Impact of Motivation and Strategy Use on Performance in a Blended Learning Course

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Understanding students' self-regulatory learning (SRL) processes is important, especially in Blended Learning (BL). This study examined the predictability of students' final scores based on indicators from students' reported measures reflecting SRL. We administrated the Motivated Strategies for Learning Questionnaire (MLSLQ) three times to measure students' motivation belief and use of learning strategies (N=189) and collected 515 viable surveys. We found that students' motivation and strategy use dropped until midterm and it increased again as the course progressed towards the end. We identified the constructs that had a high correlation with final scores. In terms of prediction, stepwise regression mostly used motivational components as predictors. The findings confirmed the importance of understanding students' motivation and SRL process and disclosed the advantages of using students' reported measures of SRL, which is meaningful to Learning Analytics. The findings also support the potential for an early final score prediction, which would be very helpful in identifying at-risk students, addressing one of the LA aims.

Keywords: self-regulated learning, students' motivation, students' strategy use, learning analytics, final score prediction

INTRODUCTION

With the rapid growth of online learning and different forms of BL environments, it is vital to understand the personal factors that may affect this environment's success (Abrami & Bernard, 2006). Several studies investigated data variables from learning management systems (LMS) to identify at-risk students through predicting students' outcomes to better design the course instructions so that fewer students drop out (Gašević, Dawson, & Siemens, 2015; Staker & Horn, 2012; Tempelaar, Rienties, & Giesbers, 2015). This approach is called Learning Analytics (LA) and finding at-risk students is one of the most important LA aim (Dawson, Gašević, Siemens, & Joksimovic, 2014). LA has been defined by Siemens and Baker (2012) as "the measurement, collection, analysis, and reporting of data about learners and their contexts, for purposes of understanding and optimising learning and the environments in which it occurs" (Siemens and Baker 2012, p.1). LA is an important approach for supporting teaching and learning and has been applied in different contexts, including higher education, massive open online courses, schools, and workplace learning (Ferguson et al., 2016). LA offers a variety of benefits for higher education institutions, including quality assurance and improvement of teaching, identification of at-risk or low performing students, and detection of learning behaviour to identify undesirable behaviour and learners' effects (Sclater, 2016). Through LA, the insights would be given to the lecturer so that they can apply the appropriate intervention to help students and prevent them from failing the course. The importance of giving the lecturers insight is more important for online lecturers where they do not have enough visual cues to take precautionary measures (Ferguson, 2012). In LA, different studies used indicators from an LMS to identify at-risk students to help them through giving feedback or adjusting instructional strategies (Dietz-Uhler & Hurn, 2013). These studies fail to quantify the impact of emotional, motivational, cognitive–metacognitive factors, and resource management. Studies such as Lonn, Aguilar, and Teasley (2015) and Wong et al. (2019) also stated that the LA field lacks motivational and empirical studies.

Different studies identified SRL as a crucial factor that affects the improvement of the learning environment (Rakes & Dunn, 2010; You & Kang, 2014). P. R. Pintrich (1999) highlighted motivation as the most important component in learning. He also stated that students having cognitive, metacognitive, and self-regulation knowledge is not enough; students need to be motivated to use them (P. R. Pintrich, 1999).

There are a number of contradictory studies about the effect of motivational belief and self-regulated learning (SRL) on performance (Mousoulides & Philippou, 2005; Niemczyk & Savenye, 2005; Pintrich, De Groot, & Elisabeth, 1990). Therefore, in this study, we investigated SRL through the administration of the Motivated Strategies for Learning Questionnaire (MSLQ) (Pintrich & Garcia, 1991) three times (515 viable surveys) during a 12-week BL course. The MSLQ is one of the most used questionnaires for measuring SRL (Roth, Ogrin, & Schmitz, 2016). We used students' self-reports as a source of data to address the challenge identified by Daniel (2019) and Ferguson (2012) related to the application of LA in higher education. Studies such as Daniel (2019) and Ferguson (2012) suggested focusing on the perspective of learners related to their motivation, confidence, enjoyment, satisfaction, and meeting career goals that have the potential for learning success. Therefore, we investigated the relationship between six motivational and nine learning strategy use components and the learning outcomes reported by students in the context of a BL course at the tertiary level to identify the personal factors that affect online learning success (BL course). We aimed to identify the constructs that could help us predict students' outcomes. Based on our results, we could identify at-risk students early enough so that appropriate intervention could be applied to help them, which is one of LA's applications (Tempelaar et al., 2015). Therefore, the following research questions guide our study.

RQ1: *What are the dynamics of the motivational belief and learning strategy use?*

RQ2: *To what extent do the different indicators of motivational beliefs and strategy use account for the students' final scores?*

From a theoretical perspective, looking at different motivation and learning strategy use components over time could enrich our understanding of students' motivation and strategy use in the online environment and their perception regarding their interaction with peers, teachers, and the learning environment. Our study contributes theoretically to debates in SRL theory by looking at the changes in their motivational and learning strategy use as the courses progress (P. R. Pintrich, Smith, Garcia, & McKeachie, 1993; Zusho, Pintrich, & Coppola, 2003). The study contributes to LA by identifying the indicators for early prediction of students' final scores using SRL data (based on theory and the constructs that have not been studied enough in the field), to identify at-risk students. The longitudinal empirical study focusing on the motivational aspect also added empirical evidence to LA, which is still lacking (Ferguson & Clow, 2017).

The study's other contribution was aiding the understanding of the relation between motivational beliefs, cognitive, metacognitive self-regulation, resource management strategies, and outcome. This study identified the constructs in the motivation and strategy use components that were important and impacted the final scores, which could further support the students. The lecturer could promote them in the class. This paper also methodologically contributed to the field by presenting longitudinal empirical data and employing stepwise regressions to understand students' final scores' predictive variables, which was not achievable through a correlation matrix.

