, and >10 indicate very strong support for the model with the smaller BIC value. From a model comparison perspective, a more complex model is preferable if it has a significant ($p < .05$) and practical (>10) reduction in BIC.

Based on the sample size for the two study mode groups (140 online and 466 blended learning students), power set at .80, and alpha = .05, the current study was sufficiently powered to detect a small, non-trivial group difference (Cohen's d > .24). Moreover, comparisons based on the two smallest classes arising from the LCA ($n = 52$ and $n = 93$) were sufficiently powered to detect effect sizes of Cohen's d > .4.

3. Results

The results are reported below according to the three primary research questions posited in this study.

3.1. How many and which different motivated self-regulated learning profiles can be distinguished?

Fit indices for the different models are shown in Table 3, and broadly support a 5-class solution. Although BIC values decrease substantially from 1- to 6-class solutions, and each subsequent model is a significant improvement upon the prior, less complex model, the 6-class solution produced several classes that were difficult to meaningfully differentiate based on mean levels across the SRL variables, whereas the 5-class solution was interpretable and had reasonable sample size for each class (minimum class size = 52). Consequently, a 5-class solution was preferred in the present study.

Table 3.

Fit indices for latent class solutions with varying number of latent classes.

Number of classes	Log likelihood	DF	Entropy	BIC	ΔBIC	H_0 Log likelihood[1]	BLRT p-value
1	-14411.68	32		29028.74			
2	-13481.38	49	0.88	27276.71	1752.04	-14411.68	<.001
3	-13231.67	66	0.86	26886.18	390.52	-13481.38	<.001
4	-13107.54	83	0.83	26746.85	139.33	-13231.67	<.001
5	-12984.46	100	0.84	26609.60	137.25	-13107.54	<.001
6	-12886.89	117	0.84	26523.39	86.22	-12984.46	<.001

Notes: [1] log likelihood value for k-1 class model for BLRT tests; DF=degrees of freedom; BIC=Bayesian information criterion; ΔBIC = change in BIC from previous to current model; BLRT=bootstrapped likelihood ratio test.

Table 4 and Figure 1 provide a breakdown of mean scores on each of the MSLQ constructs by class. Class 1 comprised 201 participants (33.2%), and consisted of participants who also tended towards low to moderate scores on self-regulated learning strategies and moderate motivation, although higher than Class 2. This first group was the largest group and was labelled the ‘restrained regulators’. Class 2, which accounted for 52 participants (8.6%), was labelled ‘minimal regulators’ because they tended to have the lowest scores of all the profiles, with low to moderate scores on all motivation factors and low scores on all the self-regulated learning factors. Class 3 consisted of 96 participants (15.8%), who were very similar to Class 4, but were distinguished by scoring the highest on test anxiety. This third class was labelled ‘anxious capable collaborators’ and on all other strategies and motivations, this class scored moderate to high. There were 164 participants (27.1%) assigned to the fourth class, labelled the ‘calm self-reliant capable regulators’ because this group scored the lowest of all groups on test anxiety, and strategies that involved peers or seeking help from others. On all other strategies and motivations, this fourth class scored moderate to high. Finally, Class 5 had 93 participants (15.3%). They were labelled ‘super regulators’ because they tended to score higher than the other profiles on most factors.

Table 4.

Mean scores and standard errors on each of the MSLQ constructs and goal grade by class.

