New Insights on Students' Perceptions, Motivations, and Learning Strategy Use to Inform Learning Analytics - through Self-Regulated Learning and Activity Theory

By

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ABSTRACT

It is vital to understand students' Self-Regulatory Learning (SRL) processes, especially in Blended Learning (BL), where students need to be more autonomous in their learning processes. We are seeing higher student enrolment rates with students who come from different backgrounds, have different knowledge bases, and need different things from higher education, we are also observing many dropouts. Therefore, it is essential to support students in a timely manner. Due to the nature of BL environments, the lecturers do not have close relationships with students to be able to take precautionary measures. Thus, it is vital to give insights to lecturers to help students.

Learning Analytics (LA) allows us to analyse, understand, and optimise learning processes. This analysis needs to be grounded in learning theories. Currently, LA lacks studies that have a theoretical foundation and are based on empirical evidence. Furthermore, students' motivational studies have not yet been sufficiently considered for analysis in LA. Therefore, this study used Activity Theory (AT) and SRL theory to understand how students' perceptions, motivations, and learning strategy use inform LA.

The aim of LA in general and this thesis, in particular, is to help the learning process. In LA, students are central to the analysis. Accordingly, we collected both quantitative and qualitative data from two groups of students (freshmen and upper-level). We collected quantitative data by running the Motivated Strategies for Learning Questionnaire (MSLQ) three times in three 12-week courses (N=419). We also collected qualitative data by interviewing 42 students. Two quantitative studies (five papers) and one qualitative study (three papers) are included in the thesis.

This thesis, by running three studies based on learning theories, added empirical evidence to LA and contributed to its theoretical foundation by linking LA with SRL and AT. This study also contributes to LA by focusing on the students' conditions (motivation and learning strategy use) mentioned in Winne's version of SRL (COPES model) and exploring the level of agency (students' perceptions regarding tool use), which are currently lacking in the field. This thesis also brings empirical evidence to LA and informs theory and practice.

Through predictive and cluster analysis, the study contributed to one of the most important aims of LA, identifying at-risk students. By identifying the constructs that help us predict students' final scores through stepwise regression analysis early in the course, the lecturer can apply appropriate interventions in order to help students and prevent dropouts. Identifying constructs

that have the highest correlation with the final score, the lecturer could promote them in the course. Also, by identifying different SRL profiles through applying the K-Means clustering algorithm and examining students' SRL profile adaptation longitudinally the study contributed to SRL theory and addressed the challenge identified regarding the cyclical nature of SRL.

The study's aim was not only to identify at-risk students or students' SRL profiles but also to use data to improve the learning process and support personalised learning. For this reason, learning theories, including AT and SRL, were applied to understand students' perceptions regarding the usefulness of tools through applying thematic analysis. We contributed to AT by identifying contradictions in students' perceptions regarding using educational tools in classes for their learning process and the changes that needed to be applied to educational settings. We also contribute to SRL when we analysed students' perceptions regarding how each tool supported a specific stage of SRL and tried to open Winne's black box.

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Overview of the Thesis

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CHAPTER 1

1 Chapter 1- INTRODUCTION

"Not everything that can be counted counts, and not everything that counts can be counted."
Albert Einstein

This thesis positions itself in the realm of informational technologies in education. Since 1960 the potential of using computers and IS in education has been recognised (Goodlad 1966). There have been different studies that looked at the design, development, implementation, and adoption of information technologies specialized in educational use (Barki et al. 1988; Barki et al. 1993). This cooperation helps overcome the challenges in the educational field and grow the IS field (Nguyen et al. 2020).

As the importance of interaction between the learners and instructors has been emphasised in the literature for the process of learning (Chickering and Gamson 1987; Fulford and Zhang 1993; Kumari 2001; Kyei-Blankson et al. 2019; Stubbs et al. 1976) and especially computer-mediated interaction (Caceffo et al. 2018; Dawson 2008), different educational tools have been used by instructors to increase the interaction between the instructor and the learners. The term tools refers to all instructional stimuli integrated into the learning tasks and learning content (Elen and Clarebout 2006). Web-based pedagogical tools (WBPT) have been divided by Dabbagh and Kitsantas (2005) into "(a) collaborative and communication tools (e.g., e-mail, discussion forums, and chat tools), (b) content creation and delivery tools (e.g., tools for instructors to upload course syllabus, course content, and assignments; and tools for students to access course resources and readings), (c) administrative tools (e.g., tools to manage general course information and functions; and student information, interactions, and contributions), and (d) assessment tools (e.g., tools to post grades and track student progress)" (Dabbagh and Kitsantas 2005, p.2).

With the rise of technology use in the 1960s and 1970s, computers became part of the instructional design in the education field environment (Lasi et al. 2014). Teachers used computers to assist with students' learning. In the 1990s, computers became a delivery system due to their interactive capabilities. In the 21st century, educational technology helps the learner learn better, faster, and more affordably (Molenda 2008). When students use educational technology tools, they leave digital traces. Winne (2010) stated that advances in technology enhance learning enabled us to capture trace data about the learners' activities in an online

learning environment, which are tracing aptitudes. We can investigate students' cognitive activities and strategies for tracing aptitudes from occurrence, temporal sequence or regular patterns of events.

For the past few years, researchers understood the potential of using big data to improve teaching and learning (Chaurasia et al. 2018). Tracing data such as students' online activities regarding reading, writing, test-taking, communication with peers and their lecturers, and performance scores will be collected by Learning Management Systems (LMS) (Mostow et al. 2005). The large quantities of data cannot be used efficiently by the learners and instructors; however, data mining brings a useful way to analyse the data to bring insights to both learners and instructors (Zaïane and Luo 2001). Data mining applied to educational data led to the emergence of educational data mining (EDM). When data mining deals with educational data to better understand and enhance learning and teaching by applying data analytics, it is called Learning Analytics (LA).

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 interdisciplinary field that involves expertise from different disciplines such as IS, computer sciences, and education (Dawson et al. 2014). Even though LA is a new field, the idea of using educational data to improve learning and teaching goes back to the last century (Nevo 1983). LA's focus is on using educational data to provide students and teachers with actionable tools to improve learning and teaching (Mor et al. 2015).

LA has been applied in different contexts, including higher education, massive open online courses, schools, and workplace learning (Ferguson et al. 2016a). 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 detecting learning behaviour and undesirable learning behaviour and effects (Sclater 2016; Sclater et al. 2016).

Ifenthaler (2015) categorised LA's benefit in an educational context into four levels; 1) at the micro-level, the learners' profit from LA. Students receive adaptive materials, support, and recommendations; 2) at the meso-level, instructional designers and course facilitators will get the insights. They can adjust learning design and course materials to the learners' needs; 3) at the macro-level, institutions can get insights from comparisons across courses and faculties, such as facilitating resource allocation and retention; 4) at the mega-level, it gives insights based on comparisons of institutions and programs that could aid policymaking.

Even though there have been many studies that used LA to enhance students' succession (Clow 2013; Dietz-Uhler and Hurn 2013), the field still lacks empirical evidence for supporting learning (Ferguson and Clow 2017; Viberg et al. 2018). These studies mostly focused on LA's technical aspects and are not sufficiently focused on students' motivation and strategy use (Lonn et al. 2015; Wong et al. 2019b). There are different issues and challenges related to the application of LA in higher education (Daniel 2019; Ferguson 2012). For example, Ferguson (2012) stated that studies need to focus on learners' perspectives regarding their motivation, confidence, enjoyment, satisfaction, and meeting career goals as they have the potential for learning success. This work aims to address the issues identified in the literature by researching LA in the higher education context through an investigation of students' perceptions regarding their motivation, strategy use, and the helpfulness of tools. The overview of the research foci is depicted in Figure 1. We follow the mixed-method approach (Creswell and Clark 2017) by collecting both qualitative and quantitative data to answer the following overarching research question of this thesis:

How students' perception, motivation, and learning strategy use inform LA?

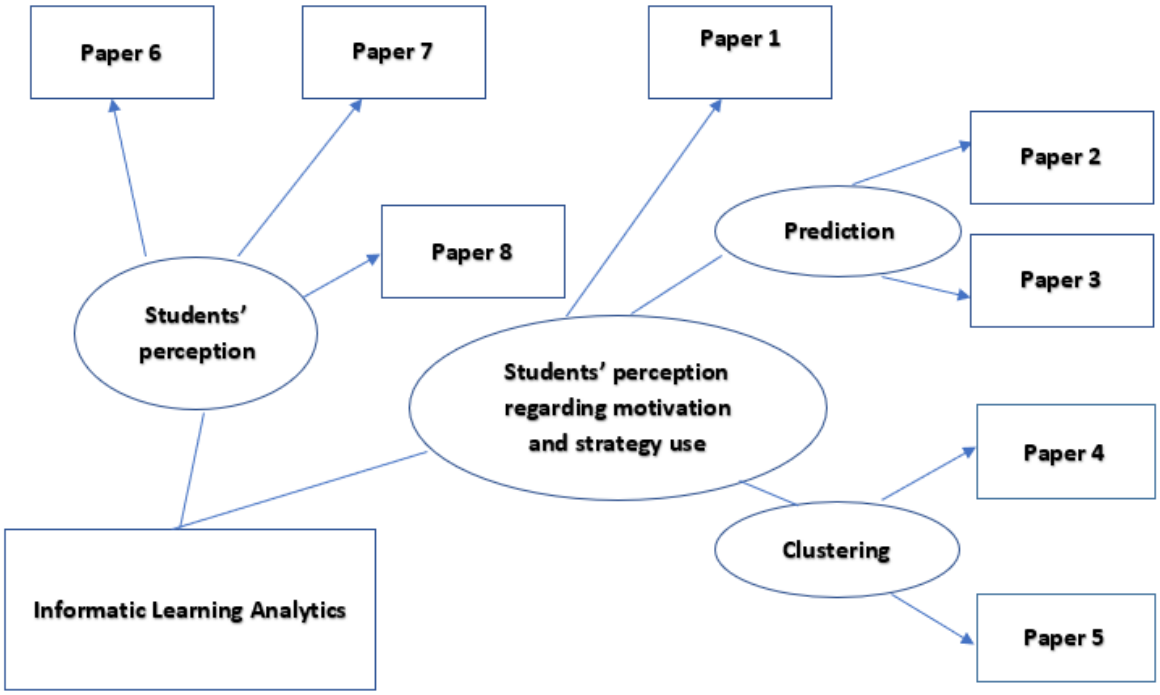

Figure 1: Overview of the research foci of the thesis and the related studies

The participants were two groups, one of freshmen students and two of upper-level students from Business School, University of Auckland. Quantitative data for this study was gathered from students when the Motivated Strategies for Learning Questionnaire (MSLQ) (Pintrich

1991) was administered three times during three courses. We also collected student data related to assignments, mid-term tests, and final scores from the LMS. Qualitative data for this study was gathered through interviews with the students. Having both quantitative and qualitative data allows us to trace the evidence and improve research quality. This study draws on both Activity Theory (AT) and Self-Regulated Learning (SRL) theories.
Below is the list of papers generated based on this study. A selection of the papers will be presented in this thesis. The PhD thesis is written as a compilation of studies that have been published or submitted. Therefore, some overlap in literature, theoretical background, and methodology exists among the various papers.

List of published papers:

- The Role of Motivation and Strategy Use in Predicting Students' Performance in a Blended Learning Environment, Shadi Esnaashari, Lesley Gardner, Tiru Arthanari, Michael Rehm, Olga Filippova, International Conference on Information Systems (ICIS), India (2020)
- The Impact of Motivation and Strategy Use on Course Outcome in Digital Learning Environment - A case Analysis of a Business School Course, S Esnaashari, L Gardner, M Rehm, Hawaii International Conference on System Sciences, Hawaii, USA (2020)
- Educational Technology Tools: Longitudinal Views of Students, S Esnaashari, L Gardner, M Rehm, The American Conference on Information Systems, Cancun, Mexico (2019)
- Students' Motivation and its Changes as the Course Progresses, S Esnaashari, L Gardner, M Rehm, The American Conference on Information Systems, Cancun, Mexico (2019)
- Longitudinal Views of Students in Regards with Educational Technology Tools, S Esnaashari, L Gardner, M Rehm, O Filippova, Pacific Asia Conference on Information Systems (PACIS), Xi'an, China, (2019)
- Characterising Students Based on Their Participation in the Class, S Esnaashari, L Gardner, M Rehm, International Conference on Artificial Intelligence in Education (AIED), 84-88, London (2018)
- Students' Perceptions of Using Technology in Flipped Classrooms Environment, S Esnaashari, L Gardner, M Rehm, EdMedia+ Innovate Learning, 190-199, Amsterdam, Netherlands (2018)

- Exploratory Analysis of Students' Perception in Regard to Using Educational Tools in the Class - Using AT, S Esnaashari, L Gardner, M Rehm, EdMedia+ Innovate Learning, 169-178, Amsterdam, Netherlands (2018)
- Is Participatory Pedagogy Useful and Satisfying for Tertiary Students? S Esnaashari, L Gardner, Paul Watters, EdMedia+ Innovate Learning, 179-189, Amsterdam, Netherlands (2018)
- Characterising Students' Behaviour Based on their Participation in Property Course in New Zealand, S Esnaashari, L Gardner, M Rehm, 32nd International Conference on Advanced Information Networking and Applications, Cracow, Poland, (2018)
- Clustering Student Participation: Implications for Education, S Esnaashari, L Gardner, P Watters, 32nd International Conference on Advanced Information Networking and Applications, Cracow, Poland, (2018)

List of papers included in the thesis:

Table 1 gives an overview of the papers included in the thesis. Six of the papers reported here are in submissions and two have been published.

Research methods	Paper title	Main research foci	Main research goal
CFA/ Cronbach Alpha N= 419	**Paper 1** The Role of Motivation and Strategy Use in Predicting Students' Performance in a Blended Learning Environment	Predicting students' performance in BL environments	**Goal 1:** Checking the reliability of our model through Cronbach Alpha and confirmatory factor analysis. **Goal 2:** Identifying changes in motivational and strategy use constructs as the course progressed **Goal 3:** Predictive validity
Regression N=189	**Paper 2** Impact of Motivation and Strategy use on Performance in a Blended Learning Course	Examining predictability of students' final scores based on their motivational beliefs and strategy use	**Goal 1:** Understanding dynamics of students' motivation and strategy use **Goal 2:** Identifying predictors of final scores and investigating the earliest we can predict the final score **Goal 3:** Understanding how we can explain the final score based on motivational and strategy use constructs
Regression N=314	**Paper 3** A Comparison of the Predictability of Final Scores for Freshmen and Upper-level Students in Blended Learning Courses - Using Motivational Beliefs and Learning Strategy Use as Predictors	Investigating the predictability of the final score for freshmen and upper-level students	**Goal 1**: Comparing the predictability of the final score based on motivational and strategy use constructs between freshman and upper-level students
Clustering N=189	**Paper 4** Unfolding Self-Regulated Learning Profiles of Students: A Longitudinal Study	Investigating different students' SRL profiles and how they unfold as the course progressed	**Goal:** Identifying distinct SRL profiles and how they unfold as the course progress

Clustering N=314	**Paper 5** Exploring the Cyclical Nature of Self-Regulation for Freshmen and Upper-level Students in Blended Learning Courses: A Longitudinal Study	Comparing how freshmen and upper-level students are different in terms of SRL profiles and their SRL unfolding processes	**Goal 1:** Identifying distinct SRL profiles and understanding how students' SRL profiles are different for freshman and upper-level students **Goal 2:** How unfolding SRL profiles are different for freshman and upper-level students
Interviews N=42	**Paper 6** Students' Perceptions of Educational Tool Use in a Blended Learning Environment: An AT Perspective	Analysing students' perception through AT	**Goal:** Understanding students' perceptions regarding tool use through AT
Interviews N=42	**Paper 7** Contradictions identified through applying AT to perspectives from students and lecturers involved in blended learning courses	Identifying contradictions from an AT perspective regarding students' tool use in BL	**Goal:** Identifying contradictions through using educational tools in three BL courses using AT
Interviews N=24	**Paper 8** Students' Use of Educational Tools: an SRL Focused Longitudinal Study	Understanding students' perceptions regarding tool use through SRL theory	**Goal:** Analysing how tools helped students in their self-regulation processes

Table 1: Overview of papers included in this thesis

In this chapter, we first provided an overview of the research and its objectives. Hereafter, the research background and motivation, research gap, and research questions will be presented. After that, the theoretical framework used in this study is described. Then, we give an overview of the methodology, data collection, and analysis. The research scope and approach are established after that. Lastly, this chapter maps out an overview of the structure of the thesis.

1.1 Research Background and Motivation

Educational tools have been increasingly implemented in the learning environment (Lasi et al. 2014; Viberg et al. 2018). It has changed the format of courses to more BL by taking advantage of online learning as well as face-to-face classroom learning (Garrison and Kanuka 2004; Picciano et al. 2013; Van Doorn and Van Doorn 2014). There is a choice between traditional and new media, and they can be replaced with each other (Thorne 2003a). Educational tools

have become an important part of the BL environment as they allow for the collection of information from students when they engage with the tools (Dahlstrom et al. 2014) and have more flexibility for students (Waha and Davis 2014). Some universities have adopted a fully online course or a blended format by adopting several digital technologies and systems in learning and teaching (Dahlstrom et al. 2014; Daniel 2015). The number of courses that use BL is increasing (Staker and Horn 2012) even though there are more responsibilities for BL students. Understanding students' SRL in this environment is more important as individuals are required to be more autonomous to be able to self-regulate their learning (Vaughan 2007). The ultimate goal for teaching is to produce lifelong learners (Candy et al. 1994) who can take control of and self-regulate their learning (Siemens et al. 2015). Not all students are capable of self-regulating their learning and it is beneficial if educators can identify the students who need help. Due to the nature of online learning, lecturers do not have close relationships with students making it hard for them to know when to take precautionary measures (Ferguson 2012), it is more obvious the importance of giving insights to the lecturers so that they can help students (Ifenthaler 2015).

The need to provide insights to the lecturers feels greater because we have a growing demand in education. It is not just because we have more undergrad students, but we have students with diverse needs (Coertjens et al. 2017; Hommel et al. 2019). Some of these students do not complete their courses (Larsen et al. 2012; Mah 2016). Given the status quo, faculty members wish to identify such students to give them feedback and encourage them to successfully finish their courses (Cohen 2017).

Through LA, we used students' data to understand and support learning processes (Siemens and Long 2011). One of the ways would be through identifying at-risk students through recognition of students' course outcome predictors mostly from students LMS usage. Identifying at-risk students is an example of LA so that appropriate intervention can be applied to prevent students' dropout (van Leeuwen et al. 2019).

Even though a lot of studies work on different aspects of LA, such as technical issues, data processing, data privacy, developing user systems, and dashboards (Costa et al. 2017; Gasevic et al. 2017; Schumacher and Ifenthaler 2018; West et al. 2016), students' motivation and strategy use have not yet been sufficiently considered for analyses in LA. Liu et al. (2017) 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 (2017) 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 (Boekaerts 1992; Pintrich 2000; Pintrich 1999). Therefore, it is essential to understand SRL to understand and support successful learning processes in higher education (Cassidy 2011).

Moos and Bonde (2016) stated that motivation is crucial for successful learning, especially in highly SRL environments, such as higher education and especially online learning. Motivation has been identified as an important driver for initiating and sustaining learning processes. Different learning theories, such as SRL, highlighted the importance of motivation for learning (Boekaerts 1999; Pintrich 1999; Zimmerman 2002). Schunk (2008) defined motivation as "the process whereby goal-directed activity is instigated and sustained" (Schunk 2008, p. 4). Zimmerman and Schunk (2011) stated that SRL processes are interdependently connected to motivational processes. Motivation affects the selection of learning strategies, consequently affecting learning processes and outcomes. Similarly, self-regulation also influences learners' motivation. It is assumed that students apply SRL strategies to their learning process. However, Efklides (2011) stated that there is a need for more research to gain insights into how these components are related to learning success.

While earlier studies that we reviewed looked at students' trace data, we used students' self-reported data on what students believe about their motivations and different learning strategies they used to self-regulate their learning. For this reason, we used the MSLQ developed by Pintrich (1991) and administrated it three times to understand students' motivation and strategy use. The methodology adopted in this study fit with the LA framework by identifying at-risk students, and identifying the group of students who share a similar profile, so that the lecturer can apply appropriate intervention to help them (Fincham et al. 2018).

Even though we researched students' motivation and strategy use longitudinally by administrating the MSLQ questionnaire (Pintrich 2000; Zimmerman 2002) three times, we also asked students about their perceptions and experience regarding using tools in their learning process through interviews. Lehmann et al. (2014) stated that students characteristics affect the self-regulation process. They interviewed students from different categories to get broader insights. We also categorised students into three and interviewed from different categories to get more comprehensive insights.

We investigated students' assumptions and feeling through the AT lens first. We tried to understand how students used tools to achieve their goals. There are also studies that looked at

the contradictors at the post-secondary level (Dippe 2006; Voigt 2006), but a very limited number looked at the secondary level (Fahraeus 2004; Murphy and Manzanares 2008). We are also aware of a few studies (Gedera 2016) run at the university level, which had looked at the contradictors when the participants just used the discussion forum. They did not look at how they used all other tools provided in the class.

Through the lens of AT, we identified the contradictors in our learning systems. The most important contradictor was the disconnection between the individual and community level. It made us concentrate on the top triangle in AT (subjects-tools-object) and investigate how tools help students self-regulate their learning. Dabbagh and Kitsantas (2005) further stated that providing various toolkits helps students choose the tool that supports their learning and stimulates SRL. However, we were not sure about students' perceptions regarding the helpfulness of tools—we postulate that perception is under-examined in the SRL literature on educational tool use. Student tool use has still remained a black box (Winne 1982). It is still unclear if all the students use and benefit from the tools provided for them by instructors. This study focuses on helping open Winne's (1982) black box by exploring how students used the tools. We investigated the second axiom in Winne et al's (2006) version of SRL mentioning students are agents (Winne et al. 2006). This means that they decide for themselves; they have the autonomy to choose when to study, what to study, and how to study? They can choose whether to use the tools and participate in the activities in the class or not.

In summary, this thesis accordingly examines the concept of LA by focusing on students' reported motivation and learning strategy use and perception longitudinally in a higher education context to

a) Investigate the dynamics of students' motivation and strategy use as the course progresses

b) Predict students' final score based on their reported motivation and learning strategy components

c) Profile students based on their motivation and strategy use (SRL profiles)

d) Investigate how students unfold their SRL profiles as the course progressed

e) Understand students' perceptions regarding tool use

Hereafter, we summarised the gaps we identified and the research questions that have been addressed in this thesis.

1.2 Research Gaps

In this section, research gaps are identified and based on them; we form the research questions to answer our overarching research questions that guided this study.

1.2.1 Gap 1: Predictability of the Final Score Based on Students' Motivation and Strategy Use

As mentioned in the previous section, one of LA's applications is predicting students' final scores (Tempelaar et al. 2015). Therefore, it is essential to identify the factors which help us predict students' final scores. Several studies investigated LMS data from various activities in which students participated to predict students' final scores and design the instructions for the courses better so that fewer students drop out (Gašević et al. 2015; Tempelaar et al. 2015). These studies either fail to quantify the impact of emotional, motivational, cognitive–metacognitive factors, and resource management or they have inconsistency in their findings, which may be due to not addressing the learners' characteristics (Arnott and Planey 2017; Mousoulides and Philippou 2005; Niemczyk and Savenye 2005; Pintrich et al. 1990; Wang 2019). Therefore, we address the gap by answering the following research question:

RQ 1: How do we predict course outcomes for two groups of students (upper-level and freshmen) based on the changes in their motivation and strategy use during the courses?

To answer RQ 1, we had to answer the following sub-questions:

- What are the dynamics of students' motivational belief and learning strategy use?
- To what extent do the different indicators of motivational beliefs and strategy use account for the students' final scores?
- Understanding the differences between freshmen and upper-level students in these regards.

Answering the above questions helped us to achieve the following objectives.

- ✓ Objective 1 - Understanding how students' motivation and strategy use change as the course progressed
- ✓ Objective 2 - Identifying the constructs that correlated with the final scores
- ✓ Objective 3 - Identifying the constructs that help us predict the final scores
- ✓ Objective 4 - Comparing freshmen and upper-level students in terms of the dynamics of the constructs, the correlation of the constructs with the final scores, and the final score's predictability

When we looked at how the constructs changed as the course progressed, we observed high standard division for each construct, which was evidence of differences among students in the class regarding their motivation and strategy use, which led us to identify the second research gap.

1.2.2 Gap 2: Understanding Distinct SRL Profiles of Students and How They Unfold as the Course Progressed

Despite studies to comprehend the self-regulation process (Özcan 2016; Peng et al. 2014), there is still a gap in understanding and evaluating SRL in online learning (Järvelä et al. 2019; Wong et al. 2019a). Some studies tried to identify students with the same learning behaviour patterns (Hong et al. 2020; Liu et al. 2014; Ning and Downing 2015; Shell and Soh 2013). However, studies such as Jang et al. (2017) showed that SRL profiles are dynamic and change. Järvelä et al. (2019) stated that studies conducted to date are not entirely sure how SRL profiles change as the course progresses. The relationship between SRL and learning outcomes through variable-oriented studies is well established (Malcom-Piqueux 2015; Masyn 2013; Morin et al. 2018). However, the person-orientated approach has just recently being investigated for profiling students and how students unfold their profiles. Therefore, we address the gap by answering the following research question:

RQ 2; How can we understand the dynamics of upper-level and freshmen students SRL profiles that have an influence on students' course outcomes?

To answer RQ 2, we had to answer the following questions.

- What are the dynamics of motivational, cognitive, metacognitive, and strategy use variables?
- What distinct student SRL profiles can be identified over time?
- To what extent do student SRL profiles unfold over time?
- Understanding the differences between freshmen and upper-level students in these regards

Answering the above questions helped us to address the following objectives.

- ✓ Objective 1 - Identifying students who have the same pattern of motivation and strategy use (SRL profile)
- ✓ Objective 2 - Understanding how the different SRL profiles perform in the final scores
- ✓ Objective 3 - Understanding how students adopt different profiles as the course progressed
- ✓ Objective 4 - Comparing freshmen and upper-level students in these regards

1.2.3 Gap3: Understanding Students' Perceptions Regarding Tool Use

It is essential to understand students' perceptions regarding the usefulness of tools. Pardo and Siemens (2014) stated that students have a major role in LA; their perceptions are essential to

investigate. Nicol and Macfarlane-Dick (2006) also stated that the focus of studies needs to be on self-regulated learners when an aim of higher education is to produce lifelong learners. Zimmerman (2002) also stated that the learning context's success depends on how students can initiate and sustain their learning process. Worldwide, educational tool use has increased and provided more learning options for students (Hammond-Kaarremaa 1994; Lee 2017; Yadegaridehkordi et al. 2019). However, there remains a lack of evidence on the usefulness of educational tools in helping students learn (Kintu et al. 2017). As Aristovnik et al. (2017) stated when a technology-based teaching method emerged in higher education, the studies focused more on the psychological aspects of learning; however, there is a gap in our understanding of students perceptions regarding the usefulness of tools in BL courses. To address the gap, we investigated students' perceptions of using educational tools in their classes through AT and SRL theories. The following research question guides our qualitative study:

RQ3: What are the students' perceptions of educational tool use in a BL environment?

Answering the above question helped us to address the following objectives.

- ✓ Objective 1 - Understanding students' perceptions regarding tool use in their learning processes through AT and SRL theories
- ✓ Objective 2 - Identifying contradictors from an AT perspective
- ✓ Objective 3 - Helping to open Winne's black box (Winne 1982)

1.3 Theoretical framework

Our study aimed to not only identify at-risk students by predicting the students' course outcome or trying to cluster students early in the courses but also to use data to improve the learning process and support personalised learning. Thus, learning theories, including AT and SRL, were applied to understand the students' tool use in their learning processes which is explained next.

1.3.1 Activity theory

AT draws on the work of Vygotsky who developed the socio-cultural approaches to learning and development (Vygotsky 1934; Vygotsky 1978; Vygotsky 1987). Vygotsky (1934) argued that human mental functionalities mediate processes organised by socio-cultural artefacts. Several socio-cultural theories have been derived from Vygotsky's work (Lantolf et al. 2000; Valsiner 2007; Van Lier 2002). All of them have one thing in common, that all human action is mediated. However, they are different in terms of how the tool mediates human action.

Leont'ev (1974) developed AT using Vygotsky's socio-cultural approaches. AT is a theory that emphasises both historical developments of ideas and the constructive role of humans.

In AT, activity and consciousness are interrelated. AT brought a new perspective to activity and learning by emphasising that learning will not emerge as a precursor to activity and will emerge from the activity. It focuses on human activities and consciousness within the context where it happened. Also, it focuses on the instructional design of the context where it happened. Therefore, it is important to understand the context of meaningful activity and instructional design when analysing an activity. When analysing one human activity, it is also important to know who is engaged, the person's intention and goal, the product of the activity, the community, and the rules and norms of the community wherein the activity happened. Engeström's (2001) version of AT is depicted in Figure 2 (Engeström 2001). The most important unit of analysis is the activity that will be accomplished through the top triangle, which considers the subject and object of the study and the tool used in the activity. Action and operation affect the outcome.

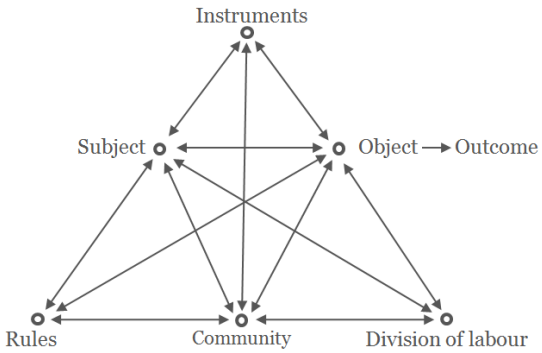

Figure 2: Activity Theory (Engeström 2001)

The subject is the individual or the group of people engaged in the activity. The object is what is acted on by the subject and motivates the subject to achieve the goals. Tools are anything that the subject will use to achieve their goals. Activity is a precursor to learning. Different objects have different affordances. Each activity will be performed through the combination of the subject, the object, and the tool (instrument). The interdependent aggregate that shares social meaning would be a community. Rules are the strategies that guide the action which would be acceptable to the community. The division of labour refers to the tasks needed to be performed by individual members of the group. The primary focus of any activity is the object. The overall aim of the activity is an outcome that would be the result of executing the activity.

The concept of tool mediation has been defined by Vygotsky (1978). He stated that when subjects want to achieve an object in the environment, subjects cannot act directly on the object, and they will do it through the mediation of various tools. Russell (2003) described tools as "anything that mediates subjects' action upon an object" (Russell 2003, p. 70). Engeström (2001) argues that the tools are not only for the subjects to use to act on the environment but also, they use the tool for learning. In AT, which has been defined by Engeström (2001), it is emphasised that human beings not only act on their environment both individually and collectively with the use of tools, but also they learn with them.

From an AT perspective, learning is a process in whose activities individuals participate with others. Their knowledge will be scaffolded by other members of the group who know that activity better. This scaffolding will be mediated through various socio-cultural means. Within the classroom context, the focus is on increasing students' learning by participating in the activities in class. Still, we cannot deny the importance of individuals and their responsibilities to improve their learning. We are looking to help individuals improve their learning through better and easier engagement with learning resources. Therefore, we concentrate on how individuals use tools to achieve their goals. In summary, the ultimate goal of education is to facilitate SRL by teaching capabilities to continue lifelong learning. In this light, learners will feel responsible for their learning and can adopt appropriate strategies when necessary. Therefore, we give an overview of SRL next.

1.3.2 Self-Regulated Learning

SRL has been an important topic in education for the last thirty years (Azevedo and Gašević 2019; Greene and Schunk 2017; Winne 2019). It is acknowledged that self-regulation is essential for learning, especially in a BL environment with limited interaction between the lecturer and students (Ally 2004). Because in this environment, individuals are required to be more autonomous to be able to achieve SRL (Broadbent and Poon 2015; Cassidy 2011). SRL has been defined by Pintrich (2000) 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). As Greene (2017) mentioned, the development of students' SRL skills is the main aim of education (Azevedo and Gašević 2019; Greene and Schunk 2017; Winne 2019). Self-regulated learners need to apply changes in their strategies when facing difficulties (Moos and Bonde 2016).

While there are different SRL versions, they all follow the same three phases: preparatory, performance, and appraisal. Among all the SRL variations, this study focuses on Winne's work which has the most heterogeneous theoretical background (Winne and Hadwin 1998). Winne's model is metacognitive and has been influenced by Bandura (1986a) and Zimmermann (2000), who present a social cognitive theory. Winne examined SRL as a recursive process (Winne 2011). In metacognitive monitoring, feedback can be given in any phase. In other words, monitoring happens in the performance phase and feedback in the appraisal phase. Winne's work is more strategy-oriented, and it is then helpful to understand the effectiveness of different strategies used by the students (Winne and Hadwin 1998).

Winne and Hadwin (1998) defined SRL in a way that has both aptitude and event properties. The stable personal attribute could be considered an "aptitude". They defined "event" as a "snapshot that freezes activity in motion, a transient state embedded in a larger, longer series of states unfolding over time" (Winne and Hadwin 1998, p. 534).

Winne (1996) looks at SRL as an inherent part of learning. He defines SRL as meta-cognitively guided behaviour that could enable students to adaptively regulate their use of cognitive tactics and strategies in performing task. Winne and Hadwin (1998) define SRL as a four-stage process.

1) Task definition; students create their understanding of the task that needs to be performed.

2) Goal setting and planning; students plan for successful task completion and achieving of their goals.

3) Enacting tactics and strategies planned and the use of actions that one needs to reach the goal set in the previous stage; students choose suitable strategies to reach the designated goals.

4) Adopting study techniques metacognitively; students adopt new strategies and change their long-term motivation and strategies to adjust their learning process for their future learning.

Winne (2006) identified three axioms, which need to be addressed in educational psychology research about learning. The axioms are 1) learners construct knowledge, 2) learners are agents, and 3) data include randomness. In this study, we are focusing on the first two axioms.

Axiom 1 is about learners who construct knowledge, it includes five facets referred to as the COPES (i.e., Conditions–Operations–Products–Evaluations–Standards) (Winne and Hadwin 1998). The five elements of COPES collectively influence the self-regulatory process of learning. The application of the first axiom is that learners use tools to operate on raw materials, to construct a product that is evaluated in a formative way or summative with respect to standards of socio-cultural kinds. Conditions are all the available resources to the students, and

the constraints that the student has inherited from the task and environment (e.g., cognition, motivation, knowledge, interests, context, and time constraint are examples of this category).