The study also has a contribution to practice. To predict students' final score early in the course, the lecturer could apply appropriate intervention to prevent students from dropping out. By identifying the constructs that affect student outcomes, the lecturer could teach students those constructs, such as promoting motivation and self-regulatory learning strategies to enhance students' learning. It is important to teach students the strategies and proper skills to control their learning and become self-regulated learners.

LITERATURE REVIEW

SRL has been identified as one of the best theories for educational studies. Pintrich (2000) defined SRL as "an active, constructive process whereby learners set goals for their learning and then attempt to monitor, regulate, and control their cognition, motivation, and behaviour, guided and constrained by their goals and the contextual features in the environment" (Pintrich 2000, p.453)

In online learning environments, SRL is getting more attention because in this environment, students need to take control of their learning more independently than in traditional classes (Joo, Joung, & Kim, 2014; You & Kang, 2014; Zimmerman, 2008). Some researchers studied the relationship between motivation and cognition (e.g. P. R. Pintrich, 1989). Azevedo, Moos, Greene, Winters, and Cromley (2008) identified that metacognitive self-regulation is related to students' achievements. Cho and Heron (2015) found a different level of correlation between motivation, emotions, metacognitive self-regulation, and final scores. They found that students' motivation can explain a small portion of the variance in achievement. However, students' motivation and emotion can explain a significant portion of the variance in satisfaction. The cognitive model focuses on the cognitive aspect and examines learners as motivationally inert (Kunda, 1987). However, the motivational model focuses on learners as cognitively empty (Kunda, 1987; McKeachie, 1994, p. 123). There was a need for a framework to bring together the two models. Pintrich (1991) developed a model with three motivational beliefs, cognitive strategies, and self-regulatory strategy components. Motivational beliefs are about the students who choose to engage in the task. Cognitive and metacognitive strategies are about the means students use to accomplish a task (Duncan, Pintrich, Smith, & Mckeachie, 2015).

P. R. Pintrich et al. (1993) developed the MSLQ questionnaire to measure motivation, cognitive and metacognitive strategies, and resource management strategies through 31 items in the motivation section and 50 items in the learning strategies section. While we build our discussion based on Pintrich's model of information processing (P. R. Pintrich, 1988), each component has its meaning, which is explained below.

Motivation

The section discusses the value, expectancy, and affect components, which are categorised under the general motivational component. The value component is about why students engage in the activity. There are three subscales for the value component (intrinsic goal orientation, extrinsic goal orientation, and task value). Goal orientation has been defined by Pintrich (1991) as a learner's general goals or orientation toward a course. Wigfield and Eccles (1992) defined task value beliefs as students' perceptions of the interest, usefulness, importance, and cost of a task. Expectancy refers to the beliefs of students as to whether or not they can accomplish the task. There are two subscales for the expectancy components (i.e. the perception of self-efficacy and control beliefs for learning). Bandura (1977) has defined self-efficacy for learning and performance as individuals' judgments about their abilities to plan and carry out the behaviours they need to display to achieve their goals (Bandura, 1977). P. R. Pintrich et al. (1993) defined control beliefs as students' beliefs regarding whether efforts to learn will result in positive outcomes. Test anxiety is another factor in motivation that has always been an important predictor of students' performance (Huang, 2011). It measures the students' worries and concerns at the time of the exam.

Learning Strategies

Three components of strategy use are cognitive, metacognitive, and resource management strategies.

Cognitive strategies are about using basic and complex strategies for processing information that includes: 1) rehearsal, 2) elaboration, 3) organisation, and 4) critical thinking. Entwistle and Ramsden (2015) divided the strategies into two groups of surface-level strategies and deep processing. They categorised rehearsal as a surface-level strategy. Critical thinking, organisation, and elaboration are considered deep processing strategies. Effeney, Carroll, and Bahr (2013) referred to rehearsal as a repetition so that the learner can remember the materials. Richardson, Abraham, and Bond (2012) referred to elaboration as the ability to connect new and existing material so that the learner can remember the new material. Effeney et al. (2013) referred to organisation as the learner's ability to highlight the main points when they were studying. Richardson et al. (2012) referred to critical thinking as the ability to examine learning materials carefully.

Metacognitive self-regulation strategies measure how students control and regulate their cognition. There are three subscales for this stage: 1) planning, 2) monitoring, and 3) regulating (Kaplan, 2008). Planning the activities is about goal setting and task analysis, which activate prior knowledge and make the comprehension of the task easier. Monitoring is about tracking reading and self-testing, which helps understand the material and connects it with prior knowledge. Regulation refers to one's ability to fine-tune and adjust cognitive activities.

The resource management component includes four subscales that control resources in addition to their cognition. They include managing their time and study environment, regulating their efforts, peer learning, and help-seeking. Time management is an element that affects students learning (Kearsley, 2000). Effeney et al. (2013) refer to time management as the ability to plan study time and tasks. Regarding effort regulation, Bandura, Freeman, and Lightsey (1999) stated that self-efficacy through goal setting or effort regulation strategies is linked to academic achievement. They argued that self-efficacy was a crucial internal resource. Richardson et al. (2012) referred to effort regulation as the capacity to persist when students were opposed to academic challenges. Effeney et al. (2013) described peer learning as collaborating with peers to help the learning process. Help-seeking is another characteristic of self-regulated learners. Richardson et al. (2012) referred to students' help-seeking as obtaining assistance from their instructors when they faced a challenge because they knew the importance of other peers in their learning.

METHOD

The participants in this study were 189 students from a business school's course at a tertiary level. We had 189 participants in the first round, 173 participants in the second round, and 153 participants in the third round from the same initial 189 students. They were aged from 17 to 24. The course lecturer had been using online educational tools for five years and had a positive attitude towards technology. This BL course was run for 12 weeks. BL has been defined as a mix of online and offline learning activities. There is a choice between traditional and new media, and they can be substituted for each other (Thorne, 2003).