	Class 1[a] Restrained Regulators (n = 201)	Class 2[b] Minimal Regulators (n = 52)	Class 3[c] Anxious Capable Collaborators (n = 96)	Class 4[d] Calm Self-Reliant Capable Regulators (n = 164)	Class 5[e] Super Regulators (n = 93)
Goal grade	4.63 (.05)[b-e]	4.21 (.12)[a,c-e]	5.00 (.07)[a,b,e]	5.21 (.05)[a,b]	5.42 (.07)[a-c]
Intrinsic G.O.	4.72 (.05)[b-e]	3.86 (.12)[a,c-e]	5.56 (.07)[a,b,d,e]	5.31 (.06)[a-c,e]	5.96 (.07)[a-d]
Extrinsic G.O.	5.10 (.07)[b-e]	4.66 (.18)[a,c-e]	5.79 (.10)[a,b,d]	5.52 (.08)[a-c,e]	6.03 (.09)[a,b,d]
Task Value	5.45 (.05)[b-e]	4.78 (.13)[a,c-e]	6.19 (.06)[a,b,e]	6.19 (.05)[a,b,e]	6.64 (.05)[a-d]
Control Beliefs	5.58 (.06)[c-e]	5.39 (.14)[c-e]	5.92 (.06)[a,b,e]	6.00 (.05)[a,b,e]	6.31 (.07)[a-d]
Self-efficacy	4.85 (.06)[b-e]	3.77 (.16)[a,c-e]	5.52 (.06)[a,b,e]	5.73 (.05)[a,b,e]	6.10 (.07)[a-d]
Test Anxiety	4.50 (.09)[d]	4.80 (.17)[d-e]	4.83 (.13)[d-e]	3.53 (.11)[a-c,e]	4.21 (.16)[b-d]
Rehearsal	3.93 (.07)[b-e]	3.43 (.15)[a,c-e]	5.05 (.09)[a,b,d,e]	4.30 (.08)[a-c,e]	5.47 (.11)[a-d]
Elaboration	4.88 (.05)[b-e]	3.84 (.12)[a,c-e]	5.63 (.07)[a,b,e]	5.70 (.05)[a,b,e]	6.48 (.05)[a-d]
Organisation	4.31 (.06)[b-e]	3.37 (.15)[a,c-e]	5.32 (.10)[a,b,e]	5.33 (.07)[a,b,e]	6.20 (.08)[a-d]
Critical thinking	3.71 (.06)[b-e]	2.67 (.12)[a,c-e]	4.99 (.08)[a,b,d]	4.01 (.09)[a-c,e]	5.19 (.09)[a,b,d]
Metacognition	4.07 (.03)[b-e]	3.18 (.08)[a,c-e]	4.85 (.05)[a,b,e]	4.79 (.04)[a,b,e]	5.65 (.05)[a-d]
Time Management	4.56 (.06)[b,d,e]	3.77 (.11)[a,c-e]	4.70 (.07)[b,d,e]	5.85 (.04)[a-c,e]	6.23 (.07)[a-d]
Effort Regulation	4.55 (.07)[b,d,e]	3.31 (.13)[a,c-e]	4.76 (.08)[b,d,e]	5.95 (.05)[a-c,e]	6.47 (.06)[a-d]
Peer Learning	3.18 (.09)[c-e]	2.72 (.17)[c,e]	4.63 (.12)[a,b,d,e]	2.42 (.08)[a,c,e]	3.77 (.15)[a-d]
Help Seeking	3.45 (.09)[b-e]	3.05 (.17)[a,c,e]	4.38 (.12)[a,b,d,e]	3.03 (.10)[a,c,e]	3.94 (.15)[a-d]

Notes. Standard errors are reported in brackets. Possible scores range from 1 to 7 for all MSLQ subscales. Scores for goal grade range 1 to 6. G.O = Goal orientation. Superscript terms for each variable denote significant group differences (p < .05).

3.2 Which profiles are associated with greater academic achievement, intention to study, and study automaticity?

The five classes were found to differ by:

- age ($F(4,601) = 9.96$, $p<.001$, $\eta^2 = .06$)
- grades ($F(4,601) = 12.06$, $p<.001$, $\eta^2 = .07$)
- intention to study ($F(4,601) = 47.04$, $p<.001$, $\eta^2 = .24$)
- automaticity ($F(4,601) = 33.98$, $p<.001$, $\eta^2 = .18$)
- gender ($\chi^2 = 10.32$, $p = .035$, $\Phi = .13$) and
- study mode ($\chi^2 = 35.84$, $p<.001$, $\Phi = .24$)

As shown in Table 5, minimal regulators were among the youngest classes, had the lowest grade average, and had considerably lower intention to study and study automaticity. Restrained regulators were also young, but had higher grades, intention to study, and study automaticity than minimal regulators, and among the highest level of on-campus learners of the various classes. Calm self-reliant capable regulators and super regulators were comparable on most indices, with the exception of study intention and automaticity for which the super-regulators scored higher. Calm self-reliant capable regulators and super regulators had the highest number of online learners. Anxious capable collaborators were the second youngest group, but tended to have higher grades, intention to study, and study automaticity than the minimal regulators.

Table 5.