Winne and Hadwin (2008) identify several conditions that can affect learning. Resource, instructional cues (involves grading online), previous learning history, time, and social context are examples of external conditions for students. Beliefs about the nature of knowledge and knowing, motivational factors, achievement, goal orientation, cognitive load, and knowledge are examples of internal conditions for students. Operations are the strategies, tactics, and cognitive processes employed by the students to achieve their goals. In this stage, the students will plan to achieve their goals (SMART - Searching, Monitoring, Assembling, Rehearsing, and Translating) (Winne 2001). Products are the operation results (creating new knowledge, or an essay would be an example of products). Evaluations are the students' feedback from other peers or their teacher and fit between the product and the available standards. Standards are the criteria by which products will be evaluated.

Axiom 2 states that learners are agents. They have the capability to exercise choice, which is affected by internal and external conditions. The external condition includes instructional design, previous learning history, and social context. Grading online is an example of instructional design. Internal conditions include motivation, achievement, goal orientation, and cognitive load.

Winne's (1996) model has a strong metacognitive perspective. This model recognises self-regulated students as active and they can manage their learning via monitoring and the use of, mainly, (meta)cognitive strategies (Winne 1996). It also stresses the goal-driven nature of SRL and the effect of self-regulatory actions on motivation (Winne and Hadwin 2008). Panadero et al. (2016) suggested Winne's (1996) model is useful for research that focuses on implementing computer-supported learning settings. Furthermore, Winne's model has an allusion to motivation (Winne and Hadwin 2008). His model has a built-in connection with Pintrich (2003) on the regulation of motivation. Pintrich (1993a) helped to clarify the SRL conceptual framework by conducting crucial empirical work on the relationship between SRL and motivation (Pintrich et al. 1993a).

Winne and Hadwin (2008) agree with Pintrich's (2000) ideas regarding motivational factors that affect the SRL process's behavioural, contextual, and cognitive variables (Pintrich 2000). The definition of the self-regulation process emphasises the agency of learners in the process, which would be affected by individual goals, and it can vary in different contexts (Pintrich 2004). Therefore, SRL is considered to include motivational, cognitive, and metacognitive

strategy use, and resource management components (Boekaerts 1992; Pintrich 2000; Pintrich 1999).

Pintrich (1999) emphasised motivation as the most important component in learning. He also stated that students having the knowledge of cognitive, metacognitive, and self-regulation is not enough; students need to be motivated to use them (Pintrich 1999). Winne and Hadwin (2008) also stated that for students to be successful in regulating cognitive and metacognitive was not sufficient. Students need to regulate their motivation.

Motivation became a crucial facet in different models of SRL (Boekaerts and Corno 2005; Pintrich 2000; Pintrich 2004; Schunk and Zimmerman 2012b). Schunk et al. (2008) stated that motivation is a process where learners pursue their goals by initiating and persisting in activities until they achieve their goals. The cognitive component is directly related to the learning process, including rehearsal, elaboration, and organisation (Boekaerts 1992; Pintrich 1999). These components are needed to control metacognitive strategies. Metacognitive strategies include knowledge of cognition and regulation of cognition, including planning, goal setting, monitoring, reflection, and regulation (Boekaerts 1992). The resource-related component includes time and study management, help-seeking, seeking information (peer learning), and structuring the learning environment (Pintrich 1999).

Learners' level of self-regulation is considered to be relevant for successful learning. However, its measurement is difficult (Boekaerts and Corno 2005). Two frameworks that use different self-reports for measuring students' motivation are student approaches to learning (SAL) and SRL. The SAL framework theorises learning as a composition of motives and strategies. SAL describes deep (meaningful learning) and surface (rote learning) approaches to learning (Entwistle and Ramsden 2015). The SRL framework is categorised by specific cognitive, motivational, and behavioural constructs (Zimmerman 2008). The MSLQ (Pintrich et al. 1993b) and the Learning and Study Strategies Inventory (LASSI) (Weinstein and Palmer 1987) are the two most commonly used questionnaires developed under the SRL framework for measuring motivation and strategy use. We used the MSLQ in this study as it is the most used instrument in SRL measurement and its validity has been checked a lot in the literature (Roth et al. 2016).

This study's theoretical foundation is based on SRL assumptions, which includes the processes and constructs that are related to learning. It considers cognitive, metacognitive, and motivational components. Ifenthaler (2012) stated students who are more capable of self-regulating associate with lifelong learning. Since our aim was to produce lifelong learners who

are capable of regulating their learning, we used SRL. Cassidy (2011) stated that SRL is a major theory for explaining students' learning performance differences, especially in higher education which would be one of our study's aim.

Among the different versions of SRL, we used Winne's (1982) SRL model (his COPES model) as suggested by Gašević et al. (2015). They stated that data needs to be collected in a way that describes the learning process in terms of events in a learning episode. They suggested using Winne's (1982) characterisation of traces and his COPE model. Winne (2017) suggested that the process view of SRL would give more fine-grained insights into actual learning processes. Winne et al. (2019) stated that the data used in LA rarely provides a clear signal on the learning process. Therefore, the next section discussed our study's methodology of collecting the longitudinal data and analysing it.

1.3.3 Methods

This section explains the study's research methodology. It starts with an overview of ethical considerations, followed by introducing the research paradigm. It describes the choice of methods, followed by the description of the research design, research context, and participants. The methods for quantitative and qualitative data collection, the validation process, and how we analyse them have been given after that.

Before we were able to collect data, we had to think about the challenge identified in LA, by Ferguson et al. (2016b), related to data collection. They talked about privacy and ethical concerns for LA when we collected and integrated students' data from different contexts. In this study, we went through the path of ethical consideration and followed the University of Auckland human ethics protocol to overcome the challenge.

1.3.4 Ethical Considerations

Collecting student data has the potential to harm; ethical considerations were significant. The nature of the qualitative and quantitative data made us think about the ethical considerations and what we could do to mitigate them. We followed the University of Auckland Human Participants Ethics Committee's (UAHPEC) ethical guidelines. The UAHPEC approved our application for this research (Ref 021131). We gave students the information sheet to provide the information they needed to have before deciding to participate or not in the study to mitigate the harm. We explained how their data could help the process of teaching and learning. We explained to the students the duration and placement of data storage and the information about

who has access to data and who analyses it. We maintained a high level of transparency with students regarding the purpose of the study, the methods of data collection, and the analysis. We demonstrated to students how we protected their privacy and mitigated the harm by anonymising the data. We also mentioned that in qualitative analysis; we used pseudonyms to prevent exposing the identity of students. After that, protect ourselves from breaching ethics, we got consent from students.

1.3.5 Research Paradigm: Research Philosophy

This study employed both positivist and interpretive philosophies. Students' motivation and strategy use (quantitative data) and their relation to course outcomes were investigated from a positivist approach to answer our first two research questions (Cavana et al. 2001). In this method, when the data collection finished, we used statistical methods to analyse the data. In the positivist approach, we begin with deductive reasoning by starting with a theoretical position and integrating empirical data. We then interviewed and analysed the relationships between the concepts to answer research question three, which we took an interpretative approach. In this approach, the researcher was interested in the real experience of people. Kaplan and Maxwell (2005) mentioned in interpretative research, the researcher does not predefine dependent and independent variables but focus instead on the complexity of human sense-making as the situation emerges. By understanding what people mean when they assign themselves to the phenomena, we can get a rich description of people's thinking and feeling in that specific situation.

1.3.6 Case Study Research - Mixed-Method Approach

The case study approach was the best method to fulfil the objective of the study. Bell et al. (2018) mentioned that the mixed-method is "used as a simple shorthand to stand for research that integrates quantitative and qualitative research within a single project" (Bell et al. 2018, p.642). Yin (2012) explained that the principle of conducting a case study includes using multiple sources of evidence, creating a case study database, and maintaining a chain of evidence. Yin (2012) explained how creating the database establishes a connection between issues to specific evidence which helps the study's conclusion.

Johnson and Onwuegbuzie (2004) defined the mixed-method design as a "class of research where the researcher mixes or combines quantitative and qualitative research techniques, methods, approaches, concepts, or language into a single study" (Johnson and Onwuegbuzie

2004, p. 17). Based on what they have stated, the quantitative research method helps researchers test and validate already constructed theories and eliminate the confounding influence of variables. It also helps to more credibly access cause-and-effect relationships and generalise the research findings. However, the qualitative research method is useful for describing a complex phenomenon and understanding and describing the phenomenon's personal experiences. It also allows researchers to collect rich detailed data and determine how participants interpret "constructs" of the theoretical frameworks.

Creswell and Clark (2017) explained how following a mixed-method research model could improve research reliability. They mentioned by collecting data from different sources using different methods, we could support other data if any of them appeared weak. The results will then be merged to understand the main research questions. Having data from various sources strengthened our understanding of the phenomena. The qualitative and quantitative methods are complementary to each other. The qualitative data help to refine, extend, or explain the general picture of the quantitative data (Creswell 2002).

This study follows a sequential mixed-method approach which starts with the researcher first conducting quantitative or qualitative research. This is followed by analysis of the results and building on the findings by explaining them in more detail with the second research approach (Creswell and Creswell 2017). Our study started by running the questionnaire and analysing it to identify the interviewees to collect qualitative data. For the first two research questions in this study, we ran the MSLQ questionnaire three times during three courses. Then the questionnaire was analysed by applying K-Means clustering. Three different clusters of students were identified and four students from each cluster were interviewed.

1.3.7 Research Design

This section explains our research design. Creswell and Clark (2017) mentioned that research design is a strategy to confirm how the data collection, analysis, and interpretation processes could help the research achieve its objectives. Planning is essential for a case study. This structure of our research is shown in Figure 3. As shown in Figure 3, we had 12 weeks of study, and we ran MSLQ (Pintrich 1991) three times, in Week 3, Week 7, and Week 11, to understand the motivation and strategy use of students. To understand students' perceptions regarding tool use, based on how students responded to the MSLQ, we grouped the students into three clusters and interviewed four students from each cluster.

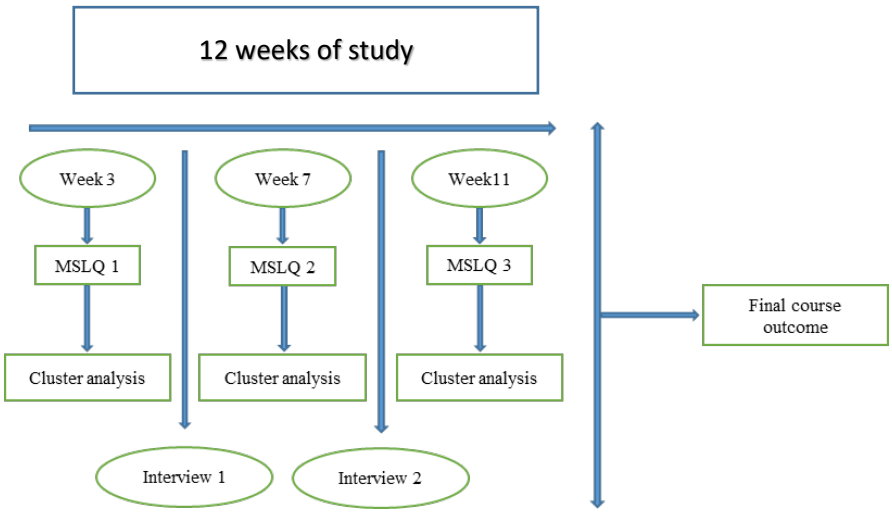

Figure 3: Structure of our study (12 weeks of study)

We also presented the structure of the course in Table 2. We showed when the students needed to hand in two assignments before and after the midterm. They also required to take part in midterm and final exams to meet the course requirements. We also presented the weight for each assignment and test.

Weeks	Students' responsibilities	Course work weights
1-2		
3	MSLQ 1	2.33%
4-5		
6	Assignment 1	5%
7	MSLQ 2	2.33%
	Test	23%
8-10		
11	MSLQ 3	2.33%
	Assignment 2A	15%
12	Assignment 2B	5%
	Final exam	45%

Table 2: Structure of the course

1.3.8 Research Context

In our study, the lecturer adopted a BL approach and prepared purpose-made online lectures with the blended classroom model being applied to the entire 12-week course. This teaching method has been employed to produce self-regulated learners, which included teachers, traditional classroom, and online learning methods (Sharma and Barrett 2008). The core material was available on the course web page and review sessions were conducted for discussion purposes.

The purpose-made online videos included a screen and audio capture of the lecturer. While recording his lectures, the lecturer spoke directly to this digital camera's lens as if communicating personally to an individual student. The lecturer's separate video was synchronised with the main screen capture video and placed to one side of the canvas in a picture-in-picture format. Each lecture video targeted a typical sitcom length and tended to range between 15 and 40 minutes in duration.

Following post-production editing, the videos were uploaded to Rev.com, a third-party producer of closed captions. The caption files were imported into the project file. Another addition included pop-up hotspot links to supplementary online content (videos, websites, online reports, etc.) which appeared off to the side of the main screen capture video which offered students an opportunity to explore additional online content related to the concepts being discussed at that specific portion of the lecture. Lastly, an embedded quiz, typically containing four or five questions, was added to the end of each lecture video. These quizzes consisted of true/false, multiple-choice, and fill-in-the-blank question types and were automatically graded, offering instant feedback to students.

The completed project was then rendered into a final MP4 video file and was uploaded to the university's video server to be accessed by students through the LMS. By streaming the lecture videos using the TechSmith Smart Player, students could conveniently toggle the closed captions on and off, do keyword searches of the captions to find particular lecture material, speed up or slow down the playback speed, and pause, rewind and skip ahead. The combination of closed captions and variable playback speeds allowed students to customise how they personally experienced the lecture and moderated the rate at which information was presented to them.

The embedded quizzes not only assisted students to interact with the course material and test their knowledge, but the quizzes were also central to the awarding of participation marks. The students were required to watch all the videos and participate in the quizzes at the end of the

videos before coming to the review sessions. There was a review session conducted weekly. Students had the option of going to class in person or watch the review session online when it was streaming and participate in the review quizzes run by the lecturer in class. The lecturer used an audience participation tool in class to engage the students' in-class activities and run tournaments in class.

After the lecturer finished going through the review questions, he would launch the first of two Top Hat tournaments which primarily contained the same embedded quiz questions featured in that week's online lectures. Top Hat tournaments were 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 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. The students had access to Piazza (students' forum) in case they needed to clarify anything among themselves or with their lecturer.

1.3.9 Participants

We collected data from three classes. We collected 1181 surveys in total. However, we used a different subset of data for different purposes. In the studies that we reviewed, we found that the number of participants was around 112 to 140 (Lopez et al. 2012; Macfadyen et al. 2010)

If we wanted to use the G power calculation to find the sample size, Mosteller (1995) suggested an effect size of 0.25 after reviewing 59 studies. Based on the effect size of 0.25 using the G power calculation, 164 students were needed in the between-subject design.

Seuring and Reiner (2005) mentioned that a sample between 100 and 200 was acceptable. Hair et al. (2014) stated that examples with observations between 50 and 400 would be acceptable.

Figure 4 outlines the structure for the mixed-method and multiple case study design. We have three classes of data. We are also presenting how we collected data from different sources, including face to face interviews and the MSLQ questionnaire. This method of collecting data from different sources helps us to get detailed knowledge.

Figure 4: An outline of the mixed-method and multiple-case study design

Using interviews and survey data helped us better understand students' motivation, strategy use, and perceptions regarding tool use. The surveys asked about their experience, but going through the interviews, we asked about students' feelings at the time and their motivation for the future. We interviewed 42 students and their instructors. We aimed to interview high, average, and low self-regulated learners to see how their perceptions were different. Bertaux (1981) mentioned that at least 15 interviews were needed to have an acceptable sample size of interviews in qualitative studies.

Table 3 shows the approximate number of students in each class, the number of survey invitations we sent to potential respondents, the actual collected data, and the respondent rate. We sent the questionnaire to students in 2018. Out of 483 students, we received 419 responses in the first round. There were 396 responses in the second round and 366 responds in the third round, respectively.

Class/ Iteration	I 1	Percentage	I 2	Percentage	I 3	Percentage	Number of students
Year 1	194	85.09%	180	78.95%	162	71.05%	228
Year 2	120	93.75%	113	88.28%	110	85.94%	128
Year2	120	93.75%	113	88.28%	110	85.94%	127

Table 3: Number of students in each iteration

1.3.10 Data Collection

For the quantitative data of this research, the MSLQ questionnaire was conducted three times. It was followed by collecting qualitative data from interviews in two rounds. The questionnaire was suggested by Oppenheim (2000) as an effective method because most people are familiar with questionnaires. This method allows the researcher to gather a large amount of data. Regarding the usefulness of the technology tools in SRL, different studies looked at students' data in an SRL environment (Winne and Hadwin 2013; Winne et al. 2006). However, previous studies can be criticised because they rely only on the students' self-reports by running surveys or questionnaires. More studies are needed that rely not only on surveys but also on observation or interviews. Because of that, we also used interviews. Maynard and Purvis (2013) suggested the interview method as in-depth, naturalistic, and narrative. In this method, it is possible for the researcher to efficiently communicate with the interviewee and shed light on matters that need more clarification. In the next section, an explanation of the tools used for collecting the data is given.

1.3.10.1 Quantitative Method

For collecting quantitative data, we used the well-established MSLQ questionnaire and Canvas. The MSLQ questionnaire is accompanied by a 7-point Likert scale, from strongly disagree to strongly agree. The validity and reliability of the MSLQ have been confirmed in the literature (Büyüköztürk et al. 2004; Lawrence Neuman 2014; Pintrich et al. 1993b). The overview of each of the questionnaire constructs is given below.

1.3.10.1.1 The Motivated Strategies for Learning Questionnaire (MSLQ)

The MSLQ is a questionnaire developed by Pintrich et al. (1993b) measuring the motivational orientations through 31 items and learning strategies through 50 items which are depicted in Figure 5.

Expectancy, value, and affect components are categorised under general motivational constructs. The value component is about why students engage in the activity. There are three subscales for value components: intrinsic goal orientation, extrinsic goal orientation, and task value beliefs. Intrinsic goal orientation focuses on learning and mastery. Extrinsic goal orientation focuses on grades and approval from others. Task value beliefs focus on how interesting, useful, and important the task to the student. The expectancy component refers to

the beliefs of students as to whether or not they can accomplish the task. There are two subscales for expectancy components (i.e., the perception of self-efficacy and control beliefs for learning). The affect component is about the responses to test anxiety. This component identifies the students' worries and concerns regarding taking part in exams.

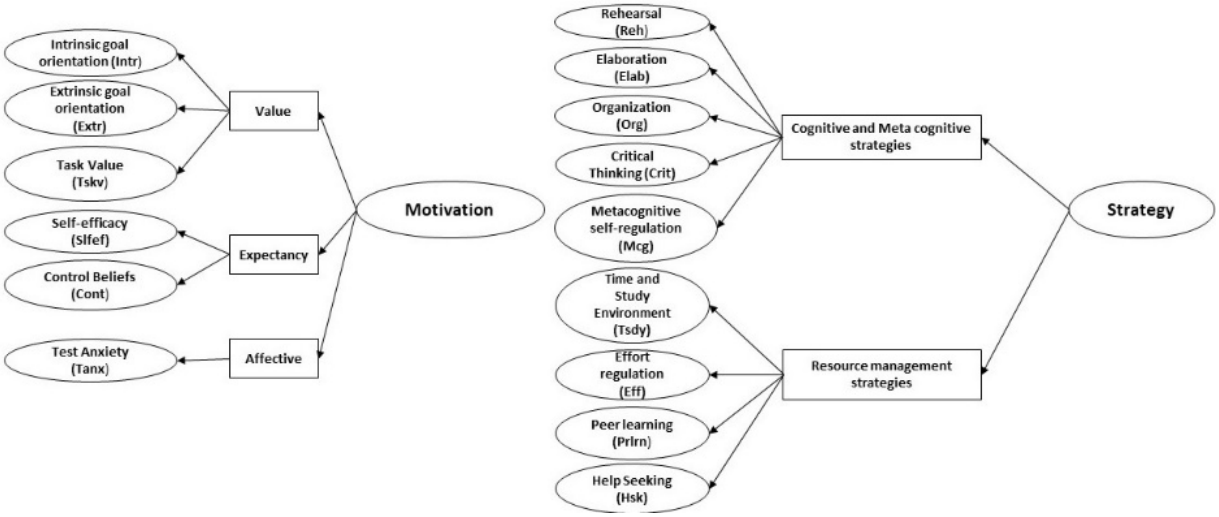

Figure 5: Structure of the MSLQ

There are scales for learning strategies, which include cognitive and metacognitive strategies and resource management. Cognitive strategies are about the use of basic and complex strategies for processing information. They are the use of a) rehearsal is the most basic strategy (e.g., repeating the words to be able to recall the information), b) elaboration strategies (paraphrasing and summarising), c) organisation strategies (outlining), d) critical thinking will also be measured by investigating how students use previous knowledge to apply it to the new situation and how students can critically evaluate the ideas. Metacognitive strategies measure how students control and regulate their cognition. There are three subscales for this stage: a) planning (i.e., setting the goal and task analysis), b) monitoring (tracing of one's attention as one read), and c) regulating (adjusting the strategies such as reading speed).

The resource management component includes four subscales that control the resources in addition to their cognition. They are a) managing their time and study environment, if the students use their time productively, whether the student has a special place to study, b) regulating their efforts, that is, whether the student persists to success even in a time of difficulty, c) peer learning, whether the student joins study groups with other students or not, and d) help-seeking, whether the student requests help from other students and the instructor. We run the MSLQ questionnaire through Canvas and also collected students' final scores from the same platform.

1.3.10.2 Qualitative Method

Qualitative research was used to explore the students' perceptions. Qualitative research helps us to understand through closely examining people's words, actions, and records rather than assigning mathematical symbols to these words, actions and records (Cavana et al. 2001). Creswell and Creswell (2017) further state that "Qualitative research is an approach for exploring and understanding the meaning individuals or groups ascribe to a social or human problem" (Creswell and Creswell 2017, p.3). Qualitative data was collected through qualitative in-depth interviews, as discussed below.

1.3.10.2.1 Qualitative In-Depth Interviews

Wellington (2015) mentioned that semi-structured interviews are flexible for researchers to inquire about research participants for further details. This study used semi-structured face-to-face qualitative in-depth interviews with 42 students. After establishing rapport with the interviewees, face-to-face interviews were conducted. The interviewees were encouraged to share their opinions and experience with the researcher after reassuring them about their guaranteed anonymity and confidentiality. When face to face interviews occurred, the researcher could make sure the interviewees understood by repeating the questions when needed. Face-to-face interviews were essential because they provide all sorts of other non-verbal cues and body language, which would otherwise be impossible to collect from the informants (Cavana et al. 2001).

The interview focused on understanding students' perceptions of using tools and the variables affecting their tool use. Through conducting interviews, where possible, twice during the course, we aimed to get rich data regarding students' choice to use or not to use tools and to change their tool use and the reasons behind that. We intended to determine students' strategies in their learning process to understand their limitations.

1.3.10.3 Role of the Researcher

There are some key considerations related to the role of the researcher for both qualitative and quantitative data collection and analysis.

The questionnaire was distributed through the LMS by the lecturer. The lecturer coded the data first to maintain the anonymity of the data. The researcher analysed the quantitative data. First, the researcher analysed the survey through an unsupervised clustering algorithm (K-Means),

and grouped students into three clusters, students from each cluster were invited for interviews. Then the researcher interviewed four students from each cluster, where possible. The interviewees were the first students from each cluster that replied to our interview invitation email. This process helped us randomly select participants for interviews with varying perspectives. We made sure that the clusters were significantly different from each other so that we interviewed students from different categories.

Kopala and Suzuki (1999) mentioned that the researcher should assume an empathic stance in the interaction with their participants and a neutral stance in the analysis of the data. The researcher actively participated in the interview events and co-constructed the interviews with the interviewees. When the interviewees discussed their feelings, the interviewers attentively participated in their stories by listening carefully to what the interviewees were airing and probing further to get more insights into the research questions. The role of the researcher was to ask questions and wait for an answer from the students. Sometimes the student could not explain their experiences of the tools. In that case, the researcher explained her own experience with other online tools she had used for her study so that the discussion could continue.

1.3.10.4Validity in Qualitative Research

Creswell and Miller (2000) identified validity in qualitative research by how accurately and credibly the phenomena under investigation are represented through the participant accounts. In what follows, we explain the design validity proposed by Venkatesh et al. (2013) for the rigour in the application of qualitative research methods.

We first checked the descriptive validity, the accuracy, or the credibility of the data we collected. We first audio-recorded all our interviews. A third party, identified by the university, was hired to transcribe all the recordings. We cross-checked the transcriptions against the audio recordings and ensured that all the recordings were accurately transcribed and ensured all the vocal changes in pitch identified in the interviews were reflected in the transcriptions. We also emailed back the transcriptions to the participant to do a member check, as suggested by Creswell and Creswell (2003) and Bigger (2005), before using them for analysis. Also, the supervisor consistently reviewed the analysis process by checking the qualitative codes and interim findings.

We also checked the credibility of our data. This determined the level of confidence in the acceptability and accuracy of our data and findings. We had interview data and questionnaire

data so that we could verify the consistency in our findings. We also explained how we chose the participants for our interviews.

We checked our result's transferability, which means to what extent it is possible to transfer the findings from our research (our method) to other research contexts, settings, and participants. We explained the context, the class environment, and the participants so that it was clear and usable for the reader.

1.3.10.5 Addressing Biases in the Study

In this section, the common method biases that we identified, controlled, or mitigated through procedural and statistical techniques are explained. When we identified the sources of common method biases, we could identify their impact on our study. We identified four sources including: a common source, item characteristics, item context, and measurement context and tried to mitigate them through procedural and statistical techniques explained next.

1.3.10.5.1 Procedural Remedies

To minimise the effect of common method bias for a common source, questions were separated for motivation and strategy use to understand the different sorts of questions. Also, an explanation was given to the students at the start of each section. Through this method, a time lag would be added between the two. The time lag was also minimised because we asked about the motivation and strategy use with just a quick description before each.

To address different sources of common method biases, we collected data (the predictors and dependent variables) from two different sources. In our case, we measured the motivation and strategy use through the survey. The dependent variable was the final score which was measured through students' participation, assignments, tests, and final exam from the LMS. In addition, we collected longitudinal data to look for whether students used the same pattern in their answers. It helped us to remove the effect of positively or negatively affected by the situation.

Through running the survey anonymously, the effect of socially desirable responses was minimised. We did not collect the demographic data to prevent students from acting rationally. The questionnaire was run anonymously so that students could feel comfortable answering truthfully.

The questions in the MSLQ are simple, used in different languages, and reliable. We chose to have a seven-point Likert scale to address measurement validity. Also, the labels for 'strongly

agree' and 'strongly disagree' have been written for each section so that students choose the correct feeling accordingly.

It is also possible that students chose not to read the whole question and they thought that there was a consistent pattern in the question design and based on the pattern students answered the questions. Cronbach alpha was the first point used to recognise the possibility of biases (Cronbach 1946; Cronbach 1950). To prevent students from just getting the effect of the context without reading the whole question, there were some reverse coded items.

We did not address the context and measurement even though Podsakoff et al. (2003) recommended counterbalancing questions to minimise the item and measurement context. We did not mix the questions for our study, as we thought it would confuse students, and we also thought students might retrieve inappropriate memories for questions. For addressing whether the source of biases was from the measurement context, we ran the questionnaire from the same LMS and did not set any specific time. Another factor is the medium used. We used a computer-based questionnaire to increase accuracy. They could answer the questions at their convenience and where they chose. We did not run the questionnaire multiple times in each iteration as we thought students would not be able to participate two to three times in the survey and answer 81 questions each time. We thought it would reduce the accuracy of their answers.

It was also important to have valid data. Studies such as Ioannidis (2005) mentioned that research does not have valid data when "the effect sizes are small; when there is a greater number and lesser preselection of tested relationships; where there is greater flexibility in designs, definitions, outcomes, and analytical models; when there is greater financial and other interest and prejudice; and when more teams are involved in a scientific field in chase of statistical significance" (Ioannidis 2005, p.1). To prevent this issue, we followed the effect size of 0.25 for G power calculations suggested by Mosteller (1995), which needs a total sample size of 164 students in a between-subject design. Also, we repeated our hypothesis testing with different independent teams. As a result of conducting the study with different samples, the effect of biases has been mitigated. However, our sampling group could be biased since they are from three classes from the same department.

For reducing biases, we used both qualitative and quantitative data, and we analysed them separately to see if the two sources of data support each other. While the interview is a technique for collecting detailed data, it can have biases as well. Myers and Newman (2007) included respondent and question bias, language ambiguity, and lack of trust as potential problems. The researcher being the interviewer herself, was a source of bias. The researcher also came from a

different background which would be another source of bias. The researcher is also the only one who would collect the data and analyse it. Therefore, the researcher tried to get advice from the supervisors when coding and analysing the data.

Choosing interviewees can be criticised, but we applied clustering to categorise students first and then tried to interviewed students from different categories. We also applied a one-way ANOVA to ensure that all variables in our clustering were statistically significantly different, and the three cluster groups were significantly different as well. This way, we can assure that we have participants for interviews from different spectrums. Having explained briefly about the procedural remedies we applied we now concentrate on statistical remedies explained in the following section.

1.3.10.5.2 Statistical Remedies

Through procedural remedies, we minimised the effect of common method biases. However, there are also statistical remedies to control method biases. Podsakoff et al. (2003) identified the single-common-method-factor approach as a remedy to control the effects of a directly measured latent method. The items would be loaded based on the way constructs were designed and a latent-common-method-variance-factor in this method. This would help us to identify whether there were common method variances. Other studies suggested using confirmatory factor analysis (CFA) to see if a single factor could account for the data's variances (Andersson and Bateman 1997; Aulakh and Gencturk 2000). The problem with the single factor test is that there is no statistical control for the method effect and the researcher cannot identify the cause of the method variance. There are also other kinds of statistical remedies suggested by Podsakoff et al. (2003) which need to be addressed when conducting the study. In this study, we ran a CFA and Cronbach Alpha analysis. CFA is a method used in recent years to test one factor's effects to account for all the data variance. CFA using maximum-likelihood estimation was also performed to check the factor structure.

We also ran the full collinearity variance inflation factors (VIFs) values to acknowledge the possibility of multicollinearity and common method bias in the model. Kock and Lynn (2012) suggested full collinearity VIFs examination for checking the common method biases. We checked VIFs through the Statistical Package for the Social Sciences (SPSS) to see if there was a correlation between the latent variables. We made VIF for each construct, each iteration, and each class. We needed to have a full collinearity VIF lower than 3.3. If it was lower than 3.3, then the model is free from common method bias. Different scholars set different thresholds for

VIF. For example, Hair et al. (2014) suggested a value higher than 10.0 for VIF. All the VIFs were less than 2, which shows we did not have collinearity among constructs.

We also made the correlation table. Because we did not have a high correlation among constructs, we did not need to delete any variables. With a cutting edge of 0.7, we did not have any high correlation between the constructs. Then, we made the regression based on all independent variables with course outcomes as a dependent variable.

1.3.10.6 Analysis Techniques

We analysed both qualitative and quantitative data. The following sections describe the different analytical techniques used in Papers 1 – 8 in this thesis.

1.3.10.6.1 Quantitative Data Analysis

We had to analyse the MSLQ questionnaire first. Therefore, we started the data analysis phase with the initial screening and cleaning of the questionnaire data. Over three rounds of surveying 419 students, a set of 1181 (419, 396, 366) viable surveys were collected.

First, we cleaned the data. Moreover, we needed to handle the missing data. For this reason, we needed to test if we had missing values at random or not. Therefore, we ran Little's Missing Completely at Random (MCAR) test for each iteration of each class (Li 2013). Our results showed that the 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. We replaced missing values with a maximum likelihood. We considered the rule of thumb by replacing less than 10 per cent of the data. Then, we prepared the data by checking the reliability and validity (Lawrence Neuman 2014).

The two-factor analysis tested our model's utility; one time for motivation and the second time for strategy use. We used SPSS and Analysis of Moment Structures (AMOS) to test the model and estimate the parameters using maximum likelihood. We also present the Cronbach Alpha and CFA for reliability testing of our model. We also provide predictive validity by presenting the correlation of the MSLQ scales with the final course outcome.

We looked at how the motivational and strategy use constructs and sub-constructs changed as the course progressed towards the end (descriptive analysis), and explored the relationship between students' motivation, strategy use, and the final score (correlation analysis). We also investigated the final score's predictability based on motivational and strategy use constructs

(predictive analysis). We further investigated different SRL profiles of students and observed how students adopted different SRL profiles as the course progressed (cluster analysis).

1.3.10.6.2 Qualitative Data Analysis

The 42 interviews, each around 30 minutes, were audio-recorded, transcribed, and analysed using thematic analysis (TA) (Braun and Clarke 2013). The qualitative data transcribed and entered into and analysed by NVivo computing software. NVivo helped us to use the computer for recording, sorting, matching, and linking. The software helped the researcher keep track of the interview data and ask complex or straightforward questions from the data and save them for further investigation (Bazeley and Jackson 2013).

We used the TA approach for analysing qualitative data (Braun and Clarke 2013). TA is a popular method of qualitative data analysis. The analysis starts with identifying patterns (themes) across a dataset. TA enables the researcher to see and make sense of the collective and shared meanings. TA does not propose a specific theoretical stance, data collection method, or epistemological and ontological framework which gives the researcher flexibility. In this case, the researcher can choose the appropriate data collection methods and theoretical framework which match their study. It also allows the researcher to identify the theme to answer the research questions.

The first step in TA is getting familiar with data. The researcher was immersing herself in the data. The interviews were transcribed with a third party. The researcher read the data and loaded it into NVivo. As the researcher read through the transcripts, she added annotations to the text. The second step in TA is initial coding. The researcher went through the data and generated codes to identify the featured data through NVivo. The coding process can be inductive or deductive. This study followed the inductive approach (the bottom-up approach). We looked at the content of data without forcing any preconceived ideas or codes. After that, the researcher looked at the identified codes in the data and tried to understand the relationship those codes have with the research question.

The third step was generating themes. The researcher looked for the broader pattern of meaning from the codes identified in the previous step. Therefore, a theme was generated from several codes. It was an iterative process to identify and merge the themes that emerged from the data. The fourth phase was reviewing the themes. In this stage, themes were reviewed to ensure that they were not repetitive and follow the story of the data. It is possible to refine the themes by splitting or deleting the emerging themes.

In the fifth phase, the themes were defined and named. The themes needed to be unique, and their focus and scope were required to be clear and the identified themes were required to address the research questions directly.