The lecturer's approach to BL involved purpose-made 30/40 minutes online lectures in lieu of traditional face-to-face delivery. His online lectures were supplemented with short, face-to-face weekly tutorials (review sessions). Each lecture video featured a short quiz at the end that tested students' understanding of the material just covered. Before each review session, the lecturer analysed the embedded quiz results and determined which course material had proven the most challenging. For the review session, students had two options, either to attend the course in person or watch the class's video streaming. The whole class followed a BL approach as students had the option of fully online or attending some review sessions in person. The lecturer then prepared a set of review questions in Top Hat (some copied from the quizzes, others entirely new) and presented these to students at the review sessions. He discussed the students' collective answers to each Top Hat question and then proceeded to give a mini-lecture on the topic.

After he finished going through the review questions, he launched the first of two Top Hat tournaments, which primarily contained the same embedded quiz questions featured in that week's online lectures (interactive review sessions). Top Hat tournaments are round-robin style competitions where students competed head-to-head and won if they were the first to answer correctly. The tournaments typically consisted of eight time-limited rounds of questions. During the competition, a leader board was populated showing the top students and their scores. At the conclusion of the tournament, the top five or six students were awarded an individually wrapped piece of candy as a prize. Students were incentivised to watch each week's online lectures and participate in the weekly in-class tutorial by means of awarding participation marks. Students' final scores were also collected through Canvas and were a combination of three assignments, midterm, and final score.

In order to understand students' motivation, we used the MSLQ (Pintrich, 1991) and ran it, three times, in Week 3, Week 7, and Week 11 of a 12-week semester. We ran the questionnaire through the LMS. The MSLQ has been used frequently in the literature, and the author of the MSLQ checks the instrument's reliability and validity (P. R. Pintrich et al., 1993). In the analysis section, we present descriptive statistics for three administered iterations of the MSLQ questionnaire and explored how each construct changed as the course progressed. Then, we provide predictive validity by presenting the correlations of the MSLQ scales with the final score. We also used stepwise regression analysis to determine the constructs that act as predictors for the final score. Stepwise linear regression is a method of regressing multiple variables while simultaneously removing those that are not important.

ANALYSIS

Over three rounds of surveying a population of 189 students, sets of 189, 173, and 153 viable surveys were collected. We cleaned the data first and handled the missing data. For this reason, we needed to test if we had missing values at random or not. Therefore, we ran a Little's Missing Completely at Random (MCAR) test for each iteration of each class. Our results showed that the data was missed at random. There were different approaches for handling missing data, for example, listwise deletion, pairwise deletion, mean imputation, and regression imputation. We replaced the missing values with maximum likelihood. We considered the rule of thumb by preplacing less than 10 per cent of the data. In this section, we provide our results, which are divided into three main sections: 1) descriptive statistics, 2) correlation analysis, and 3) stepwise regression analysis.

Descriptive Statistics

To address the first research question, we summarised the descriptive statistics for motivation and strategy use components and their sub-constructs in Table 1.

TABLE 1
DESCRIPTIVE STATISTICS FOR THE MSLQ SUB-CONSTRUCTS AT ITERATION1, ITERATION 2, AND ITERATION 3

	Iteration 1 (189 students)		Iteration 2 (173 students)		Iteration 3 (153 students)	
	M	**SD.**	**M**	**SD**	**M**	**SD**
Motivation	**4.92**	**0.63**	**4.80**	**0.62**	**4.82**	**0.69**
Intrinsic Goal Orientation	4.71	0.84	4.53	0.89	4.55	0.94
Extrinsic Goal Orientation	5.30	1.06	5.04	1.14	5.10	1.09
Task Value	5.30	0.98	5.110	0.96	5.12	0.99
Control of Learning Beliefs	5.15	0.87	5.14	0.82	5.06	0.89
Self-Efficacy for Learning Performance	4.92	0.86	4.84	0.92	4.84	0.97
Test Anxiety	4.61	1.16	4.51	1.15	4.60	1.18
Strategy	**4.23**	**0.55**	**4.20**	**0.62**	**4.31**	**0.66**
Rehearsal	4.38	1.03	4.64	1.00	4.78	1.04
Elaboration	4.58	0.83	4.58	0.93	4.73	0.94
Organisation	4.83	0.87	4.76	0.91	4.84	0.93
Critical Thinking	3.87	1.05	3.88	1.01	3.95	1.13
Metacognitive Self-Regulation	4.29	0.67	4.39	0.70	4.45	0.70
Time Study Environmental Management	4.76	0.78	4.66	0.86	4.63	0.85
Effort Regulation	4.83	1.05	4.64	1.06	4.65	1.05
Peer Learning	3.36	1.32	3.32	1.38	3.57	1.42
Help Seeking	3.25	1.19	3.15	1.24	3.34	1.31

We calculated the values for components (motivation and strategy use) based on the mean of the items that made up that component. In contrast to the studies run by Pintrich and Garcia (1991) and P. R. Pintrich et al. (1993), our analysis shows that even though there is a decline in the motivation and strategy use components as the course reaches midterm, these constructs increased again as the course gets close to the end. This is not unusual that students are faced with a lot of material and assessment that have built up as the course gets to the midterm. Therefore, they would be less motivated. Besides, as the course gets close to the end, they become more anxious and cognitively involved.

Correlation Analysis

This section explored and summarised the correlation between motivational and strategy use components and sub-constructs, and final scores to answer the second research question. We chose the constructs based on the hierarchical structure of the MSLQ. Table 2 and their narratives explained the different level and commensurate details.

Two Constructs (Motivation and Strategy Use) From Three Iterations

We considered the correlation between motivational and strategy use components and final scores in TABLE . Motivation from three iterations has the highest correlation with final scores. In terms of strategy use, this construct has a higher correlation with final scores in the second and third iterations. There was a high correlation between motivation and strategy use in all three measurements, which shows that highly motivated students applied more learning strategies. This is consistent with a study run by Pintrich and

García (1993), who showed that students who reported higher levels of intrinsic orientation and task value tended to report higher cognitive and self-regulatory strategy use.