Correlates of self-regulation classes

	Class 1 Restrained Regulators[a]	Class 2 Minimal Regulators[b]	Class 3 Anxious Capable Collaborators[c]	Class 4 Calm Self-Reliant Capable Regulators[d]	Class 5 Super Regulators[e]
Age	22.03[d,e]	21.50[d,e]	21.64[d,e]	25.59[a,b,c]	26.00[a,b,c]
Grade	71.51[b,d,e]	64.48[a,c,d,e]	71.12[b,d,e]	76.02[a,b,c]	76.17[a,b,c]
Intention	16.23[b,c,d,e]	14.63[a,c,d,e]	16.89[a,b,d,e]	18.57[a,b,c,e]	19.45[a,b,c,d]
Automaticity	10.32[b,d,e]	8.06[a,c,d,e]	11.17[b,d,e]	12.41[a,b,c,e]	14.68[a,b,c,d]
Female^	.82[e]	.85	.79[e]	.88	.94[a,c]
On campus^	.86[d,e]	.83[d,e]	.87[d,e]	.68[a,b,c]	.60[a,b,c]

Notes: ^ denotes categorical variables for which the reported mean values range from 0 to 1, and represent proportions (i.e., 0.4 for female indicates that 40% of the participants in a given class are female). Post-hoc comparisons were adjusted for Type I error inflation. * Goal grade was measured on a scale of 1-6, for ease interpretability in this table it has been rescaled to out of 100.

3.3 Are online students over-represented in any one profile or show different motivation and strategy use?

Table 5 shows that calm self-reliant capable regulators and super regulators contained significantly more online learners than the remaining three classes. To determine whether there were other differences between the online and on-campus students, an ANCOVA was conducted. ANCOVA analyses (controlling for differences in age across groups) revealed significant differences in group means between online and blended learners in terms of more intrinsic goal orientation, task value, self-efficacy, elaboration, organisation, metacognition, time management, effort regulation strategies and less peer learning, and help seeking strategies for online learners than for on-campus students. However, differences were usually small in magnitude according to Cohen's guidelines, with the exception of help seeking, which had a moderately sized group difference in means. Even so, it should be noted that the absolute difference for this variable was less than 1 unit on a scale ranging from 1 to 7. Significant differences were not found for the remaining SRL strategies or motivational variables (see Table 6 for all group differences).