The last stage was about writing the report based on the narratives identified with the corresponding data extracts. The rigours of qualitative data were checked through the trustworthiness of the findings.

In this study, a multi-model approach was followed (Patton 2015), where the qualitative and quantitative data were analysed separately and then compared to increase the findings' credibility. In the next section, we explain the research scope and approach and how the study contributed to theory and practice.

1.4 Research Scope and Approach

This study focuses on LA, an interdisciplinary domain of educational psychology, statistics, and educational tools. It used students' data regarding their motivation and strategy use (educational psychology), regression and cluster analysis (statistics), and educational tools (students' perceptions regarding educational tool use) to inform LA. This study brings empirical evidence to LA (Ferguson and Clow 2017) with the focus on the students' condition (motivation, learning strategy use) identified in Winne's version of SRL (COPES model (Winne and Hadwin 1998)) and the level of agency students have (based on understanding students' perceptions regarding tool use). With the focus on LA, it informs the understanding of students' learning processes which enhances theory and practice. It checks the predictability of the final score based on students' motivation and strategy use (identifying at-risk students which is an aim of LA). It identifies different SRL profiles of students and checks how students unfold their SRL profiles as the course progress (contribution to SRL literature). It also investigated students' perceptions regarding tool use at the tertiary level, which helps practice. In this study, we focus on LA mostly at the micro-, macro-, and meso-level as we focus on understanding and supporting the SRL processes of students. This information helps instructional designers and course facilitators to get insights. By running three studies based on learning theories, we added empirical evidence based on theories to LA and again contributed to LA by running motivational studies, which are still lacking in LA (Ferguson and Clow 2017). The results of our study include but not limited to:

1) The thesis contributes to LA's theoretical foundation by linking LA with SRL and AT.

2) Through choosing motivation and strategy use, the study addressed the gap in motivational research in LA (i.e. Lonn et al. 2015; Wong et al. 2019b).

3) Predictive analysis – We checked the predictability of students' final scores for the freshmen and upper-level students based on motivation and strategy use constructs (contribution to one of the most important aims of LA, identifying at-risk students and then interventions can be applied early to help students (Aldowah et al. 2019)).

4) Correlation analysis – Identifying constructs that have the highest correlation with the final score. The lecturer can teach those important strategies to students and encourage them to improve those motivational factors.

5) Through clustering students based on theory (i.e. Lerche and Kiel 2018; Rosé et al. 2019) and looking at their movement among clusters, we contributed to the SRL literature and the challenge identified by Järvelä et al. (2019) regarding the cyclical nature of SRL.

6) Optimising the learning path – Identifying SRL profiles of students longitudinally means the lecturer can help students adopt a better path, consequently preventing dropouts and increasing the success rate.

7) Perception analysis – Informs LA about students' experiences regarding using tools, which all add empirical evidence for LA.

- Contributing to AT by identifying contradictors in students' perceptions regarding using educational tools in their classes for their learning processes.
- Contributing to SRL when we analysed students' perceptions regarding how each tool supported a specific stage of SRL and helped to open Winne's black box (Winne 1982).

8) Summative – We understand students' learning habits through clustering and analysing learning outcomes through understanding motivation and strategy use. We identified different SRL profiles of students; we understood how students changed their SRL profile as the course progressed. We understood how different groups of students (different SRL profiles) were affected by the test and assignment results and how they consequently changed their profiles.

At the micro-level – by identifying at-risk students, the lecturer can help students by applying interventions to prevent students from dropping out (helping students receive support to adopt a better profile).

At the macro-level – through applying appropriate and timely interventions, the study helped students because fewer students would drop out, which is good for a university's reputation.

At the meso-level – the instructional designer can get insights from students and adjust learning design and course materials to the learners' needs.

In the next section, the structure of the thesis will be given.

In the light of COVID-19 pandemic, the contributions and implications of this thesis have more significant impact and their usage in this context may accelerate the successful move to blended learning.

1.5 Structure of the Thesis

This section will give an overview of the thesis structure and the papers generated from the study. The thesis is based on publications. The details of the chapters and the list of papers in each chapter are shown in Figure 6. The thesis includes five chapters.

Chapter 1 – presented the purpose of this study by describing the study's motivation, research gap, research questions, theoretical foundations of the thesis, and methodology for collecting and analysing data. We also gave an overview of the contributions and thesis structure.

Chapter 2 – This chapter investigates the relationship between students' motivation and strategy use with the final scores. The first paper, published in The International Conference on Information Systems (ICIS), starts by giving the three classes of data descriptive analysis then testing the utility and reliability of our model through the Cronbach Alpha and CFA. We also provide predictive validity by presenting the correlations of the MSLQ scales with the final scores. Paper 2 used freshmen's motivational and strategy use data to investigate the dynamics of motivation and strategy use for this group. Then it investigated the predictability of the final score based on the freshmen's motivation and strategy use data. Paper 3 used upper-level students' data and repeated the same analysis that we did in Paper 2 for upper-level students and compared them together.

Chapter 3 – Paper 4 used freshmen data and investigated students' distinct SRL profiles and how different SRL profiles unfold as the courses progressed. Paper 5 used upper-level students' data and did the same analysis we did for the freshmen students and compared the results for the two groups.

Chapter 4 – Paper 6 used the students' interview data and applied AT to interpret the students' perceptions regarding tool use in their classes. We identified the contradictors in students and their lecturer's perceptions regarding using educational tools through using AT. Paper 7, continued using AT to investigate students' perceptions and digs further to identify more contradictors in our BL environment. It became the introduction to the third paper for using SRL for interpreting data. Paper 8, which has been published in The Pacific Asia Conference on Information Systems (Pacis), used students' perception data and analysed it through the SRL lens.

Chapter 5 – This chapter presents the quantitative and qualitative study findings to answer the main research question. We gave an overview of the findings of each study presented in the thesis, their limitations, and then gave the path for future research.

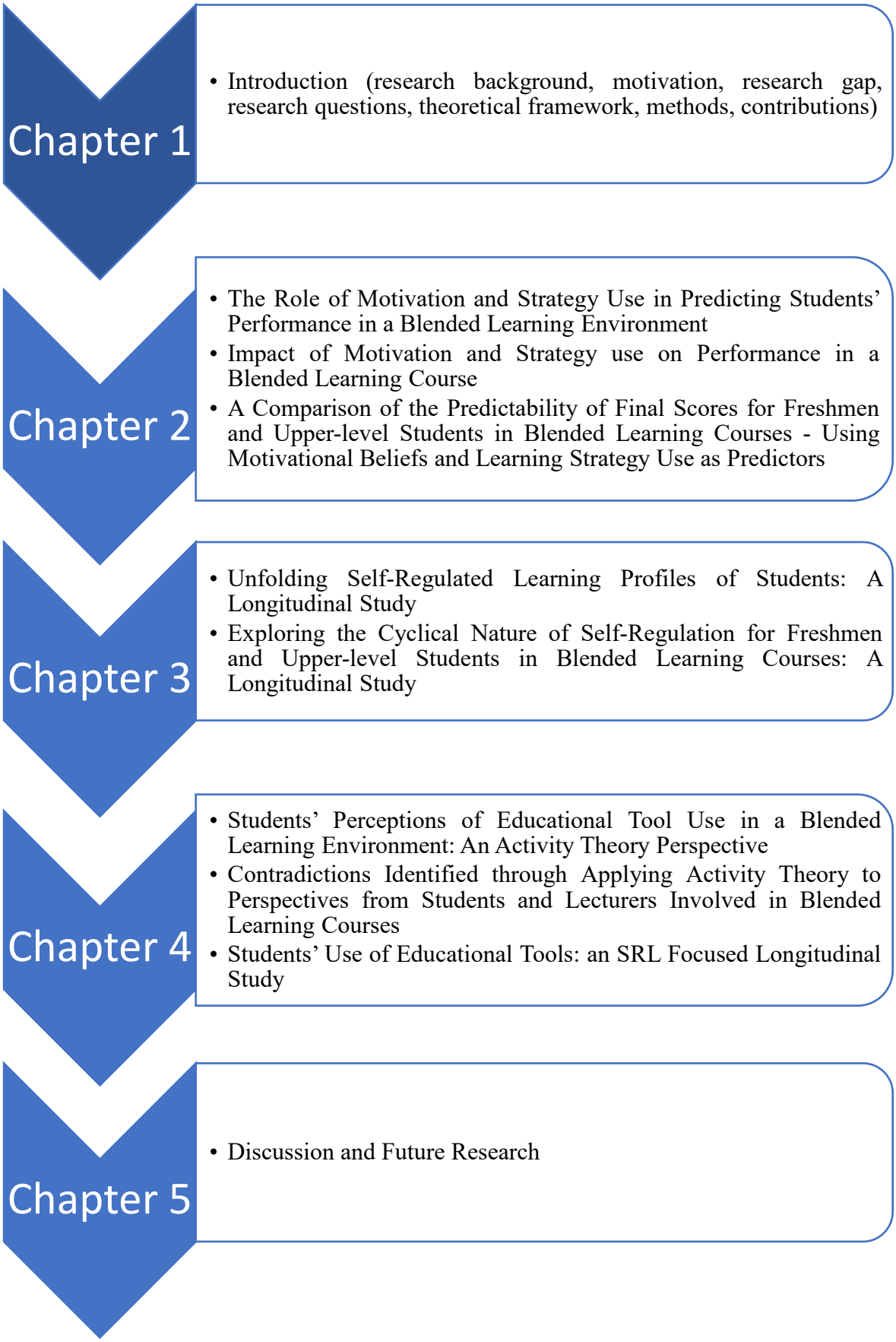

Figure 6: Structure of the thesis

Chapter 2

CHAPTER 2

2 Chapter 2 - QUANTITATIVE ANALYSIS - PREDICTIVE ANALYSIS

This chapter focuses on students' self-reported motivation and strategy use data gathered by administrating the MSLQ three times. Three papers address the first research question. The first paper, published in the ICIS, focuses on the dynamics of students' motivational and strategy use from three undergraduate courses. We checked the internal consistency, reliability, and predictive analysis in this paper and identified the constructs that had the highest correlations with the final score. In the second paper, we used freshmen students' data and looked at the dynamics of students' reported motivation and strategy use and their relationship with the final scores. We also tried to predict students' final scores based on their level of motivation and strategy use. In the third paper, we repeated the analysis used in the second paper for the upper-level students and compared the results between the freshmen and upper-level students.

2.1 The Role of Motivation and Strategy Use in Predicting Students' Performance in a Blended Learning Environment

(International Conference on Information Systems (ICIS)- published)

2.1.1 Abstract

Emerging educational technologies have changed the form of face to face classes and given greater flexibility to learning. Some university classes have adopted a fully virtual or blended format which has consequently changed students' and lecturers' responsibilities. The benefit of Blended Learning (BL) depends on how students adapt educational technologies in their learning. Previous studies show that adapting tools in BL environments depends on different factors including students' motivation. This study examined how students' motivation and strategy use changed as the course progressed and impacted final score. This paper reports on the findings of three iterations of a longitudinal survey administered in a degree program cohort. This study found that motivational and strategy use constructs varied significantly as the course progressed, increasing and decreasing at different sampling points, our analysis highlights evidence of predictors of final course performance.

Keywords: Students' motivation, students' strategy use, MSLQ, Students' final score

2.1.2 Introduction

Technology is now involved in every aspect of our life, and education is not an exception. Some universities have adopted a fully online course or a blended format. BL combines the benefit of using online technologies as well as face to face teaching for a richer experience (Garrison and

Kanuka 2004; Van Doorn and Van Doorn 2014). Besides, it has more flexibility for students. However, in BL, there is more responsibility for students to get autonomy over their learning (Vaughan 2007).

The ultimate goal for teaching is to produce lifelong learners (Candy et al. 1994) who can self-regulate their learning (Siemens et al. 2015). Educators and psychologists have always emphasised the importance of self-regulation and motivation in students' achievement (Pintrich and Schrauben 1992; Zimmerman 2013b). Even though there are different versions of self-regulation learning in the literature, they all agree that this would be a students' ability in monitoring and regulating own learning through a range of cognitive and metacognitive strategies (Pintrich 2004; Winne and Perry 2000; Zimmerman 2001).

Motivation determines whether students would put effort into the process of self-regulating in their study. Pintrich (1995) stated that self-regulated learners need to control their behaviour, context, motivation/affect, and cognition. Controlling behaviour for students involves taking active control of the resources which have been available to them such as their time, their study environment, and peers' and faculty members' support to get help from them. Controlling and changing motivational beliefs for students involves efficacy and goal orientation. To improve their learning, students learn how to control their emotions and affect (e.g. anxiety). Self-regulation of cognition for students includes getting control of various cognitive strategies. Strategies for students include using deep processing strategies to learn and perform better. The context for students starts by understanding the perception of task and context and monitoring it to see if changes are applied or need to be applied to them. For this reason, they need to evaluate their task and context regularly (Pintrich 2004).

It is not easy for all students, but students need to take responsibility and control of their learning. Knowing cognitive and metacognitive strategies is not enough for students' achievement. Students need to be motivated to use the strategies and also regulate their learning. Even though different factors can affect motivation, individual motivation is not neglectable (Ames and Archer 1988). Lynch and Dembo (2004) stated that a critical component is a motivation for learning. Pintrich (2003) studied the link between mastery goals to positive outcomes, and performance goals to adaptive ones. Studies also showed that highly motivated students exhibited self-regulation and achieved well academically (Linnenbrink and Pintrich 2002a; Pintrich and Schunk 2002). Other studies showed that a lack of persistence in online environments was associated with a low level of motivation (Hart 2012; Vanthournout et al. 2012).

Even though the importance of motivation has been emphasised in the literature (Boekaerts 1999; Schunk 2008; Zimmerman 2002), little is known about the changes in the motivational level of students in BL as the course progresses. Therefore, in this study we examined how students' motivation and strategy use changed as the course progressed and impacted final score. We do not know about students' motivation when they join the course and how different their motivation is when they finish their course. We investigated motivation as a dynamic state. For that reason, each student who enters the environment with a specific level of motivation is likely to experience a change in his/her level of motivation as the course progresses although we do not know how that changes will evolve. We also know that there would be different factors along the way, which could affect students' motivation as well, but we do not have control over them. Our qualitative study showed that students displayed differences in self-controlling and self-regulating their learning when it came to the BL environment. We identified students who stacked up the material for the final and students who could manage their study on time. These students were different in terms of their motivational level.

Two frameworks that use different self-reports for measuring students' motivation are student approaches to learning (SAL) and self-regulated learning (SRL). The SAL framework theorises learning as a composition of motives and strategies. SAL describes deep (meaningful learning) and surface (rote learning) approaches to learning (Entwistle and Ramsden 2015). The SRL framework is categorised by specific cognitive, motivational, and behavioural constructs (Zimmerman 2008). SRL regards learning as a process. The Motivated Strategies for Learning Questionnaire (MSLQ) (Pintrich et al. 1993b) and the Learning and Study Strategies Inventory (LASSI) (Weinstein and Palmer 1987) are two mostly used questionnaires developed under SRL framework for measuring motivation and strategy use. We used the Motivated Strategies for Learning Questionnaire (MSLQ), which was invented by Pintrich et al. (1993b). We follow Pintrich motivational model (Pintrich 2004), which is explained in the next section. After that, we give an overview of the methods on how we collect data and then an overview of the analysis. Finally, we present our conclusion.

2.1.3 Theory

While there are different motivational models related to students' learning, we follow Pintrich's social-cognitive perspective that regards motivation as a composite of constructs (Pintrich 2003; Pintrich and Schunk 2002). These constructs are distinct but interacting with each other. Figure 7 represents the concept map of the constructs and their relationships. From Pintrich's

point of view, motivation is a dynamic state that an individual brings to the class, which can change over time.

Pintrich et al. (1993b) developed the MSLQ questionnaire to measure motivation, cognitive and metacognitive strategies, and resource management through 31 items in the motivation section and 50 items in the learning strategies section. MSLQ is an instrument to measure the motivational orientations and different learning strategies that students use. MSLQ follows a cognitive perspective when students' beliefs and cognition are the instructional input for being an active processor of information in class. MSLQ is based on the following general motivational and learning strategies constructs.

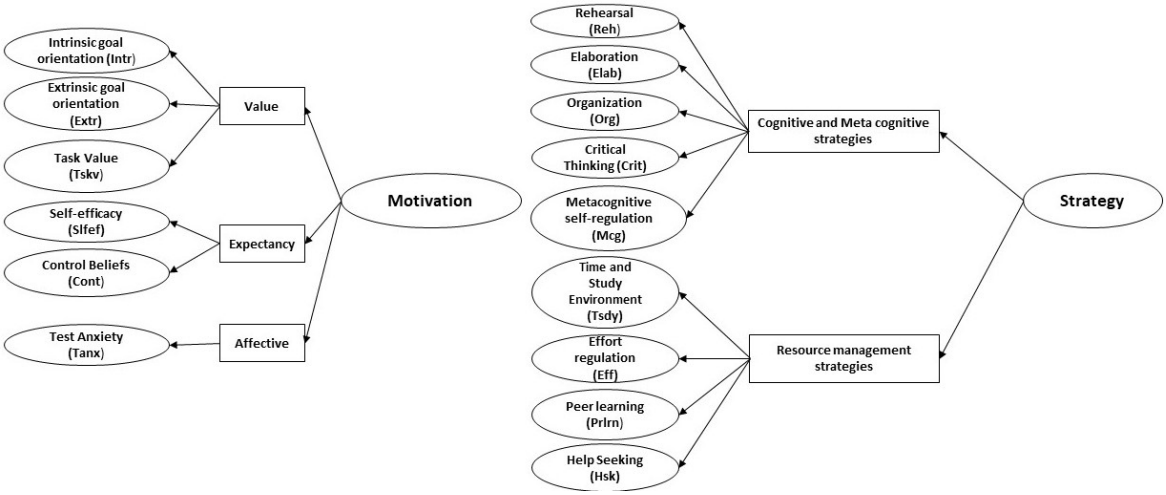

Figure 7: MSLQ concept map

2.1.3.1 Motivation

The section below discusses value, expectancy, and affect components which are categorised under general motivational constructs.

2.1.3.1.1 Value Components

The value component is about why students engage in the activity. There are three subscales for 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. Studies such as (Gibson 1998; Schrum and Hong 2002) stated that taking control over learning goals, methods, and evaluation strategies are important for good achievements. Task value beliefs defined by Wigfield and Eccles (1992) as students' perceptions of the interest,

usefulness, importance, and cost of a task. Most studies which examined value beliefs used expectancy-value theory (Wigfield and Eccles 1992). They examined the reasons why students believed the task was important for them. Pintrich et al. (1990) stated that students who had a high value for the task used deeper cognitive and metacognitive strategies.

2.1.3.1.2 Expectancy Components

This component refers to the beliefs of students, whether or not they can accomplish the task. There are two subscales for expectancy components (i.e. the perception of self-efficacy and control beliefs for learning). Self-efficacy has been defined by Bandura as the judgments of individuals about their abilities to plan and carry out the behaviours they need to display to achieve their goals (Bandura 1977). Linnenbrink and Pintrich (2002b) stated that adaptive self-efficacy beliefs could enable academic success. Pintrich et al. (1993b) defined control belief as students' beliefs whose efforts to learn will result in positive outcomes. Iskender (2009) examined the relationship between control beliefs and learning. And, in their correlation analysis, they found that self-kindness correlated positively with self-efficacy and control belief for learning; self-judgment had a negative correlation with self-efficacy.

2.1.3.1.3 Affective Components

Test anxiety has always been an important predictor for students' performance (Huang 2011). It measures the students' worries and concerns at the time of the exam. Daniels et al. (2009) ran a predictive study to estimate relationships from affective experiences to mastery and performance-approach goals. They showed that anxiety was negatively correlated with mastery goals. They also found that it was positively predicted by performance goals and exerted a negative predictive influence on achievement.

2.1.3.2 Learning Strategies

Three components of strategy use are cognitive, metacognitive, and resource management. Cognitive strategy use concerns students using basic and complex strategies for information processing. The second component is metacognitive control strategies which refer to the strategy that students use to control and regulate their cognition. The third component is resource management which refers to the resources that students use beside cognitive and metacognitive ones. Richardson et al. (2012) contended that students who employ SRL

strategies impacted their performance. Broadbent and Poon (2015) studied the relationship between SRL strategies and academic achievement. They found that strategies of time management, metacognition, effort regulation, and critical thinking were positively correlated with academic outcomes. However, rehearsal, elaboration, and organisation had the least empirical support.

2.1.3.2.1 Cognitive and Metacognitive Self-Regulation

Cognitive strategies are about the use of basic and complex strategies for processing information that includes1) 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 in surface-level strategies. Critical thinking, organisation, and elaboration (i.e. linking course material to previous knowledge and other situations) are considered to be deep processing strategies. Effeney et al. (2013) referred to rehearsal as a repetition so that the learner can remember the materials. Puzziferro (2008) found a weak positive significant relationship between rehearsal and achievement. However, Klingsieck et al. (2012) did not find a significant relationship between the two. Richardson et al. (2012) referred to elaboration as the ability to connect the new and existing material so that the learner can remember the new material. Puzziferro (2008) found a weak positive significant relationship between elaboration and achievement. However, Klingsieck et al. (2012) did not find any significant association between elaboration and achievement.

Effeney et al. (2013) referred to the organisation as the ability of the learner to highlight the main points when they were studying. Puzziferro (2008) found a weak positive significant relationship between organisation and academic performance. However, Klingsieck et al. (2012) did not find a significant relationship between organisation on academic performance. Richardson et al. (2012) referred to critical thinking as the ability to carefully examine learning materials. Puzziferro (2008) found a weak positive significant relationship between critical thinking and academic performance. However, Wang and Wu (2008) did not find a significant relationship between critical thinking and academic performance.

Metacognitive strategies measuring how students control and regulate their own cognition. There are three subscales for this stage: A) planning, B) monitoring, and C) regulating. Planing 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 to understand the material and connect it with prior knowledge. Regulation refers

to one's ability to fine tuning and adjustment of cognitive activities. Flavell (1979) defined metacognition as the awareness and control of thoughts. Carson (2011) studied the effect of metacognitive strategies on online academic outcomes and found a significant positive relationship between the two. However, Klingsieck et al. (2012) found a non-significant relationship between the two.

2.1.3.2.2 Resource Management Strategies

The resource management component includes four subscales that control the 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 affecting students learning (Kearsley 2000). Effeney et al. (2013) refer to time management as the ability to plan study time and tasks. Zimmerman and Risemberg (1997) stated that students who use their time efficiently are more likely to achieve better at the end. Self-regulated learners know how to manage their time by considering deadlines to achieve better. Zimmerman also discussed other characteristics of self-regulated learners, those who were able to choose the environment that worked better for them. ChanLin (2012) found a significant positive relationship between time management and final score. However, Klingsieck et al. (2012) did not find a significant relationship. With regard to effort regulation, Bandura et al. (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. Carson (2011) found a significant positive relationship between effort regulation and academic grades. However, ChanLin (2012) did not find a significant relationship between the two.

Effeney et al. (2013) described peer learning as collaborating with other peers to help the learning process. Michinov et al. (2011) found a significant positive relationship between peer learning and academic achievement. 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. Wang and Newlin (2002) discussed the importance of help-seeking in learning. Puzziferro (2008) studied the relationship between help-seeking strategies and achievement and found a weak significant association between the two.

2.1.4 Method

This study is part of a larger mixed-method study. Our focus for this paper is quantitative although we will allude to qualitative from time to time. We looked at students' motivation and strategy use of 419 students in the first round, 396 students in the second round, and 366 students in the third round from three business school's courses in a high-ranking university in New Zealand during the 2018 and 2019. The course lecturer has used online educational tools for the last five years and had a positive attitude towards technology. This was a BL course that was run for 12 weeks. BL has been defined as a mix of online and off-line learning activities. There is a choice between traditional and new media and they can be replaced with each other (Thorne 2003a). With the goal of producing self-regulated learners, this method of teaching was employed which included teachers, traditional classroom, and online learning methods (Sharma and Barrett 2008). The courses were designed based on BL methodology. 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. Prior to each review session, the lecturer analysed the embedded quiz results and determined which course material had proven most challenging. For the review session students had two options of attending the course in person or watching the video streaming of the class from their most convenient place. 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. The questions were a mix of multiple-choice, true/false and fill-in-the-blank types. 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 were 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 candy as a prize. Students were also incentivised to watch each week's

online lectures and participated in the weekly in-class tutorial by means of awarding participation marks. Final students' score has also been collected through Canvas and was a combination of three assignments, midterm and final exam. For the assignment they had options of doing the project individually or in a group. The core material was available on the course web page, and review sessions were conducted for discussion purposes. The students were required to watch all the videos and participate in the quizzes at the end of videos before coming to the review sessions. The students had access to Piazza (i.e. the students' forum) in case they needed to clarify anything among themselves or with their lecturer.

Iteration= I	**Class size**	**I 1**	**Percentage**	**I 2**	**Percentage**	**I 3**	**Percentage**
Class1	228	194	85.09%	180	78.95%	162	71.05%
Class2	127	105	82.68%	103	81.10%	94	74.01%
Class3	128	120	93.75%	113	88.28%	110	85.94%

Table 4: The approximate number of students in each class

In order to understand student motivation, we used the Motivated Strategies for Learning Questionnaire (MSLQ). Using the University LMS, we ran MSLQ questionnaire, three times in Week 3, Week 7, and Week 11 of a 12 week semester. Table 4 shows the approximate number of students in each class, the number of survey invitations we sent to potential respondents, the actual collected data, and the respondent rate.

The utility of our model was tested by two-factor analysis; firstly for motivation and secondly for strategy use. We used SPSS and AMOS to test the model and estimate the parameters. We used maximum likelihood to estimate the parameters in AMOS. Cronbach's alpha was used to check internal consistency to understand the reliability of each construct. Confirmatory factor analysis (CFA) was used to see if a single factor could account for the variances in the data (Andersson and Bateman 1997; Aulakh and Gencturk 2000). Through CFA we estimated the parameters and check the model. Then, we looked at the descriptive statistics for three iterations of MSLQs to see how constructs and sub constructs changed. We applied t-tests on each iteration of MSLQ to understand if there were significant differences between each iteration. We also looked at the correlation between the constructs and final scores for three different iterations of MSLQ to identify the constructs which have an effect on final score. In the next section, we discuss our analysis and results.

2.1.5 Results

Over three rounds of surveying of a population of 483 people, a set of 1181 (419, 396, 366) viable surveys were collected. First, we prepared the data by checking the reliability and validity of it (Lawrence Neuman 2014). Then we cleaned the data. Moreover, we needed to handle the missing data. For this reason, we needed to test if we had missing values at random or not. Therefore, we ran 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 the missing data, for example, listwise deletion, pairwise deletion, mean imputation, and regression imputation. We replaced missing values with maximum likelihood. We considered the rule of thumb by preplacing less than 10 percent of the data. Here we present Cronbach Alfa and confirmatory factor analysis for reliability testing of our model. We also provide predictive validity by presenting the correlations of the MSLQ scales with final score.

2.1.5.1 Internal Consistency and Reliability Analysis

The adopted level of acceptance for Cronbach's alpha was 0.7 (Hair et al. 2014). The Cronbach alpha values calculated for all the factors of the scale and were between 0.54 and 0.87. Confirmatory factor analysis (CFA) was used to see if a single factor could account for the variances in the data (Andersson and Bateman 1997; Aulakh and Gencturk 2000). In CFA, correlated errors may be treated as part of the model being tested (Pedhazur 1991; Pedhazur and Schmelkin 2013).

Descriptive statistics for three administered iterations of MSLQ questionnaire are presented in Table 5. Students, on average, gave higher scores to motivational constructs compared to strategy use. In line with the study run by Zusho et al. (2003) self-efficacy of students dropped as the course progressed. However, in contrast with their study, intrinsic and extrinsic goal orientation, task value, and anxiety dropped for the second round and increased for the third iteration. In contrast to the study run by Zusho et al. (2003), our students' use of rehearsal and elaboration increased in line with their study, organisation and metacognitive strategy use increased. Three factors that got minimum scores by students in all three iterations were critical thinking, peer learning, and help-seeking.

Constructs	Sub Constructs	Iteration 1		Iteration 2		Iteration 3		
		M	SD	M	SD	M	SD	Cronbach's α
Value	Intrinsic Goal Orientation (Intr)	4.47	.72	4.38	.80	4.40	.83	.64
	Extrinsic Goal Orientation (Extr)	4.88	.79	4.61	1.12	4.62	1.10	.63
	Task Value (Tskv)	4.78	.83	4.64	.94	4.69	.94	.78
Expectancy	Control of Learning Beliefs (Cont)	4.58	.83	4.60	.93	4.53	1.03	.57
	Self-Efficacy for Learning Performance (Slfef)	4.69	.72	4.59	.84	4.60	.86	.87
Affective	Test Anxiety (Tanx)	4.32	.89	4.31	.94	4.36	.95	.69
Cognitive and metacognitive strategies	Rehearsal (Reh)	4.30	.86	4.40	.84	4.55	.93	.62
	Elaboration (Elab)	4.46	.76	4.48	.84	4.49	.90	.74
	Organization (Org)	4.63	.79	4.54	.89	4.54	1.00	.54
	Critical Thinking (Crit)	3.87	.94	3.87	.94	3.92	.99	.78
	Metacognitive Self- Regulation (Mcg)	4.22	.59	4.27	.64	4.33	.61	.73
Resource management strategies	Time Study Environmental Management (Tsdy)	4.71	.66	4.57	.77	4.54	.74	.60
	Effort Regulation (Eff)	4.57	.86	4.46	.94	4.40	.93	.62
	Peer Learning (Prlrn)	3.86	1.1	3.70	1.28	3.81	1.34	.64
	Help Seeking (Hsk)	3.73	.95	3.63	1.15	3.68	1.17	.59

Table 5: Descriptive statistics for three rounds of MSLQ

Peer learning and help-seeking had a high standard deviation (SD) in iteration 1, iteration 2, and iteration 3 compared to other constructs. Their SD also increased as the course progressed. Critical thinking did not have a high standard deviation, but it increased for both iterations 2 and 3. We observed the same thing in our qualitative study that students believed that there was no community for them to connect with. Even though the lecturer introduced the online community to the students since students did not know other peers, they could not trust other peers in class, and that is why they did not get help from them. They also believed that critical thinking was not needed for the course as they had to just listen to the videos and take part in the quizzes at the end of each video. They mostly used rehearsal, elaboration, organisation, and metacognitive strategies.

Extrinsic goal orientation in iteration 2 and iteration 3 had high standard deviation, and it increased as the course progressed. It provided evidence of having more differences among students' ideas in regard to external motivation's effect. The organisation was the same; it had a SD of 1 in iteration 3 and the organisation's SD increased as the course progressed. When we look at the correlation of these constructs we identified in this section such as critical thinking, peer learning, and help-seeking with final score; we observed that they had a very low correlation with final score. SRL theories emphasised that whenever students used more self-regulatory strategies, they performed better at the end. It would be necessary to check with other studies as well. It is possible that some of the strategies that proved to be helpful for physical face to face classroom would not be helpful for online classes.

After considering the changes that happened through each iteration, we needed to see if constructs' changes were significant among different iterations. Firstly, we ran a t-test for all the constructs between iteration 1 and iteration 3. Constructs include control beliefs about learning, test anxiety, elaboration, critical thinking, peer learning, and help seeking have t value lower than what we expected and also did not significantly change between iterations.

These constructs also indicated low correlations with final scores in the next phase of our analysis. We also looked to see if a 95% confidence interval crossed 0.0. The same constructs that we identified that did not significantly change were identified based on these criteria too. Having a negative t value shows that the number in the second group was higher than the first group. Test anxiety, elaboration, and critical thinking increased at the end of the course compared to the beginning of the course in contrast to other constructs which decreased as the course progressed towards the end. Learning new strategies was what we expected students to do as the course progressed. Anxiety is a construct that measures students' thinking about how they will perform on the test. We expected this construct, which is about students' anxiety, to increase as it got closer to the final exam. The P values needed to be less than .05, but some constructs had a P-value larger than .05. Therefore, we reported that students had significant changes in intrinsic goal orientation 1, extrinsic goal orientation 1, self-efficacy for learning and performance, rehearsal, metacognitive self-regulation, Time, and Study Environment, and effort regulation. As expected, the students' motivational component and deep learning strategies increased significantly. We see in the next section that these constructs have high correlations with final scores. All the motivational construct except anxiety in iteration 3 was lower than the beginning. This is consistent with other studies (e.g. Zusho et al. 2003) that

motivation decreased as the course progressed, but anxiety increased as the course got closer to the final exam.

We then, investigated whether changes in constructs between interactions 1 and 2 were significant. Constructs that significantly changed included intrinsic goal orientation, extrinsic goal orientation, task value, self-efficacy for learning and performance, time and study environment, and effort regulation. They are motivational and deep learning strategies constructs. Thus, we understand that the same constructs have significantly changed among the three iterations. In terms of anxiety, as we expected, we observed that students' stress increased as they got even to the midterm. Motivational constructs such as intrinsic goal orientation, extrinsic goal orientation, task value, self-efficacy for learning and performance, and even test anxiety decreased in the second round. However, the changes in intrinsic goal orientation, extrinsic goal orientation, task value, and self-efficacy for learning and performance were significant. While control beliefs about learning and test anxiety decreased, they were not significant. Strategy use constructs all decreased in the second iteration except rehearsal, elaboration, and metacognitive self-regulation but not significant. However, time and study environment and effort regulation were significantly decreased. In the next phase of our analysis, we noted a high correlation between the second iteration' constructs such as extrinsic goal orientation, task value, self-efficacy for learning and performance, organisation, metacognitive self-regulation, time and study environment, effort regulation, and peer learning with final score.

After that, we investigated whether these construct's changes between interactions 2 and 3 were significant. Some constructs that have significantly changed include rehearsal, time and study environment, and effort regulation. What we understood was that changes between iterations 2 and 3 were not significant. Whatever changes happened, they were mostly between iterations 1 and 2.

2.1.5.2 Confirmatory Factor Analysis

In this section, we explored the confirmatory factor analysis of the motivational and learning strategy items to test the factor structure that shows the motivation and learning strategy Subscale. The results for the motivation subscale are presented in Figure 8 to see if the data supports our model.