TABLE 2
CORRELATION OF MOTIVATION AND STRATEGY USE AT ITERATION 1, ITERATION 2, ITERATION 3

	Iteration 1		Iteration 2		Iteration 3		
M=Motivation S= Strategy	**M1**	**S1**	**M2**	**S2**	**M3**	**S3**	**Final Score**
Motivation 1	1.000						0.222**
Strategy 1	0.320**	1.000					0.140
Motivation 2	0.631**	0.256**	1.000				0.327**
Strategy 2	0.281**	0.671**	0.433**	1.000			0.254**
Motivation 3	0.604**	0.275**	0.762**	0.449**	1.000		0.366**
Strategy 3	0.263**	0.630**	0.289**	0.735**	0.490**	1.000	0.289**

∗ $p < .05$, ∗∗ $p < .01$, ∗∗∗ $p < .001$.

Five Constructs From Three Iterations

We considered the correlation of the constructs underneath motivation and strategy use components in Table 3 to determine the constructs with a high correlation with the final score. In terms of the motivational components, value and affective constructs from three iterations had a high correlation with the final score.

In terms of the strategy use component, cognitive, metacognitive, and resource management strategies from all three iterations had a high correlation with final scores except cognitive and metacognitive strategies in the first iteration. We expected students to develop their strategy learning skills throughout the course. These students had just joined the university from high school. Therefore, they were expected to have lower learning strategy skills and, consequently, lower correlation with final scores. As shown in Table 3, the correlations between motivation and final scores and strategy use and final scores increased as time passed. The lowest correlations were between Expectancy 1, Affective 2, and Affective 3, and Cognitive and Metacognitive Strategies 1 with final scores.

In terms of correlation among motivational and strategy use components from three iterations, they are all highly correlated except resource management strategies that did not correlate with affective. Plus, resource management strategies do not correlate with expectancy in the first and second iterations. But as the course progressed, this construct correlated with expectancy.

TABLE 3
CORRELATION OF MOTIVATION AND STRATEGY USE COMPONENTS AT ITERATION 1, ITERATION 2, ITERATION 3

	Cognitive and Metacog1	Resource Management1	Cognitive and Metacog2	Resource Management2	Cognitive and Metacog3	Resource Management3	Final Scores
Value1	0.345**	0.315**	0.374**	0.328**	0.279**	0.301**	0.162*
Expectancy1	0.206**	0.132	0.108	0.046	0.036	0.013	0.123
Affective1	0.195**	0.012	0.280**	-0.060	0.270**	0.062	0.179*
Value 2	0.214**	0.347**	0.492**	0.464**	0.340**	0.301**	.338**
Expectancy2	0.196**	0.111	0.302**	0.130	0.137	0.007	.324**
Affective2	0.084	0.016	0.263**	0.007	0.249**	0.030	0.094
Value3	0.232**	0.301**	0.484**	0.448**	0.548**	0.390**	0.389**
Expectancy3	0.274**	0.161*	0.261**	0.202*	0.378**	0.194*	0.344**
Affective3	0.125	-0.008	0.341**	0.017	0.346**	0.056	0.128
Final Score	0.086	0.147*	0.198**	0.237**	0.242**	0.257**	1.000

$*$ $p < .05$, $**$ $p < .01$, $***$ $p < .001$.

Fifteen Constructs From Three Iterations

In this section, we considered the correlation between motivational and strategy use sub-constructs and final scores from three iterations, which is depicted in Table 4. Among motivational components, self-efficacy for learning and performance and extrinsic goal orientation from three iterations and task value from two iterations had the highest correlation with final scores.

Among the motivational components, control beliefs and anxiety always had the lowest correlation with final scores. The only exception was anxiety at the beginning of the course, then the correlation of anxiety at iteration 1 was higher than the correlation of anxiety at iteration 2 and iteration 3.

In terms of the strategy use components, time and study environment from the three iterations and effort regulation from two iterations had the highest correlation with final scores. Among strategy use components, help-seeking, and peer learning had the lowest correlation with final scores. The correlation between the sub-constructs in our study was much lower than the numbers reported by Stolk and Harari (2014) and P. R. Pintrich (1999), which could be the effect of the pedagogical approach.