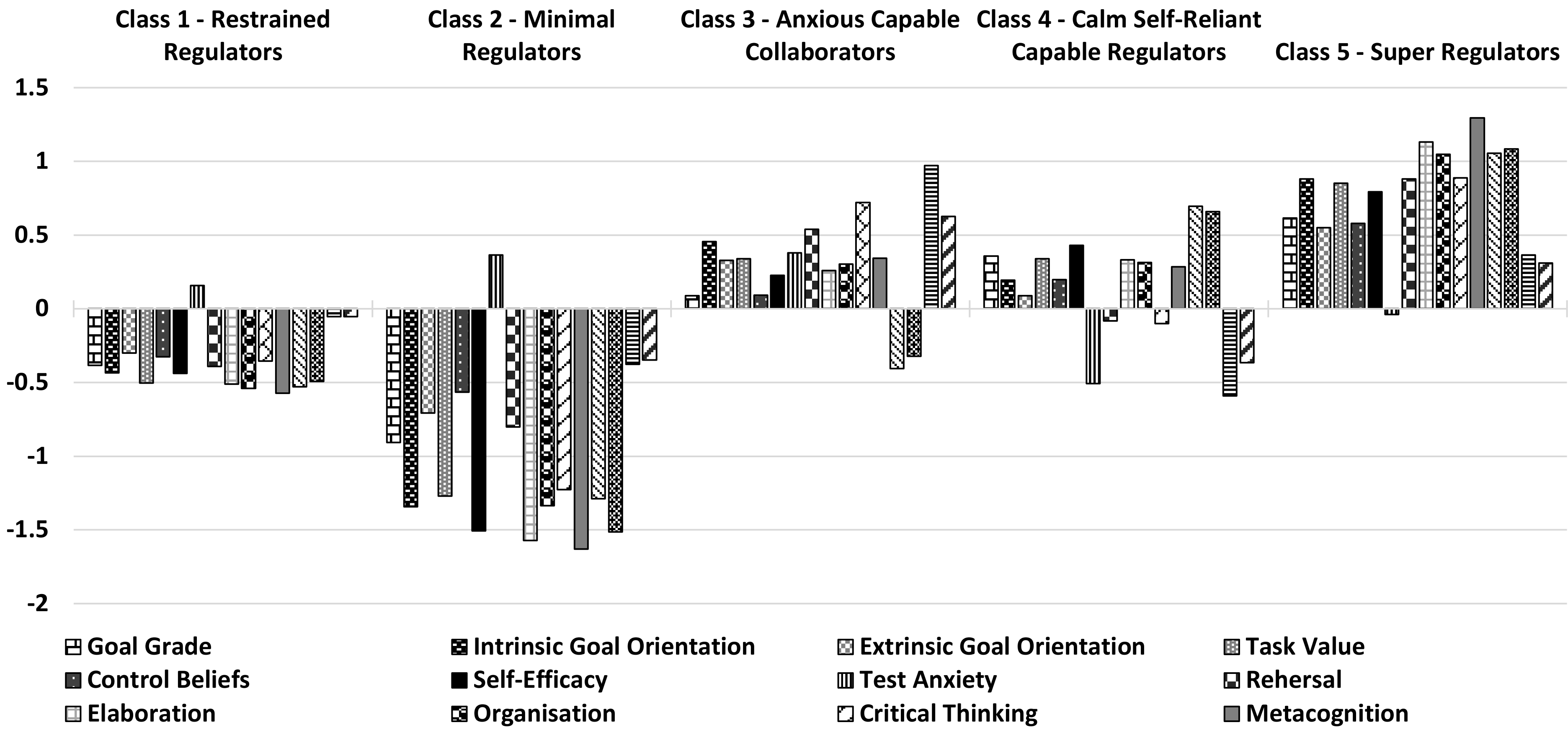

Figure 1. Z scores on each of the MSLQ constructs and goal grade by class. *Note: order of labels matches order in bar graph.*

Table 6.

Comparison of SRL and motivation variables by study mode

	On-campus	Online			
	M (SE)	M (SE)	F	p	Cohen's d
Grade goal	4.93 (.04)	4.94 (.07)	0.01	.927	-.01
Intrinsic G.O.	5.08 (.04)	5.27 (.08)	4.00	.046	-.20
Extrinsic G.O.	5.42 (.05)	5.46 (.10)	0.16	.688	-.04
Task Value	5.82 (.04)	5.96 (.07)	13.56	<.001	-.37
Control Beliefs	5.81 (.04)	6.15 (.08)	3.55	.060	-.18
Self-efficacy	5.23 (.05)	5.51 (.09)	7.43	.007	-.27
Test Anxiety	4.33 (.07)	4.09 (.13)	2.48	.116	.16
Rehearsal	4.36 (.06)	4.55 (.11)	2.46	.118	-.16
Elaboration	5.30 (.05)	5.65 (.09)	12.43	<.001	-.36
Organisation	4.90 (.06)	5.16 (.11)	4.52	.034	-.21
Critical thinking	4.10 (.06)	4.25 (.11)	1.68	.195	-.13
Metacognition	4.51 (.04)	4.70 (.08)	4.98	.026	-.22
Time Management	5.06 (.05)	5.31 (.09)	5.53	.019	-.24
Effort Regulation	5.08 (.06)	5.39 (.11)	6.58	.011	-.26
Peer Learning	3.41 (.06)	2.75 (.12)	21.72	<.001	.47
Help Seeking	3.72 (.06)	2.88 (.12)	37.28	<.001	.61

Notes. Means are adjusted for age. Possible scores range from 1 to 7 for all MSLQ subscales. Scores for goal grade range 1 to 6. G.O = Goal orientation.

4. Discussion

The present study used a person-centered approach to: (1) identify how many different self-regulated learning profiles could be distinguished; (2) which of these profiles was associated with greater academic achievement, intention to study, and study automaticity; and (3) whether online students were over-represented in any one profile or whether they show different motivations and strategy use. Guided by these aims, we found support for all three hypotheses. That is: (1) the most adaptive motivated self-regulated learning profiles (high in motivational self-regulation, high in the use of self-regulated learning strategies) had the highest academic achievement, intention to study, and high automaticity; (2) non-adaptive motivated self-regulated learning profiles (low in motivational self-regulation, low in the use of self-regulated learning strategies) had the lowest academic achievement, intention to study, and automaticity; and (3) online learners were found to be more likely to belong to adaptive profiles with less interact with peers and instructors. These are discussed in sequence and in more detail below.

