A Comparison of the Predictability of Final Scores for Freshmen and Upper-Level Students in Blended Learning Courses

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***Abstract*—This study investigates final scores predictability based on students' longitudinally reported motivation belief and the use of learning strategies in blended learning (BL) courses for freshmen and upper-level students. The Motivated Strategies for Learning Questionnaire was administered three times to measure students' motivation belief and use of learning strategies (N=314) and collected 850 viable surveys. Firstly, an investigation of the dynamics of the factors involved with students' motivational belief and use of learning strategies was completed. It was found that freshmen students' motivation dropped until the mid-term and it increased again as the course progressed towards the end, whereas, upper-level students' motivation continued to drop throughout the course. In terms of the predictability of final scores, at construct level, stepwise regression chose motivation as predictors of freshmen's final score and strategy used as a predictor for upper-level students. The paper also discusses the implications of the study related to self-regulation learning theory, learning analytics, and instructional design.**

***Index Terms*—Final score, learning analytics, prediction, self-regulated learning, students' motivation, students' strategy use**

I. Introduction

Knowing the factors which affect student achievement is necessary. Studies have identified different factors that affect student's performance [1–4]. Lynch [5] identified self-efficacy and effort regulation as strong predictors of student achievement for the two groups, freshman and upper-level students. Lynch further showed that intrinsic motivation was associated with the final grade, but extrinsic motivation was not. With the rapid growth of online learning and different forms of blended learning (BL) environments, and the challenges of online learning, it is vital to understand the personal factors that may affect BL environment's success [6, 7]. In online learning environments, self-regulated learning (SRL) has received significant attention as these online environments needs students to take independent control of their learning more than traditional classes [8].

Not all students are able to self-regulate their learning, and due to the nature of online learning, the lecturers do not see students physically to take remedial measures [9, 10]. Therefore, it is necessary to provide performance insights to the lecturer. Learning Analytics (LA) allows us to analyze, understand, and optimize learning processes. LA has been defined by Siemens and Baker [11] as "the measurement, collection, analysis, and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs". This study investigated motivation and strategy use (self-regulated learning, SRL) as this field has not been studied enough in LA [12, 13]. While earlier studies looked at students' trace data, in this study students' self-reported data on how their beliefs about their motivation and different learning strategies usage influenced their self-regulate their learning was investigated. This study built on previous studies [14, 15], which suggested using the motivated strategies for learning questionnaire (MSLQ) [16] that is a well-established questionnaire based on well-founded theory [17].

Two frameworks that use different self-reports for measuring students' motivation are student approaches to learning (SAL) and SRL. The SAL framework theories learning as a composition of motives and strategies. SAL describes deep (meaningful learning) and surface (rote learning) approaches to learning [18]. The SRL framework is categorized by specific cognitive, motivational, and behavioral constructs [8]. The MSLQ [17] and the Learning and Study Strategies Inventory (LASSI) [19] are the two most commonly used questionnaires developed under the SRL framework for measuring motivation and strategy use. The MSLQ was used in this study as it is the most used instrument in SRL measurement and it has been frequently validated in the extant literature [20].

Following McCardle and Hadwin [21] that mentioned "SRL cannot be measured as aggregated across time and tasks, nor can it be measured as a single learning event" (p. 60), this study measured motivation, cognitive, and metacognitive SRL longitudinally [22, 23]. It is believed that a longitudinal study would help to gain insights into the evolution of students' motivational beliefs and strategies over time. Moreover as, Lynch and Trujillo [14] stated, students are different in terms of how they are aware of SRL, and therefore, they adopt different learning strategies. Thus, this study compared how freshmen and upper-level students differ in this regard.

This study, comprises of a level one course with 194 students and a level two courses with 120 students. using data collected the relationships between motivation, cognitive, and metacognitive strategy use, resource management and final scores was explored. This was done through exploring SRL measures at the beginning of, in the middle of, and at the end of the courses for two groups of freshmen and upper-level students. Additionally, the motivation and strategy use dynamics between upper-level and freshmen

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students was compared. Finally, how the early construct measurements could help us predict final scores in the BL environment as investigated. This study's overarching research questions were:

RQ1: What are the dynamics of the students' motivational belief and use of learning strategies in two BL courses?

RQ2: To what extent do the motivational beliefs and strategy use variables account for upper-level and freshmen students' final scores in each BL course?

This study contributes theoretically to debates in SRL theory by exploring how students SRL changes as the course progresses [17, 24] and methodologically by presenting longitudinal empirical data about university students' perceptions of their motivation, cognitive, and metacognitive SRL in the classroom environment. Our findings provide a perspective on tertiary students' psychological needs by investigating their perceived motivation and strategy use in the context of two business school courses. The study highlights implications for practice, looking at students' reported motivation and use of learning strategy constructs over time enriches our understanding of students' motivation and strategy use (SRL) and students' perceptions regarding their interaction with peers, teachers, and their learning environment in the new context of the online environment. This also gives an insight to the lecturers of the class, especially in an online environment in which the lecturers do not have the opportunity to interact with the students in a physical environment. It was recognized that the dynamic patterns of motivation and strategy use changed throughout the course and was different between freshmen and upper-level students. This helped us understand the nature of academic development in our classes and through timely information gathering, their learning.