TABLE 4
CORRELATION BETWEEN MOTIVATION AND STRATEGY USE SUBSCALES AT ITERATION 1, ITERATION 2, ITERATION 3

	Reh1	Ela1	Org1	Cri1t	Mcg1	Tsdy1	Eff1	Prlrn1	Hsk1	Reh2	Ela2	Org2	Crit2	Mcg2	Tsdy2	Eff2	Prlrn2	Hsk2	Reh3	Ela3	Org3	Crit 3	Mcg 3	Tsdy 3	Eff 3	Prlrn 3	Hsk 3	Final Score
Intr 1	0.1 1	.29 6**	.29 0**	.33 9**	.27 5**	.23 6**	0.1 13	.18 2*	.15 8*	0.1 48	.33 5**	.27 6**	.30 1**	.32 4**	.28 6**	.25 1**	.20 8**	0.06 7	0.0 31	.27 0**	.29 7**	.25 0**	.29 0**	.31 2**	.25 2**	.23 8**	0.02 6	0.0 49
Extr 1	0.1 43	0.0 77	.17 7*	- 0.0	.14 4*	.23 8**	.16 9*	- 0.0	- 0.0	.26 1**	0.1 42	0.1 23	0.0 93	.23 1**	.27 5**	.29 7**	- 0.0	0.03 4	.21 7**	0.0 28	0.0 13	- 0.0	0.0 74	.24 0**	.21 5**	- 0.0	- 0.03	.18 7*
Tskv 1	0.1 11	.38 4**	.33 5**	.22 3**	.36 6**	.41 1**	.31 9**	0.0 93	0.0 83	.16 0*	.38 0**	.22 7**	.24 8**	.37 0**	.44 2**	.40 1**	0.0 58	0.02 5	0.1 54	.37 6**	.31 4**	.18 5*	.39 1**	.35 8**	.34 9**	.16 5*	- 0.04	0.1 25
Cont1	0.0 56	0.1 29	.17 5*	0.0 66	.16 2*	.15 9*	0.1 1	- 0.0	- 0.0	0.1 2	0.1 07	0.0 33	0.0 03	0.0 85	0.0 86	0.0 76	- 0.1	- 0.11	0.0 09	0.0 39	- 0.0	- 0.0	0.0 76	- 0.0	0.1	- 0.0	- 0.15	0.0 03
Slfef1	0.1 29	.18 0*	.24 5**	0.0 85	.29 0**	.22 5**	.27 2**	0.0 19	0.0 1	0.1 19	0.0 67	0.0 62	0.0 45	.17 1*	.19 6**	.29 3**	0.0 1	- 0.09	0.0 46	0.0 74	0.0 4	0.0 63	.20 0*	0.1 15	.31 0**	- 0.0	- 0.12	.20 9**
Tanx1	.23 0**	0.0 78	.19 5**	0.0 67	- 0.0	0.0 29	- 0.1	.15 1*	- 0.0	.31 8**	0.1 25	.19 3*	.20 8**	.23 5**	- 0.0	- 0.0	- 0.0	- 0.05	.36 6**	0.0 92	.19 3*	.17 3*	0.1 57	0.0 83	- 0.0	0.1 09	- 0.02	.17 9*
Intr2	0.0 52	.30 2**	.25 4**	.22 5**	.24 5**	.32 9**	.20 6**	0.1 39	.18 9*	.20 2**	.47 9**	.38 5**	.41 7**	.44 9**	.35 8**	.40 4**	.28 5**	.187 *	0.0 54	.30 9**	.36 1**	.28 6**	.29 1**	.36 1**	.30 9**	.22 2**	0.01 9	.23 0**
Extr2	0.1 05	0.1 38	.18 0*	- 0.1	0.0 63	.21 3**	.20 2**	0.0 23	.15 3*	.32 1**	.25 8**	.24 9**	0.1	.27 9**	.32 2**	.41 0**	0.0 35	0.08 6	.24 9**	.17 9*	.18 1*	- 0.0	0.1 17	.30 1**	.21 3**	0.0 12	- 0.02	.27 9**
Tskv2	- 0.0	.22 2**	.23 1**	0.0 33	.17 6*	.28 8**	.32 3**	- 0.0	0.0 92	.17 6*	.49 3**	.35 8**	.17 6*	.38 3**	.42 9**	.47 2**	0.0 86	0.00 8	.19 8*	.35 7**	.35 6**	0.0 7	.32 1**	.42 4**	.42 0**	0.0 13	- 0.08	.27 9**
Cont2	0.1 32	.19 5*	.24 5**	- 0.0	.17 7*	.22 7**	.16 8*	- 0.1	- .15	.23 3**	.16 1*	0.1 43	- 0.0	.21 6**	.20 8**	0.1 38	- 0.1	- .239	0.1 15	0.0 96	0.1 2	- 0.0	0.1 43	0.1 21	.19 0*	- .17	- .250	0.0 66
Slfef2	0.0 49	.20 9**	.26 0**	- 0.0	.20 6**	.24 9**	.31 9**	- 0.0	- 0.0	.28 8**	.29 5**	.29 4**	0.1 12	.41 8**	.37 1**	.49 1**	- 0.0	- 0.05	.16 9*	0.1 01	.20 7*	0.0 37	.23 4**	.26 4**	.42 1**	- 0.1	- 0.14	.45 2**
Tanx2	0.0 84	0.0 72	0.0 96	0.0 04	- 0.0	- 0.0	- .18	0.1 47	0.0 64	.29 0**	0.1 48	.22 9**	0.1 33	.19 6**	- 0.0	- 0.1	0.0 98	- 0.00	.33 3**	0.0 66	.18 2*	.17 7*	0.0 5	0.0 89	- 0.0	0.0 91	- 0.04	0.0 94
Intr 3	0.0 52	.28 0**	.19 0*	.33 2**	.20 3*	.23 4**	0.1 2	.19 9*	.19 1*	.21 1**	.47 9**	.27 0**	.49 4**	.36 4**	.32 7**	.27 5**	.35 8**	.211 **	.22 6**	.46 9**	.41 2**	.48 1**	.41 6**	.39 0**	.31 2**	.35 1**	0.13 7	.26 1**
Extr3	0.1 26	0.0 39	.19 3*	- 0.0	0.0 57	.22 1**	.28 4**	- 0.0	- 0.0	.31 8**	.29 3**	.26 3**	.22 9**	.31 5**	.34 1**	.33 2**	0.0 22	- 0.05	.41 9**	.28 6**	.27 9**	.19 5*	.30 7**	.33 7**	.31 1**	0.0 08	- 0.07	.38 2**
Tskv3	- 0.0	.25 6**	.20 7*	0.1 18	0.1 49	.28 1**	.32 8**	0.0 5	0.1 54	.16 6*	.43 9**	.28 7**	.29 5**	.33 3**	.45 1**	.46 8**	.26 6**	0.04 3	.29 3**	.46 3**	.47 6**	.23 7**	.40 8**	.40 7**	.41 2**	.16 5*	0.01 2	.30 5**
Cont3	.18 7*	.23 9**	.29 8**	0.0 56	.17 0*	.21 0**	.20 4*	- 0.1	- 0.1	.23 0**	.17 7*	0.0 79	0.0 81	.21 1**	.30 1**	.29 5**	- 0.0	- .280	.27 3**	.25 6**	.28 3**	0.0 45	.28 3**	.17 5*	.26 9**	- 0.0	- .203	0.1 29
Slfef3	0.0 83	.23 6**	.26 3**	0.1 11	.20 1*	.24 4**	.30 9**	0.0 28	0.0 62	.22 0**	.20 6*	.21 6**	.20 6*	.31 3**	.35 6**	.39 9**	.18 1*	- 0.09	.29 8**	.31 0**	.35 4**	.25 9**	.38 1**	.35 2**	.44 6**	0.1 16	- 0.06	.46 2**
Tanx3	.16 3*	0.0 82	0.1 21	0.0 02	- 0.0	0.0 84	- 0.0	0.0 29	- 0.0	.34 2**	.19 4*	.28 4**	.23 9**	.21 5**	0.1 41	- 0.0	0.0 23	- 0.07	.44 5**	0.1 39	.25 8**	.21 7**	0.0 93	0.1 41	- 0.0	0.1 04	- 0.05	0.1 28
Final Score	0.1 4	0.0 33	.21 0**	- 0.1 16	0.0 19	.15 3*	0.1 27	0.0 48	0.0 52	.22 2**	.16 6*	.18 1*	0.0 38	.15 0*	.20 4**	.23 5**	0.1 31	0.06 9	.20 2*	.23 9**	.26 7**	0.0 62	.16 9*	.28 0**	.30 6**	0.0 73	0.07 3	1