4.1. Adaptive vs non-adaptive profiles and their relationship to academic achievement and other indices

In line with our hypothesis, the class with highest grade (super-regulators) had an SRL profile with highest levels of time management and organisation, effort regulation, metacognition, and critical thinking, consistent with prior reviews of key SRL-based predictors of academic performance (Broadbent & Poon, 2015; Richardson et al., 2012). Participants in this group also set the highest grade goals, and were more internally driven to succeed and confident in their abilities (see also Heikkilä et al., 2006; Heikkilä et al., 2011; Liu et al., 2014). In contrast, but in support of our hypothesis, the group with lowest engagement across the various indicators of SRL (minimal regulators) had substantially lower academic performance, intention to study and automaticity than the other classes. These minimal regulators were also the youngest group in the LPA results.

The remaining subgroups have typically comprised students who either have moderate levels of engagement across the various SRL indicators (e.g., Abar & Loken, 2010; Barnard-Brak et al., 2010), or show relative engagement or disengagement (Barnard-Brak et al., 2010; Heikkilä et al., 2012; Liu et al., 2014) for a subset of SRL variables. In the present study, there were two further groups that, while not as extreme as the super-regulator class, exhibited moderate-to-high level engagement in many of the SRL strategies and motivation variables. The anxious capable collaborators were distinguishable from the calm self-reliant regulators in their higher level of test anxiety and their greater engagement in interaction-based methods for learning (peer support and help seeking). Indeed, the latter group had the lowest test anxiety, peer support, and help-seeking of all classes, and their level of independence coincided with having a greater proportion of online students in this class than all bar the super-regulator class. Differentiation on the basis of anxiety level and/or level of interaction versus independence in learning has also been found previously (Heikkilä et al., 2011; Liu et al., 2014).

4.1.1 Adaptive profiles and academic achievement

Despite their superior motivated self-regulated learning profile, super-regulators did not academically outperform self-reliant regulators. Barnard-Brak et al. (2010) also found academic success was equivalent between their two most adaptive profiles, super self-regulators and competent self-regulators. In their study, competent self-regulators were hypothesised to do what it takes and nothing more to achieve the same academic success as super-regulators, who utilised more self-regulated learning strategies. We speculate in our own research that our super-regulators also go beyond what is necessary for their subsequent grade, in a similar fashion to super-regulators in the Barnard-Brak et al. (2010) study.

Test-related anxiety may also account for lack of difference in performance despite differences in breadth and extent of SRL strategy use between the two best performing groups. The exaggerated profile of broad and strong engagement in various SRL strategies in the super-regulator group may be a manifestation of task-related anxiety rather than genuine need for this level of SRL strategy engagement to succeed. Anxiety is also known to adversely impact performance (Liu et al., 2014; Seipp, 1991; Richardson et al., 2012), and thus may have more direct and counter-acting effects for these super-regulating students. Test anxiety can create irrelevant thoughts, preoccupation, and decreased attention and concentration, and reduce one’s ability to retrieve information from memory storage, thus leading to academic difficulties (Eysenck, 2001; Pintrich & De Groot, 1990; Sansigiry & Sail, 2006). If their level of anxiety were comparable to the calm self-reliant regulator group (rather than being elevated), we might have instead observed the anticipated greater performance in the super-regulator group.

4.1.2. Non-adaptive profiles and academic achievement

The least adaptive profiles, those with the lowest motivation and self-regulated learning strategies, were named minimal regulators and restrained regulators. Minimal regulators were moderately motivated, more driven to study due to grades rather than personal interest, and appeared anxious, less well organised and critical in their thinking, and lacking confidence in their study ability. Their pattern of scores suggested potential disengagement from their learning process. Restrained regulators, although still lower than other groups, adopted a variety of learning strategies to moderate levels, typically scoring higher than the minimal regulators. Compared to minimal regulators, restrained regulators were less anxious and more effective at regulating the time and effort they put into their study.