The most important constructs for predicting final scores which addresses one of the most important aims of LA were identified. Understanding the motivational and learning strategy constructs that affect students' final scores can inform available support and pedagogies. Running this study helped us understand that for each BL course, students needed different learning strategies to perform well in that course. It is important to teach students appropriate strategies and skills so that they are capable of taking control of their learning and becoming self-regulated learners. It was observed that students had different experiences, freshmen were new to the system, while upper-level students had previous university experience, therefore, each cohort needed to learn different strategies. Students who directly joined a university course after finishing high school may need some advice regarding how to adopt and adjust to the new methods of learning (effort regulation and time and study environment). Otherwise, they may rely on their previously acquired learning strategies only. Monitoring students' motivation and strategy use helps ensure that they have appropriate study patterns. The lecturers could change the instructional design and prepare the environment for students to enhance their learning.

The organization of the rest of this paper is as follows. The preceding introduction provides a contextual background. This is followed by an overview of the literature and the methodology, data collection, and analyses. Finally, our findings are discussed and conclusions are presented.

II. Literature Review

The significance of the interaction between learners and instructors and its role in the learning process is traditionally emphasized in the literature [25–32]. In recent years, computer-mediated interaction has gained attention [33–36]. Academics have used different tools to increase the interaction between the instructor and the learners in online platforms. The term tools refers to all instructional stimuli integrated into learning tasks and content [37–39]. Dabbagh and Kitsantas [40] confirmed that different web-based pedagogical tools supported different stages of SRL processes (e.g., goal setting, self-monitoring). There are different definitions available for SRL. However, they all agree that there are cycles in SRL which consist of different phases and subprocesses. Winne and Hadwin [41] define SRL as a four-stage process, including (1) task definition, (2) goal setting and planning, (3) enacting tactics and strategies planned in the previous stage, and (4) adopting study techniques metacognitively. The ultimate goal for teaching is to produce lifelong learners [42] who can control and self-regulate their learning [43].

By introducing technology tools in the classroom, the traditional teaching method has changed to more BL by using the advantages of online learning and face-to-face classroom learning [44]. BL combines the benefit of using online technologies and face-to-face teaching for a richer experience [45, 46] and it has more flexibility for students [47, 48].

In online learning, lecturers do not see students physically so that they take appropriate actions [9]. Therefore, the lecturer needs to access more student data to meet students' needs. Understanding students' SRL in this environment is important as individuals are required to be more autonomous and able to self-regulate their learning [49]. The ultimate goal for teaching is to produce lifelong learners [42] who can take control of and self-regulate their learning [43]. Not all students are capable of self-regulating their learning, so it is beneficial for educators to identify students who need help. As a consequence of online learning, lecturers do not have close relationships with students making it difficult for them to identify when precautionary measures are necessary [9], therefore, it is very important to provide insights to instructors so that they can help students [50].

Due to the nature of the BL environment and using a variety of educational tools, a huge amount of data has been collected from students [51, 52]. The data needs to be processed and be available for the lecturers of the course. The ultimate goal is to help students by giving insights to their educators. One way would be by identifying the students who would be at risk of failure through the recognition of students' final score predictors. Identifying students at risk of failure is an example of LA so that appropriate intervention can be applied and prevent student dropout [53].

Different studies used educational data mining algorithms to identify at-risk students by predicting students' final scores, for example, from their forum activities, content requests, and time spent online, e.g., [1, 2, 54–65]. These studies have many inconsistencies in their findings which may be due to not addressing the learners' characteristics or failing to quantify the impact of emotional, motivational, cognitive-metacognitive factors, and resource management [12, 66, 67]. They also did not look at the issues longitudinally.

Even though many studies work on different aspects of LA, such as technical issues, data processing, data privacy, developing user systems, and dashboards [68–71], students' motivation and strategy use have not yet been sufficiently considered for analyses in LA. Liu, Kang, Zou, Lee, Pan and Corliss [72] stated that for LA to be helpful for students, the analysis needs to be based on learners' motivational states, perceptions about their efficacy, control beliefs, the importance of the task, their level of anxiety, and the cognitive strategy use styles to give insights to the lecturer.

Panadero [73] stated that SRL is a core conceptual framework for understanding the cognitive, motivational, and emotional aspects of learning. SRL is considered to include motivational, cognitive, metacognitive, and resource management components [74–76]. Therefore, it is essential to understand SRL to understand and support successful learning processes in higher education [77]. The next section gives an explanation how the methodological gap was addressed.