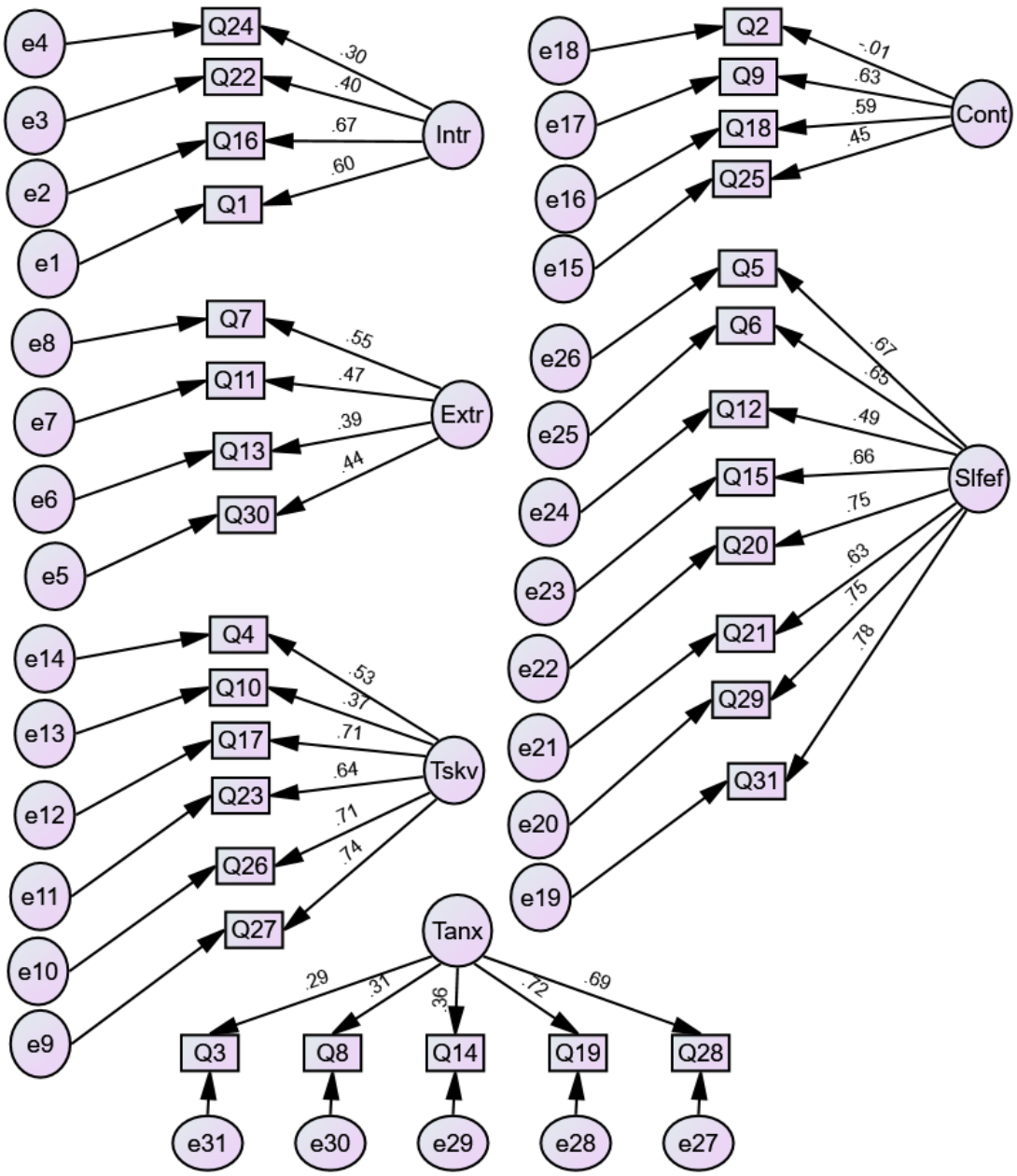

Figure 8: A model for motivation scales

We also provided the factor loadings for each subscale. The first indices we report is Chi-Square. Based on what was recommended by Kline (2015) for Root Mean Square Error of Approximation (RMSEA), we have rules of thumb. If RMSEA <= .05 then we have a close fit. If RMSEA <= .08, then we have an adequate fit. If RMSEA > 0.1, then we have a poor fit. Bentler (1990) recommended that if CFI values were close to 1, then it showed a very good fit. For the motivation section, we had CFI (Comparative Fit Index) =.84, RMSEA=0.05, factor loading between 0.3 and .78 and all the loadings were statistically significant.

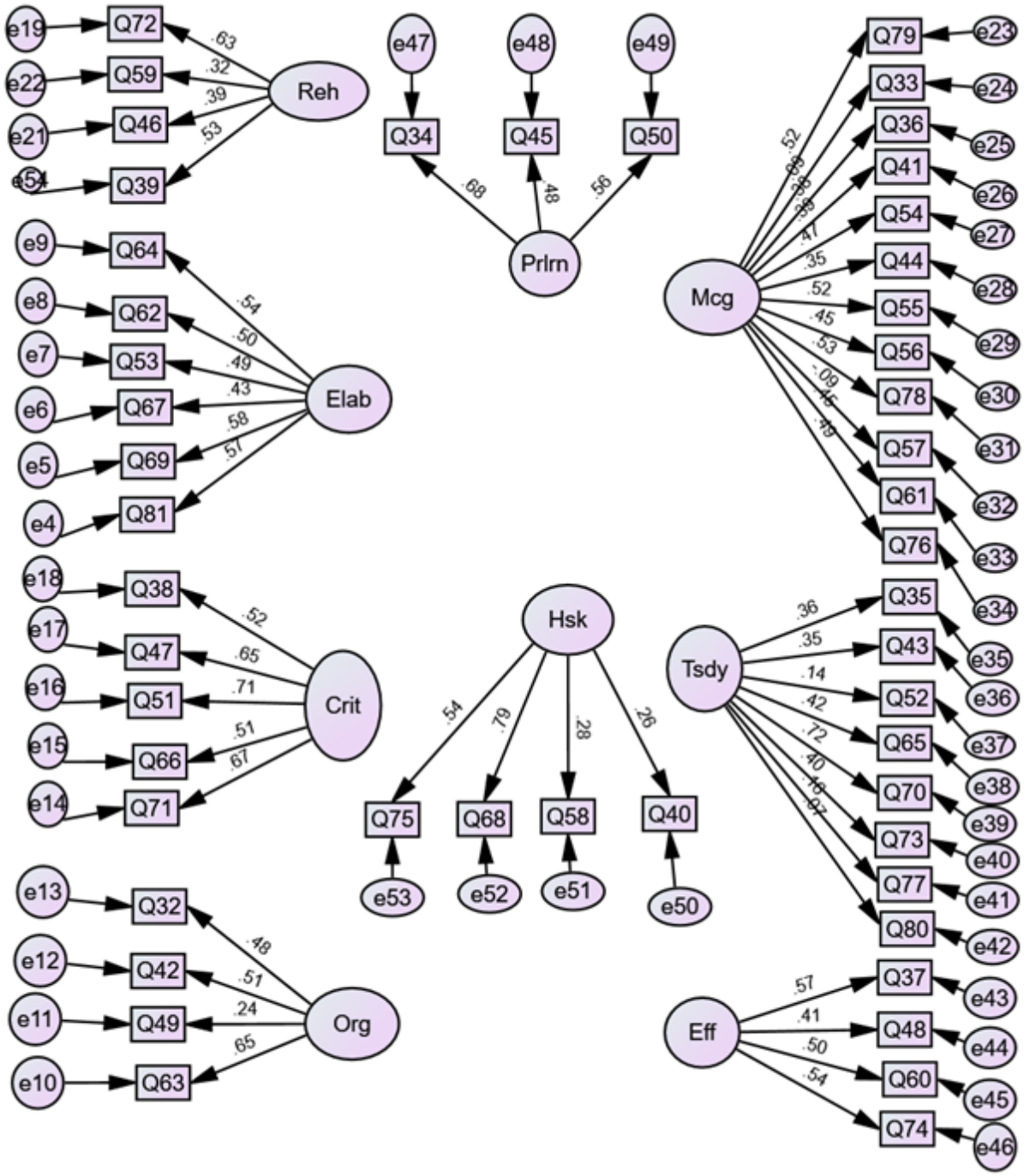

Figure 9: A model for strategy use scales

We also reported that minimum was achieved, Chi-square = 835.73, Degrees of freedom = 419, Probability level = .00. We deleted some items which had loading less than 0.4. After deleting the items with factor loading less than 0.4, then we had CFI=.89, RMSEA=0.05, Minimum was achieved, Chi-square = 865.31, Degrees of freedom = 419, Probability level = .000.

The result from the confirmatory factor analysis of the learning strategy items and all the subscales under that is shown in Figure 9. The factor loadings for each subscale were shown too. We had CFI=.66 and RMSEA=.05, and factor loadings were not very high. We deleted

some items which had loading less than 0.4. After deleting the items with factor loading less than 0.4, then we achieved better in CFI=.78 and RMSEA=.045.

2.1.5.3 Predictive Validity Analysis

In this section of our analysis, we present the correlation between the constructs and final scores for three different iterations of MSLQ. We also looked at how constructs were correlated with each other. Based on the study run by Pintrich and Schunk (2002), we expected that motivational components would have positive relations with performance, and anxiety would have negative relations with the final course grade. In terms of strategy use components, we expected rehearsal strategies to be negatively related to students' grades, and other strategy use such as organisation, elaboration, and self-regulatory strategies to be positively related to achievement. Zusho et al. (2003) showed that self-efficacy, task value, and mastery goals were positively related to the final course. However, anxiety was negatively related to the final grade. They also showed that rehearsal strategies were positively related to achievement. They also showed that students who had higher levels of self-efficacy, task value, and mastery goals used deeper-processing cognitive strategies such as elaboration and metacognition. In their study, in contrast with the literature, they showed that students with higher levels of self-efficacy, task value, and mastery goals also reported using rehearsal strategies.

2.1.5.3.1 Iteration 1

In Table 6, we present the correlation of the first iteration of MSLQ's constructs with final scores. Constructs such as intrinsic goal orientation, extrinsic goal orientation, self-efficacy for Learning and Performance, time and study environment, organisation, and effort regulation had significant correlations with final scores. These were the constructs that we showed in our previous phase of analysis that had significantly changed. Students who had high motivation and believed in their efficacy and successfully managed their time and study environment were able to manage their efforts by persisting on the difficult task which was performed better.

In motivational scale, the highest correlation was observed between self-efficacy for learning and performance and outcome followed by extrinsic goal orientation and effort regulation. Students who believed in the efficacy and wanted to achieve, for example, higher scores achieved better. Bandura (1977) stated that students who believed that they could complete a task, and they would have confidence in their abilities to perform better and also engaged more

in academic behaviours which affected learning. Contrary to what we expected; critical thinking had a negative relation with final score.

	Intr	Extr	Tskv	Cont	Slfef	Tanx	Reh	Ela	Org	Crit	Mcg	Tsdy	Eff	Prlrn	Hsk	Final
Intr	1	.21**	.48**	.11*	.47**	0.02	.17**	.42**	.25**	.38**	.36**	.24**	.24**	.17**	0.08	.11*
Extr		1	.32**	.16**	.27**	.18**	.15**	.20**	.14**	0.08	.12*	.20**	.14**	-0.03	0.01	.12*
Tskv			1	.22**	.47**	0.04	.17**	.41**	.30**	.29**	.33**	.22**	.31**	.13**	-0.01	0.08
Cont				1	.18**	0.03	0.05	.11*	0.10	0.03	0.08	0.03	.10*	0.05	0.02	0.01
Slfef					1	-0.01	.2**	.28**	.25**	.21**	.27**	.21**	.29**	.11*	0.03	.21**
Tanx						1	.16**	.14**	.14**	.14**	0.09	0.07	-0.05	.12*	0.04	0.04
Reh							1	.37**	.34**	.35**	.35**	.15**	0.03	.27**	.17**	0.06
Ela								1	.43**	.48**	.58**	.30**	.20**	.28**	.23**	0.04
Org									1	.24**	.37**	.21**	0.09	.23**	.12*	.12*
Crit										1	.44**	0.08	-0.04	.28**	.17**	-0.08
Mcg											1	.35**	.24**	.21**	.19**	0.09
Tsdy												1	.33**	-0.04	-0.06	.17**
Eff													1	-.126*	-0.099	.2**
Prlrn														1	.378**	0.02
Hsk															1	0.01
Final																1

Table 6: Pearson correlation coefficients between motivation and strategy use subscales' points in iteration 1

In iteration 1, time and study environment, effort regulation, and self-efficacy for learning and performance have high correlation with outcome and intrinsic goal orientation, extrinsic goal orientation, and organisation have medium correlation with outcome.

Besides the correlation of constructs with final score, the correlation among MSLQ scales was also important for us. All motivational scales such as intrinsic goal orientation, extrinsic goal orientation, task value, control beliefs about learning, self-efficacy for learning, and performance had positively correlated with each other. Test anxiety had a moderate correlation with intrinsic goal orientation, task value, and control beliefs about learning. As we expected, test anxiety had a negative correlation with self-efficacy. Students who had high self-efficacy and believed in their own ability to do the task felt less anxious. Test anxiety also had a high correlation with extrinsic goal orientation which showed when students had the extrinsic motivation to get good scores, they would face more anxiety. All cognitive and metacognitive strategy scales were positively correlated with each other. Time and study environment and effort regulation which belonged to deep strategy use had negative correlations with peer learning and Help seeking. This was what we expected to see. Those who effort regulate do not believe in learning from other peers. The value component which consists of (intrinsic goal orientation, extrinsic goal orientation, and task value) has a high correlation with all the cognitive, metacognitive, and resource management strategy use. Task value is correlated with deep-processing cognitive strategies. Intrinsic goal orientation has a high correlation with cognitive and metacognitive. It shows when students understand the value of the task; they use a variety of strategies to achieve their course. Task value has a high correlation with cognitive and metacognitive strategy use. Task value has a high correlation with final score as well. We also observed that when a student has a high self-efficacy, they still use a variety of strategies again except peer learning and help seeking. We also observed that self-efficacy had a high correlation with the use of deep-processing strategies. The only exceptions are peer learning and help seeking. This proved that in online learning these two constructs were not helpful in students' learning. All the motivational constructs had a very low correlation with help seeking. Students who were high in motivation did not seek help from others especially in an environment where they did not know anyone.

Cognitive and metacognitive strategy components such as rehearsal, elaboration, organisation, critical thinking, and metacognitive self-regulation had a high correlation with each other. Time and study environment and effort regulation which were deep strategy use had negative correlations with peer learning and help seeking. The students who used deep strategies did not

trust others and not get help from them. But time and study environment and effort regulation had high correlations with each other. On the other hand, peer learning and help seeking that did not have correlations with other constructs had a high correlation with each other. The students who believed in peer learning got help from other peers as well. The correlation between these two constructs (peer learning and help seeking) were very low with final score.

2.1.5.3.2 Iteration 2

We looked at the correlation of the second iteration of MSLQ and final score (Table 7). Pearson Correlation Coefficients between motivation and strategy use subscales' points are presented. We observed that the correlation of almost every construct and final score increased. Almost the same construct that had correlations in iteration 1, correlated iteration 2 and had a high correlation in iteration 3 as well. In iteration 2, extrinsic goal orientation, self-efficacy for Learning and Performance, organisation, metacognitive self-regulation, time and study environment, effort regulation, and peer learning have high correlation with outcome and intrinsic goal orientation and task value had medium correlation with final score.

In motivational sales, intrinsic goal orientation , extrinsic goal orientation, task value, and self-efficacy for learning and performance had high correlations with final scores. Bandura (1977) stated that students who believed that they could complete a task, and had confidence in their abilities to perform better, also engaged more effectively in academic behaviours which affected their learning. Bandura (1977) stated that students who had high task value believed in the importance of the task, and used a deeper level of cognitive processing and achieved higher performance. Dweck and Leggett (1988) had a different result and showed that students who adopted a performance goal, or the goal to validate one's competence about others, harmed their performance.

In terms of correlation of constructs with each other, motivational constructs such as intrinsic goal orientation, extrinsic goal orientation, task value, control beliefs about learning, and self-efficacy for learning and performance had a high correlation with each other. Cognitive and metacognitive strategies such as rehearsal, elaboration, organisation, critical thinking, and metacognitive self-regulation also had high correlations with each other. Also, cognitive and metacognitive strategy use had high correlations with each other. Peer learning and help seeking had high correlations with each other too. As we expected, students who had high effort regulation would not trust peer learning, and students who had high motivation used a variety of cognitive and metacognitive strategy use.

	Intr	Extr	Tskv	Cont	Slfef	Tanx	Reh	Ela	Org	Crit	Mcg	Tsdy	Eff	Prlrn	Hsk	Final
Intr	1	0.08	.36**	.11*	.49**	0.04	.25**	.35**	.18**	.40**	.37**	.24**	.19**	.12*	0.10	.10*
Extr		1	.29**	.18**	.29**	.18**	.16**	.17**	.21**	0.10	.19**	.14**	.14**	.18**	0.07	.27**
Tskv			1	.22**	.36**	0.05	.18**	.27**	.34**	.20**	.23**	.20**	.14**	.16**	.13*	.12*
Cont				1	.23**	0.08	0.05	.15**	.15**	.13*	0.09	0.08	-0.01	0.07	0.05	.06
Slfef					1	-0.08	.20**	.26**	.15**	.22**	.31**	.23**	.32**	0.10	0.04	.39**
Tanx						1	.22**	.18**	.17**	.16**	.15**	0.01	-0.08	.19**	.05	-.02
Reh							1	.35**	.22**	.37**	.45**	.20**	.21**	.20**	.10	.07
Ela								1	.47**	.47**	.57**	.39**	.24**	.28**	.21**	.08
Org									1	.27**	.35**	.20**	.15**	.28**	0.09	.14**
Crit										1	.53**	.15**	0.07	.31**	.22**	-.04
Mcg											1	.41**	.40**	.19**	.16**	.17**
Tsdy												1	.48**	.09	.02	.24**
Eff													1	-.02	0.0	.24**
Prlrn														1	.51**	.14**
Hsk															1	.09
Final																1

Table 7: Pearson correlation coefficients between motivation and strategy use subscales' points in iteration 2

2.1.5.3.3 Iteration 3

In the third phase of analysis, we looked at the correlation of MSLQ constructs in iteration 3 and final score. The results are presented in Table 8. Correlations among the constructs in iteration 3 were upper than correlation of iteration 1 and 2 constructs with final score. As expected, all the motivational components had a high correlation with final score (intrinsic goal

orientation, extrinsic goal orientation, task value, control beliefs about learning, and self-efficacy for learning and performance).

	Intr	Extr	Tskv	Cont	Slfef	Tanx	Reh	Ela	Org	Crit	Mcg	Tsdy	Eff	Prlrn	Hsk	Final
Intr	1	.18**	.41**	.18**	.51**	.13*	.28**	.40**	.26**	.49**	.46**	.24**	.17**	.21**	0.03	.16**
Extr		1	.43**	.36**	.26**	.22**	.21**	.32**	.20**	.13*	.12*	.15**	.21**	0.02	0.04	.20**
Tskv			1	.41**	.44**	.13*	.19**	.49**	.43**	.26**	.30**	.20**	.24**	0.08	0.03	.15**
Cont				1	.22**	.20**	0.10	.34**	.23**	.11*	.15**	.13*	0.08	0.08	0.04	.11*
Slfef					1	0.00	.21**	.31**	.21**	.27**	.38**	.33**	.34**	.11*	0.02	.40**
Tanx						1	.24**	.21**	.16**	.19**	.14**	0.03	-0.01	0.06	0.02	0.00
Reh							1	.42**	.47**	.27**	.39**	.23**	.34**	.19**	.12*	0.10
Ela								1	.56**	.41**	.52**	.28**	.30**	.29**	.21**	.16**
Org									1	.33**	.44**	.24**	.30**	.18**	0.10	0.09
Crit										1	.52**	0.06	0.05	.31**	.20**	-0.01
Mcg											1	.37**	.30**	.25**	.19**	.20**
Tsdy												1	.39**	0.04	0.08	.34**
Eff													1	-0.03	0.01	.29**
Prlrn														1	.56**	0.09
Hsk															1	0.06
Final																1

Table 8: Pearson correlation coefficients between motivation and strategy use Subscales' points in iteration 3

Self-efficacy had the highest correlation with final score. As anticipated, test anxiety had the lowest correlations with final score, close to zero. The anxious students performed less efficiently. Self-efficacy for learning and performance and time and study environment had the highest correlation with final score among all the strategy use constructs. Cognitive strategy use such as elaboration, metacognitive self-regulation, time and study environment, and effort regulation had a high correlation with final score. Students who had self-regulatory skills such

as time and study environment and effort regulation used metacognitive skills to perform better at the end.

The correlation of Critical thinking and final score stayed negative all way through the three iterations. Students who had deepest strategy use such as time and study environment and effort regulation, and also were able to manage their learning meta cognitively, got better at the end. In iteration3, intrinsic goal orientation, extrinsic goal orientation, task value, self-efficacy for learning and performance, elaboration, metacognitive self-regulation, time and study environment, and effort regulation have high correlation and control beliefs about learning have medium correlation.

In terms of correlations among the constructs, motivational constructs such as intrinsic goal orientation, extrinsic goal orientation, task value, control beliefs about Learning, self-efficacy for learning and performance had high correlations with each other. Interestingly test anxiety close to the end of the course had high correlations with intrinsic goal orientation, extrinsic goal orientation, task value, and control beliefs about learning. However, test anxiety had a low correlation with self-efficacy for learning and performance. Value components comprising of intrinsic goal orientation, extrinsic goal orientation, and task value had a high correlation with cognitive and metacognitive strategy use. Intrinsic motivation had a high correlation with all the strategy use constructs except help seeking which meant students who had high intrinsic motivation would use cognitive and metacognitive strategies and all the resources available to them except help seeking. In terms of correlation among strategy use, cognitive and metacognitive strategy use had high correlations with each other. Still, effort regulation had a negative relation with peer learning means students who could manage their own, did not get help from others. In iteration 3 when all the constructs had the highest correlation with each other, we looked at those who had lower correlations. We identified that peer learning and help seeking were the constructs that we believed were not used in the online system.

2.1.6 Discussion and Conclusion

We looked at students' motivation and strategy use of 419 students in the first round, 396 students in the second round, and 366 students in the third round from three business school's courses in a high-ranking university in New Zealand. We administrated MSLQ three times to see how students' motivational and learning strategy use changed. We looked at six constructs in motivation and nine constructs in strategy use. This information is also helpful for the students, as they need to understand how to utilize SRL strategies to achieve academic success

in online environments. We checked the reliability of our model through Cronbach Alfa and confirmatory factor analysis. The Cronbach alpha values calculated for all the factors of the scale varied between 0.541 and 0.871. We tested our model through two confirmatory factor analyses of the data that we gathered for both motivation and strategy use and reported the results of factor analysis. We also looked at the changes in motivational and strategy use constructs as the course progressed. We checked the significance of the changes by applying t-tests. We also reported the constructs that significantly changed between iteration 1, iteration 2, and iteration 3. We checked the predictability of the constructs by looking at the correlations of each construct and final score. We identified that almost all the motivational components except anxiety had a high correlation with final score. Self-efficacy had the highest correlation with final score. Test anxiety had the lowest correlations with final score. Time and study environment had the second highest correlation with final score. These three constructs (self-efficacy for learning and performance, time and study environment, and effort regulation) showed high correlation in three iterations. Cognitive strategy use such as elaboration, metacognitive self-regulation, time and study environment, effort regulation had a high correlation with final score (iteration 2 and 3). Students who had self-regulatory skills such as time and study environment and effort regulation used metacognitive skills to perform better at the end. The correlation of critical thinking and final score stayed negative all way through the three iterations. As it is shown in iteration 3, some strategy constructs might not be useful in the online learning environment. Students spent their time on, rehearsal, organisation, peer learning, help seeking which were not helpful and might not increase the likelihood of academic success. We also observed very low community participation and peer learning among students in our BL course. Even in our qualitative study, we observed the same thing. Students did not get help from other peers, and they did not have peer learning. In the BL classroom, they did not know other peers. Therefore, they could not trust to ask any questions of them. As the course progress the correlations of the constructs increased with final. Peer learning, help seeking, and critical thinking stayed low or negative all the way through.

This study contributes to the fields of motivation and education by extending existing motivation research through researching motivational beliefs and learning strategies of students as their courses progressed towards the end. We believe that the domain of this study (SRL environment) would straighten our understanding of students learning and SRL process that they take. While different studies that we explained looked at students' trace data, we are looking at students' self-reported data, data on how students believe are about their motivations

and how they used the strategies for the learning process. It also helped us to understood that we need to facilitate motivational believe of students at least the adaptive one. The non-adaptive one could be anxiety. But adaptive one like intrinsic goal orientation, extrinsic goal orientation, self-efficacy have high impact on final. Therefore, it is important that we consider increasing them. The lecturer can talk about the role of effort regulation and strategies when we know for example self-efficacy is important. The lecturer can also talk about the value of the task. For example, the lecturer can update the pedagogy and focus more on task value. It is also important that the lecturer help students by facilitating strategy use. Through different tools and mechanism the lecturer can teach the students to take control of their learning. Or for example when we know time and study environment, organisation, and effort regulations have significant correlation with final, the lecturer can teach students ways to improve them.

We also identified the issues regarding online teaching and learning that teachers first needed to be aware so that they could be addressed them in their instructional course design. For example, he needs to make students familiar with other classmates, make the students familiar with the tools, make the importance of each tool clear for students in their learning. He also needed to inform students about the most popular topics in the discussion and encourage students to participate in the discussion board and try to make more group projects so that students could start to know each other. In this study, we identified the constructs which had the predictability ability, and we reported them. In our future study, we will research how we can improve each of these identified constructs and also the impact of them on students' participation and performance in BL environments. We intend to see what would happen to the students who are high in motivation at the beginning and how they achieve at the end. Also, we intend to see what will happen to those who are low at motivation at the beginning of the course. Finally, we intend to see how early we can predict students' final score based on their motivational level. The limitation of our study was that, we used the data from a relatively small data set from 419 students from one department and one university. Future research is needed to validate our findings. For us, the webcast was a replacement for the classes. Therefore, students required to watch all the lecture if they wanted to learn the whole topic. Review session recordings were the only repetitive material for students. In the future, we will give students more freedom by replicating the entire class.

(This is the end of paper 1)

2.2 Paper 2- Impact of Motivation and Strategy Use on Performance in a Blended Learning Course.

(Submitted to International Journal of Information and Education Technology)

2.2.1 Abstract

Understanding students' self-regulatory learning (SRL) processes is important, especially in Blended Learning (BL), when students need to be more autonomous in their learning process. In this study, we examined the predictability of students' final scores based on indicators from students' reported measures reflecting SRL (Motivational beliefs, Cognitive and Metacognitive Strategies, and Resource Management Strategies). The participants were 189 students from a BL course in the Business School. We administered the Motivational Strategies for Learning Questionnaire (MSLQ) three times to measure students' motivation and learning strategy use. Using stepwise regression at construct level, between motivation and learning strategy use, mostly, the motivational components were chosen by the stepwise regression as predictors. We also understood that among the motivational components; self-efficacy for learning performance had the highest correlation with the final score. Whilst among the strategy use components, effort-regulation had the highest correlation with the final score in the second and third iteration. These 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 (LA) as well, opposed to simple frequency measures. 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 most important LA aims. Furthermore, the paper discusses the potential implication of the study related to SRL theory, LA, and instructional design.

Keywords: Self-regulated learning, Students' Motivation, Students' Strategy Use, Learning analytics, Final score prediction

2.2.2 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 and 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 et al. 2015; Staker and Horn 2012; Tempelaar et al. 2015). This approach is called Learning Analytics (LA) and finding at-risk students is one of the most important LA aim (Dawson et al. 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. 2016a). 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 and Hurn 2013). These studies fail to quantify the impact of emotional, motivational, cognitive–metacognitive factors, and resource management. Studies such as Lonn et al. (2015) and Wong et al. (2019a) 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 and Dunn 2010; You and Kang 2014). 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 (Pintrich 1999).

There are a number of contradictory studies about the effect of motivational belief and self-regulated learning (SRL) on performance (Mousoulides and Philippou 2005; Niemczyk and Savenye 2005; Pintrich et al. 1990). Therefore, in this study, we investigated SRL through the administration of the Motivated Strategies for Learning Questionnaire (MSLQ) (Pintrich and 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 et al. 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 (Pintrich et al. 1993b; Zusho et al. 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 and 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.

2.2.3 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 et al. 2014; You and Kang 2014; Zimmerman 2008). Some researchers studied the relationship between motivation and cognition (e.g. Pintrich 1989). Azevedo et al. (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). 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 et al. 2015).

Pintrich et al. (1993b) 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 (Pintrich 1988), each component has its meaning, which is explained below.

2.2.3.1 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). Pintrich et al. (1993b) 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.

2.2.3.2 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 et al. (2013) referred to rehearsal as a repetition so that the learner can remember the materials. Richardson et al. (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 et al. (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.

2.2.4 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 2003a).

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 (Pintrich et al. 1993b). 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.

2.2.5 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.

2.2.5.1 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 9. 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 Pintrich et al. (1993b), 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.

	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

Table 9: Descriptive statistics for the MSLQ sub-constructs at iteration1, iteration 2, and iteration 3 (freshmen)

2.2.5.2 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 10, Table 11, and Table 12 and their narratives explained the different level and commensurate details.

2.2.5.2.1 Two Constructs (Motivation and Strategy Use) from Three Iterations

We considered the correlation between motivational and strategy use components and final scores in Table 10. 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.

	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**

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

Table 10: Correlation of motivation and strategy use at iteration 1, iteration 2, iteration 3 (freshmen)

2.2.5.2.2 Five Constructs from Three Iterations

We considered the correlation of the constructs underneath motivation and strategy use components in Table 11 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 11, 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 does not correlate with expectancy in the first and second iterations. But as the course progressed, this construct correlated with expectancy.

	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

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

Table 11: Correlation of motivation and strategy use components at iteration 1, iteration 2, iteration 3 (freshmen)

2.2.5.2.3 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 12: Correlation between motivation and strategy use subscales at iteration 1, iteration 2, iteration 3 (freshmen) 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 Pintrich (1999), which could be the effect of the pedagogical approach.

	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
Intr 1	0.110	.296**	.290**	.339**	.275**	.236**	0.113	.182*	.158*	0.148	.335**	.276**	.301**	.324**	.286**	.251**	.208**	0.067	0.031	.270**	.297**	.250**	.290**	.312**	.252**	.238**	0.026	0.049
Extr 1	0.143	0.077	.177*	-0.004	.144*	.238**	.169*	-0.019	-0.018	.261**	0.142	0.123	0.093	.231**	.275**	.297**	-0.099	0.034	.217**	0.028	0.013	-0.043	0.074	.240**	.215**	-0.019	-0.032	.187*
Tskv 1	0.111	.384**	.335**	.223**	.366**	.411**	.319**	0.093	0.083	.160*	.380**	.227**	.248**	.370**	.442**	.401**	0.058	0.025	0.154	.376**	.314**	.185*	.391**	.358**	.349**	.165*	-0.048	0.125
Cont1	0.056	0.129	.175*	0.066	.162*	.159*	0.110	-0.059	-0.065	0.120	0.107	0.033	0.003	0.085	0.086	0.076	-0.112	-0.117	0.009	0.039	-0.014	-0.065	0.076	-0.047	0.100	-0.030	-0.151	0.003
Slfef1	0.129	.180*	.245**	0.085	.290**	.225**	.272**	0.019	0.010	0.119	0.067	0.062	0.045	.171*	.196**	.293**	0.010	-0.097	0.046	0.074	0.040	0.063	.200*	0.115	.310**	-0.013	-0.129	.209**
Tanx1	.230**	0.078	.195**	0.067	-0.005	0.029	-0.140	.151*	-0.037	.318**	0.125	.193*	.208**	.235**	-0.010	-0.081	-0.007	-0.055	.366**	0.092	.193*	.173*	0.157	0.083	-0.008	0.109	-0.027	.179*
Intr2	0.052	.302**	.254**	.225**	.245**	.329**	.206**	0.139	.189*	.202**	.479**	.385**	.417**	.449**	.358**	.404**	.285**	.187*	0.054	.309**	.361**	.286**	.291**	.361**	.309**	.222**	0.019	.230**

Extr2	0.105	0.138	.180*	-0.103	0.063	.213**	.202**	0.023	.153*	.321**	.258**	.249**	0.100	.279**	.322**	.410**	0.035	0.086	.249**	.179*	.181*	-0.019	0.117	.301**	.213**	0.012	-0.022	.279**
Tskv2	-0.014	.222**	.231**	0.033	.176*	.288**	.323**	-0.013	0.092	.176*	.493**	.358**	.176*	.383**	.429**	.472**	0.086	0.008	.198*	.357**	.356**	0.070	.321**	.424**	.420**	0.013	-0.085	.279**
Cont2	0.132	.195*	.245**	-0.015	.177*	.227**	.168*	-0.130	-.154*	.233**	.161*	0.143	-0.006	.216**	.208**	0.138	-0.146	-.239**	0.115	0.096	0.120	-0.090	0.143	0.121	.190*	-.179*	-.250**	0.066
Slfef2	0.049	.209**	.260**	-0.031	.206**	.249**	.319**	-0.059	-0.004	.288**	.295**	.294**	0.112	.418**	.371**	.491**	-0.009	-0.059	.169*	0.101	.207*	0.037	.234**	.264**	.421**	-0.132	-0.142	.452**
Tanx2	0.084	0.072	0.096	0.004	-0.055	-0.034	-.188*	0.147	0.064	.290**	0.148	.229**	0.133	.196**	-0.009	-0.100	0.098	-0.002	.333**	0.066	.182*	.177*	0.050	0.089	-0.055	0.091	-0.045	0.094
Intr 3	0.052	.280**	.190*	.332**	.203*	.234**	0.120	.199*	.191*	.211**	.479**	.270**	.494**	.364**	.327**	.275**	.358**	.211**	.226**	.469**	.412**	.481**	.416**	.390**	.312**	.351**	0.137	.261**
Extr3	0.126	0.039	.193*	-0.012	0.057	.221**	.284**	-0.076	-0.021	.318**	.293**	.263**	.229**	.315**	.341**	.332**	0.022	-0.059	.419**	.286**	.279**	.195*	.307**	.337**	.311**	0.008	-0.074	.382**

Tskv3	-0.025	.256**	.207*	0.118	0.149	.281**	.328**	0.050	0.154	.166*	.439**	.287**	.295**	.333**	.451**	.468**	.266**	0.043	.293**	.463**	.476**	.237**	.408**	.407**	.412**	.165*	0.012	.305**
Cont3	.187*	.239**	.298**	0.056	.170*	.210**	.204*	-0.123	-0.110	.230**	.177*	0.079	0.081	.211**	.301**	.295**	-0.069	-.280**	.273**	.256**	.283**	0.045	.283**	.175*	.269**	-0.028	-.203*	0.129
Slfef3	0.083	.236**	.263**	0.111	.201*	.244**	.309**	0.028	0.062	.220**	.206*	.216**	.206*	.313**	.356**	.399**	.181*	-0.090	.298**	.310**	.354**	.259**	.381**	.352**	.446**	0.116	-0.065	.462**
Tanx3	.163*	0.082	0.121	0.002	-0.057	0.084	-0.077	0.029	-0.036	.342**	.194*	.284**	.239**	.215**	0.141	-0.018	0.023	-0.070	.445**	0.139	.258**	.217**	0.093	0.141	-0.025	0.104	-0.057	0.128
FinalScor	.14	0.033	.210**	-0.116	0.019	.153*	0.127	0.048	0.052	.222**	.166*	.181*	0.038	.150*	.204**	.235**	0.131	0.069	.202*	.239**	.267**	0.062	.169*	.280**	.306**	0.073	0.073	1

Table 12: Correlation between motivation and strategy use subscales at iteration 1, iteration 2, iteration 3 (freshmen)

2.2.5.3 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 13. 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 13, 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.