While the least adaptive profile (minimal regulators) of SRL strategies (particularly their low levels of self-efficacy, internal drive, and help seeking) is, at first blush, consistent with disengagement from the learning process, these minimal regulators had the second highest level of test-related anxiety, suggesting they do care about the outcome of their studies. Given their young age relative to the higher performing classes, it is possible that the poor performance of minimal regulators also reflects relative lack of experience and limited prior exposure to successful learning approaches. As many of these SRL processes are malleable, and subject to influence from feedback loops (Zimmerman, 2015), poor performance in prior tasks (despite effort) may adversely affect their self-confidence and deter them from continuing to exert effort in completing academic tasks (Zimmerman, 2015).

4.2. To which profiles do online learners most likely belong?

Online learners were found to be more likely to belong to adaptive profiles characterised by less interaction with peers and instructors. The latent profile analysis did not produce a group solely comprising online students; nor were there any classes for which online students were not represented. However, online students were more highly concentrated in the two high performing classes (based on grades) which were characterised by strongest time management, effort regulation, level of organisation, and grade goals levels relative to other groups. One of these classes had lowest level endorsement of SRL strategies involving interaction (peer support and help seeking). Combined, these results from the latent profile analysis are consistent with the notion that those who choose online studies are more comfortable with working independently and prefer to work according to their own timeframe (Roblyer, 1999). Nevertheless, the representation of online students across all classes suggests heterogeneity among online students in their approach to learning, and that viewing them all as independent, internally driven, and effective time managers – as may be concluded from the results of group difference analyses – may be an oversimplification. Even so, most group differences between online and on-campus students were small in magnitude (with absolute differences of less than 1 unit on scales ranging from 1 to 7), suggesting that in practice, online and traditional learner groups may not be noticeably different at the level of individual strategies in how they approach learning, but may be more easily discerned from the pattern of strategies they commonly employ.

Interestingly, the two groups in which online learners were most concentrated, super regulators and calm self-reliant capable regulators, did have low peer and help-seeking strategy use but were not the lowest profiles. However, peer and help-seeking strategies were less likely to be used by individuals in these profiles, with both groups scoring on average less than the neutral point of four. So, while latent profile analysis results show heterogeneity of online learners and strategy use, additional findings from group difference tests do suggest that they prefer to use peer and help-seeking strategies less often than their on-campus counterparts.

In the Australian higher education context, the older age of online relative to on-campus students - as found in the present study - is not uncommon (Johnson, 2015; Norton, Sonnemann & McGannon, 2013). Many of these students enjoy the flexibility of online learning because they can balance study with work and/or family commitments (Henry, Pooley & Omari, 2014). Online students' older age may also be a proxy for greater experience with learning, and may thus partially account for the correspondence found in the present study between age and use of SRL strategies among the various classes identified. After all, SRL use may be predicted by prior experiences and prior knowledge (Moos & Azevedo, 2008; Taub, Azevedo, Bouchet & Khosravifar, 2014; Trevors, Duffy & Azevedo, 2014).

Students do not always select online options by choice, and their decision to select online study may arise due to personal constraints (e.g., geographical location, work and/or family commitments) or constraints of the education provider (some courses only available in online mode, etc.). As such, the online environment may also influence the way students learn as students must adapt to their forced or chosen study mode. A growing body of research is showing how online course design may actively encourage SRL strategy use (Azevedo, Cromley & Seibert, 2004; Azevedo, Cromley, Winters, Moos & Greene, 2005; Delen, Liew & Willson, 2014; Lin & Tsai, 2016; Moos & Bonde, 2016) and reflection on the importance of SRL strategies (Barak, Hussein-Farraj & Dori, 2016). Encouragingly then, despite clear differences observed in the range and depth of SRL strategy use among university students, SRL appears amenable to improvement provided the learning environment is designed to facilitate self-regulatory aspects of the learning process.

4.4. Limitations

Present findings should be considered in light of several study limitations. It is worth noting that the timing of measurement may have impacted findings. In the present study, students could complete the MSLQ at any point during the semester. This may be problematic, as Timmons and Preachers' (2015) study of temporal design argues that large measurement intervals can be associated with less accuracy in parameter estimation. It is possible that the impact of motivation and self-regulated learning strategies on academic performance may differ if measured earlier versus later in the trimester. Although beyond the scope of the present study, future research could explore the extent to which the relative importance of the self-regulation profiles differ as a function of when they are assessed within a teaching period.