Regression Analysis

To answer our second research question, in this section, we report on stepwise regression analysis using IBM SPSS (version 26) to do the exploratory model building, focuses on exploring the effect of student motivational beliefs and strategy use on outcomes. This automated method chose the predictors from motivational and strategy use based on how significant the predictors were. We ran the stepwise regression with the final score as the dependent variables and the MSLQ constructs as independent variables. We reported when the system chose the constructs and sub-constructs from different iterations in Table 5. We report what the significant predictors are for each model.

First, we explore the predictability of the final scores based on constructs from three iterations. Then, we look at the predictability of final scores based on constructs from the first, second, and combined first and second iterations of data to see how early we can predict students' final scores. Early prediction of students' final scores helps the course instructor identify at-risk students so that the lecturer could apply appropriate interventions to help them.

For each iteration of our analysis presented in Table 5, we presented three models (M). Each model is based on a specific number of constructs (2, 5, and 15 variables based on the architecture of the MSLQ). For each model, we presented the predictors and their characteristics.

Regression Analysis Based on Three Iterations

In this section of the analysis, we used data collected from three iterations to investigate how we can explain the final score based on motivation and strategy use.

Stepwise Regression With Only Two Components. For the first step, we used motivation and strategy use components from three iterations and asked the stepwise regression procedure to find the best model. The system generated two models. Model one used motivation2, and model two used motivation2 and strategy3 as the independent variables (M1-Table 5).

Adjusted R-square tells the proportion of the variability in the final scores that is explained by the model, which tells us how good the prediction is. Looking through the model summary, we understood that in the first model, 11.7% of the variance in outcome could be contributed to the predicted variable (i.e., the current model) and Model 2 can explain 14.7% of the variability in the final score.

The ANOVA table showed us that both models are significant. We see the weight (or slope) for motivation2 and strategy3 in these two different models from the coefficient table. Motivation2 had the highest unstandardised beta value. All the *B* values are significant. Motivation2 had the largest beta value, and strategy3 had the second largest. Motivation2 was the strongest contribution to explaining the dependent variable (i.e., final score).

Stepwise Regression With Five Constructs. In the next stage of our analysis, we ran a stepwise regression procedure to find the best model determining predictors from the value, expectancy, affective, cognitive, metacognitive, and resource management strategies in three iterations. The system generated four models based on R-square; we can say that Model 4 with value 2, expectancy 2, resource management strategies 3, and resource management strategies 1 as predictors explained the final scores better (M2- Table 5). And those constructs were all significant. The adjusted R-square for Model 4 was 21.7%, which is the proportion of the variability in the final scores that is explained by the model.

TABLE 5
STEPWISE REGRESSION ANALYSIS RESULTS ON THE FINAL SCORE BASED ON DIFFERENT ITERATIONS (FRESHMEN N=189)

		Model	**Predictors**	**Final score**			
				B	***SE***	**ß**	R^2
Based on three Iterations	2 Constructs	M1	Motivation2 Strategy3	6.134 3.908	1.643 1.580	0.294 0.195	0.158
	5 Constructs	M2	Value2, Expectancy2,				0.237

			ResourceManagement3, ResourceManagement1				
	15 Constructs	M3	Self-Efficacy for Learning Performance3, Extrinsic Goal Orientation3, Control of Learning Beliefs3	6.401 2.810 - 3.432	1.214 0.943 1.256	0.473 0.235 - 0.231	0.278
Based on first iterations	2 Constructs	M4	Motivation1	5.985	1.920	0.222	0.222
	5 Constructs	M5	Affective1, ResourceManagement1	2.595 3.830	1.044 1.887	0.178 0.145	0.053
	15 Constructs	M6	Organisation1, Critical Thinking1, Self-Efficacy for Learning Performance1, Test Anxiety1	3.300 - 2.870 3.612 2.327	1.439 1.140 1.412 1.031	0.170 - 0.178 0.183 0.159	0.123
Based on second iterations	2 Constructs	M7	Motivation2	7.582	7.582	1.678	0.107
	5 Constructs	M8	Value2, Expectancy2	4.249 3.965	1.543 1.662	0.232 0.201	0.14
	15 Constructs	M9	Self-Efficacy for Learning Performance2, PeerLearning2	7.048 1.395	1.055 0.701	0.453 0.135	0.222
Based on first and second iterations	2 Constructs	M10	Motivation2	7.582	1.678	0.327	0.107
	5 Constructs	M11	Value2, Expectancy2, Expectancy1	4.166 6.410 - 3.673	1.529 2.029 1.783	0.227 0.324 - 0.189	0.164
	15 Constructs	M12	Self-Efficacy for Learning Performance2, Control of Learning Beliefs, Test Anxiety1, Metacognitive Self-Regulation1	8.090 - 3.062 2.015 - 3.178	1.081 1.120 0.820 1.403	0.520 - 0.187 0.162 - 0.152	0.288