III. METHOD

Data was collected three times from 314 students in two undergraduate courses (194 and 120 students, in total 850 questionnaires). Preparation material for students was online for these three courses to review before coming to class. Materials were study, web lectures, books, and formative quizzes at the end of each video recording. The lecturer's online lectures were supplemented with short, face-to-face weekly tutorials (review sessions). The lecturer's approach to BL involved purpose-made 30/40 minutes of online lectures in lieu of traditional face-to-face delivery. Each lecture video featured a short quiz at the end that tested students' understanding of the material just covered. Prior to each review session, the lecturer analyzed the embedded quiz results and determined which course material had proven the most challenging. For the review session, students had two options, to attend the course in person or watch the video streaming of the class from a place convenient for them. The method of teaching was based on discussing formative questions. The lecture asked questions in the class based on the questions that most students got wrong in their quizzes.

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 compete head-to-head and win if they are 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 candy as a prize. Students were incentivized to watch each week's online lectures and participate in the weekly in-class tutorial by means of awarding participation marks.

By preparing material, the goal was to activate prior knowledge of students and for them to identify gaps in their knowledge. The aim was that face-to-face sessions could be used to further the processing of materials. In face-to-face sessions, the lecturer gave a mini-lecture based on the concepts that students showed difficulty understanding, as evident in the quizzes at the end of the videos. The face-to-face lectures were streamed so students who could not attend the course could watch them online. The lecturer asked questions of the students in the class. There was a discussion in which students needed to contribute to so that they could get the participation marks. These questions were available to students afterwards if they wanted to practice.

A. Instrument and Procedure

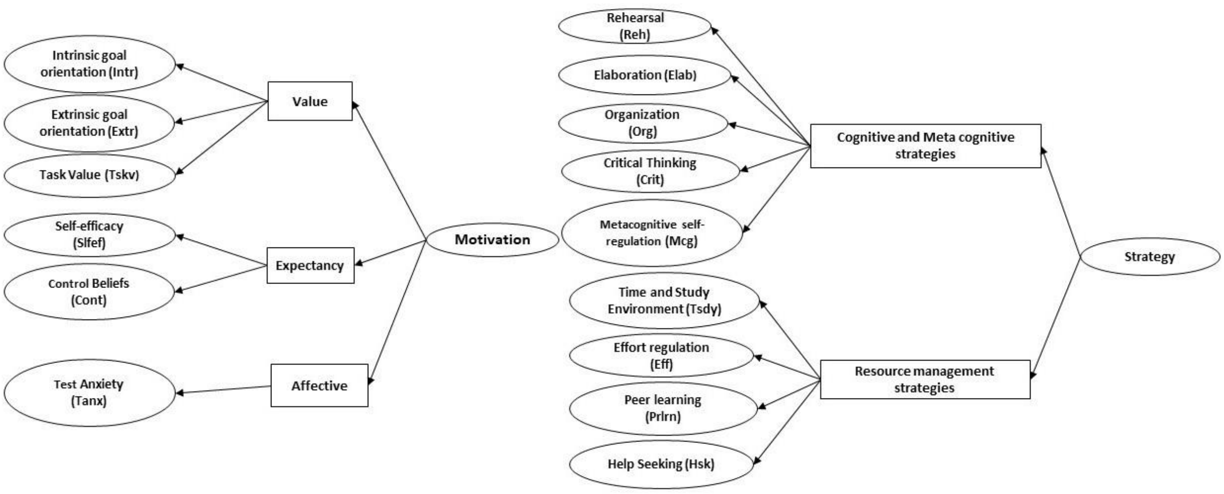

Fig. 1. Structure of the MSLQ.

To understand students' motivation and use of learning strategies, the MSLQ [16] was used. The questionnaire measures motivational factors, learning strategies, and how students manage the learning context or resources. The

MSLQ measures motivational components through Value, Expectancy, and Affective factors. Learning Strategy components are measured through Cognitive, Metacognitive, and Resource Management Strategies and each has associated factors (Fig. 1). For example, Value has the associated factors of intrinsic goal orientation, extrinsic goal orientation, and task value. Expectancy has the associated factors of self-efficacy and control beliefs for learning. Affective has the associated factors of test anxiety. Cognitive strategies have the associated factors of rehearsal, elaboration, organization, and critical thinking. Metacognitive self-regulation strategies have the associated factors of Planning, Monitoring, and Regulating. Resource management has the associated factors of Managing their time and study environment, regulating their efforts, peer learning, and help seeking. The MSLQ was run three times in Week 3, Week 7, and Week 11 of a 12-week semester through the learning management system (LMS).

IV. Analysis

Over three rounds of surveying a population of 314 students, a set of 850 viable surveys were collected. First, the data was cleaned. There was a need to handle the missing data. For this reason, the data was tested to see whether missing values at random. To do this little's missing completely at random (MCAR) test for each class's iteration was run. The results showed that data was missed at random. There were different approaches for handling the missing data, for example, listwise deletion, pairwise deletion, mean imputation, and regression imputation. Missing values were replaced with maximum likelihood, recognizing the rule of thumb by replacing less than 10 percent of the data. This section describes the results, which are divided into three main sections: (1) descriptive statistics, (2) correlation analysis, (3) stepwise regression analysis.