The use of self-report measures within this study is also fraught with difficulty, particularly learner's perceptions of how often (and how well) they use a particular learning strategy. There is ample evidence that learner-perceived use of strategies may not correspond to actual learner behavior (Veenman, 2011a). Further, learners may be disposed to giving socially desirable answers, or to recall strategies never used or used to a lesser degree than reported (Veenman, 2011b). Nevertheless, the advantage of using self-report questionnaires is that they can be administered to large groups, and is a time and cost effective way to measure self-regulation (Schellings & Van Hout-Wolters, 2011). Alternatives to self-report measures, such as eye tracker technology, learning analytics, or observation can be intrusive, time consuming, and may not adequately capture thoughts and beliefs underlying the behaviour (Veenman, 2011b).

Age and gender composition of the present sample may also have influenced present results. Although the older age of our online students is consistent with known demographic profiles in the Australian higher education context (Johnson, 2015; Norton et al., 2013), age may also be a proxy for increased learning experiences, and hence we were unable to isolate age-related effects from experience in predicting type and level of SRL strategy use. Initial group difference tests with control of age differences (i.e., ANCOVAs) did suggest, however, that age alone was insufficient explanation for differences between online and blended learning students in predicting SRL strategy engagement. Similarly, the greater proportion of female participants in the present study may have also influenced LPA results, given prior findings of potential gender differences in SRL use (Pajares, 2002; Zimmerman & Martinez-Pons, 1990, although see Yukselturk & Bulut, 2009), and gender differences also observed in the present study.

Finally, the latent profile analysis used in the present study makes several simplifying assumptions that may not hold in practice: equivalence of within-group variances across classes and no association between indicators within class. While there was no evidence of homogeneity of variance across classes for the indicators used in the present study, comparison of presently used techniques for identifying latent profiles against other statistical approaches (e.g., cluster analysis) may be a helpful future research direction. Further, observation of anticipated and interpretable differences between classes in terms of academic performance and study mode is encouraging, but requires replication.

4.5. Conclusion

The present study illustrates a person-centered approach to self-regulated learning among University students, extending both the range of indicators and the population sampled. Findings broadly support prior results by identifying subgroups at the extreme ends of SRL strategy engagement and subgroups with moderate engagement or elevated, selective use of SRL strategies. In general, breadth and strength of engagement in SRL strategies were associated with higher grades, reinforcing the point that the way an individual approaches the learning process impacts performance. However, a key finding from the present study is that anxiety may be associated with poorer student performance, even in the presence of strong SRL. The stress an individual feels in relation to their studies and assessment should not be overlooked when attempting to help students. Teachers should be mindful of how highly anxious students react, especially concerning high stakes assessment. Student learning should be supported and scaffolded with clear student and assessment expectations. Students who struggle with anxiety may be encouraged to practice mindfulness techniques and/or seek University counselling (if available). Another factor to keep in mind is the use of interaction-based methods for learning. Both groups of high achieving learners had different interaction preferences. The super-regulators prefer some help from teachers and peers, while the calm self-reliant capable regulators preferred to have minimum interaction. As a teacher, it is essential to recognise that lack of interaction does not mean lack of engagement or motivation to succeed. Both super-regulator and calm self-reliant capable regulator groups, despite interaction differences, were academically equally successful.

The incorporation of both online and blended learning students in sampling showed a greater proportion of online students in the more adaptive SRL profiles. Given that online study is not always a personal choice, it seems likely that the stronger endorsement of SRL strategies (especially those based on self-reliance) in this sub-population may be influenced by their study mode as well as being a reason for preferring this type of study (where choice is possible). Thus, continued focus on ways to structure the learning experience – whether online or face-to-face – to enhance SRL use should be prioritized (Greene, Moos & Azevedo, 2011). More broadly, the person-centered focus on profile across a range of learning-related indicators, as conducted in the present study, may provide a more nuanced and comprehensive assessment of a student's risk of poor performance and drop-out, as well as identifying the areas in which a student may need greatest assistance. Further research should explore whether identifying subgroups based on SRL strategy deployment may facilitate a more personalized learning experience and, in turn, enhance student outcomes.

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