2.2.5.3.1 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.

2.2.5.3.1.1 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 13)

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.

		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, ResourceManagement3, ResourceManagement1				0.237
	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	0.143
	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

Table 13: Stepwise regression analysis results on the final score based on different iterations (freshmen N=189)

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).

2.2.5.3.1.2 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 13). 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.

2.2.5.3.1.3 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 beliefs3 as predictors (M3- Table 13). All the predictors were chosen from the third iteration. Control of learning beliefs3 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.

2.2.5.3.2 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.

2.2.5.3.2.1 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 13). 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.

2.2.5.3.2.2 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 13). The R-square did not improve much 0.053. We went further with sub-constructs in the next section of our analysis.

2.2.5.3.2.3 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 13). 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.

2.2.5.3.3 Regression Analysis Based on the Second Iteration

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

2.2.5.3.3.1 Stepwise regression with two constructs

This section used motivation2 and strategy2. The system chose motivation2 again and deleted strategy2 (M7- Table 13). 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.

2.2.5.3.3.2 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 13). Looking at the R-square (0.143), we understood that we generated a better model compared to the previous model.

2.2.5.3.3.3 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 13). 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.

2.2.5.3.4 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.

2.2.5.3.4.1 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 13).

2.2.5.3.4.2 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 13). In this model, expectancy 1 had a negative weight, and this construct also did not correlate with the final score.

2.2.5.3.4.3 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 13). 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.

2.2.6 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 (1986b), 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 origanisation1, 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.

2.2.7 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.

(This is the end of paper 2)

2.3 Paper 3- A Comparison of the Predictability of Final Scores for Freshmen and Upper-level Students in Blended Learning Courses - Using Motivational Beliefs and Learning Strategy Use as Predictors

(Submitted to Journal of Higher Education Theory and Practice)

2.3.1 Abstract

This study investigates final scores predictability based on students' longitudinally reported motivation belief and use of learning strategies in Blended Learning (BL) courses for freshmen and upper-level students. We administrated the Motivated Strategies for Learning Questionnaire three times to measure students' motivation belief and use of learning strategies (N=314) and collected 850 viable surveys. We first investigated the dynamics of the factors involved with students' motivational belief and use of learning strategies. We found that freshmen students' motivation dropped until midterm and it increased again as the course progressed towards the end. However, 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 use 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.

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

2.3.2 Introduction

Knowing the factors which affect student achievement is necessary. Studies identified different factors that would affect student's performance (Gašević et al. 2015; Tempelaar et al. 2015). Lynch (2006) 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 associated with the final grade. With the rapid growth of online learning and different forms of BL environments, and the challenges of online learning, it is vital to understand the personal factors that may affect this environment's success (Abrami and Bernard 2006; Staker and Horn 2012). In online learning environments, Self-Regulated Learning (SRL) has received attention as this environment needs students to take independent control of their learning more than traditional classes (Zimmerman 2008).

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 precautionary measures (Ferguson 2012). Therefore, it is needed to provide insights to the lecturer. Learning Analytics (LA) allows us to analyse, understand, and optimise learning processes. 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). This study investigated motivation and strategy use (SRL) as this field has not been studied enough in LA (Lonn et al. 2015; Wong et al. 2019b). While earlier studies looked at students' trace data, we need to study students' self-reported data on how their beliefs about their motivation and different learning strategies they used to self-regulate their learning. This study built on previous studies such as Lynch and Trujillo (2011) and Ng et al. (2016), which suggested using the Motivated Strategies for Learning Questionnaire (MSLQ) (Pintrich 1991) that is a well-established questionnaire based on well-founded theory (Pintrich et al. 1993b).

Following McCardle and Hadwin (2015) that mentioned "SRL cannot be measured as aggregated across time and tasks, nor can it be measured as a single learning event" (McCardle and Hadwin 2015, p.60), we measured motivation, cognitive, and metacognitive SRL longitudinally. We believe that a longitudinal study would help us get insights into the evolution of students' motivational beliefs and strategies over time. Moreover as, Lynch and Trujillo (2011) stated, students are different in terms of how they are aware of SRL, and therefore, they adopt different learning strategies. Thus, in this study, we compare how freshmen and upper-level students are different in this regard.

We explored the relationships between motivation, cognitive, and metacognitive, SRL awareness and final scores through exploring SRL measures at the beginning of, in the middle of, and at the end of the courses, and compared their dynamic between upper-level and freshmen students. We also checked how early the constructs could help us predict final scores in the BL environment. In our study, we had a level one course with 194 students and a level two courses with 120 students. Our 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?

Running the study contributes theoretically to debates in SRL theory by checking how students SRL changes as the course progress (Pintrich et al. 1993b; Zusho et al. 2003) and methodologically by presenting longitudinal empirical data about university students' perceptions regarding their motivation, cognitive, and metacognitive SRL in the classroom

environment. Our study's 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. In terms of the implication of the study for practice, looking at students' reported motivation and use of learning strategy constructs over time could enrich 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. We learned 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 the information regarding their learning.

We identified the most important constructs for predicting final scores which addresses one of the most important aims of LA. 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 the strategies and proper skills so that they become capable of taking control of their learning and becoming self-regulated learners. We understood students had different experiences; some were new to the system (i.e., freshmen), some had university experience (upper-level students), and we understood that they needed to learn different strategies. Students who directly joined a university course after finishing high school may need some advice regarding how to adopt 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 through checking their motivation and strategy use helps ensure that they have regular study patterns. The lecturers could change the instructional design and prepare the environment for students to enhance their learning.

The organisation 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, how we collected data, and how we analysed it. Finally, we discuss our findings and present the conclusions.

2.3.3 Literature Review

The significance of the interaction between learners and instructors and its role in the learning process is traditionally emphasised in the literature (Bambaeeroo and Shokrpour 2017; Chickering and Gamson 1987; Deslauriers et al. 2019; Fulford and Zhang 1993; Kearsley 1995; Kumari 2001; Stubbs et al. 1976). In recent years, computer-mediated interaction (Azevedo 2015; Dawson 2008; Lajoie et al. 2020) has gained attention, and 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 which are integrated into the learning tasks and learning content (Dabbagh and Bannan-Ritland 2005; Dabbagh and Kitsantas 2004; Elen and Clarebout 2006). Dabbagh and Kitsantas (2005) 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 (1998) 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 (Candy et al. 1994) who can control and self-regulate their learning (Siemens et al. 2015).

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 (Picciano et al. 2013). BL combines the benefit of using online technologies and face-to-face teaching for a richer experience (Garrison and Kanuka 2004; Van Doorn and Van Doorn 2014) and it has more flexibility for students (Waha and Davis 2014).

In online learning, lecturers do not see students physically so that they take precautions (Ferguson 2012). Therefore, the lecturer needs to access more data from students to meet students' needs and help them. 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 (Dahlstrom et al. 2014; Romero et al. 2008). 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 through identifying the students who would be at risk of failure through recognising the students' final score predictors. Identifying students at risk of failure is an

example of LA so that appropriate intervention can be applied and prevent dropout (van Leeuwen et al. 2019).

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. Ayers and Junker 2006; Chen et al. 2000; Cocea and Weibelzahl 2006; Gašević et al. 2015; Grudnitski 1997; Hämäläinen and Vinni 2006; Kotsiantis and Pintelas 2005; Minaei-Bidgoli and Punch 2003; Pistilli and Arnold 2010; Pokay and Blumenfeld 1990; Ransdell 2001; Talavera and Gaudioso 2004; Tempelaar et al. 2015; Ting and Man 2001). These studies have inconsistency 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 (Arnott and Planey 2017; Lonn et al. 2015; Wang 2019). They also did not look at the issues longitudinally. One popular way to measure SRL is through the MSLQ (Pintrich 1991). Therefore, in the next section, we explain how we addressed the methodological gap.

2.3.4 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 also 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 analysed 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. His method of teaching was based on discussing formative questions. He asked questions in the class based on the questions that most students got wrong.

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 incentivised 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. We aimed for students to become aware of the gap 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.

2.3.4.1 Instrument and Procedure

To understand students' motivation and use of learning strategies, we used the MSLQ (Pintrich 1991). 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. 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, organisation, 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. We ran the MSLQ three times in Week 3, Week 7, and Week 11 of a 12-week semester through the Learning Management System (LMS).

2.3.5 Analysis

Over three rounds of surveying a population of 314 students, a set of 850 viable surveys were collected. We cleaned the data first. We also needed to handle the missing data. For this reason, we needed to test whether we had missing values at random. Therefore, we ran Little's Missing Completely at Random (MCAR) test for each class's iteration. Our 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. We replaced missing values with maximum likelihood. We considered the rule of thumb by replacing less than 10 percent of the data. This section gives our results, which are divided into three main sections: 1) descriptive statistics, 2) correlation analysis, 3) stepwise regression analysis.

2.3.5.1 Descriptive Statistics

In this section, we report descriptive analysis for each construct for the two groups separately. Then we summarised how they were different between the two groups. We calculated the values for constructs based on the mean of the scales that made up that construct.

2.3.5.1.1 Freshmen

The descriptive statistics, including means and standard deviations, of the freshmen students, are depicted in Table 14. For freshmen, in contrast to the studies run by Pintrich and Garcia (1991) and Pintrich et al. (1993b), 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, organisation, 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.

	Iteration1(N=189)		Iteration2 (N=173)		Iteration3 (N=153)	
Mean=M	**M**	**SD**	**M**	**SD**	**M**	**SD**
Intrinsic Goal Orientation	4.71	.84	4.53	.89	4.55	.94
Extrinsic Goal Orientation	5.30	1.06	5.04	1.14	5.10	1.09
Task Value	5.30	.98	5.110	.96	5.12	.99
Control of Learning Beliefs	5.15	.87	5.14	.82	5.06	.89
Self-Efficacy for Learning Performance	4.92	.86	4.84	.92	4.84	.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	.83	4.58	.93	4.73	.94
Organisation	4.83	.87	4.76	.91	4.84	.93
Critical Thinking	3.87	1.05	3.88	1.01	3.95	1.13
Metacognitive Self-Regulation	4.29	.67	4.39	.70	4.45	.70
Time Study Environmental Management	4.76	.78	4.66	.86	4.63	.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	.63	4.80	.62	4.82	.69
Strategy	4.23	.55	4.20	.62	4.31	.66
Final Score	66.98	16.96				

Table 14: Descriptive statistics for the MSLQ sub-constructs at iteration 1, iteration 2, iteration 3 (Freshmen)

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 use continuously increased while their motivation was decreasing so that they could manage to achieve their goals.

2.3.5.1.2 Upper-Level Students

The descriptive statistics for all the constructs and sub-constructs for upper-level students are depicted in Table 15. As seen in Table 15, motivation in contrast to the Year 1 course continuously decreased. And, strategy use in contrast to the Year 1 course 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, we 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 organisation 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.

	Iteration1 (N=118)		**Iteration2 (N=110)**		**Iteration3 (N=108)**	
	M	**SD**	**M**	**SD**	**M**	**SD**
Intrinsic Goal Orientation	4.55	.90	4.38	.93	4.48	.94
Extrinsic Goal Orientation	5.29	.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	.82	4.95	.94	4.94	.98
Self-Efficacy for Learning Performance	4.93	.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	.90	4.69	1.05
Organisation	4.91	.94	4.85	.87	4.89	.93
Critical Thinking	3.49	1.16	3.70	1.07	3.81	1.12
Metacognitive Self-Regulation	4.18	.73	4.37	.70	4.48	.72
Time Study Environmental Management	4.82	.82	4.66	.84	4.76	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	.58	4.68	.67	4.66	.67
Strategy	4.30	.62	4.34	.60	4.40	.68
Final Score	69.36	14.66				

Table 15: Descriptive statistics for the MSLQ sub-constructs at iteration 1, iteration 2, iteration 3 (Upper-level students)

We 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. We believe 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 (Woods-McConney et al. 2013; Zusho et al. 2003). However, their level of strategy use increased.

2.3.5.2 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 et al. (2007) mentioned that the correlation of independent variables needed to be less than 0.70.

2.3.5.2.1 Freshmen Students

This section explores and summarises the correlation between motivation, strategy use constructs, and the final scores for freshmen. We presented the correlation among motivational and strategy use constructs with final scores for freshmen students in Table 16. 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 organisational 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.

M=Motivation S=Strategy	M1	S1	M2	S2	M3	S3	Final Score
Motivation 1	1						.222**
Strategy 1	.320**	1					0.140
Motivation 2	.631**	.256**	1				.327**
Strategy 2	.281**	.671**	.433**	1			.254**
Motivation 3	.604**	.275**	.762**	.449**	1		.366**
Strategy 3	.263**	.630**	.289**	.735**	.490**	1	.289**

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

Table 16: Correlation of motivation and strategy use at iteration 1, iteration 2, iteration 3 (freshmen)

2.3.5.2.2 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 17 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.

M=Motivation S=Strategy	M1	S1	M2	S2	M3	S3	Final Score
Motivation 1	1						0.166
Strategy 1	.389**	1					.197*
Motivation 2	.588**	.282**	1				.232*
Strategy 2	.351**	.650**	.446**	1	`		.358**
Motivation 3	.499**	.308**	.734**	.469**	1		.329**
Strategy 3	.226*	.660**	.332**	.691**	.469**	1	.217*

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

Table 17: Correlation between Motivation and Strategy Use at iteration 1, iteration 2, iteration 3 (Upper-level students)

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 though the correlations between each construct and the final scores dropped, the correlations across the constructs increased in this course. We 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. We have investigated the correlation between constructs and sub-constructs with final scores and identified the constructs that had the highest correlation with final scores; next, we consider the predictability of the final scores through stepwise regression analysis.

2.3.5.3 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, we first explore the predictability of final scores based on constructs from the first iteration for each class. Then, we considered the predictability of final scores based on constructs from iteration 2, and then from iteration 1 and iteration 2 of data to see how early and with what accuracy we can predict students' final scores. Early prediction of students' final scores helps the course instructor identify at-risk of failure students so that the lecturer could help them.

2.3.5.3.1 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 18).

2.3.5.3.1.1 Stepwise Regression with Two Constructs from the First Iteration:

We employed stepwise regression 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 .050 (M1- Table 18).

2.3.5.3.1.2 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 organisation 1, critical thinking 1, self-efficacy for learning performance 1, and test anxiety 1, was the best model among all. The R square was .123, which was an improvement compared to the previous models (M2-Table 18). Self-efficacy for learning performance 1 had the maximum weight in the model. Critical thinking 1 had a negative weight.

		Model	Predictors	Final score			
				B	*SE*	ß	*R2*
Based on first iteration	2 Constructs	M1	Motivation1	5.985	1.92	.222	.222a
	15 Constructs	M2	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	.170 -.178 .183 .159	.123
Based on second iteration	2 Constructs	M3	Motivation2	7.582	7.582	1.678	.107
	15 Constructs	M4	Self-Efficacy for Learning Performance2, PeerLearning2	7.048 1.395	1.055 .701	.453 .135	.222
Based on first and second iterations	2 Constructs	M5	Motivation2	7.582	1.678	.327	107
	15 Constructs	M6	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 .820 1.403	.520 -.187 .162 -.152	.288

Table 18: Stepwise regression analysis results on the final scores based on different iterations (Freshmen N = 189)

2.3.5.3.1.3 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 square amount became doubled (.107) compared to the model based on iteration 1 of the data (M3-Table 18).

2.3.5.3.1.4 Stepwise Regression with Fifteen Sub-Constructs from the Second Iteration:

As time passed (in iteration 2), the R squares 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 square for this model was .222, which was a significant improvement compared to other models (M4-Table 18).

2.3.5.3.1.5 Stepwise Regression with Two Constructs from the First and Second Iterations:

Even when we merged iteration 1 and iteration 2 of the data, stepwise regression still chose motivation 2 as a final score predictor. The system did not select any predictor from iteration 1. Therefore, the R square was .107, the same as the prediction based on iteration 2 of the data (M5-Table 18).

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

This section used 15 sub-constructs from iteration1 and iteration2 to see if we could make a better model. 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 square for the model was .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 18).

2.3.5.3.2 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 19).

2.3.5.3.2.1 Stepwise regression with Two Constructs from the First Iteration:

We employed stepwise regression 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 square was .039 (M1- Table 19).

2.3.5.3.2.2 Stepwise Regression with Fifteen Sub-Constructs from the First Iteration:

We again used stepwise regression 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 square for this model was .215 (M2- Table 19). Task value had a negative weight, and time and study environment had the highest weight. This model had a higher R square value compared to the model generated based on the 15 constructs for Year 1 students.

		Model	Predictors	Final score			
				B	SE	ß	R2
Based on first iteration	2 Constructs	M1	Strategy1	4.672	2.164	.197	.039
	15 Constructs	M2	TimeStudyEnvironmentalManagement1, SelfEfficacyforLearningPerformance1, TaskValue1, Peer Learning1	6.815 4.294 -3.168 1.801	1.543 1.584 1.370 .901	.384 .255 -.222 .173	.215
Based on second iteration	2 Constructs	M3	Strategy2	7.139	1.803	.358	.128
	15 Constructs	M4	SelfEfficacyforLearningPerformance2, TimeStudyEnvironmentalManagement2, CriticalThinking2, Peer Learning2, ControlofLearningBeliefs2	5.893 3.552 -2.505 1.987 -2.573	1.140 1.165 .895 .716 1.240	.490 .251 -.225 .225 -.195	.375
Based on first and second iterations	2 Constructs	M5	Strategy2, Strategy1	10.186 -4.717	2.323 2.316	.510 -.237	.161
	15 Constructs	M6	SelfEfficacyforLearningPerformance2, CriticalThinking1, TimeStudyEnvironmentalManagement1, Peer Learning2, EffortRegulation2, Help Seeking1	4.369 -2.766 3.110 3.023 2.835 -2.220	1.082 .815 1.202 .782 1.085 .878	.364 -.273 .213 .343 .246 -.218	.462

Table 19: Stepwise regression analysis results on the final scores based on different iterations (Upper-level students)

2.3.5.3.2.3 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 square for this model was .128 (M3-Table 19), which was higher compared to the Year 1 model.

2.3.5.3.2.4 Stepwise Regression with Fifteen Sub-Constructs from the Second Iteration:

In this section, we had 15 sub-constructs from iteration 2 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 square of .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 19).

2.3.5.3.2.5 Stepwise Regression with Two Constructs from the First and Second Iterations:

Even when we merged iteration 1 and iteration 2 data, 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 square value was .161 (M5- Table 19).

2.3.5.3.2.6 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 we could get better results. 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 square of .462 (M6- Table 19).

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 we were aware that if we used three iterations of data, our prediction accuracy would be higher, but our goal was to have an early prediction so that the lecturer could apply early intervention. Therefore, first, we considered the prediction of final scores based on the two constructs of motivation and strategy use. Then, we used 15 sub-constructs as the predictors each time based on different iterations of data. Based on stepwise regression analysis, we identified the constructs and sub-constructs that were important in predicting final scores, which were helpful for teaching practice. We 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.

2.3.6 Discussion and Conclusion

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 (Arnott and Planey 2017). This study checked students' reported motivation and strategy use differences in two BL courses (freshmen and upper-level students). We started with checking the dynamics of students' motivation and strategy use in these BL courses. We 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.

We 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 (Woods-McConney et al. 2013; Zusho et al. 2003). In terms of strategy use, we 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 the motivation or teach them proper strategies at that time.

We also checked the correlation of motivation and strategy use constructs with final scores. We 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.

We also investigated to identify the constructs that could help us predict final scores. We first made a prediction for final scores based on iteration 1 of data because we aimed to make an early prediction for final scores, but the accuracy was not high. Thus, we tried prediction with data from iteration 2, for which we had improvement in accuracy, and finally, we used data from both iteration 1 and iteration 2. 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 we identified.

In this study, we relied on one source of data (students' reported motivation and strategy use). 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. We also checked how students as a whole changed as the course progressed. In future, through clustering, we will investigate how each group's motivation and strategy use changed as the course progress. We also ran this study in Business School; it is better to check with the other problematic courses in different departments to see if we could get the same results. Also, we understand that still, there is a contradiction between the predictive constructs identified in the literature and predictors we identified in this paper.

More research is needed to check the predictability of the constructs in some other courses in different departments, especially regarding peer learning and help seeking subscales.

(This is the end of paper 3)

Chapter 3

CHAPTER 3

3 Chapter 3 - QUANTITATIVE ANALYSIS - CLUSTERING

This chapter investigates students' distinct SRL profiles and explores how students adopt different SRL profiles as the course progresses. In contrast to other studies that used variable-centred approaches, we followed a person-centred approach to answer the second research question. We employed a longitudinal clustering approach through three iterations of data and identified three different SRL profiles in each class for each iteration. We reported the results of the analyses in two papers. In Paper 4, we used data from the freshmen students and identified three distinct student SRL profiles. We compared how students from different profiles performed. We also investigated how students changed their profiles as the course progressed. In Paper 5, we repeated the analysis from Paper 4 for the upper-level students and compared the analysis between the freshmen and upper-level students.

3.1 Paper 4- Unfolding Self-Regulated Learning Profiles of Students: A Longitudinal Study

(Submitted to Journal of Computer Assisted Learning)

3.1.1 Abstract

It is vital to understand students' Self-Regulatory Learning (SRL) processes, especially in Blended Learning (BL), when students need to be more autonomous in their learning process. In studying SRL, most researchers have followed a variable-centred approach. Moreover, little has been known about the unfolding process of students' SRL profiles. We present the insights derived from a study that measured motivation and the learning strategies used by 198 students of a university entry-level, business school, BL course to develop an understanding of students' SRL processes. By administering the Motivated Strategies for Learning Questionnaire (MSLQ) three times during a semester, we investigate SRL profiles and how they unfolded as the course progressed using a person-centred approach. We concentrated on motivation as its importance has been emphasised by different SRL theories, and extant research into motivation in learning analytics (LA) is still lacking. Through the longitudinal clustering approach, we identified minimally, average, and highly SRL profiles. We acknowledged that students might change their SRL profiles as the course progressed as a result of their evaluations. This study contributes to the SRL theory by examining students' SRL profiles adaptation longitudinally (addressing the challenge identified regarding the cyclical nature of SRL). This study contributes to LA by investigating motivational constructs currently lacking in the field and bringing forward empirical evidence to inform theory and practice.

Keywords: Self-regulated learning, learning analytics, MSLQ, longitudinal clustering, profiling learners, unfolding profiles

3.1.2 Introduction

For the last thirty years, Self-Regulatory Learning (SRL) has become an important topic in education and psychology (Azevedo and Gašević 2019; Greene and Schunk 2017; Winne et al. 2019). With the rapid growth of the use of educational tools in online learning (Viberg et al. 2018), and BL environments, understanding student's SRL and the factors that may affect the success of this environment are more vital (Abrami and Bernard 2006; Staker and Horn 2012). In online learning, SRL is getting more attention as this environment needs students to take independent control of their learning compared to in traditional classes (Broadbent and Poon 2015; Zimmerman 2008). Not all students can self-regulate their learning (Larsen et al. 2012). Given the status quo, faculty members wish to identify such students to give them feedback and encourage them to finish their courses (Cohen 2017).

In the online learning space, lecturers lack the visual cues that they rely on to take precautionary measures (Ferguson 2012). Therefore, the importance of giving insights to the course lecturer so that they can help students is more obvious (Ifenthaler 2015). Through Learning Analytics (LA), students' data will be used to understand and support their learning processes (Siemens and Long 2011). For example, by giving insight to the lecturers so that they apply appropriate interventions to support students. 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). Even though a lot of studies work on a different aspect of LA, such as technical issues and data processing, data privacy, developing user systems, and dashboards (Costa et al. 2017; Gasevic et al. 2017; Schumacher and Ifenthaler 2018; West et al. 2016), students' motivation and strategy use have not yet sufficiently been considered for analyses in LA (Lonn et al. 2015; Wong et al. 2019b). Panadero (2017) stated that SRL is a core conceptual framework for understanding the cognitive, motivational, and emotional aspects of learning. SRL has been defined by Pintrich (2000) 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).

Previous studies (Dörrenbächer and Perels 2016; Liu et al. 2014) show that students' reported motivational beliefs and learning strategies are connected to classroom performance. These showed that in a typical classroom having different grades for students highlights different SRL capabilities for students. Despite studies to comprehend the self-regulation process (Özcan 2016; Peng et al. 2014) there is still a gap in understanding and evaluating SRL in online learning (Järvelä et al. 2019; Wong et al. 2019a). Some studies identified students with the same learning behaviour pattern (Hong et al. 2020; Liu et al. 2014; Ning and Downing 2015; Shell and Soh 2013). However, studies such as (Fryer and Vermunt 2018; Jang et al. 2017; Nelson et al. 2015) showed that SRL profiles are dynamic and change. A recent study by Järvelä et al. (2019) stated that we are not completely sure how SRL profiles change as the course progresses.

While earlier studies that we reviewed leveraged the multimodal online interaction trace data (Bernacki 2018; Li et al. 2020), this study investigated students' self-reported data (N=198) longitudinally regarding their motivations and how they used different strategies to enhance their learning to address the gap (investigating the cyclical nature of SRL). To do so, we administrated the Motivated Strategies for Learning Questionnaire (MSLQ) (Pintrich 1991) three times (515 viable surveys). We chose all the MSLQ constructs as recommended by Li et al. (2020). They mentioned that SRL is a multi-dimensional construct that needs to consider metacognition, emotion, and motivation on top of strategic behaviour. The relationship between SRL and learning outcome through variable-oriented studies is well established (Malcom-Piqueux 2015; Masyn 2013; Morin et al. 2018). However, the person orientation approach has just recently been investigated for profiling students, which is an approach through which we can identify the learners who have the same self-regulatory characteristics pattern (Von Eye et al. 2006). Therefore, this study applied a person-centred LA approach (Zheng et al. 2020) to answer the following research questions.

1. What are the dynamics of motivational, cognitive, metacognitive self-regulatory variables?
2. What distinct SRL profile characteristics can be identified over time?
3. To what extent students' SRL profiles unfold over time?

Understanding different SRL profiles that share the same pattern of motivation and strategy use, identifying their characteristics, and investigating the unfolding SRL profiles are essential for both practice and theory building.

We believe that this study's domain will improve our understanding of students' learning and the SRL process they use through deeply comprehending the complex and reciprocal relationships between different SRL behaviours. Identifying student subgroups (different SRL profiles) and investigating students' SRL profiles unfolding as the course progressed contributed to the SRL theory. We understood SRL profiles are not static and they changed as the course progressed.

Unlike previous research, this study used clustering variables based on theory and the variables that have not sufficiently been studied in LA (Lonn et al. 2015; Wong et al. 2019a; Wong et al. 2019b). Previous studies have been criticised because they used all the data from the learning management system to get the best fit for their model without understanding whether these data are meaningful concerning LA (i.e. Lerche and Kiel 2018; Rosé et al. 2019). We contributed to LA by choosing these variables for the clustering and also bringing empirical evidence. Moreover, through student clustering, we were able to identify students who were at higher risk of failure so that the lecturers could help them. This model of prediction also contributed to one of the main aims of LA (Tempelaar et al. 2015).

This study contributes to practice by enabling educators to better understand their students' SRL and how students could adopt quite different SRL profiles over time to employ effective teaching strategies to raise their motivation. It also helps educators' understanding of students' strategic adaptation through the presence of adaptive SRL. This information informs the lecturers about necessary intervention designs for students with different SRL profiles to enable students to move to higher SRL profiles. In this study, we map how the progress through different course stages, such as receiving test scores and assignments, affects the students' motivation, strategy use, and adaptation of different SRL profiles. Pedagogically, this information informs the intervention designs for students with different SRL profiles.

The organisation 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 theoretical framework that guided the study. Next, we present the methodology, data collection, and analysis. Finally, we discuss our findings and present our conclusions.

3.1.3 Literature Review

SRL has become an important topic in education and psychology (Azevedo and Gašević 2019; Greene and Schunk 2017; Winne 2019). As Greene (2017) mentioned, the development of students' SRL skills is the main aim of education. SRL has been defined by scholars in the

field (Boekaerts 1997; Pintrich 2004; Winne and Perry 2000; Zimmerman 2008) as the ability to actively monitor and regulate their learning. This process will happen through cognitive, metacognitive, and behavioural strategies such as exerting effort, managing resources, organising, processing information, and self-testing.

Research has investigated the relationship between motivation and cognition (Pintrich 1989; Pintrich and Garcia 1994). Where cognitive models suggest that the learner is "motivationally inert", motivational models consider the learner as "cognitively empty" (Pintrich and García 1993, p.3). However, there was a need for a framework containing both.

Pintrich (1991) developed a model that consisted of three aspects, including motivational beliefs, cognitive strategies, and self-regulatory strategies. Motivational beliefs refer to students' reasons for wanting to engage in the task. Cognitive and metacognitive strategies are about the means students use to accomplish the task (Duncan et al. 2015).

Schunk and Zimmerman (2012a) argued that the differences in learning outcomes could be explained in terms of their capacity to self-regulate learning, their characteristics, and their motivation. Studies (e.g. Lehmann et al. 2014; Zimmerman and Schunk 2008) examined the relationship between SRL and the motivational process. They showed that motivation affected how students selected learning strategies, the learning process, and student achievement at the end.

Studies used motivational constructs for grouping profiling (Bembenutty 1999; Meece and Holt 1993; Rosenzweig and Wigfield 2017), but some others used both motivational and strategy use constructs (Alexander et al. 1995; Alexander and Murphy 1998; Pintrich 1989). While many studies researched group effects on SRL behaviour (Jang et al. 2017; Järvelä et al. 2016; Lajoie et al. 2015; Nelson et al. 2015), recently, the interest has shifted toward more learner profiles and changes over time (Dörrenbächer and Perels 2016; Greene et al. 2019; Hong et al. 2020; Jang et al. 2017; Shell and Soh 2013). For example, Shell and Soh (2013) identified five student profiles and studied how the SRL strategies were different among students. Ning and Downing (2015) identified four different student profiles with different SRL strategy use. They compared the student profiles based on their academic performance. Zheng et al. (2020) identified four student profiles based on patterns of SRL behaviours. Hong et al. (2020) identified three distinct student profiles based on metacognitive learning.

While these studies identified different numbers of SRL profiles, other researchers such as Järvelä et al. (2019) identified the challenges regarding SRL studies and mentioned that SRL is not a state, and it involves a series of contingencies over time. They called for studies that

examine the changes in regulatory processes and regulation types over time (i.e., temporality). Ben-Eliyahu and Bernacki (2015) also stated that to understand the complexity of the phenomena, investigating cognitive, metacognitive, motivational, and emotional processes in the collaborative learning context, there is a need to trace behaviour over time.

To understand the learning process and changes in the behavioural and temporal SRL processes, Gašević et al. (2015) suggested using Winne (1982)'s version of self-regulation. Winne's model opens new opportunities for temporal and sequential SRL analysis which shows promising insights into the field (Winne 2006). Winne (2006) examined SRL as a recursive process. He defined SRL in a four-stage process: 1) task definition, 2) goal setting and planning, 3) enacting tactics and strategies planned in the previous stage, and 4) adopting study techniques metacognitively. Based on Winne (1997)'s version of SRL, there are three axioms: 1) learners construct knowledge, 2) learners are agents, and 3) there is randomness in data, but a central tendency prevails (Winne 1997). For this study's purpose, we focus on axiom 1. Axiom 1, which is about learners who construct knowledge, includes five facets, referred to as the COPES (i.e., Conditions, Operations, Products, Evaluations, and Standards). These five elements collectively influence the self-regulatory process of learning (Winne 1997).

Conditions are all the resources that are available to the students and the constraints that the students have inherited from the task and environment (e.g., cognition, motivation, knowledge, interests, context, and time constraint are examples of this category). Operations are strategies, tactics, and cognitive processes employed by the students to achieve their goals. In this stage, students will plan to achieve their goals (SMART - Searching, Monitoring, Assembling, Rehearsing, and Translating). Products are the results of the operation. Creating new knowledge would be an example of a product. Evaluations are the feedback generated by the students, peers, or their teacher and fit between the product and the available standards, and standards are the criteria by which products will be evaluated.

After all, there is a need for understanding the complex SRL processes and the change of SRL profiles, especially in online learning. , Moos and Bonde (2016) highlighted the importance of understanding the effects of motivation on achievement in a highly SRL environment such as higher education and online learning environments. Therefore, we addressed the gap by looking at unfolding students' SRL profiles over time in a BL environment and the next section discusses the study's data collection and how we analysed it.

3.1.4 Method

Out of 228 students in an entry-level business school course at a tertiary level, 189 students agreed to participate in our research. They were aged from 17 to 24. We collected their motivation and self-regulatory strategies through administering the MSLQ (Pintrich 1991) in Weeks 3, 7, and 11 of the semester. To meet the coursework requirements for this course, there were four assessments, two assignments which were due in Week 6 and Week 11 and a midterm test in Week 7, and the final exam in Week 14.

3.1.4.1 Instrument

We used the MSLQ and built our discussion based on Pintrich's information processing model (Pintrich 1988). In his model, each component has its meaning which is explained below. Under motivation, there are value, expectancy, and affective components. Under strategy use, there are cognitive and metacognitive strategy use and resource management.

The value component is about students' reasons for engaging in activities. It includes students' intrinsic goal orientation, extrinsic goal orientation, and task value beliefs. Intrinsic goal orientation refers to students' approaches to the course in terms of focussing on mastery and learning. Extrinsic goal orientation refers to external motivation, for example, getting good grades, outperforming others, or impressing authority figures. In task value, students' perceptions, e.g., how important, how interesting, and how useful the course was, has been assessed by students. The expectancy component includes self-efficacy beliefs and control of learning beliefs. In self-efficacy beliefs, we explore what students think about their capability in performing the task required for the course. Control belief is about how much control students think they have over their learning and how they think their effort helps them achieve their goals. The affective component is about students' test anxiety if they feel worried or emotional about the exam. It also includes other effects such as pride, shame, and guilt.