A. Descriptive Statistics

In this section, descriptive analysis for each construct is reported for the two groups separately. Then how they were different between the two groups is summarized. The values for constructs were calculated based on the mean of the scales that made up that construct

1) Freshmen

The descriptive statistics, including means and standard deviations, of the freshmen students, are depicted in Table I. For freshmen, in contrast to the studies run by Pintrich [16] and Pintrich *et al.* [78], our analysis shows that even though there is a decline in motivation and strategy use constructs as the course reaches midterm, these constructs increased again as the course got closer to the end.

It is not unusual that students faced with a lot of material that has stacked up and a lot of assignments due to submit as the course gets to the midterm. Therefore, they would be less motivated to do their part. Besides, as the course gets closer to the end, they become more anxious and cognitively involved. Most sub-constructs such as intrinsic goal orientation, extrinsic goal orientation, task value, test anxiety, organization, effort regulation, peer learning, and help seeking decreased as the course progressed towards midterm, but they increased again as the course got close to the end. Sub constructs such as control of learning beliefs, self-efficacy for learning performance, time and study environmental management continuously decreased. Time and study environmental management constantly decreased; perhaps it was because students learned how to appropriately use their time. They also constantly lost their confidence in their ability to control their learning and self-efficacy. Perhaps students expected more from themselves but seeing their midterm results made them lose trust in their capabilities and expectations.

TABLE I: Descriptive Statistics for the MSLQ Sub-constructs at Iteration 1, Iteration 2, Iteration 3 (Freshmen)

	Iteration1 (N=189)		Iteration2 (N=173)		Iteration3 (N=153)	
Mean=M	M	SD	M	SD	M	SD
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
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
Organization	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
Motivation	4.92	0.63	4.80	0.62	4.82	0.69
Strategy	4.23	0.55	4.20	0.62	4.31	0.66
Final Score	66.98	16.96				

Sub-constructs such as rehearsal, elaboration, critical thinking, and metacognitive self-regulation constantly increased as the course progressed. These were strategy use sub-constructs that continued to increase. It shows that students strategy uses continuously increased while their motivation was decreasing so that they could manage to achieve their goals.

2) Upper-level students

The descriptive statistics for all the constructs and sub-constructs for upper-level students are depicted in Table II. As seen in Table II, motivation in contrast to the Year 1 course continuously decreased. In contrast to the Year 1 course strategy use continuously increased.

As for sub-constructs, there were some sub-constructs such as extrinsic goal orientation, control of learning beliefs, self-efficacy for learning performance, and effort regulation that continuously decreased. For upper-level students, it was observed that when students were less motivated or their level of motivation dropped, their effort regulation also decreased. In terms of motivational constructs, intrinsic goal orientation and task value are the two constructs that decreased and then increased. The organization and time study environmental management decreased first but then increased again. Sub-constructs such as rehearsal, elaboration, critical thinking, metacognitive self-regulation, peer learning continuously increased. The sub-constructs that constantly increased are the same as the Year 1 course. The difference was peer learning because Year 1 students did not believe in peer learning, and it decreased for them. Constructs such as help seeking, and Affective increased first and then decreased.

TABLE II: DESCRIPTIVE STATISTICS FOR THE MSLQ SUB-CONSTRUCTS AT ITERATION 1, ITERATION 2, ITERATION 3 (UPPER-LEVEL STUDENTS)

	ITERATION1 (N=118)		ITERATION2 (N=110)		ITERATION3 (N=108)	
Mean=M	M	SD	M	SD	M	SD
Intrinsic Goal Orientation	4.55	0.90	4.38	0.93	4.48	0.94
Extrinsic Goal Orientation	5.29	0.96	4.94	1.03	4.89	1.06
Task Value	4.83	1.03	4.68	1.13	4.75	1.04
Control of Learning Beliefs	5.11	0.82	4.95	0.94	4.94	0.98
Self-Efficacy for Learning Performance	4.93	0.89	4.65	1.00	4.63	1.08
Test Anxiety	4.50	1.22	4.57	1.24	4.49	1.26
Rehearsal	4.47	1.05	4.68	1.02	4.94	1.03
Elaboration	4.59	1.05	4.61	0.90	4.69	1.05
Organization	4.91	0.94	4.85	0.87	4.89	0.93
Critical Thinking	3.49	1.16	3.70	1.07	3.81	1.12
Metacognitive Self-Regulation	4.18	0.73	4.37	0.70	4.48	0.72
Time Study Environmental Management	4.82	0.82	4.66	0.84	4.76	0.5
Effort Regulation	4.73	1.07	4.67	1.03	4.52	1.02
Peer Learning	3.75	1.40	3.92	1.35	4.03	1.42
Help Seeking	3.61	1.16	3.62	1.20	3.57	1.31
Motivation	4.80	0.58	4.68	0.67	4.66	0.67
Strategy	4.30	0.62	4.34	0.60	4.40	0.68
Final Score	69.36	14.66				