Stepwise Regression With Fifteen Sub-Constructs. In the third section of our analysis, we used a stepwise regression procedure to find the best model choosing from 15 sub-constructs from three periods. Sub-constructs are intrinsic goal orientation, extrinsic goal orientation, task value, control of learning beliefs, self-efficacy for learning performance, test anxiety, rehearsal, elaboration, organisation, critical thinking, metacognitive self-regulation, time and study environmental management, effort regulation, peer learning, and help-seeking from three iterations of data. The system generated three models. The third model had the best R-squared value. The adjusted R-square of the third model was the highest and equalled 26.3%, which is the proportion of the variability in the final scores that was explained by the model. This model was generated based on self-efficacy for learning performance 3, extrinsic goal orientation 3, and control of learning beliefs 3 as predictors (M3- Table 5). All the predictors were chosen from the third iteration. Control of learning beliefs 3 had a negative weight on our regression model. The ANOVA table showed that all the predictors were significant. In the coefficient table, we considered the beta values and especially in Model 3 that had the best R-square. So far, we chose data from three measurements for our predictions which helped us understand how we could explain the final scores based on three iterations. Now that we have used all three iterations of data in predictions, it is beneficial to check if we can predict the final score based on just the first or second iteration of data since our goal was an early prediction.

Regression Analysis Based on the First Iteration

In this section of the analysis, we used data collected from Week 3 to explore if we could predict students' final scores early in the course.

Stepwise Regression With Two Components. We employed stepwise regression and let the system choose between motivation 1 and strategy1. The system chose motivation 1 and removed strategy 1 for making the regression model (M4- Table 5). The R-squared for the generated model was very low at 0.050. Therefore, we went further with constructs and sub-constructs and let the system choose among them and see if we could create a more accurate model.

Stepwise Regression With Five Constructs. We used stepwise regression and let the system choose from the five constructs in the first iteration. Two models were generated. The first model used the affective construct as a predictor, and the second model used affective 1 and resource management strategies 1 as a predictor (M5-Table 5). The R-square did not improve much 0.053. We went further with sub-constructs in the next section of our analysis.

Stepwise Regression With Fifteen Sub-Constructs. This section used 15 sub-constructs from the first iteration. Four models were generated. The best model, Model four, was based on organisation1, critical thinking 1, self-efficacy for learning performance 1, and test anxiety 1 had an R-square of 0.123. Self-efficacy for learning performance 1 had the highest weight in the model (M6- Table 5). Critical thinking had a negative weight. This was the construct that we identified in the qualitative and quantitative analyses, which had a negative correlation all the way through the three rounds of analysis with the final scores. This analysis helped us understand if motivation and strategy use from the first iteration could be used as predictors of final scores.

Regression Analysis Based on the Second Iteration

This section used data from the second iteration to see if we could generate a better model.

Stepwise Regression With Two Constructs. This section used motivation2 and strategy2. The system chose motivation2 again and deleted strategy2 (M7- Table 5). The R-square amount doubled (0.107) compared to the model based on the first iteration of data. The system always chose motivation as a predictor compared with strategy use at a construct level.

Stepwise Regression With Five Constructs. This section used five constructs and the system generated two models. Both models used the motivational component as predictors. The first model used value 2 as a predictor, and the second model used value 2 and expectancy 2 as predictors (M8- Table 5). Looking at the R-square (0.143), we understood that we generated a better model compared to the previous model.

Stepwise Regression With Fifteen Constructs. This section used 15 subscales from the second iterations. As time passed, the R-squares for the generated models got better, especially for sub-constructs. Two models were generated. Self-efficacy for learning performance was chosen from different analysis. This sub-construct had a high correlation with the final score as well. The best model used both self-efficacy for learning performance and peer learning as predictors (M9- Table 5). The B value for self-efficacy for learning performance was much higher than the B value for peer learning. The R-square for this model was 0.222, which was a significant improvement compared to other models.

Regression Analysis Based on the First and Second Iterations

This section used the first and second iterations' data to see if we could have a more accurate model.

Stepwise Regression With Two Constructs. Even when we merged the first and second iteration data, stepwise regression still chose motivation2 as a final score predictor. The system did not select any predictor from the first iteration. Therefore, the R-square was 0.107, as much as the prediction based on second international data (M10- Table 5).

Stepwise Regression With Five Constructs. This section used five constructs from both iteration 1 and iteration 2. Still, the system chose the predictors from the motivational component. The third model, based on value 2, expectancy 2, and expectancy 1, was the best model with an R-square of 0.164, which was an improvement compared to the previous model (M11- Table 5). In this model, expectancy 1 had a negative weight, and this construct also did not correlate with the final score.

Stepwise Regression With Fifteen Constructs. This section used 15 sub-constructs from the first and second iterations to see if we could make a better model. The first three models used the predictors among the motivational component. The fourth model used three constructs from the motivational sub-constructs, and one construct from the strategy use constructs. The fourth model, which used self-efficacy1 for learning performance2, control of learning beliefs1, test anxiety 1, and metacognitive self-regulation 1 as predictors, was the best with the R-square of 0.288 (M12- Table 5). Control of learning beliefs1 and also metacognitive self-regulation 1 had negative weights in this model. This analysis helped us understand if motivation and strategy use from the first and second iteration could be used as predictors of final scores. We understood we could make a reasonably good prediction based on the first and second iteration data.

DISCUSSION

This research's main purpose was to understand the relation between motivation and learning strategy use and final scores to identify the extent to which motivation and strategy use beliefs can predict students' final scores. We first looked at each of the constructs and observed how they changed as the course progressed. This information helped us understand students' beliefs regarding their motivation and strategy use and understanding the relationship between their beliefs and their achievement.

Among the motivational components, self-efficacy for learning performance and extrinsic goal orientation had the highest correlation with final scores throughout the three iterations. Self-efficacy for learning performance also had a high correlation with strategy use. Students who had self-efficacy used several strategies, which consequently helped them to achieve highly. Interestingly, in contrast to other studies, intrinsic goal orientation was not among the highest correlation constructs. In terms of the strategy use components, time and study environment in three iterations and effort regulation in two iterations had a high correlation with final scores. Identifying the constructs and sub-constructs that had a correlation with students' final scores could enable the teachers to promote them and update the instructional design to help students. They could teach them the appropriate strategies.