The cognitive component is about students' use of rehearsal, elaboration, organisation, and critical thinking to read and study their course material. Rehearsal strategies are about repeating words or text material over and over. In elaboration, we check how students, for example, paraphrase and summarise text material or create analogies. In organisational strategies, we check how students outline the concepts in the text material, how they structure the concepts in some type of visual display such as diagrams, concept maps, or tree-like pictures. Critical thinking will also be measured by investigating how students use previous knowledge and apply it to new situations and how they can critically evaluate ideas.

In self-regulatory strategies, we explore metacognitive and resource management strategies. Metacognitive control strategies are strategies that students use to control their cognition. In metacognitive strategies, we investigate how students make a plan, (i.e., how they set goals), skim, or generate questions; how they monitor their performance, (i.e., how they do self-testing, attention focus, or test-taking strategies); and how they regulate their behaviour based on monitoring activities (i.e., how they adjust the reading rate, reread, review, and test-taking strategies). Resource management strategies focus on how students manage time (i.e., how they do scheduling and goal setting); control their environment (i.e., how they define the area, quiet area, or organising the area); effort management (i.e., how they do self-talk, persistence, and self-reinforcement); and support others (i.e., how they seek help from teacher or peers, and how they do peer or group learning).

The validity and reliability of the MSLQ have been confirmed in the literature (Büyüköztürk et al. 2004; Lawrence Neuman 2014; Pintrich et al. 1993b). Therefore, we first considered each construct's descriptive analysis at each iteration and sought to find the relationships among the constructs and how these constructs changed as the course progressed.

3.1.4.2 Case Study

The course was designed based on a BL methodology. The lecturer's approach to BL involved purpose-made online lectures in place of traditional face-to-face delivery. His online lectures were supplemented with short, face-to-face weekly tutorials. Each lecture video featured a short quiz at the end that tested students' understanding of the material just covered. Before each tutorial, the lecturer analysed the embedded quiz results and determined which course material had proven most challenging. He then prepared a set of review questions in an audience participation tool, TopHat (https://tophat.com/), and presented these to students at the tutorial.

After completing the review questions, the lecturer launched the first of two TopHat tournaments which primarily contained the same embedded quiz questions featured in that week's online lectures. TopHat tournaments were round-robin style competitions where students competed head-to-head and won if they were the first to answer correctly. During the competition, a leader board was populated, showing the top students and their scores. After the tournament, the top five or six students were awarded a prize of a piece of candy. Therefore, students were incentivised to watch each week's online lectures and participated in the weekly in-class tutorial through awarding participation marks.

3.1.5 Results

This research used the Statistical Package for Social Sciences (SPSS) version 26 to analyse data and shed light on our research questions. Firstly, students' self-reports on their motivation and strategy use, how each construct changed, and how they correlated with the final score were analysed. We identified different SRL profiles by applying the K-Means clustering algorithm. The optimal cluster-solution was selected based on 'elbow' (Tibshirani et al. 2001). Then, we explained different SRL profiles and compared them based on students' levels of motivation, strategy use, and their final score. We applied a one-way analysis of variance (ANOVA) to consider cluster group mean differences on individual dependent variables. For understanding how clusters were different from each other, we employed a multivariate analysis of variance (MANOVA). Furthermore, we considered how students' profiles unfolded as the course progressed.

3.1.5.1 The Dynamics of Motivational and Strategy Use

This section addresses the first research question: understanding the dynamics of motivational, cognitive, self-regulatory strategies at three-points in time.

	Iteration 1 (N=189)		**Iteration 2 (N=173)**		**Iteration 3 (N=153)**	
	M	**SD**	**M**	**SD**	**M**	**SD**
Intrinsic Goal Orientation	4.71	.84	4.53	.89	4.55	.94
Extrinsic Goal Orientation	5.30	1.06	5.04	1.14	5.10	1.09
Task Value	5.30	.98	5.11	.96	5.12	.99
Control of Learning Beliefs	5.15	.87	5.14	.82	5.06	.89
Self-Efficacy for Learning Performance	4.92	.86	4.84	.92	4.84	.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	.83	4.58	.93	4.73	.94
Organisation	4.83	.87	4.76	.91	4.84	.93
Critical Thinking	3.87	1.05	3.88	1.01	3.95	1.13
Meta Cognitive Self-Regulation	4.29	.67	4.39	.70	4.45	.70
Time and Study Environment	4.76	.78	4.66	.86	4.63	.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	.63	4.80	.62	4.82	.69
Strategy	4.23	.55	4.20	.62	4.31	.659

Table 20: Descriptive statistics for MSLQ sub-constructs at Time 1, Time 2, and Time 3

In contrast to previous studies (e.g. Pintrich and Garcia 1991; Pintrich et al. 1993b), our study (Table 20) showed that even though there was a decline in motivation and strategy use constructs as the course reached midterm, these constructs increased again as the course got close to the end. It is not unusual that students accumulate significant coursework and assignments that are due to submit at a key point in the semester, and thus it is possible for them to become less motivated due to work pressure.

After measuring motivation and strategy use, we considered sub-constructs underneath them, as depicted in Table 20, where the number of students (N) was 189, 173, and 153, respectively. Table 20 presents the mean and standard deviation (SD) for each sub-construct. The first trend was the sub-constructs that decreased towards midterm and then increased as the course got close to the end. All motivational components are reported under this trend except self-efficacy and control belief. Students also mentioned that the midterm test was a time for them to reflect. Based on the scores they got for their tests and assignments, they were able to gauge how well they had used material and tools and change their strategies.

The second trend continuously decreased constructs. Time and study environment continuously decreased; we postulate that this is because students are proficient time managers. They also continuously lost confidence in their ability to control their learning. Perhaps students expected more from themselves but seeing their midterm results made them lose trust in their capabilities and expectations. The third trend continuously increasing indicates the students' level of cognitive and metacognitive strategy use continuously increased while their motivation decreased to manage to achieve their goals.

Next, we present the pair-wise correlations of the constructs from three measurements and the final score in Table 21 (a full table is available on request). We use the following acronyms in Table 21 presentations for brevity. Intr: Intrinsic Goal Orientation, Extr: Extrinsic Goal Orientation, Tskv: Task Value, Cont: Control Beliefs about Learning, Slfef: Self-Efficacy for Learning and Performance, Tanx: Test Anxiety, Reh: Rehearsal, Elab: Elaboration, Org: Organisation, Crit: Critical Thinking, Mcg: Metacognitive Self-Regulation, Tsdy: Time and Study Environment, Eff: Effort Regulation, Prlrn: Peer Learning, and Hsk: Help-Seeking.

Among motivational constructs, self-efficacy for learning and performance and extrinsic goal orientation from three iterations and task value from the last two iterations had the highest correlation with course outcome. Control beliefs and Anxiety always had the lowest correlation with the final course outcome. The only exception was the Anxiety construct at the beginning of the course. Lynch (2006) also showed that self-efficacy, intrinsic and

extrinsic orientation, and task value had notable correlations with final scores. Among strategy use constructs, their study showed that elaboration correlated with final scores.

Motivation						Strategy Use					
Iteration 1		Iteration 2		Iteration 3		Iteration 1		Iteration 2		Iteration 3	
	Final Score		Final Score		Final Score		Final Score		Final Score		Final Score
Intr1	0.04	**Intr2**	.230*	**Intr3**	.261*	**Reh1**	.146*	**Reh2**	.222*	**Reh3**	.202*
Extr1	.187*	**Extr2**	.279*	**Extr3**	.382*	**Ela1**	0.033	**Ela2**	.166*	**Ela3**	.239*
Tskv1	0.12	**Tskv2**	.279*	**Tskv3**	.305*	**Org1**	.210*	**Org2**	.181*	**Org3**	.267*
Cont1	0.00	**Cont2**	0.06	**Cont3**	0.12	**Crit1**	-	**Crit2**	0.038	**Crit3**	0.062
Slfef1	.209*	**Slfef2**	.452*	**Slfef3**	.462*	**Mcg1**	0.019	**Mcg2**	.150*	**Mcg3**	.169*
Tanx1	.179*	**Tanx2**	0.09	**Tanx3**	0.12	**Tsdy1**	.153*	**Tsdy2**	.204*	**Tsdy3**	.280*
						Eff1	0.127	**Eff2**	.235*	**Eff3**	.306*
						Prlrn1	0.048	**Prlrn2**	0.131	**Prlrn3**	0.073
						Hsk1	0.052	**Hsk2**	0.069	**Hsk3**	0.073

Table 21: Significant correlations between sub-constructs and final score across three

Among strategy use constructs, effort regulation and time and study environment have the highest correlations with the final score. As the course progresses, rehearsal and organisation get more attention. Among strategy use constructs, help seeking, and peer learning had the lowest correlation with course outcome. Our study results differ significantly from other studies such as (Liu et al. 2014; Ng et al. 2016; Pintrich 1999; Stolk and Harari 2014) which could be the effect of the pedagogical approach. Therefore, there is a need for more studies in different contexts.

3.1.5.2 Self-Regulated Behavioural Profiles

This section of analysis addresses question two, identifying and distinguishing the different SRL profiles of students. We applied the K-Means clustering algorithm, which allowed us to identify distinct SRL profiles and track the developmental patterns. In the following sections, we present our clustering results based on three iterations of data (Table 22). We identified minimally, average, and highly SRL profiles in each iteration which are explained next.

3.1.5.2.1 Minimally Self-Regulated Learners' Profile

Minimally self-regulated learners in iteration 1 were students in Cluster 1, who had a minimum motivational and strategy use but had an average critical thinking, help seeking, and peer learning. There were 67 students in this cluster who got an average 62.01 in their final

score and this was the largest cluster. Therefore, at the beginning of the course, our minimally SRL profile contained the highest number of students. In iteration 2, minimally self-regulated learners were students in Cluster 1 with a minimum score in all sub-constructs except for peer learning and help seeking. Cluster 1, with 55 students, achieved an average of 62.80 for their final course outcome. The minimally self-regulated learner cluster in the second iteration contained the fewest students.

	Iteration 1			Iteration 2			Iteration 3		
Cluster	**C1**	**C2**	**C3**	**C1**	**C2**	**C3**	**C1**	**C2**	**C3**
Intrinsic Goal Orientation	4.23	4.65	5.25	3.90	5.01	4.66	2.00	4.22	5.07
Extrinsic Goal Orientation	4.69	5.59	5.67	4.08	5.33	5.64	1.50	4.89	5.48
Task Value	4.46	5.48	6.00	4.27	5.35	5.64	2.00	4.86	5.55
Control of Learning Beliefs	4.75	5.33	5.40	4.91	5.07	5.42	4.25	4.91	5.28
Self-Efficacy for Learning Performance	4.41	5.12	5.27	4.20	4.94	5.33	2.06	4.66	5.17
Test Anxiety	4.33	4.55	4.95	4.27	4.88	4.40	3.00	4.41	4.91
Rehearsal	4.11	4.25	4.76	4.00	4.92	4.97	2.25	4.41	5.35
Elaboration	4.20	4.37	5.13	3.94	4.98	4.78	2.17	4.34	5.33
Organisation	4.37	4.78	5.35	3.99	5.23	5.01	2.63	4.43	5.45
Critical Thinking	3.77	3.37	4.40	3.34	4.62	3.69	1.50	3.45	4.69
Metacognitive Self-Regulation	3.95	4.23	4.69	3.77	4.77	4.60	2.92	4.15	4.90
Time and Study Environment	4.23	5.04	5.07	4.07	4.77	5.07	3.38	4.37	5.02
Effort-Regulation	4.17	5.29	5.11	3.85	4.73	5.28	3.50	4.43	4.98
Peer Learning	3.57	2.12	4.19	2.89	4.72	2.43	1.33	2.92	4.51
Help-Seeking	3.35	2.15	4.09	2.91	4.21	2.42	2.38	2.90	3.94
Student numbers	67	56	66	55	56	62	2	86	65
Final	62.02	68.43	70.86	62.81	71.61	72.78	45.74	67.79	73.89

Table 22: Clustering based on three iterations of data

In iteration 3, minimally self-regulated learners are Cluster 1 students with a minimum score in all sub-constructs. The students in this cluster achieved the minimum score, which was an average of 45.73. There were only two students in this cluster. Having a low number of

students in the minimum level cluster was a good achievement in this course. The course lecturer was able to help students move to the highest- and average-level SRL clusters.

3.1.5.2.2 Average Self-Regulated Learners' Profile

The average self-regulated learners' profile in iteration 1, included 56 students in Cluster 2, who had an average score in all the sub-constructs, achieving an average of 68.43 as their final score. However, this group had the lowest critical thinking, help-seeking, and peer-learning scores. This cluster had the fewest students in iteration 1.

In iteration 2, the average self-regulated learners in Cluster 2 were students with the highest intrinsic goal orientation, who also had the highest test anxiety level. This group used the highest cognitive strategies such as elaboration, organisation, and critical thinking, and had the highest metacognitive self-regulation. These students also used the highest level of peer-learning and help-seeking. This cluster had the average in the remaining motivational sub-constructs such as extrinsic goal orientation, task value, control of learning beliefs, and self-efficacy for learning performance. Students in this cluster had an average score in motivation and high strategy use. Cluster 2 with 56 students**,** achieved an average of 71.60. Students in Cluster 2 had the highest test anxiety level, which might have prevented them from performing well. In iteration 3, the average self-regulated learners' profile was Cluster 2 students who had an average score in all sub-constructs. They achieved an average score in the final assessment. The average score for this cluster was 67.78. There were 86 students in this cluster, which was also the largest cluster.

3.1.5.2.3 Highly Self-Regulated Learners' Profile

In iteration 1, highly competent self-regulated learners were 65 students in Cluster 3, who had the highest scores in all the sub-constructs, making it the second-largest cluster. These were the most motivated students who always used the maximum number of strategies. The students in this cluster achieved on average the highest scores in their final score which was 70.85. In iteration 2, the highly self-regulated learners' profile had an average intrinsic goal orientation but maximum scores in other motivational sub-constructs. This group was average in elaboration, organisation, critical thinking, and metacognitive self-regulation. These students also used the minimum level of peer learning and help seeking. This group had a high score in most motivation constructs (e.g., extrinsic goal orientation, task value, control of learning beliefs, self-efficacy for learning performance), a moderate score at most strategy use

constructs (e.g., intrinsic goal orientation, test anxiety), and achieved the highest score at the end. Cluster 3 with 61 students achieved 72.78 in their final score. In iteration 3, the highly self-regulated learners' profile were students who had the maximum amount in all motivational and strategy use sub-constructs. They achieved the highest at the end, and the average score for this group was 73.89. There were 64 students in this cluster. This cluster was the second-largest cluster.

We also show different clusters in the three iterations based on different sub-constructs in Figure 10 (Cluster 1 minimally, Cluster 2 average, Cluster 3 highly SRL). There is a clear differentiation among clusters at each time. We also had a mix of profiles in iteration 2. In each iteration, as the course progressed, there were clear differences in SRL patterns between the three different profiles. In iteration 3, we had marked differences between them. In iteration 3, Cluster 3 was the highest in terms of all constructs, average clusters had an average amount in all constructs, and minimally clusters had the lowest in all constructs. A MANOVA was conducted to test whether motivation and self-regulation variables significantly differed across the three clusters. The clusters were significantly different. We checked through ANOVA how the adoption of different learning profiles affected students' final scores. The final scores were significantly different across profiles.

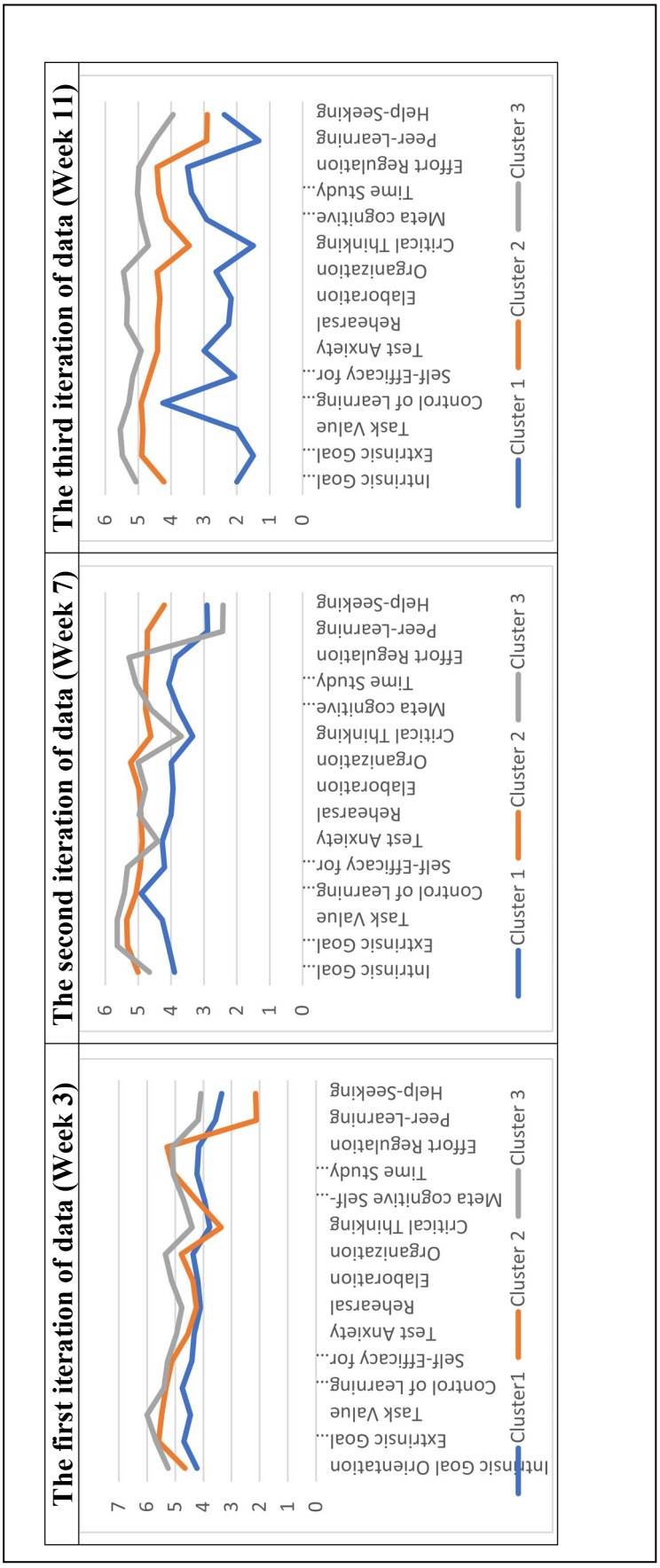

Figure 10: Clustering of freshmen students based on three Iterations of data

3.1.5.3 Students' SRL Behaviours Unfolding

This section address question three, identification of the extent to which students' SRL profiles unfolded as the course progressed. Figure 11 indicates MSLQ values for the three times in the course. In addition to these questionnaires, students had to submit coursework assignments and sit a midterm test and final examination. Here it can be seen that students moved between the clusters as they received results and feedback.

In the first iteration, we measured the level of motivation and strategy use and identified three SRL profiles. Then, we looked at how students used the tools (exams and assignment scores) as the evaluation tools and how they reflected on their skills. We further considered how each SRL profile was affected by their first test results in iteration 2. After the second iteration measurement, students submitted their next assignment. Once they had received their results, measurements were repeated for iteration 3. In our movement analysis, we checked how students' SRL profiles changed after receiving their scores. As we can observe, students moved to upper-level profiles as the course progressed.

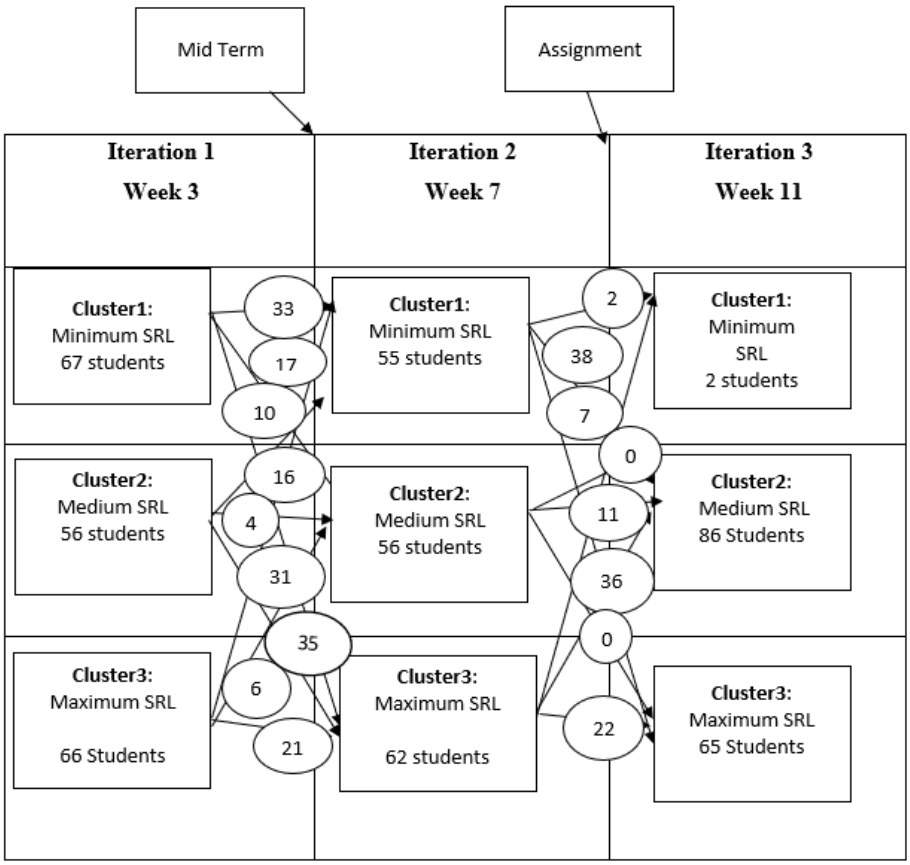

Figure 11: Representation of changes in cluster membership

Table 23 presents the number of students whose cluster memberships changed as the course progressed. In the first iteration, there were 67 students in Cluster 1 (minimally SRL), 56 students in Cluster 2 (average SRL), and 66 students in Cluster 3 (highly SRL). The number of students at the highest SRL level did not change. However, students moved from a minimally SRL to an average SRL. Cluster 1 (minimally SRL) was the largest group at iteration 1, but at iteration 2, it had the fewest students in it. Cluster 1, which was the Minimally SRL cluster, was the most stable cluster at iteration 2. The largest movement was from Cluster 3 (highly SRL) to Cluster 2 (average SRL), which meant a decrease in motivation and strategy use at the midterm. But still, we had the highest number of students in Cluster 3 (highly SRL) at iteration 2.

Iteration 1	**Iteration 2**			**Iteration 3**		
	Cluster 1 minimally SRL	**Cluster 2 average SRL**	**Cluster 3 highly SRL**	**Cluster 1 minimally SRL**	**Cluster 2 average SRL**	**Cluster 3 highly SRL**
Cluster 1: (minimally SRL) (67 students)	33	17	10	2	38	7
Cluster 2: (average SRL) (56 students)	16	4	31	0	11	36
Cluster 3: (highly SRL) (66 Students)	6	35	21	0	36	22

Table 23: Shifts in cluster membership

Cluster 3 (highly SRL) is the most stable cluster at iteration 3. The largest movement at iteration 3 was from Cluster 1 (minimally SRL) to Cluster 2 (average SRL), which is a good achievement. It was followed by movement from Cluster 2 (average SRL) to Cluster 3 (highly SRL). Notably, at iteration 3 we did not have any movement from Cluster 3 to Cluster 1 or from Cluster 2 to Cluster 1. In the third measurement, there were two students in Cluster 1 (minimally SRL), 86 students in Cluster 2 (average SRL), and 65 students in Cluster 3 (highly SRL). This analysis helped us understand how students adopted different profiles, how different categories of students reflected on their work and moved among clusters as they received feedback, and how the course progressed which helped us understand the nature of academic development in the course.

3.1.6 Discussion

In this study, we researched students' SRL processes in a BL environment. In a BL environment, students need to have the ability to manage their learning process. The lecturers also do not have the opportunity to interact with the students like in a physical environment to take precautionary measures. Therefore, the lecturer needs to access more data from students to meet students' needs and be able to help them. While it has been shown that SRL plays an important role in doing tasks, our knowledge regarding how self-regulation leads to different student outcomes is limited. We argued that several studies considered the correlation between SRL strategies and learning outcomes. These studies focused more on variable-oriented statistical approaches (Burić and Sorić 2012; Peng et al. 2014). However, we do not know enough about different SRL profiles and how these profiles may lead to a different outcome. Therefore, in this study, first, we examined the SRL constructs and saw how students' reports changed as the course progressed. Then, we identified three SRL profiles and investigated how different SRL profiles could also lead to different achievements.

To understand the SRL process, we drew on Winne's model of individuals' SRL cycles involving three axioms at a micro-level with COPES (i.e., Conditions, Operations, Products, Evaluations, and Standards). The application of Axiom 1 is that students use tools to operate on raw materials, to construct a product that is evaluated in a formative or summative way with respect to standards of socio-cultural kinds. As students engage in the learning process, they go through several stages, as mentioned before. It starts with task perception, goal setting and planning, and translating plans into strategies based on the goals they set for themselves. Then they evaluate themselves during the learning process, it is also important to understand how much their evaluation of themselves affects their motivation and strategy use and how much they are willing to interact with learning materials. We observed that each of the phases is cycled through COPES by metacognitive monitoring. Based on the monitoring they adopt, their perception of the task changes and the goals, strategies, and shifts between the phases would happen. It was also important to understand the relationship between students' motivation, strategy use, and achievement. To achieve this, we examined the correlation between constructs and final scores in three iterations. We understood that among motivational constructs, extrinsic goal orientation and self-efficacy had the strongest correlation with the final score. Among strategy use constructs, time and study environment and effort regulation had the highest correlation with final scores in all three iterations. The correlation between constructs and the final score increased as the course progressed.

Understanding the constructs that had a high correlation with the final score was very important as the lecturer could teach students and update the instructional design.

We also examined how the evaluation tools used along the way helped students evaluate themselves and reflect on their learning, and how the tools affected the students' motivation, strategy use, and changing profiles. We measured students' motivation and strategy use for the first time, then they went through their midterm test and assignment. We observed how the assessment results affected students' feelings regarding the course and their motivation and self-regulation in the second iteration. We repeated the measurement and observed the effect of the second assessment on students' motivation and self-regulation. We observed how each student's profile reflected differently on themselves. This helped us better understand how the temporal, behavioural, and self-regulation processes of the students worked.

Clustering of students each time in this study was based on one iteration of data. We realised that we could identify the students who would get a low score in the final assessment based on the first measurement data which addresses one of the most important LA aims (identifying at-risk students). We aimed to identify the students at risk early enough, so that appropriate intervention could be applied to prevent students from dropping out. Now we understood that by looking at the first measurement data, we could categorise students, identify at-risk students, and ask the lecturer to apply appropriate intervention to help the students. We also showed that students who were high in motivation and strategy use achieved high scores at the end. Therefore, it is vital to improve students' motivation and strategy use so that students can get good scores at the end. We also understood that differences between students' performance could be explained in terms of differences in their motivation and strategy use. From clustering based on iteration 2, we identified that students who were high in motivation or strategy use performed well in their final score. Therefore, the class lecturers need to consult with students and encourage them to use new strategies for their learning. They also can update their instructional design by giving students proper instructions so that they more easily relate to the instructions and achieve better.

In our study, the lecturer of our class used different techniques to increase the motivation of students. In so doing, the lecturer was successful and had two students in the lowest SRL cluster in iteration 3. The lecturer ran tournaments and introduced gamification in his class. He also threw chocolates to students who won in the tournaments. The lecturers can also imply other different techniques to increase students' motivation. Using iteration 3 data for clustering helped us understand how students believed that their motivation and strategy use increased.

In iteration 3 the clusters were well-differentiated, and all students except two moved to upper SRL profiles. We believed that this was an achievement for the course lecturer.

Our cluster analysis showed different numbers of clusters compared to other studies (Çebi and Güyer 2020). Therefore, more studies with different contexts are needed to cross-validate our analysis. We also identified different motivation and strategy use patterns (Iteration 2), which led to a similar achievement, which raises a question for us whether motivation, cognitive, and self-regulatory components work together to achieve a specific achievement level. It is important to understand what the level of each construct is that triggers other constructs or if there is any triggering process? This needs to be researched in future.

While previous research studies (Çebi and Güyer 2020; Shell and Soh 2013) has studied the issue once and profiled the students based on one iteration of data, other studies (i.e. Jang et al. 2017; Järvelä et al. 2019) identified that the SRL profiles are dynamic. They showed that students adopted quite different SRL profiles over time. They claimed that students' learning profiles needed to be updated based on how learners interacted with specific tasks so that immediate and dynamic feedback would be given to them. Therefore, in this study, we looked at how students' profiles unfolded. We observed that students could show and adopt quite different SRL profiles over time. Even though we identified three clusters of highly, average, and minimally SRL in all three iterations, we observed how students moved between the clusters as time passed. This movement among clusters also showed us the trajectories of students' beliefs about their motivation and strategy use (self-regulatory skills) over time, as also suggested by Ng et al. (2015).

3.1.7 Conclusion

This study investigated students' learning profiles who shared common motivational and SRL characteristics. Further, it investigated how students adopted different profiles along the way until they reached the end of the course. We highlighted the functional and adaptive roles of motivation and cognition for achieving good grades. We understood that we might be able to teach students about cognitive and self-regulating strategies; however, the motivational beliefs were very important and effective when these strategies would be used for tasks. We identified the strategies that could be taught to the students who had a low level of motivation through correlation analysis.

We identified three distinct profiles of self-regulated learners based on motivation and strategy use for three different measurements. We observed that students who had higher levels of

motivation and strategy use achieved higher at the end, and at the same moderate level motivation and strategy use students achieved moderately, and low achievers had the lowest levels of motivation and strategy use. Therefore, we could conclude we had highly, average, and minimally self-regulators. High self-regulators were more self-efficacious, highly anxious, more self-regulated, and more motivated students. In contrast, to the study run by Liu et al. (2014), our study showed that students who had the highest motivation and used the highest strategy use showed the highest anxiety as well. They also obtained the highest results in final assessments. The second group had a low level of motivation, low level of SRL, and low achievement. Also, we had average self-regulators who were moderate in all of the measured variables.

We were also struck by observing the consistency in the profile of students. Most of the changes were to the upper-level SRL. More adaptive clusters had a higher level of motivational belief, cognition, and metacognition. These were the students who were active self-regulators. Close to the end of the course, we had just two students in the lowest level of motivation cluster. We aimed to produce highly self-regulated learners. Considering the number of high and moderate students in the self-report, and based on their final achievement, we were able to produce learners who could control their learning. It is worth mentioning that students' motivation and cognitive strategy use could be influenced by teachers' instructional design and teaching style. Therefore, we needed to create a learning environment that could convert reluctant students into more focused students. It was also important to be able to keep the initial motivation of students.

This study's unique and significant contribution is to the literature on SRL by examining SRL profile changes using a longitudinal approach. This study also contributes to the fields of motivation and education by extending existing motivation research through longitudinally classifying motivational beliefs and learning strategies of three different groups of students (highly, average, minimally SRL).

This study has also brought out the importance of studying student clusters based on motivation, thus making a novel contribution to LA. This study has shown how tracking students' profiles and dynamics can be used by lecturers fruitfully to design proper interventions so that students can migrate to higher SRL profiles. Two of the limitations of the study are 1) it is based on only one course, and 2) it is based on student self-reporting. To rectify these, we have planned to have multiple courses be considered for study with the courses varying in level of academic maturity needed and complexity of the subject matter

taught. We may use, where possible, alternatives to self-reporting, such as participation (trace data from actual students' tool use). Another interesting research question to address in future is: Why some students shift between different SRL profiles, while others are static? Overall, this study has novel contributions to LA, SRL, and teaching practice in a BL scenario.

(This is the end of paper 4)

3.2 Paper 5- Exploring the Cyclical Nature of Self-Regulation for Freshmen and Upper-Level Students in Blended Learning Courses: A Longitudinal Study

(Submitted to Computers in Human Behavior journal)

3.2.1 Abstract

Understanding Self-Regulated Learning (SRL) is vital for helping students' learning, especially in the online learning environment. In contrast to previous studies that adopted a variable-centred approach, this study employed a person-centred approach and investigated the self-regulatory profiles of freshman and upper-level students in Blended Learning (BL) courses. We had 314 participants at a tertiary level and collected 850 viable surveys using the Motivated Strategies for Learning Questionnaire at three different times. Applying the K-Means clustering algorithm, this study identified three distinct SRL profiles in each class; highly, average, and minimally self-regulated and looked at how students' SRL profiles unfolded as the courses progressed, of which little is known. The findings of our longitudinal cluster-analysis and investigation of the cyclical nature of SRL for two groups contribute to the literature in SRL theory. This study also contributes to Learning Analytics by studying motivational constructs and bringing empirical evidence based on the theory, which is lacking in the extant literature in the field. The findings also contribute to educational research's practice by giving meaningful insights to researchers and practitioners.

Keywords: Self-regulated learning, learning analytics, MSLQ, longitudinal clustering, profiling learners, unfolding profiles

3.2.2 Introduction

In a world in which learning happens beyond the education context, producing lifelong learners who can self-regulate their learning is an important matter. It is widely acknowledged that self-regulation is more essential for online learning and BL formats as students have more responsibilities for their learning (Ifenthaler 2012; Steffens 2006). Self-regulated learning (SRL) has been defined as by Pintrich (2000) "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). Different learning theories, such as SRL, emphasise the importance of motivation and strategy use for learning (Boekaerts 1999; Pintrich 2000; Schunk 2008; Zimmerman 2002). Panadero (2017) stated that SRL is a core conceptual framework for understanding the cognitive, motivational, and emotional aspects of learning. There are contradictory studies (e.g., Reid et al. 2017; Zheng 2016) on the support of metacognition in facilitating SRL and learning outcomes. One reason for having contradictory results is potential variance in students' SRL during the learning process.

Therefore, the learning process of students considering their variances needs to be studied more.

Winne (2010) stated that advances in technology-enhanced learning enable us to capture fine-grained trace data about the learners' activities in online learning environments. Information about the occurrence, temporal sequence, or regular patterns of events about learners' cognitive activities and strategies would be collected which allows for tracing aptitudes in practice. The large quantities of data cannot be used efficiently by the learners and instructors; however, Learning Analytics (LA) provides a useful way to analyse the data to bring insights to both learners and instructors. 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). With the emergence of LA, there are new opportunities that could give insights to the lecturer by collecting information from students. It is more important to provide insights to the lecturers because in online learning; the lecturers do not see students physically, which limits their ability to take precautionary measures.