It was observed that students were different in these two groups. Students in the Year 1 course joined the course with higher motivation and lower strategy use constructs than the Year 2 course. In terms of peer learning, help seeking, and critical thinking, the Year 1 course reported the lowest score. It is believed that this is to a great extent affected by the structure and nature of the course. Year 2 students knew about the course even before they enrolled in the course which is why they reported the highest strategy use at the beginning when they were prepared to take the course. At the end of the course, students in Year 2 were still lower in motivational constructs than Year 1 students. Students in Year 2 were mostly higher in terms of strategy use constructs compared to Year 1 students. This was consistent with previous studies that showed students' motivational levels drop as they move up to higher levels [24, 79]. However, their level of strategy use increased.

B. Association between the MSLQ and Final Scores (Predictive Validity Analyses)

Correlation analysis was performed to check the correlation of constructs with each other and identify the constructs with a high correlation to the final score. Tabachnick, Fidell and Ullman [80] mentioned that the correlation of independent variables needed to be less than 0.70.

1) Freshmen students

This section explores and summaries the correlation between motivation, strategy use constructs, and the final scores for freshmen. The correlation among motivational and strategy use constructs with final scores for freshmen students are presented in Table III. Motivation from the three iterations had the highest correlation with final scores. In total, our correlations analysis supported the general finding that students with high motivational beliefs were more likely to be involved in deep processing and use elaboration and organizational strategies. They are more likely to regulate their cognition through planning, monitoring, and regulating their use of study strategies. They are also more likely to manage their time and study environment and manage their effort to achieve their goals.

2) Upper-level students

Correlation between each of the constructs and final scores for each iteration for upper-level students is presented in this section. Table IV presents the correlation between motivation and strategy use constructs with final scores. Similar to the Year 1 course, motivation and strategy use had high correlations with each other in all three iterations. In contrast to Year 1, motivation 1 did not have a high correlation with final scores. In contrast to the Year 1 course, strategy 1 had a high correlation with final scores.

TABLE III: CORRELATION OF MOTIVATION AND STRATEGY USE AT ITERATION 1, ITERATION 2, ITERATION 3 (FRESHMEN)

M=Motivation S=Strategy	M1	S1	M2	S2	M3	S3	Final Score
Motivation 1	1						0.22**
Strategy 1	0.32**	1					0.14
Motivation 2	0.63**	0.26**	1				0.33**
Strategy 2	0.28**	0.67**	0.43**	1			0.25**
Motivation 3	0.60**	0.27**	0.76**	0.45**	1		0.37**
Strategy 3	0.26**	0.63**	0.29**	0.74**	0.49**	1	0.29**

* Correlation is significant at the 0.05 level. ** Correlation is significant at the 0.01 level.

The correlations between motivation and final scores, and strategy use and final scores were mostly lower for upper-level students compared to freshmen students. Even final scores dropped, the correlations across the constructs though the correlations between each construct and the increased in this course. From this it is understood that in the Year 1 course the motivation construct and in the Year 2 course strategy use had a high correlation with final scores.

The correlation between constructs and sub-constructs with final scores was investigated and identified the constructs that had the highest correlation with final scores; next, the predictability of the final scores was consider through stepwise regression analysis

TABLE IV: CORRELATION BETWEEN MOTIVATION AND STRATEGY USE AT ITERATION 1, ITERATION 2, ITERATION 3 (UPPER-LEVEL STUDENTS)

M=Motivation S=Strategy	M1	S1	M2	S2	M3	S3	Final Score
Motivation 1	1						0.17
Strategy 1	0.39**	1					0.20*
Motivation 2	0.59**	0.28**	1				0.23*
Strategy 2	0.35**	0.65**	0.45**	1	`		0.36**
Motivation 3	0.50**	0.39**	0.73**	0.47**	1		0.33**
Strategy 3	0.23*	0.66**	0.33**	0.69**	0.47**	1	0.22*

* Correlation is significant at the 0.05 level. ** Correlation is significant at the 0.01 level.

C. *Regression Analysis*

Linear stepwise regression analysis was performed using different numbers of variables as predictors, from the MSLQ constructs and subscales to predict final scores. Stepwise regression chooses the constructs and sub-constructs that significantly contribute to the variance in achievement and delete those that do not significantly contribute to variance in achievement. In this section, first the predictability of final scores based on constructs from the first iteration for each class was explored. Then, the predictability of final scores based on constructs from iteration 2 was considered, and then from iteration 1 and iteration 2 of data to see how early and with what accuracy students' final scores can be predicted. Early prediction of students' final scores helps the course instructor identify at-risk of failure students so that the lecturer could help them.