This information also helps instructors develop a better learning environment, plan a better instructional design for students to follow, and participate in lecturers' activities, which could help their self-regulatory skills, help them become self-regulated learners, and encourage their motivation. It is also important for the lecturers to spend time with students, understand their perceptions and needs, and help them be aware of their beliefs and their learning and study strategies.

We also considered the predictively of the variables and consistent with studies such as Pintrich et al. (1990) and Bandura (1986), self-efficacy for learning performance was always chosen by stepwise regression as one of the most reliable predictors. When we could predict the final score based on their beliefs about their motivation and strategy use, we could identify the students who were at-risk of failure and try to help them. Between motivation and learning strategy use components, mostly motivational components, were chosen by the system as predictors.

When we used the data from all three iterations, the system chose motivation2 and strategy3 from the components. Identifying iteration 3 constructs as predictors would be too late to help students, but we could understand the most important constructs that affect the final scores that would be very helpful for the lecturer to update the instructional design and teach appropriate learning strategies to the students. However, when we used all three iterations of data, we explained how motivational and strategy use components explained outcomes. But our goal was an early prediction, which is why we checked if we could use just the first iteration data or at the most the first two iterations of data and achieve the same level of accuracy as we had from three iterations. Therefore, we used constructs from the first iteration. Based on stepwise regression analysis, we identified the constructs and sub-constructs that were important in final score prediction, which were helpful for teaching practice.

Based on the first iteration, the system chose motivation 1 from the components, affective 1 and resource management strategies 1 from the constructs, and origianisation1, critical thinking 1, self-efficacy for learning performance 1, and test anxiety 1 from the sub-constructs as predictors of the final scores. The R-square for the models which were generated based on the first iteration was not very high. Therefore, we checked to see if we could make better models based on the second iteration data.

Based on the second iteration of data, the system chose motivation2 from the components, value 2 and expectancy 2 from the constructs, self-efficacy for learning performance, and peer learning from the sub-constructs as predictors of the final scores. In the next section of our analysis, we used constructs from the first and second iterations of data to see if we could improve the accuracy of our model's predictively.

Based on the first and second iterations of data, the system chose motivation2 at the component level, value 2, expectancy 1, and expectancy 2 at the constructs level and self-efficacy for learning performance 2, control of learning beliefs, test anxiety 1, and metacognitive self-regulation 1 at the sub-construct level by stepwise regression as predictors. We understood we could make a reasonably good prediction based on the first and second iteration data. However, in our future study, we will merge motivation with participation data to hopefully improve our prediction accuracy.

This analysis helped us identify the constructs that help us predict the final score based on each iteration of data. As the course progresses, the predictability of the final scores increased based on the SRL constructs. However, our goal in LA was the early prediction of the final score so that the lecturer could help students.

The findings from this study helped us understand the importance of SRL constructs in early predictions. We identified how the construct and sub-constructs under motivational and strategy use components were good predictors of the final scores. It is really important to check the predictability of the final score based on the constructs that have a link to the theory and relevance to LA and not just use all the data we could collect from the LMS for the sake of improving accuracy.

CONCLUSION

This study looked at how students reported their motivation and strategy use at three different points during a 12-week course. We looked at how students' motivation and strategy use changed as the course progressed. In contrast to other studies in the literature, we identified that even though we had a drop in motivation and strategy use until midterm, these constructs increased again as the course progressed toward the end. One of this study's main contribution was to investigate the relationship between motivation, strategy use, and final scores. We identified the constructs that had a high correlation with final scores. We observed a high correlation between motivational and strategy use, which meant a highly motivated student used more strategies. At a construct level, motivation from three measurements and strategy use from the last two iterations had the highest correlation with the final score. In terms of prediction, stepwise regression mostly used motivational components as predictors. We aimed to be able to make an early prediction. Therefore, we tried different combinations of data from different iterations. We generated different prediction models based on constructs and sub-constructs. We compared them and identified the best model among all.

Like other studies, this study had limitations. In this study, we relied on motivational data and did not consider students' participation data in explaining the final score. Our future studies will include data on participation as well and see if we can better understand students' SRL. Moreover, in this study, we just used data from one class. We plan to study whether there will be any difference in the predictability of final scores based on these predictors if we consider different courses in the study. And finally, the relationships between students reported data on motivation and strategy use and the final scores that were obtained in this study were based on correlations. It is not necessarily showing us causation. Therefore, we have to consider this in our interpretations.

Regardless of the study's limitations, this study contributed to both theory and practice. From a theoretical perspective, looking at different motivation and learning strategy use (cognitive, metacognitive, and SRL strategies) components over time contributes theoretically to the literature in SRL theory. Longitudinal empirical studies focusing on the motivational aspect and added empirical evidence based on theory to LA are lacking. The study contributes to LA by identifying the indicators for early prediction of students' final scores using SRL data which helped identify at-risk students.

This paper also methodologically contributed by presenting longitudinal empirical data and employing stepwise regressions to understand students' final scores' predictive variables, which was not achievable through a correlation matrix.

The study also has a contribution to practice. It gives insight to lecturers by looking at the dynamics of students' motivation and strategy use. Lecturers could understand how the results of tests and assignments affected the level of motivation and strategy use. This gives insight to the lecturer about the state of the class so that they can apply appropriate interventions. This information is more important for the BL lecturers as in this environment they do not have close relation with their students to make the take precautionary measures. Therefore, this insight would help them.

By identifying the constructs that affect student outcomes, lecturers could teach students those constructs, such as promoting motivation, teaching self-regulatory learning strategies, or giving instructions through updating their instructional design. Also predicting students' final scores early in the course, lecturers could identify the students who are at-risk of failure early in the course and then they would have time to apply appropriate intervention to prevent the students from dropping out.

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