Many studies used variable-centred approaches and looked at the relationship between motivation and strategy use across individuals (Morin et al. 2018; Mousoulides and Philippou 2005; Niemczyk and Savenye 2005; Pintrich et al. 1990). However, these constructs are related to each other within individuals. Therefore, the person-centred method has been employed in this study to examine intra-individual differences through making SRL profiles (Hayenga and Corpus 2010; Howard and Hoffman 2018; Liu et al. 2014; Perera et al. 2009; Shell and Soh 2013; Zheng et al. 2020). These studies did not look at the issue from the perspective of self-regulation theory. Additionally, they did not look at the longitudinal changes and the cyclical nature of SRL. Studies (i.e. Ben-Eliyahu and Bernacki 2015; Jang et al. 2017; Järvelä et al. 2019) identified that SRL is not linear and it involves cyclical adaptation consisting of series of contingencies over time (Molenaar and Järvelä 2014). They mentioned learners metacognitively monitor their learning, to control and adapt their strategies if needed. Molenaar and Järvelä (2014) also stated that what we do not know is when those actions take place and how they influence each other. Therefore, it is important to understand the changes in regulatory processes (temporality) over time.

As Winne et al. (2019) stated, the data which has been used in LA rarely provides a clear signal on the learning process. In this regard, Gašević et al. (2015) described that data needs to be collected in a way that describes the learning process in terms of events in a learning

episode. They suggested using Winne (1982) characterisation of traces and his COPES model (Conditions–Operations–Products–Evaluations–Standards). Therefore, this study built its discussion based on Winne's (2006) version of SRL and looked at the motivational and strategy use constructs longitudinally to address the challenge identified by Järvelä et al. (2019) regarding the cyclical nature of self-regulation for two groups of students (upper-level and freshmen). We concentrated on motivational constructs as they have not yet been sufficiently considered for analyses in LA (Lonn et al. 2015; Wong et al. 2019b). The methodology adopted in this study fits with the LA framework. By identifying the group of students who share a similar profile, it identifies the students who would be at risk of failure so that the lecturer could apply appropriate interventions to help them (Fincham et al. 2018).

In contrast to other studies that considered students' trace data, we use students' reported data to understand their motivations and how they used strategies in their learning process. We used motivational and strategy use data, as emphasised by Li et al. (2020). They stated that SRL is a multi-dimensional construct that needs to consider metacognition, emotion, and motivation on top of strategic behaviour. There are different schools of thought for understanding students' learning. The class of cognitive thought (Ausubel 1969) looks at learners as motivationally inert. This class of thought looks at learners as not having purposes, goals, or intentions. However, motivation models look at learners as cognitively empty. This class of thought looks at learners as not having knowledge, strategies, or thinking processes (Kunda 1987). However, we follow Pintrich's (1991) model, which is based on an information-processing model of cognition and a social-cognitive view of motivation (Pintrich 1989; Pintrich and Schrauben 1992). We administrated the Motivated Strategies for Learning Questionnaire (MSLQ) (Pintrich 1991) three times on students from two different BL courses (N=314 students) measuring motivation, cognition, metacognition, and on top of strategic behaviour to answer the following two overarching questions.

RQ1: How many distinct SRL profiles of students can we identify in the upper-level and freshmen students in two different BL courses at three points in time?

RQ2: How do upper-level and freshmen students' SRL profiles unfold in two different BL courses as the courses progress?

The object of this study was to understand the students' performance through a person-centred approach. We hypothesised that through cluster analysis, we would understand that highly competent students' profiles would have the highest motivation and strategy use and the lowest level of anxiety.

We had 314 students from two groups of freshmen and upper-level students from different BL courses. Identifying different SRL profiles for two groups of students and understanding the clusters' stability as the course progressed (cyclical nature of SRL) contribute to the literature in SRL, which is very important for both practice and theory building. Through studying motivation and strategy use, the study also addressed the lack of motivational and empirical studies in LA. Clustering students also helps us identify at-risk students, which addresses one of the most important LA aims.

We aimed to understand the differences between the two classes (upper-level and freshmen students) and identified the constructs that were more likely to be evoked and differentiate the groups in different courses. We understood how the clustering was different for Level 1 and Level 2 courses. This raises the question of which different course contexts, classroom environments, intra-individual differences in students' motivation, cognition, and self-regulation would affect or evoke and differentiate the groups therefore which need to be researched in the future. We also identified different motivation and strategy use patterns, which led to a similar achievement, which raises a question for us as to whether motivation, cognitive, and self-regulatory components work together to achieve a specific achievement level. It is important to understand what the level of each construct is that triggers other constructs or whether there is any triggering process. This needs to be researched in the future.

This study also has contributions for an applied perspective on teachers' practice. It enables educators to understand better their students' subgroups (SRL profiles), their SRL process, and how they could adopt different SRL profiles over time. Teachers could look for a different profile of students in class and apply appropriate interventions or teaching strategies so that students attain better profiles. They can also update the instructional design to help students better.

The organisation 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 theoretical framework that guides the study. Next, we present the methodology, how we collected data, and how we analysed it. Finally, we discuss our findings and present the conclusions.

3.2.3 Literature Review

Over the last thirty years, SRL has become an important topic in education (Azevedo and Gašević 2019; Greene and Schunk 2017; Winne 2019). It is acknowledged that self-regulation is essential for learning, especially in a BL environment where there is limited interaction

between the lecturer and students (Ally 2004). In the BL environment, individuals are required to be more autonomous to be able to be self-regulated. While there are different versions of SRL available, all the versions of SRL follow the same three phases of preparatory, performance, and appraisal. Among all the variations of SRL, this study focuses on Winne et al.'s (2006) work.

Winne (1996) considers SRL an inherent part of learning. He defines SRL as meta-cognitively guided behaviour that could enable students to adaptively regulate their use of cognitive tactics and strategies in performing a task. Winne and Hadwin (1998) define SRL as a four-stage process including 1) task definition (i.e., students should be able to clearly understand the task they are being asked to complete), 2) goal setting and planning (i.e., students set appropriate goals for accomplishing a given task. It would be along with plans for how students are expected to achieve those goals), 3) enacting tactics and strategies planned in the previous stage, which involves students using learning strategies (cognitive, metacognitive, and SRL processes), and 4) adopting study techniques metacognitively (i.e., students can change their goals, plans, and use of learning strategies to make sure they use them efficiently). SRL sets out five facets of tasks that can happen in the four phases of SRL. These five facets are referred to as the COPES (i.e., conditions–operations–products–evaluations, and–standards). These five COPES elements collectively influence the self-regulatory process of learning (Winne 1997). Conditions are the resources available to the students, and the constraints that the students have inherited from the task and environment (e.g., cognition, motivation, knowledge, interests, context, and time constraints are examples of this category). Operations are the strategies, tactics, and cognitive processes employed by the students to achieve their goals. In this stage, the students plan to achieve their goals, referred to as SMART- searching, monitoring, assembling, rehearsing, and translating. Products are the results of the operation (creating new knowledge is an example of a product). Evaluations are the feedback generated by the students, peers, or their teacher and fit between the product and the available standards. Standards are the criteria by which products are evaluated.

There are different studies (i.e., Hong et al. 2020; Ning and Downing 2015; Shell and Soh 2013) that consider the SRL process by identifying students' profiles through applying person-centred approaches. Shell and Soh (2013) identified five students' SRL profiles and studied how their strategies were different. Ning and Downing (2015) identified four students' profiles with different SRL strategy uses and compared the students' profiles based on their academic performance. Zheng et al. (2020) identified four students' profiles based on patterns of SRL

behaviours. Hong et al. (2020) identified three distinct profiles of students based on metacognitive learning. While many studies examine group effects on SRL behaviour (Jang et al. 2017; Järvelä et al. 2016; Lajoie et al. 2015; Nelson et al. 2015), recently, interest has shifted more toward learner profiles and changes over time (Dörrenbächer and Perels 2016; Greene et al. 2019; Hong et al. 2020; Jang et al. 2017; Shell and Soh 2013). Järvelä et al. (2019) stated that we are still not sure how cyclical the nature of SRL profiles is. Therefore, this study investigated the temporal and sequential SRL process in BL environments through researching students' motivation and use of metacognitive monitoring and controlling to strategically adapt their learning whenever it is required (Zimmerman 2013a). This was very important to identify the changes that happen in the regulatory process. Thus, we dive into the gap in the methodology on how to capture the evolving process and in the next section, we discuss the study's data collection and analysis process to understand how students adopt different SRL profiles as the course progresses.

3.2.4 Methods

3.2.4.1 Participants

The participants were students at a university level. Three hundred and fourteen students were invited; while their participation was voluntary, 307 students gave us consent to use their data. We had a Year 1 course with 194 students and a Year 2 course with 120 students. This enabled us to collect 850 surveys in three rounds of data collection.

3.2.4.2 Structure of the Course

The study was conducted in two BL courses that were conducted over 12 weeks. BL has been defined as a mix of online and offline learning activities. There is a choice between traditional and new media, which can be replaced with each other (Thorne 2003a). This teaching method was employed to produce self-regulated learners, which included teachers, traditional classrooms, and online learning methods (Sharma and Barrett 2008). The courses were designed based on a BL methodology. The lecturer's approach to BL involved purpose-made 30-40 minute online lectures instead of traditional face-to-face delivery. Their 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 1) to attend the course in person or 2) to watch the class's video streaming from a place of their convenience. 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. They discussed students' collective answers to each Top Hat question and then proceeded to give a mini-lecture on the topic.

After they finished going through the review questions, the lecturers 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 were 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. After the tournament, the top five or six students were awarded an individually wrapped candy as a prize. Students were also incentivised to watch each week's online lecture and participated in the weekly in-class tutorial by employing the awarding participation marks. Final student course outcomes were collected through Canvas and combined three assignments, midterm, and final exam. For the assignment, they had the option of doing the project individually or in a group. The core material was available on the course web page, and review sessions were conducted for discussion purposes. The students were required to watch all the videos and participate in the quizzes at the end of the videos before coming to the review sessions. The students had access to Piazza (i.e., the student forum) in case they needed to clarify anything among themselves or with their lecturer.

3.2.4.3 Procedure

The research procedure has been depicted in Table 24. The MSLQ was administered three times in weeks 3, 7, and 11 of two BL courses. We collected 850 surveys. We considered students' motivation and strategy use of 307 students in the first round, 283 students in the second round, and 260 students in the third round. The students needed to complete two assignments before and after the midterm, as is shown in Table 24.

They also needed to take part in midterm and final exams to be able to meet the requirements of the course. We also presented the weight for each assignment and test in Table 24.

Weeks	**1-2**	**3**	**4-5**	**6**	**7**		**8-10**	**11**		**12**	
Assignments		MSLQ1		Assign 1	MSLQ2	Test		Assign 2A	MSLQ 3	Assign 2B	final exam
Coursework weight		2.33%		5%	2.33%	23%		15%	2.33%	5%	45%

Table 24: Research procedure

3.2.4.4 Data Collection

We collected data from two sources, the MSLQ questionnaire and final grade data.

3.2.4.4.1 MSLQ

Pintrich et al. (1993b) developed the MSLQ questionnaire to measure motivation, cognitive, metacognitive, and resource management strategies through 31 items in the motivation section and 50 items in the learning strategies section. We measured six motivation and nine learning strategy use constructs including value (intrinsic goal orientation, extrinsic goal orientation, and task value), expectancy (control of learning beliefs, self-efficacy for learning performance), affective (test anxiety), cognitive (rehearsal, elaboration, organisation, critical thinking), metacognitive self-regulation (planning, monitoring, regulating), and resource management strategies (time study environmental management, effort regulation, peer-learning, and help-seeking).

3.2.4.4.2 Grade

We collected students' final scores from those students who participated in our study and filled out the questionnaire.

3.2.5 Analysis

We employed the K-Means clustering algorithm (longitudinal person-centred method) to identify students' distinct SRL profiles and track the developmental patterns. We used all 15 MSLQ subscales as clustering variables and considered the issue longitudinally. To understand the association between the MSLQ variables and the final score, we used a one-way analysis of variance (ANOVA). To understand how the clusters are different from each other, we employed multivariate analysis of variance (MANOVA). We also considered how

students moved among clusters as the course progressed. All the analyses were performed using IBM SPSS 26.

We addressed the first research question by giving the descriptive statistics (mean and standard deviation) for each construct. Then we reported on how we identified distinct SRL profiles of freshmen and upper-level students through clustering. To answer the second research question, we explored how students moved among clusters (unfold their SRL profiles).

3.2.5.1 Freshmen Students

This section gives the descriptive statistics for the high-level MSLQ's constructs from different iterations. Then it reports on how we identified freshmen students' SRL profiles based on the MSLQ sub-constructs.

3.2.5.1.1 Descriptive Statistics

The descriptive statistics (mean and standard deviation) for the MSLQ constructs of the freshmen students are depicted in Table 25. 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 be faced with a lot of material and assignments that have been stacked up and 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.

M=Mean	**Iteration 1 (N=189)**		**Iteration 2 (N=173)**		**Iteration 3 (N=153)**	
	M	**SD**	**M**	**SD**	**M**	**SD**
Motivation	4.92	0.63	4.80	0.62	4.82	0.69
Strategy Use	4.23	0.55	4.20	0.62	4.31	0.66

Table 25: Descriptive statistics of the freshmen students

3.2.5.1.2 Self-Regulated Behavioural Profiles

In the first section of our cluster analysis, we identified distinct SRL profiles of students each based on one measurement of the MSLQ data (Table 26). We identified three SRL profiles in each iteration.

	Iteration 1			Iteration 2			Iteration 3		
C= Cluster	**C 1**	**C 2**	**C 3**	**C 1**	**C 2**	**C 3**	**C 1**	**C 2**	**C 3**
Intrinsic Goal Orientation	4.23	4.65	5.25	3.90	5.01	4.66	2.00	4.22	5.07
Extrinsic Goal Orientation	4.69	5.59	5.67	4.08	5.33	5.64	1.50	4.89	5.48
Task Value	4.46	5.48	6.00	4.27	5.35	5.64	2.00	4.86	5.55
Control of Learning Beliefs	4.75	5.33	5.40	4.91	5.07	5.42	4.25	4.91	5.28
Self-Efficacy for Learning Performance	4.41	5.12	5.27	4.20	4.94	5.33	2.06	4.66	5.17
Test Anxiety	4.33	4.55	4.95	4.27	4.88	4.40	3.00	4.41	4.91
Rehearsal	4.11	4.25	4.76	4.00	4.92	4.97	2.25	4.41	5.35
Elaboration	4.20	4.37	5.13	3.94	4.98	4.78	2.17	4.34	5.33
Organization	4.37	4.78	5.35	3.99	5.23	5.01	2.63	4.43	5.45
Critical Thinking	3.77	3.37	4.40	3.34	4.62	3.69	1.50	3.45	4.69
Metacognitive Self-Regulation	3.95	4.23	4.69	3.77	4.77	4.60	2.92	4.15	4.90
Time Study Environmental Management	4.23	5.04	5.07	4.07	4.77	5.07	3.38	4.37	5.02
Effort Regulation	4.17	5.29	5.11	3.85	4.73	5.28	3.50	4.43	4.98
Peer-Learning	3.57	2.12	4.19	2.89	4.72	2.43	1.33	2.92	4.51
Help-Seeking	3.35	2.15	4.09	2.91	4.21	2.42	2.38	2.90	3.94
Number of Students in Each Cluster	67	56	66	55	56	62	2	86	65
Final	62.02	68.43	70.86	62.81	71.61	72.78	45.74	67.79	73.89

Table 26: Clustering freshmen students based on the three iterations

3.2.5.1.2.1 Minimally Self-Regulated Learner Profile

Minimally self-regulated learners in iteration 1 were students in Cluster 1, who had the lowest motivational and strategy use but had an average score for critical thinking, help-seeking, and peer-learning. Sixty-seven students in this cluster got an average of 62.01 in their final score and this was the largest cluster. Therefore, at the beginning of the course, our minimally self-

regulated learner profile contained the highest number of students. In iteration 2, minimally self-regulated learners were students in Cluster 1 with the lowest score in all sub-constructs except for peer learning and help seeking. Cluster 1, with 55 students, achieved an average of 62.80 for their final score. The minimally self-regulated learner cluster in the second iteration contained the fewest students. In iteration 3, minimally self-regulated learners are Cluster 1 students with the lowest score in all sub-constructs. Across the groups, the students in this cluster achieved the lowest scores in their final. It was an average of 45.73 for the final score. There were only two students in this cluster. Having a low number of students in the lowest level cluster in iteration 3 was a good achievement in this course. The course lecturer was able to help students move to the high and average SRL clusters.

3.2.5.1.2.2 Average Self-Regulated Learner Profile

The average self-regulated learner profile (Cluster 2) in iteration 1 included 56 students, who had an average score in all the sub-constructs, achieving an average of 68.43 in their final score. However, this group had the lowest critical thinking, help-seeking, and peer-learning scores. This cluster had the lowest number of students. In iteration 2, the average self-regulated learners were students with the highest intrinsic motivation, who also had the highest anxiety level. This group used the highest cognitive strategies such as elaboration, organisation, and critical thinking, and had the highest metacognitive self-regulation. These students also used the highest level of peer-learning and help-seeking. This cluster had average scores in the remaining motivational sub-constructs such as extrinsic goal orientation, task value, control of learning beliefs, and self-efficacy for learning performance. Students in this cluster had average scores in motivation and high strategy use. Cluster 2 with 56 students, achieved an average of 71.60 as their final score. Students in Cluster 2 had the highest anxiety level, which might have prevented them from performing well. In iteration 3, the average self-regulated learner profile was Cluster 2, students who had an average score in all sub-constructs. They achieved an average score of 67.78 in the final assessment. There were 86 students in this cluster, which was also the largest cluster.

3.2.5.1.2.3 Highly Self-Regulated Learner Profile

In iteration 1, the highly competent self-regulated learners (Cluster 3) were 65 students who had the highest scores in all the sub-constructs, making it the second-largest cluster. These

were the most motivated students who always used the maximum number of strategies. The students in this cluster achieved an average of the highest scores in their final score, which was 70.85. In iteration 2, the highly self-regulated learners had an average intrinsic motivation but the highest scores in other motivational sub-constructs. This group had average scores in elaboration, organisation, critical thinking, and metacognitive self-regulation. These students also used the lowest level of peer learning and help seeking. This group had a high score in most motivation constructs (e.g., extrinsic goal orientation, task value, control of learning beliefs, self-efficacy for learning performance), an average score at most strategy use constructs (e.g., intrinsic goal orientation, test anxiety), and achieved the highest score at the end. Cluster 3 with 61 students achieved an average of 72.78 in their final score. In iteration 3, the highly self-regulated learners were students who had the highest scores in all motivational and strategy use sub-constructs. They achieved the highest score of 73.89 at the end. There were 64 students in this cluster. This cluster was the second-largest cluster.

The different clusters in the three iterations based on different sub-constructs are shown in Figure 12 (Cluster 1 minimally, Cluster 2 average, Cluster 3 highly SRL). As the courses progressed, there were clear differences in SRL patterns between the three different profiles. A MANOVA was conducted to test whether motivation and self-regulation variables significantly differed across the three clusters. The clusters were significantly different. We checked through ANOVA how the adoption of different learning profiles affected students' final scores. The final scores were significantly different across profiles.

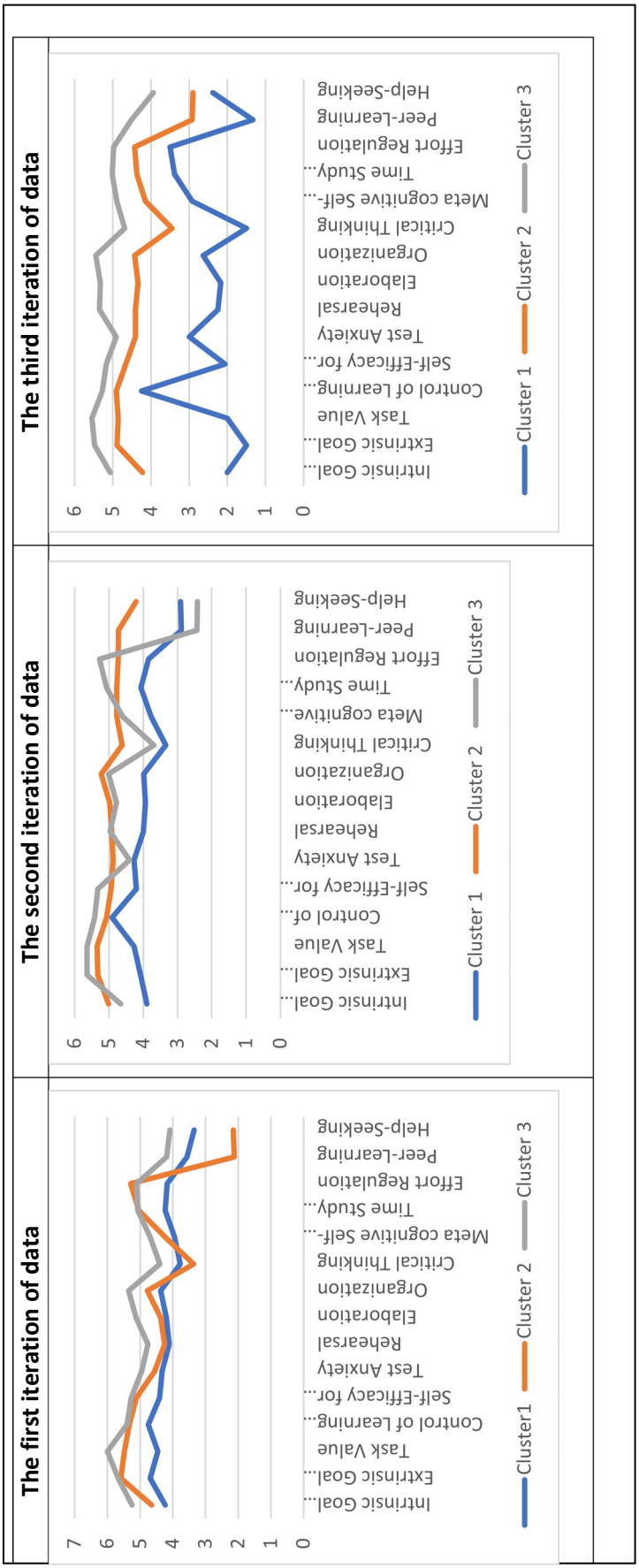

Figure 12: Clustering of freshmen students based on three Iterations of data

3.2.5.2 Upper-Level Students

This section gives the descriptive statistics for the high-level MSLQ constructs from different iterations and then identifies how we identified upper-level students' SRL profiles based on the MSLQ sub-constructs.

3.2.5.2.1 Descriptive Statistics

The descriptive statistics of the constructs for the upper-level students are presented in Table 27. As it is shown, motivation, in contrast to the freshmen students, continuously decreased. And, strategy use, in contrast to the freshmen students, continuously increased.

	Iteration 1 (N=118)		**Iteration 2 (N=110)**		**Iteration 3 (N=107)**	
M=Mean **SD=Standard deviation**	**M**	**SD**	**M**	**SD**	**M**	**SD**
Motivation	4.80	0.58	4.68	0.67	4.66	0.67
Strategy Use	4.30	0.62	4.34	0.60	4.40	0.68

Table 27: Descriptive statistics of the upper-level students

3.2.5.2.2 Self-Regulated Behavioural Profiles

In this section of our analysis, we identified three SRL profiles for upper-level students, each based on one iteration of MSLQ data (Table 28) which are explained next.

3.2.5.2.2.1 Minimally Self-Regulated Learner Profile

In iteration 1, the minimally self-regulated learners were students in Cluster 1, who had the lowest motivation and strategy use, but they had average scores in test anxiety and help seeking. Forty-two students in this cluster achieved 66.11 in their final score. They were the largest cluster at the beginning of the course. In iteration 2, the minimally self-regulated learners were Cluster 1 students with the lowest score in most sub-constructs and average scores for control of learning beliefs, critical thinking, peer-learning, and help-seeking. Cluster 1, with 44 students, achieved 67.80 for their final score. Minimally self-regulated learners in iteration 2 included the highest number of students. In iteration 3, minimally self-regulated learners were Cluster 1 students with the minimum score in most sub-constructs and average scores in peer-learning, help-seeking, critical thinking, and test anxiety. The students

in this cluster achieved the lowest average score of 68.46 for their final score. There were 44 students in this cluster, which was the largest cluster all the way through the course.

	Iteration 1			Iteration 2			Iteration 3		
Cluster	**C 1**	**C 2**	**C 3**	**C1**	**C 2**	**C 3**	**C 1**	**C 2**	**C 3**
Intrinsic Goal Orientation	3.88	4.73	5.16	4.00	4.13	5.04	3.97	4.55	5.09
Extrinsic Goal Orientation	4.99	5.03	5.96	4.42	5.21	5.36	4.39	5.13	5.32
Task Value	3.98	4.95	5.70	3.99	4.74	5.45	3.89	5.19	5.47
Control of Learning Beliefs	4.66	5.40	5.31	4.82	4.66	5.33	4.51	5.18	5.31
Self-Efficacy for Learning Performance	4.33	5.05	5.51	4.19	4.51	5.31	3.93	4.65	5.53
Test Anxiety	4.98	3.58	5.00	4.28	4.80	4.73	4.38	4.13	4.96
Rehearsal	4.11	4.20	5.24	4.06	4.98	5.18	4.36	5.12	5.53
Elaboration	3.91	4.46	5.56	4.03	4.65	5.25	3.92	4.79	5.60
Organization	4.27	4.91	5.69	4.26	5.16	5.31	4.25	4.97	5.66
Critical Thinking	2.92	3.46	4.19	3.46	3.05	4.48	3.58	3.33	4.53
Metacognitive Self-Regulation	3.68	4.09	4.90	3.89	4.39	4.93	4.02	4.43	5.08
Time Study Environmental Management	4.50	4.78	5.26	4.063	5.211	4.943	4.369	4.850	5.191
Effort Regulation	4.15	4.66	5.51	3.99	5.28	5.01	4.01	4.70	5.01
Peer-Learning	3.31	3.71	4.31	3.95	2.86	4.72	4.04	2.64	5.25
Help-Seeking	3.49	3.23	4.21	3.59	2.62	4.45	3.74	2.10	4.66
Number of students in each Cluster	42	41	35	44	29	37	44	30	34
Final	66.11	69.50	73.00	67.80	72.19	73.83	68.46	72.86	74.68

Table 28: Clustering upper-level students based on three iterations

3.2.5.2.2.2 Average Self-Regulated Learners' Profile

In iteration 1, the average self-regulated learners were students in Cluster 2 who had a medium score in most of the sub-constructs in terms of motivation and strategy use and the highest score in control of learning beliefs and lowest score in help seeking. The forty-one students in

this cluster achieved an average of 69.50 in their final score. In iteration 2, the average self-regulated learners had average scores in motivation (intrinsic goal orientation, extrinsic goal orientation, task value), cognitive (rehearsal, elaboration, organisation), and metacognitive self-regulation. They also had the highest score in self-efficacy for learning performance, test anxiety, time study environmental management, and effort regulation. They also had the lowest scores in motivation (control of learning beliefs), cognitive (critical thinking), resource management (peer-learning, and help seeking). Cluster 2, with 29 students, achieved an average of 72.19 in their final score. In iteration 3, the average self-regulated learners were students who had an average score in most sub-constructs excluding peer-learning, help-seeking, critical thinking, and test anxiety. They achieved an average score of 72.86 in the final score. There were 30 students in this cluster, which was the smallest cluster.

3.2.5.2.2.3 Highly Self-Regulated Learner Profile

In iteration 1, the highly competent self-regulated learners were Cluster 3, who had the highest scores in all the sub-constructs except for control of learning beliefs which they had an average score in. These were the highest motivated students who always used the maximum strategies. The students in this cluster achieved the highest in their final score (73.00). There were 35 students in this cluster, which was the smallest cluster. In iteration 2, the highly self-regulated learners in Cluster 3 were students with the highest motivation constructs except for self-efficacy for learning performance and test anxiety which they had an average score in. They also had the highest strategy use constructs, cognitive and metacognitive strategy use, and resource management. They had medium scores in time study environmental management 2 and effort regulation 2. Cluster 3, with 37 students, achieved 73.83 in their final score. In iteration 3, highly self-regulated learners had the highest amount in all motivation and strategy use sub-constructs. The average score for this group was 74.68, which was the highest. There were 34 students in this cluster, which was the second-largest cluster.

The different clusters in the three iterations based on different sub-constructs are shown in Figure 13 (Cluster 1 minimum, Cluster 2 average, Cluster 3 highly). A MANOVA was conducted to test whether motivation and self-regulation variables significantly differed across the three clusters. We checked through the ANOVA table that all the variables for clustering were significant. Through that, we identified the relationship among different motivation and strategy use constructs for each group. We also identified how different groups achieve differently in their course outcome.

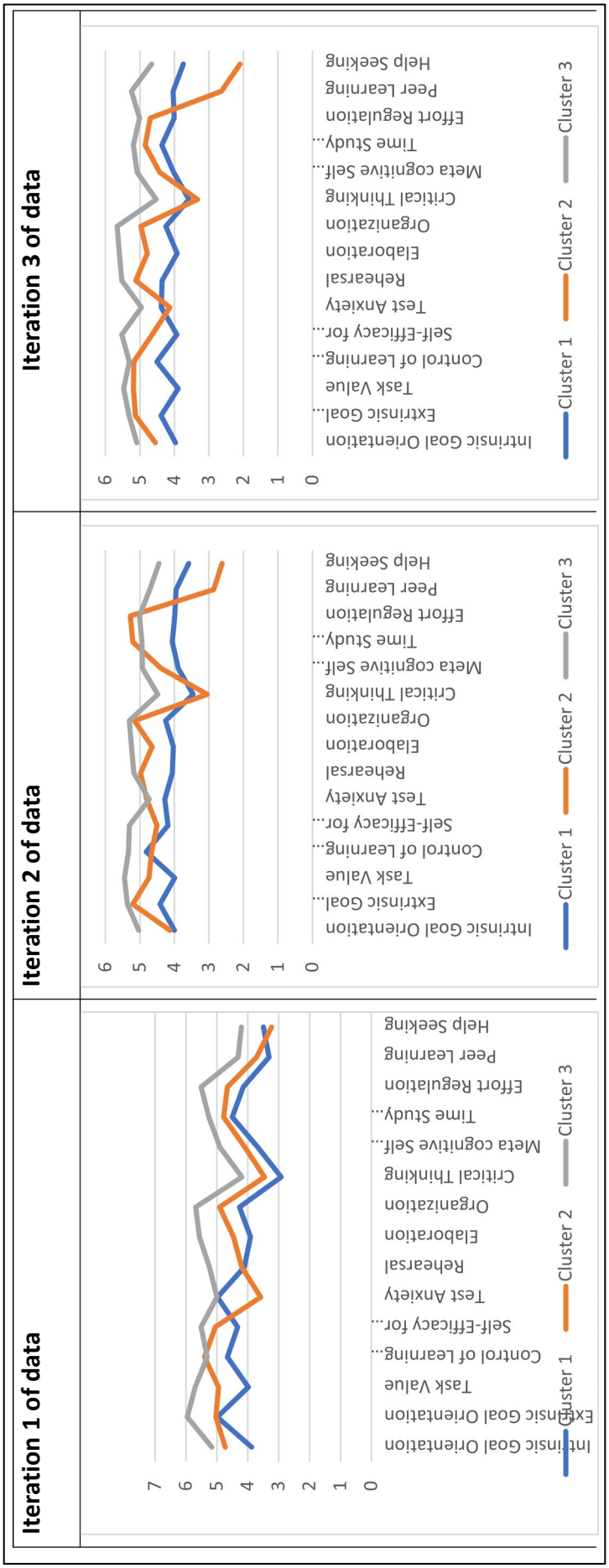

Figure 13: Clustering of upper-level students based on the three Iterations of data

3.2.5.3 Students' Unfolding Process

This section address question two, which is about identifying the extent to which students unfolded their profiles as the course progressed. We tracked students' movements in the two academic contexts across one semester to examine the changes that occurred in individual students. We report the movement for the freshmen and upper-level students.

3.2.5.3.1 Freshmen Students' SRL Behaviours Unfolding

In Figure 14, we show that we measured students' motivation and strategy use three times in the course, the students also had to submit assignments and go through two exams. We show how many students moved among the clusters as the results of the feedback they received throughout the course.

We measured the level of motivation and strategy use for the first time in Week 3 (iteration 1) and identified three SRL profiles. Then, we looked at how students used the tools (exams and assignment scores) as evaluation tools and how they reflected on themselves. We considered how each SRL profile was affected by their first test results when we measured students' motivation and strategy use at iteration 2. After measuring students' motivation and strategy use at iteration 2, students had to submit their next assignment. Based on the results they achieved from their assignment, one more time, we examined their motivation and strategy use at iteration 3. Again, we examined how they moved among clusters as the result of the feedback they received from their assignments. In our movement analysis, we checked how students changed their SRL profiles after receiving their scores. As we can observe, students moved to upper-level profiles as the course progressed. Figure 14 explains the movement of students between clusters as noted in Table 29.