1) *Freshmen students*

This section presents the results of applying stepwise regression based on different constructs and sub-constructs from different iterations for freshmen students (Table V).

- **Stepwise Regression with Two Constructs from the First Iteration**

Stepwise regression was employed and let the system choose between motivation 1 and strategy 1. The system chose motivation 1 and removed strategy 1 to make the regression model. The R squared for the generated model was 0.050 (M1—Table V).

- **Stepwise Regression with Fifteen Sub-Constructs from the First Iteration**

This section used 15 subscales from iteration 1. Four models were generated. Model four, based on organization 1, critical thinking 1, self-efficacy for learning performance 1, and test anxiety 1, was the best model among all. The R^2 was 0.123, which was an improvement compared to the previous models (M2—Table V). Self-efficacy for learning performance 1 had the maximum weight in the model. Critical thinking 1 had a negative weight.

- **Stepwise Regression with Two Constructs from Second Iteration**

This section had motivation 2 and strategy use 2 to choose from, and it chose motivation 2 as a predictor and deleted strategy use 2. The R^2 amount became doubled (0.107) compared to the model based on iteration 1 of the data (M3—Table V).

- **Stepwise Regression with Fifteen Sub-Constructs from the Second Iteration**

As time passed (in iteration 2), the R^2 for the generated models improved, especially at the sub-construct level. Two models were generated. The second model used both self-efficacy for learning and performance and peer learning as predictors. The B value for self-efficacy for learning and performance was much higher than the B value for peer learning. The R^2 for this model was 0.222, which was a significant improvement compared to other models (M4—Table V).

- **Stepwise Regression with Two Constructs from the First and Second Iterations**

Even when iteration 1 and iteration 2 of the data was merged, stepwise regression still chose motivation 2 as a final score predictor. The system did not select any predictor from iteration 1. Therefore, the R^2 was 0.107, the same as the prediction based on iteration 2 of the data (M5—Table V).

- **Stepwise Regression with Two Constructs from Second First and Second Iterations**

This section used 15 sub-constructs from iteration 1 and iteration 2 to see if the model could be made better. The fourth model, which used self-efficacy for learning performance 2, control of learning beliefs, test anxiety 1, and metacognitive self-regulation 1 as predictors, was the best model. The R^2 for the model was 0.288, which was the best model among all. Control of learning beliefs and Metacognitive Self Regulation1 (the only construct chosen from strategy use constructs) had negative weights in this model (M6—Table V).

2) *Upper-level students*

This section presents the results of applying stepwise regression based on different constructs and sub-constructs from different iterations for upper-level students (Table VI).

- **Stepwise regression with Two Constructs from the First Iteration**

Stepwise regression was employed and allowed the system to choose between motivation 1 and strategy use 1. The system interestingly chose strategy use as a predictor, and the model's R^2 was 0.039 (M1—Table VI).

- **Stepwise Regression with Fifteen Sub-Constructs**

from the First Iteration

Again, stepwise regression was used and allowed the system to choose predictors from the fifteen constructs in iteration 1. The best model was generated based on predictors, including time study environmental management 1, self-efficacy for learning performance 1, task value 1, and peer learning 1. The R^2 for this model was 0.215 (M2—Table VI). Task value had a negative weight, and time and study environment had the highest weight. This model had a higher R^2 value compared to the model generated based on the 15 constructs for Year 1 students.

- **Stepwise Regression with Two Constructs from the Second Iteration**

This section used motivation 2 and strategy 2 and allowed the system to choose the best predictor. The system chose the strategy use construct instead of motivation that was chosen for the Year 1 course. The R^2 for this model was 0.128 (M3—Table VI), which was higher compared to the Year 1 model.

- **Stepwise Regression with Fifteen Sub-Constructs from the Second Iteration**

In this section, 15 sub-constructs from iteration 2 were available to choose from. The best model used Self Efficacy for Learning Performance 2, time study environmental management 2, critical thinking 2, peer learning 2, and control of learning beliefs 2 as predictors. The model had an R^2 of 0.375. Critical thinking 2 and control of learning beliefs 2 had negative weight. Self-efficacy for learning performance 2 had the highest weight (M4—Table VI).

- **Stepwise Regression with Two Constructs from the First and Second Iterations**

Even when iteration 1 and iteration 2 data was merged, stepwise regression still chose strategy use from both iterations as predictors. Both models chose strategy use constructs (strategy use 1 and strategy use 2) as predictors. The R^2 value was 0.161 (M5—Table VI).

- **Stepwise Regression with Fifteen Sub-Constructs from the First and Second Iterations**

This section of our analysis used 15 sub-constructs from iteration 1 and iteration 2 to see if a better result could be reached. Six models were generated. The best model was generated based on self-efficacy for learning performance 2, critical thinking 1, time study environmental management 1, peer learning 2, effort regulation 2, and help seeking 1. The model had the best R^2 of 0.462 (M6—Table VI).

Our stepwise linear regressions carried out to investigate whether motivation, strategy use, and SRL-awareness factors could predict final scores, showed us different results for the two groups. Even though it was recognized that using three iterations of data, our prediction accuracy would be higher, but the goal was to have an early prediction so that the lecturer could apply early intervention. Therefore, first, the prediction of final scores based on the two constructs of motivation and strategy use was used. Then, 15 sub-constructs were used as the predictors each time based on different iterations of data. Based on stepwise regression analysis, the constructs and sub-constructs that were important in predicting final scores, which were helpful for teaching practice were identified. It was understood that at the construct level, for the Year 1 course, motivation constructs were chosen by stepwise regression, and for Year 2 courses strategy use constructs were chosen as predictors.

TABLE V: STEPWISE REGRESSION ANALYSIS RESULTS ON THE FINAL SCORES BASED ON DIFFERENT ITERATIONS (FRESHMEN N=189)

		Mode l	Predictors	Final score			
				B	SE	β	R^2
Based on first iteration	2 Constructs	M1	Strategy1	4.672	2.164	0.197	0.039
	15 Constructs	M2	Time Study Environmental Management1	6.815	1.543	0.384	0.215
			Self Efficacy for Learning Performance1	4.294	1.584	0.255	
			Task Value1	−3.168	1.370	−0.222	
			Peer Learning1	1.801	0.901	0.173	
Based on second iteration	2 Constructs	M3	Strategy2	7.139	1.803	0.358	0.128
	15 Constructs	M4	Self Efficacy for Learning Performance2	5.893	1.140	0.490	0.375
			Time Study Environmental Management2	3.552	1.165	0.251	
			Critical Thinking2	−2.505	0.895	−0.225	
			Peer Learning2	1.987	0.716	0.225	
			Control of Learning Beliefs2	−2.573	1.240	−0.195	
Based on first and second iterations	2 Constructs	M5	Strategy2	10.186	2.323	0.510	0.161
			Strategy1	−4.717	2.316	−0.237	
	15 Constructs	M6	Self Efficacy for Learning Performance2	4.369	1.082	0.364	0.462
			Critical Thinking1	−2.766	0.815	−0.273	
			Time Study Environmental Management1	3.110	1.202	0.213	
			Peer Learning2	3.023	0.782	0.343	
			Effort Regulation2	2.835	1.085	0.246	
			Help Seeking1	−2.220	0.878	−0.218	

TABLE VI: STEPWISE REGRESSION ANALYSIS RESULTS ON THE FINAL SCORES BASED ON DIFFERENT ITERATIONS (UPPER-LEVEL STUDENTS)

		Model	Predictors	Final score			
				B	SE	β	R^2
Based on first iteration	2 Constructs	M1	Strategy1	4.672	2.164	0.197	0.039
	15 Constructs	M2	TimeStudyEnvironmentalManagement1	6.815	1.543	0.384	0.215
			SelfEfficacyforLearningPerformance1	4.294	1.584	0.255	
			TaskValue1	−3.168	1.370	−0.222	
			Peer Learning1	1.801	0.901	0.173	
Based on second	2 Constructs	M3	Strategy2	7.139	1.803	0.358	0.128
	15 Constructs	M4	SelfEfficacyforLearningPerformance2	5.893	1.140	0.490	0.375

iteration			TimeStudyEnvironmentalManagement2	3.552	1.165	0.251	
			CriticalThinking2	−2.505	0.895	−0.225	
			Peer Learning2	1.987	0.716	0.225	
			ControlofLearningBeliefs2	−2.573	1.240	−0.195	
Based on first and second iterations	2 Constructs	M5	Strategy2	10.186	2.323	0.510	0.161
			Strategy1	−4.717	2.316	−0.237	
	15 Constructs	M6	SelfEfficacyforLearningPerformance2	4.369	1.082	0.364	0.462
			CriticalThinking1	−2.766	0.815	−0.273	
			TimeStudyEnvironmentalManagement1	3.110	1.202	0.213	
			Peer Learning2	3.023	0.782	0.343	
			EffortRegulation2	2.835	1.085	0.246	
			Help Seeking1	−2.220	0.878	−0.218	

V. Discussion

The expansion of online learning opened new opportunities for students and lecturers by providing more flexibility. However, the new classroom approach's effectiveness is arguable [66]. This study checked students' reported motivation and strategy use differences in two BL courses (freshmen and upper-level students). Firstly, the dynamics of students' motivation and strategy use in these BL courses was checked. It was understood that freshmen joined the course with a higher level of motivation and lower level of strategy use compared to upper-level students. At the end of the course our analysis revealed that both courses followed the same pattern.

It was also understood in terms of motivational constructs, students' motivation in Year 1 course dropped until midterm and increased again as the course got close to the end. However, students' motivation in Year 2 courses dropped as the course progressed towards midterm and decreased again as it got close to the end. This was in contrast to other studies that showed the motivation of students always dropped as the course progressed [24, 79]. In terms of strategy use, it was believed that students' strategy use to a great extent related to the nature of the course and students' experience. For Year 1 students who have transitioned directly from high school to university with limited learning strategies, their strategy use level decreased until midterm, but when they got their midterm exam score, they reflected on themselves and started using more strategies. In Year 2, students use of strategies increased as the course progressed. This Year 2 course started with a basic concept and by introducing the evaluation concepts, the students parallel reflected on their strategies. This information informs lecturers in Year 1 that they should be mindful that students have high levels of motivation at the beginning of the course. They are still evolving their practice in terms of learning strategy usage (they are developing study skills). Students in Year 2 constantly use learning strategies while their motivation drops. This information is very helpful for the lecturer to understand what happens to the students when their motivation is falling. What they do in their classes when they see the test results, what are the effects on students' self-regulation. This information needs to be considered when updating instructional design, for example, when they know students' motivation gets affected by the results of tests. For example, they can do something to increase student motivation or endeavor to teach them proper strategies at that time.

The correlation of motivation and strategy use constructs with final scores was also checked. It was understood for the Year 1 course students' motivation from three iterations had the highest correlation with final scores and for the upper-level students, strategy use had the highest correlation with final scores. Identifying the constructs that had a high correlation with the final scores and the predictability of final scores could help the lecturer. The lecturer could pay attention to those constructs by updating their instructional design for the course. They should also be mindful when they are designing teaching strategies. It was then possible to design learning activities and support services to help students. For example, the lecturer could design activities that meet learners' task values and raise their metacognitive awareness. The lecturer could help them better manage their cognitive learning or set them deadlines to manage their time better. The lecturer could also increase the Motivation of students, especially the adaptive ones as he did in our study.

It was also identified the constructs that could help to predict final scores. First, a prediction for final scores based on iteration 1 of data was made to enable the aim to make an early prediction for final scores, but the accuracy was not high. Then predictions based on data from iteration 2 were tried, where improvement in accuracy were found, and finally, the data from both iteration 1 and iteration 2 were used. Interestingly, predictors for freshmen at construct level were chosen from motivation constructs, and for upper-level students were mostly used from strategy use constructs. Predicting the final score based on motivation and strategy use helps to identify at-risk students which would address one of the most important aims of LA. We are also researching students' motivation and strategy use through the empirical study that is contributing to LA. Our study identified that there were differences among motivational Beliefs, SRL variables, and final scores with respect to the years that were identified.

VI. Conclusion

In this study the dynamics of students' motivational belief and learning strategy were explored, use as the course progressed for two groups of students (freshmen and upper-level). After that, the constructs that had the highest correlation with the final score were investigated. Using two classes of data, the dynamics of motivation and strategy use were different as the course progressed were found. Freshmen students' motivation and strategy use constructs dropped until midterm, and they increased again as the course got close to the end. However, upper-level students' motivation dropped as the course progressed towards midterm and decreased again as it got close to the course's end, and their strategy use constructs constantly increased. It was understood that freshmen and upper-level students were different not only in terms of the dynamics of motivation and strategy use but also in terms of their level of these constructs when they joined, during the course, and when they finished the course. Freshmen had higher motivation when they entered the course; however, they had lower strategy use, and they needed more help and advice on how to use new learning strategies. Otherwise, they might rely only on their previously acquired learning strategies. Upper-level students had lower motivation at the beginning of the course, but they were higher in terms of strategy use, and they followed the following pattern until the course finished (still lower in motivation and higher in strategy use).

Then identified the constructs that had the highest correlation with each other and the final scores. A high correlation between motivational and strategy use was observed, which meant a higher motivated student used more strategies. Regarding correlation, for the freshmen, at the construct level, motivation from three measurements and strategy use from the last two measurements had the highest correlation with the final scores. For upper-level students, strategy use constructs from three iterations and motivation from the last two iterations had the highest correlation with the final scores at the construct level.

Subsequently, the predictability of freshmen and upper-level students' final scores was examined separately based on their motivational beliefs and strategy use constructs. In terms of predictability, stepwise regression at the construct level mostly chose motivational constructs as predictors of freshmen's final scores and strategy use constructs as final score's predictor for upper-level students. The reasons for this are uncertain. One of the reasons could be year differences between participants or having different contexts.

In our future study, we will look at other data sources, such as how students participated in the activities, how they used the available tools, and consider their tool use as a strategy in their learning process from different courses with different instructional design and discipline.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Shadi did 75% of the work by theorizing, data collection, analysis and writing. Lesley did 10% of the work by doing theorizing, analysis and writing. Tiru did 10% of the work by theorizing, modelling, and analyzing. Michael and Olga did 2.5% each in data collection and participation.

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