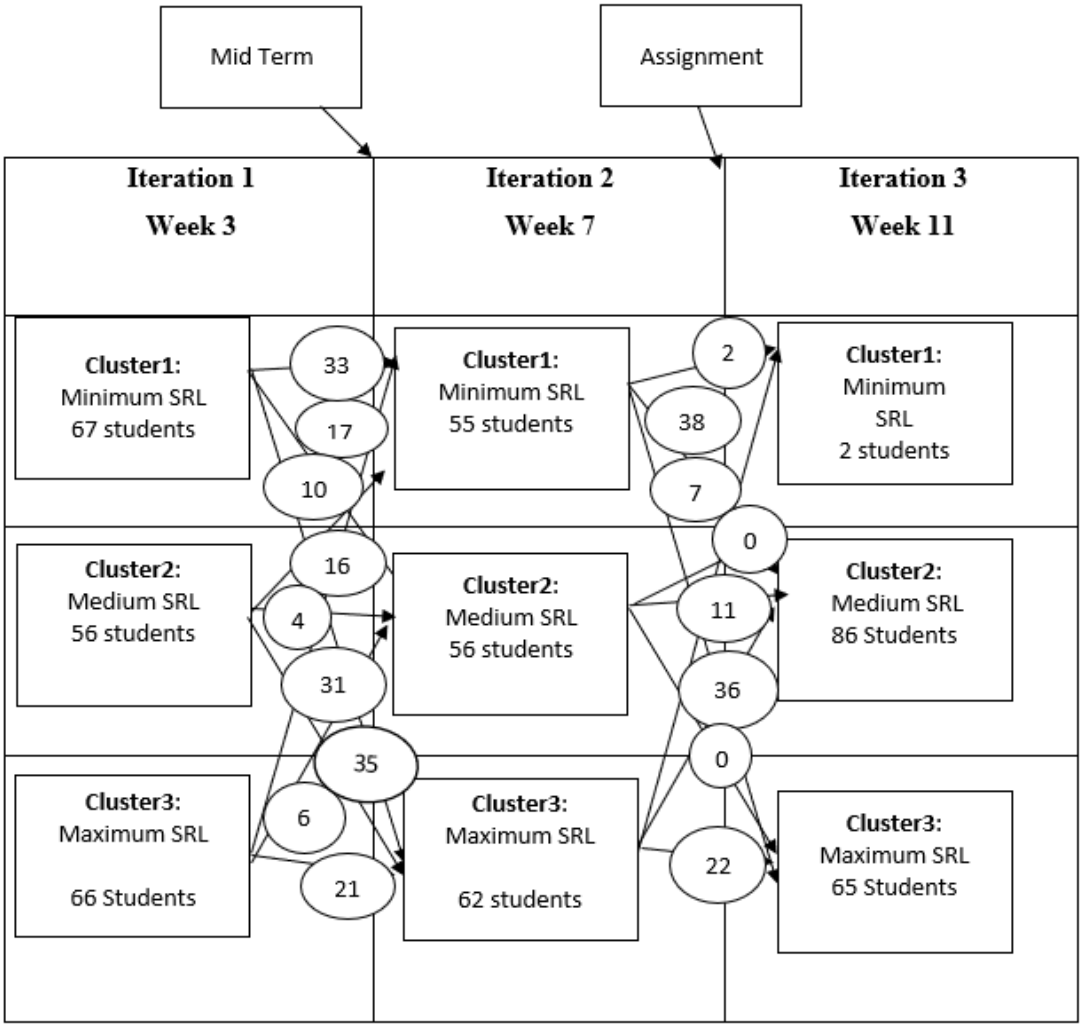

Figure 14: Representation of the changes in cluster membership for freshmen students

Table 29 presents the number of students who changed their cluster memberships as the course progressed. In the first iteration, there were 67 students in Cluster 1 (minimally SRL), 56 students in Cluster 2 (average SRL), and 66 students in Cluster 3 (highly SRL). The number of students at the highly SRL level did not change that much. However, students moved from a low SRL to an average SRL profile. Cluster 1 (minimally SRL) was the largest group at iteration 1, but at iteration 2, it had the lowest number of students. Cluster 1, which was the smallest SRL cluster, was the most stable cluster at iteration 2. The largest movement was from Cluster 3 (highly SRL) to Cluster 2 (average SRL), which meant a decrease in motivation and strategy use at the midterm. But still, we had the highest number of students in Cluster 3 (highly SRL) at iteration 2.

Cluster 3 (highly SRL) is the most stable cluster at iteration 3. The largest movement at iteration 3 was from Cluster 1 (minimally SRL) to Cluster 2 (average SRL), which is a good

achievement. It was followed by movement from Cluster 2 (average SRL) to Cluster 3 (highly SRL). Notably, at iteration 3 we did not have any movement from Cluster 3 to Cluster 1 or from Cluster 2 to Cluster 1.

Iteration 1	**Iteration 2**			**Iteration 3**		
	Cluster 1 minimally SRL	Cluster 2 average SRL	Cluster 3 highly SRL	Cluster 1 minimally SRL	Cluster 2 average SRL	Cluster 3 highly SRL
Cluster 1 (67 students)	33	17	10	2	38	7
Cluster 2 (56 students)	16	4	31	0	11	36
Cluster 3 (66 Students)	6	35	21	0	36	22
Total	55	56	62	2	86	65

Table 29: Cluster movements for freshmen students

In the third measurement, there were 2 students in Cluster 1 (minimally -SRL), 86 students in Cluster 2 (average SRL), and 65 students in Cluster 3 (highly SRL). This analysis helped us understand how students adopted different profiles, how different categories of students reflected on their work and moved between clusters as they received feedback, and how the course progressed which helped us understand the nature of academic development in the course.

3.2.5.3.2 Upper-level Students' SRL Behaviours Unfolding

Figure 15 presents how upper-level students changed among the clusters as the course progressed. Cluster 1 was the minimally SRL. Cluster 2 was average SRL. Cluster 3 was the highly SRL. We show the number of students in each cluster in each iteration and the number of students who moved between clusters. Between each iteration of the MSLQ, students needed to hand in an assignment or participate in a test. We looked to see how the feedback students received from their assignment or test scores affected their motivation and strategy use level.

Figure 15 explains the movement of students between clusters as noted in Table 30. In Table 30, we present how students changed their cluster memberships as the course progressed. In iteration 1, there were 42 students in Cluster 1 (minimally SRL), 41 students in Cluster 2

(average SRL), and 35 students in Cluster 3 (highly SRL). Cluster 1 (minimally SRL) was the largest group at iteration 1, and this cluster stayed the largest all the way through the course.

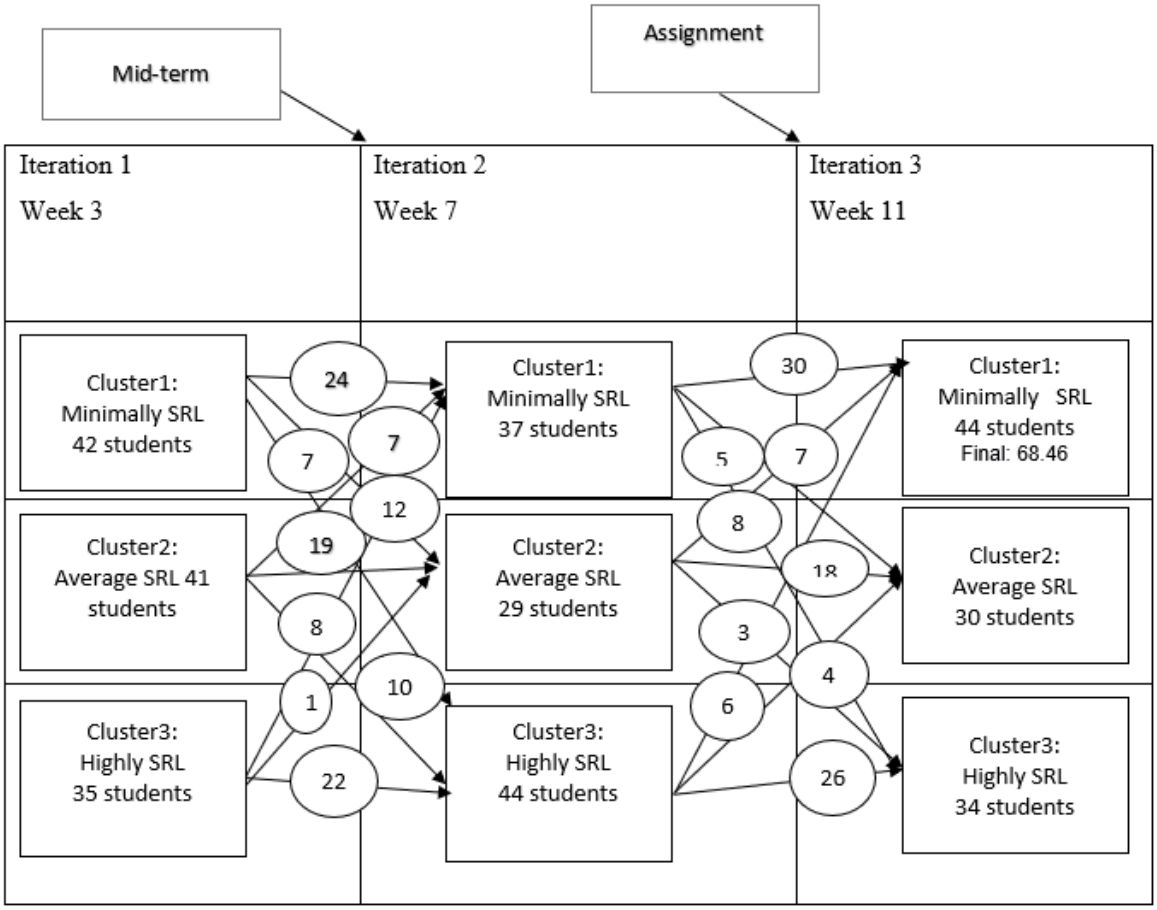

Figure 15: Representation of changes in cluster membership for upper-level students

Cluster 1, which was the smallest SRL cluster, was the most stable cluster at iteration 2. Cluster 3 was the second most stable cluster at iteration 2. The largest movement was from Cluster 2 (average SRL) to Cluster 1 (minimally SRL) in iteration 2, which meant a decrease in motivation and strategy use at midterm. And still, we had the highest number of students in Cluster 1 (minimally SRL) in iteration 2. This showed us that students' self-regulation profiles are not static and changed as the course progressed. Cluster 1 (minimally SRL) was still the most stable in iteration 3. The largest movement at iteration 3 was from Cluster 2 (average SRL) to Cluster 1 (minimally SRL). It was followed by movement from Cluster 1 (minimally SRL) to Cluster 2 (average SRL). Cluster 1 (minimally SRL) was still the largest cluster and the most stable cluster in the third measurement. This analysis helped us understand how students adopted different profiles, how different categories of students reflected on their work and moved between clusters after they received feedback, which helped us understand the

nature of academic development. In contrast to the Level 1 course, students in this course did not move to the higher SRL clusters. We understood that not all students were able to do self-regulation and used the tools as an evaluation for learning.

Iteration 1	Iteration 2			Iteration 3		
	Cluster 1 Minimally SRL	**Cluster 2 Average SRL**	**Cluster 3 Highly SRL**	**Cluster 1 Minimally SRL**	**Cluster 2 Average SRL**	**Cluster 3 Highly SRL**
Cluster 1 (42 students)	24	7	7	30	7	5
Cluster 2 (41 students)	19	12	8	8	18	3
Cluster 3 (35 Students)	1	10	22	6	4	26
Total	44	29	37	44	30	34

Table 30: Cluster movements for upper-level students

3.2.6 Discussion

This study employed a longitudinal approach to shed light on the formation and adaptability of students' beliefs about their motivation, cognitive and metacognitive strategy use, and resource management. We looked at individual differences in the pattern of motivation, cognitive, metacognitive, and self-regulatory strategies among 314 freshmen and upper-level students. We examined motivation and strategy use, not as static but changing, we examined how they changed as the course progressed. In contrast to the study run by Zusho et al. (2003), we understood that freshmen's motivation dropped as the course progressed towards midterm and increased again as it got close to the end of the course. In terms of strategy use, freshmen's strategy use level decreased up to midterm and then increased as it got closer to the end of the course. For upper-level students, motivation levels continuously dropped as the course progressed, which was consistent with previous research results (Pintrich and Schunk 2002; Wigfield and Eccles 2000). However, in our study, upper-level students' level of strategy use continuously increased. This information is helpful for updating the instructional design. It is important to consider the dynamics of students' motivation and strategy use and the effect of assignments and tests results on students' levels of motivation and strategy use when designing courses for students. It is also important to identify the ways to promote those constructs which drop throughout the course.

We applied the K-Means clustering algorithm to identify different SRL profiles based on students' motivation and strategy use. We identified three different SRL profiles of students (highly, average, and minimally self-regulated learners) in these two classes three times at the beginning, middle, and end of the course. Following previous research (Pintrich and Schunk 2002) on the relationship between motivation and learning strategy use, students with the highest levels of motivation reported deeper processing strategies (elaboration and metacognitive strategies), while students with the lowest levels of motivation reportedly used fewer learning strategies. It also helped us to understand how, in one class, we had students who reported the highest level of motivation and strategy use and at the same time students who reported the lowest level of motivation and strategy use. We also observed that in iteration 2, students adopted mixed profiles of either high motivation and low strategy use, or vice versa which would be the path for our future study. This longitudinal study provided insight into the evolution of students' beliefs and strategy use over time and how they work towards each other to help students achieve goals.

After identifying the different SRL profiles of the students and explaining their differences, we investigated how students moved between clusters. This was important as recent studies (e.g. Fryer and Vermunt 2018; Jang et al. 2017; Nelson et al. 2015) mentioned that SRL profiles were dynamic and they identified this as a challenge for the field. Therefore, in this study, we investigated this challenge with 314 students from two classes to see how SRL profiles were different in these two classes and, most notably, how students adopted different SRL profiles as the course progressed.

As per the suggestion of Hadwin et al. (2018) and Järvelä et al. (2019), we used Winne and Hadwin's (1998) SRL model, which was a premise for building theoretical and empirical understanding in group-level regulatory processes. We modelled our students' regulation at a micro-level with COPES, which we explained in the theoretical background.

This study measured the level of motivation and strategy use for the first time in Week 3 of the course (MSLQ 1). Students had to submit two assignments and go through two exams. We considered how students used the tools (exams and assignment scores) as evaluation tools and how they reflected on themselves. Each time we measured students' motivation and strategy use before and after students received a score. Then we considered how students used tools to evaluate their learning and applied changes to their strategies. We considered how each cluster of students got affected by their test results when we measured students' motivation and strategy use (MSLQ 2). After iteration 2 of the MSLQ, students had to submit

their next assignment and based on the results they achieved, again we examined the movement among clusters (MSLQ 3). In our movement analysis, we checked how students changed their SRL profiles after receiving their scores. Freshmen and upper-level students followed a different pattern of movement between clusters. Freshmen students mostly moved to upper-level motivation, and strategy use as the course progressed. However, upper-level students mostly moved to lower-level motivation and strategy use clusters. As mentioned before, when students engaged in the process of learning, they went through several stages. It started with task perception, goal setting and planning, and translating plans into strategies based on the goals they set for themselves; then, they went through a reflection on what they had done. The different phases we recalled were not linearly sequenced and they were loosely ordered. Each of the phases was cycled through COPES by metacognitive monitoring. Based on the monitoring students adopted, their perception of the task changed, leading to changes in their goals and strategies, and therefore, shifts between the phases would happen. The students' learning processes were active, and it was constantly changing when that did not proceed according to the goals. Looking at students' movement among clusters, we identified that SRL profiles are not static and they changed as the course progressed. Therefore, it is always beneficial for the lecturer to identify the students' SRL profiles and try to help students from different clusters to adapt to a better profile. This information is more important for the lecturer in fully online or BL who have limited interactions with students compared to traditional face-to-face classrooms.

Even though we reported differences among the clusters and their movements, there was also some consistency across the two different groups. We observed the same cluster differences between the two groups and identified the same number of SRL profiles for the two groups. We also observed that students with higher motivation reported higher strategy use. Both courses showed that a higher level of motivation and strategy use was associated with a higher achievement level. This consistency in observed SRL profiles gives credibility to the pattern we identified. In iteration 2, the clusters always had a mixed profile. In future, we need to study the relationship between motivational and strategy use constructs among SRL profiles to understand if there is any special amount for each construct that triggers the other constructs. Both groups' minimally SRL profiles were the largest cluster at the beginning of the course. For upper-level students, all the way through the course the minimally SRL profile was the largest cluster. For freshmen students, the number of students in the lowest SRL profile decreased as the course progressed.

We understood that for each course, the constructs that made a difference among clusters were different. We identified that critical thinking and peer-learning constructs had more potential. These are the constructs that the lecturer can try promoting them through, for example, updating the instructional design.

In our analysis, we understood students' adaptation of SRL profiles was different in different courses. Also, the constructs that evoke the differences were different for the two groups. This was a limitation of our study since we did not consider the contextual differences between the two courses. However, our study confirmed the cyclical nature of SRL by showing how students adapted to different SRL profiles during the course. Our goal was to produce self-regulated learners. We considered their learning process by observing their movement among clusters. The best movement towards self-regulation was among the freshmen. They mostly moved to higher clusters. Upper-level students did not move to higher clusters. The average group profile's numbers for upper-level students reduced and moved to higher and lower clusters. In future studies, we need to see how we can target this group of students to motivate them better.

After three rounds of clustering of students, each time based on one iteration of data, we understood that we could identify the students who would get a minimum score in their course outcome based on the first measurement data. We aimed to identify the students who were at risk early enough. We understood that we could categorise students by considering the first measurement data and asking the lecturer to apply the intervention to help those students. This addresses one of the most important LA aims. We also showed that students who were high in motivation and strategy use got the highest scores at the end. We understood that differences between students' performance could be explained in terms of their motivation and strategy use. Therefore, it is important to improve students' motivation and strategy use to get good scores in the end.

From clustering based on iteration 2, we also identified that students who were high in motivation or strategy use performed well in their final course outcomes. We are not sure if one construct triggers the other at a specific level of motivation or strategy use. We identified a future study path to see how and at which level this construct would be triggered. Lecturers need to consult with students and suggest new strategies for students. They could also update the instructional design to give students proper instructions to follow and achieve well. Our Year 1 lecturer used a different technique to increase students' motivation, with which he was successful as we had just two students in the lowest cluster. The lecturer ran tournaments and

brought gamification to his class. He also threw chocolates to those students who won in his tournaments. The lecturers could apply other different techniques to increase students' motivation and strategy use. Using iteration 3 data for clustering, we understood how students' performances were explainable based on students' motivation and strategy use level.

3.2.7 Conclusion

In this study, based on the challenges identified by recent studies (Jang et al. 2017; Järvelä et al. 2019), we investigated the SRL profiles of students who shared common motivation and SRL characteristics for two groups of students (freshmen and upper-level). We first examined the dynamics of these constructs. The patterns of changes in motivation and strategy use were different between the two groups. Further, we identified three distinct profiles of highly SRL, average SRL, and minimally SRL based on motivation and strategy use for three different measurements in two courses. Each time clustering of students gave insight to the lecturer about the class's subgroups. It helped the lecturer identify students who might be at risk of failure; the lecturer could support at-risk students by applying interventions that would address LA aims.

We compared different SRL profiles of students based on their level of motivation and strategy use constructs. Further, we investigated how students adopted different profiles as the course progressed. We understood that students' SRL profiles were not static and had a cyclical nature. In terms of movement, freshmen students moved to the upper-level SRL group as the course progressed. However, upper-level students moved to lower-level SRL clusters. We showed that students moved among clusters, but the pattern of movement among clusters was different for the two groups. We also understood that not all students were able to self-regulate their learning. Some of them could not reflect on their learning. They did not use the test and assignment as evaluation tools to reflect on their strategy use.

We identified different SRL profiles based on motivation and strategy use (different pathways), which showed the same level of achievement. This showed us that we need to identify the level at which each construct triggers the other constructs in our future study. Clustering two groups of freshmen and upper-level students based on their level of motivation and strategy use, and investigating their dynamics addressed the lack of motivational and empirical study in LA. Clustering students also helps us identify at-risk students, which is addressing one of the most important LA aims. Also, identifying different SRL profiles for the groups of freshmen and upper-level students and understanding the clusters' stability as

the course progressed contributes to the literature in SRL as well. It addresses the challenge identified by Järvelä et al. (2019) regarding the cyclical nature of SRL, which is very important for both practice and theory building. We understood that students unfold their SRL profiles as the course progresses.

This is also a contribution to an applied perspective for teachers' practice by enabling them to understand better their students' SRL process, having different subgroups of students (SRL profiles) in the class, and how they adopt different SRL profiles as the course progresses. Thus, the lecturer could employ effective teaching strategies to raise their motivation and help them to adapt to the appropriate profiles.

As a limitation of this study, we had students from two courses only. We need to have different cohorts of students in future research to cross-validate our findings regarding the three SRL profiles that we identified. The other limitation of this study was that we looked at motivation and strategy use variables through self-report. Even though self-report instruments (i.e., Pintrich 1995) were successful in identifying the students' general beliefs about their learning, motivation, cognitive and metacognitive SRL, and their resource management, they did not consider how they happened and affected one another. Now a clear understanding of our data is known, in our future study, we will investigate the effects of students' participation from actually using the tools and merge it with motivation so that we can better understand students' SRL processes.

(This is the end of paper 5)

Chapter 4

CHAPTER 4

4 Chapter 4 - QUALITATIVE ANALYSIS

This chapter investigates students' perceptions regarding using educational tools in their classes. Different tools have been used in higher education for students to take control of their learning. It is believed that these tools are helpful for the self-regulation process. However, we were unsure of how students think these tools help them in their learning processes. It is relevant to understand students' experiences of and expectations from the system. In this chapter, we analyse students' perceptions from three classes using AT and SRL theory in three papers. The first two papers used AT to understand students' perceptions regarding tool use. In the third paper, we used SRL theory in understanding students' perceptions.

4.1 Paper 6- Students' Perceptions of Educational Tool Use in a Blended Learning Environment: An Activity Theory Perspective

(Submitted to The British Journal of Educational Technology)

4.1.1 Abstract

This paper draws on Activity Theory (AT) and its principle of contradictions to investigate students' perceptions of educational tools' effectiveness to support Blended Learning (BL). The paper presents an overview of studies that used AT as a theoretical lens to examine BL environments and access to educational tools. The paper synthesises the previous studies' assumptions, their overarching research questions, methodologies, analyses, findings, and implications and offers the analytical process that this paper adopted. The AT lens and its contradictions provided a tool to investigate the challenges of the BL methodology. The study findings show that the significance of community building in offline environments is key to developing effective online interactions in BL environments. Contradictions offer insights about transforming traditional classrooms into BL environments using online tools in educational contexts.

Keywords: students' perception; blended learning environment; activity theory; contradictions

4.1.2 Introduction

Activity theory (AT) has been used to interpret the human-technology interaction (Kaptelinin and Nardi 1997). AT positions human-technology interaction in a wider human activity context that provides a richer and more meaningful appreciation of technology and what it means to individuals (Kaptelinin and Nardi 2018). Researchers have used AT to study the interaction between human and computers in Information Systems (IS) (Bodker 1989; Kuutti

1991), which is believed to have entirely transformed the system of activities (Engeström et al. 1990)

This study uses AT and its principle of contradictions both as a theoretical framework and as an analytical methodology. As a theory, it has been used for data analysis as described by Kuutti (1996) as "a philosophical and cross-disciplinary framework for studying different forms of human practices as development processes" (Kuutti 1996, p.24). As AT uses tools as mediators to conduct activities, this study adopted AT to understand the mediating role of online tools in students' learning. As an analytical methodology, AT offers a lens to explore students' online interactions together with learning. Students' learning experiences are interpreted when they use educational tools and whether using educational tools can enhance learning. Contradiction is an established principle in AT (Engeström 2001). Contradictions are frequently occurring within and between activity systems because "activities are not isolated units but are more like nodes in crossing hierarchies and networks, and are influenced by other activities and other changes in their environment. External influences change some elements of activities, causing imbalances between them. AT uses the term contradiction to indicate a misfit within elements, between them, between different activities, or between different developmental phases of a single activity" (Kuutti 1996, p.29).

Though it is crucial in the field of learning and instructional design, few studies have applied the most prominent elements of AT (Cole and Engeström 1993; Hewitt 2004; Kaptelinin and Nardi 2018; Murphy and Rodriguez-Manzanares 2008; Nardi 1996a; Nardi 1996b). Our study specifically used AT to identify contradictions in the learning environment from the students' perspective to improve practice and to inform instructional design. The study's analysis is not focused on tools' capabilities, but it is rather concentrated on the activities that students need to do so that they achieve their goals.

The use of educational tools has increased worldwide, providing more learning options for students (Hammond-Kaarremaa 1994; Lee 2017; Yadegaridehkordi et al. 2019). However, there remains a lack of evidence on educational tools' usefulness for helping students' learning. Educational tools enable teachers to deliver content to large numbers of students and allow students to use the information actively. It is often assumed that technologies can mediate and automate the action of learning. Dabbagh and Kitsantas (2005) argued that providing various toolkits would help students choose the tool that would support their learning and stimulate self-regulated learning (SRL). However, sometimes tools fail to

automate actions and support students to self-regulate their learning. For example, Engeström (2001) mentioned that quality suffers if the technology is misused.

Squires et al. (2000) provide a substantial body of research regarding the use of educational tools in higher education. They focused on the design of systems, the learning outcomes, and the nature of the interactions between learners and technology. It is mentioned that the introduction of technology has not fundamentally changed education. However, understanding the student experience when they use technology for learning warrants further exploration. Initial studies in technology-based teaching methods in higher education focused on learning's psychological aspects (Aristovnik et al. 2017). However, there is a gap in understanding students' perceptions regarding BL courses.

It is essential to understand what student perceptions are of their tool use. Shuell and Farber (2001) identified student perceptions as key factors in understanding the relationship between technology and the learning process. Perception is under-examined in the literature on educational tool use. This study examines students' perceptions using time-sequenced interviews. To remove the effect of "technology novelty," this study follows Clark (1983) who interviewed each student twice, before and after a substantial tool-based learning experience. Understanding students' perceptions of tool use and its functionality help both tools and instructional designers develop experiences that will be more adaptive to students' needs.

Participants were first and second-year undergraduate students from a high ranking university which drew both domestic and international students from many cultures. We interviewed Forty-two students across three twelve-week BL courses. The results showed that students mostly had a positive disposition regarding using tools in class. However, we also identified contradictors in BL environment when educational tools were used. We identified several issues students faced when using tools that would inform learning design. The organisation of the paper is as follows. An overview of the literature, the theoretical framework used in the analysis and the related studies are presented. Next, the methodology, data collection, and analysis are provided. Finally, the findings and conclusions are presented.

4.1.3 Literature Review

This section begins with a review of AT as the theoretical framework underpinning this study. Then, a review of studies using AT in a BL environment is presented.

4.1.3.1 Theoretical Framework

AT draws on the work of Vygotsky who developed the socio-cultural approaches to learning and development (Vygotsky 1934; Vygotsky 1978; Vygotsky 1987). Vygotsky (1934) argued that human mental functionalities mediate processes organised by socio-cultural artefacts. Several socio-cultural theories have been derived from Vygotsky's work (Lantolf et al. 2000; Valsiner 2007; Van Lier 2002). All of these theories have one thing in common: human action is mediated through artefacts. However, they differ in terms of how the tools facilitate learning. AT emphasises both historical developments of ideas and the constructive role of humans. It is a framework for studying human praxis behaviours both at individual and social levels.

AT brings a new perspective to activity and learning by emphasising that learning will not emerge as a precursor to activity but will emerge from and with activity. It focuses on human activities and consciousness within the context where it happens. Central to this theory is context; it is important to understand the setting of meaningful activity and instructional design when analysing activity. It is important for one human activity to know who is engaged in it, what the person's intentions and goals are, what the product of the activity is, and what the community, rules, and norms in which the activity is situated are. Engeström's (2001) version of AT is depicted in Figure 16. The most important unit of analysis in AT is the activity that will be accomplished through the top triangle- the study's subject and object and the tool or instrument used.

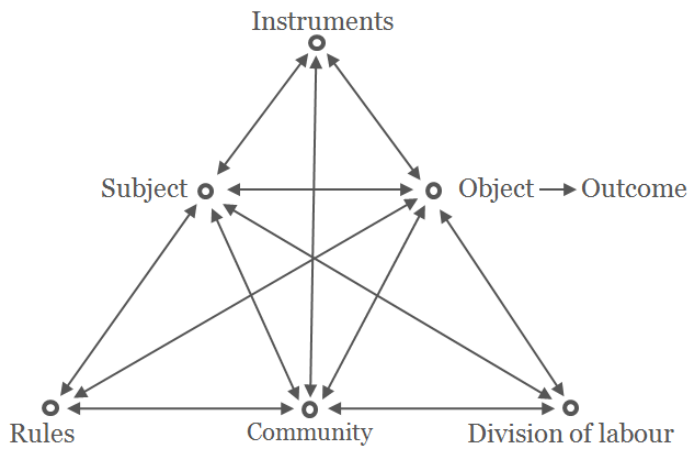

Figure 16: Activity theory (Engeström 2001)

Learning occurs as individuals engage in an activity. Different objects have different affordances. Each activity is performed through the combination of the subject, the object, and the tool (instrument). The interdependent aggregate that shares social meaning is a

community. Rules are the strategies that guide the action and are accepted by the community. The division of labour (DoL) refers to the tasks needed to be performed by individual members of the group. The primary focus of any activity is the object. Understanding the study's object is important because based on their objects (i.e. intentions), students decide to participate in online activities using the tools. The overall aim of the activity is an outcome that is the result of executing the activity that leads to deeper learning. Engeström (2001) believes that there is no start and no end to the outcome. There are only *ongoing changes* and *learning to learn*. The contradiction is an established concept in AT (Engeström 2001). Contradictors are not just conflicts and problems; however, Engeström (2001) stated that they are "historically accumulating structural tensions within and between activity systems" (Engeström 2001, p.137). When applied to a BL environment, an AT analysis could help us understand the contradictors in students' learning in the context of educational technology use activities and its results in teaching and learning practice and educational innovation.

4.1.3.2 Related studies

With a focus on implementing technology, the AT lens has been applied to different fields of education (Isssroff and Scanlon 2002; Roth 2004; Squires et al. 2000). The purpose of this study has been to give teachers insight into their practice by highlighting the significance of technologies in teaching and paying attention to the learners' learning trajectories (Buell 2004). Isssroff and Scanlon (2002) described learning enhancement through the use of technology in the education system. They used AT to explain the learning experience in two classes from different disciplines. Scanlon and Issroff (2005) used AT for the evaluation practice in e-learning. While they were evaluating learning, they identified contradictions in learning activities. Kahveci et al. (2008) explored technology use in two different secondary schools to see how technology could support student-centred and active learning. They used BL and a virtual learning environment extensively. Karasavvidis (2009) used AT to examine the use of Moodle at the university level. He understood that students made minimal use of the resources provided for them and used AT to conceptualise and explain student activity patterns. Murphy and Rodriguez-Manzanares (2008) applied AT and identified contradictors in educational technology research, which helped them understand ICT use in educational contexts.

Barhoumi (2015) investigated the effectiveness of WhatsApp mobile learning activities in BL environments using an AT perspective and compared two groups of students' performances.

The results showed that the App had benefits for students' achievement and changed students' attitudes towards mobile learning and teaching. Other studies (e.g. Fredriksen and Hadjerrouit 2020; Gedera 2016) also used AT to analyse university classes activities. They identified contradictors when the participants used, for example, the discussion forum.

Lin and Yang (2011) used Wiki technology and peer reviews for language learning purposes in class to investigate whether the system was helpful for students' learning. The results showed that most students felt positive about their ability using Wiki tools and that social interaction played a significant role in the students' perceived benefits of this system. Brine and Franken (2006) employed AT to evaluate an academic writing course through web conferencing features at a New Zealand university. Using AT, they understood students' approaches to and issues with the teacher's activities.

4.1.4 Methods

This article is part of a larger study that investigated different aspects of students' learning. This part of the study focuses on students' perceptions of using tools in the classroom. Participants were freshmen and upper-level students at a tertiary level. The study investigated three courses in a BL environment over twelve weeks. The core material was developed and delivered through a LMS in a BL manner.

The lecturers of the courses designed activities for the students before each face-to-face class session. Students were required to watch the associated lecture videos prior to coming to that session of the class and answer a few quiz questions embedded at each video's end. Then, weekly, face-to-face review sessions were conducted for discussion purposes, during which there were opportunities for further discussion among the students and the lecturer. Besides, the lecturers designed discussion quizzes for the lecture's review sessions, based on how students performed in the video quizzes. When answering the in-class discussion quiz questions, students had the opportunity to compete with their peers. Names of those who provided the quickest and highest number of correct answers appeared on a leader board.

To understand our participants' motivations, we gathered data by conducting Motivated Strategies for Learning Questionnaires (MSLQ) (Pintrich 1991) three times during the course. This data gave us some insights into our group's motivation and self-regulation strategy use. We used the K-Means clustering algorithm on the data, and classified students into high, average, and low motivation based on their responses to the questionnaire. All students were invited for an interview while the first four students who accepted the invitation from each

group were selected for an interview. We conducted 30 - 45 minute semi-structured interviews with forty-two students twice during the course where we explored students' perceptions of using online class tools.

4.1.5 Analysis and Findings

The interviews were transcribed and imported to NVivo, a qualitative data analysis software application. The data was reviewed and systematically open-coded. These open codes were grouped, and themes emerged from the data. We used AT to understand students' perceptions and identify any contradictions in using tools in BL environments. An analysis of the students' goals (i.e., objects) was essential from the point of view of activity theorists (Kaptelinin and Nardi 2006) to understand subjects and what they did when alone or in groups. We explored and identified students' goals (i.e., objects) for attending the course while using the tools (Kaptelinin and Nardi 2006). Some students wanted to keep up-to-date and deeply learn the material, while some simply wanted to learn enough to pass the course. Having different goals or objectives, students used the tools differently. In the following sections, we unpack staying up-to-date and meeting the course expectations or passing the course, and we also unpack the constructs involved in the process of students achieving their goals.

4.1.5.1 Keeping Up-To-Date or Passing the Course

We mapped AT to our case study in Figure 17 where the students (subjects) had the goal of staying up-to-date or just passing the course. To stay up-to-date, students used the tools and tried to catch up weekly. Keeping up-to-date (object) was mediated through having continuous access to the materials (tools). The students (subjects) had access to the tools and, based on their available time, motivation, and their objects, students watched the lecture videos (i.e., tools) weekly. They also participated in the video quizzes (i.e., tools) weekly to evaluate their learning and identify the sections that they found difficult. When the students were preparing for their exams, they reviewed the lecture video quizzes, re-attempted the Top Hat discussion quizzes, and asked questions online via the Piazza discussion forum and the lecturer directly (i.e., DoL).

In this situation, technology was used to support the students at the activity level while the materials were ready for them to use. The students mentioned they sometimes needed to apply changes to their strategies when they evaluated their learning and understood they did not learn properly; this led to changes in their DoL. They needed to stay more focused and stop

doing parallel things (a DoL), which is discussed in the next section. The DoL for students was to watch the videos, participate in the video quizzes, and participate in in-class activities based on the lecturer's rules. The lecturer's share in the DoL was to prepare the materials and put them online for students. All these activities were shared among the community members to achieve the real object. The lecturer set rules of the activities. For example, he set a deadline to complete watching the videos, specified what to watch, and what to do. The lecturer communicated the instructional design by speaking with the students in the review sessions in class, within the discussion forum, or in the course content description. The community in this activity was the classroom, including all the students and their lecturer in the classroom and also the online environment. The outcome was for students to be able to control their studies and facilitate their learning.

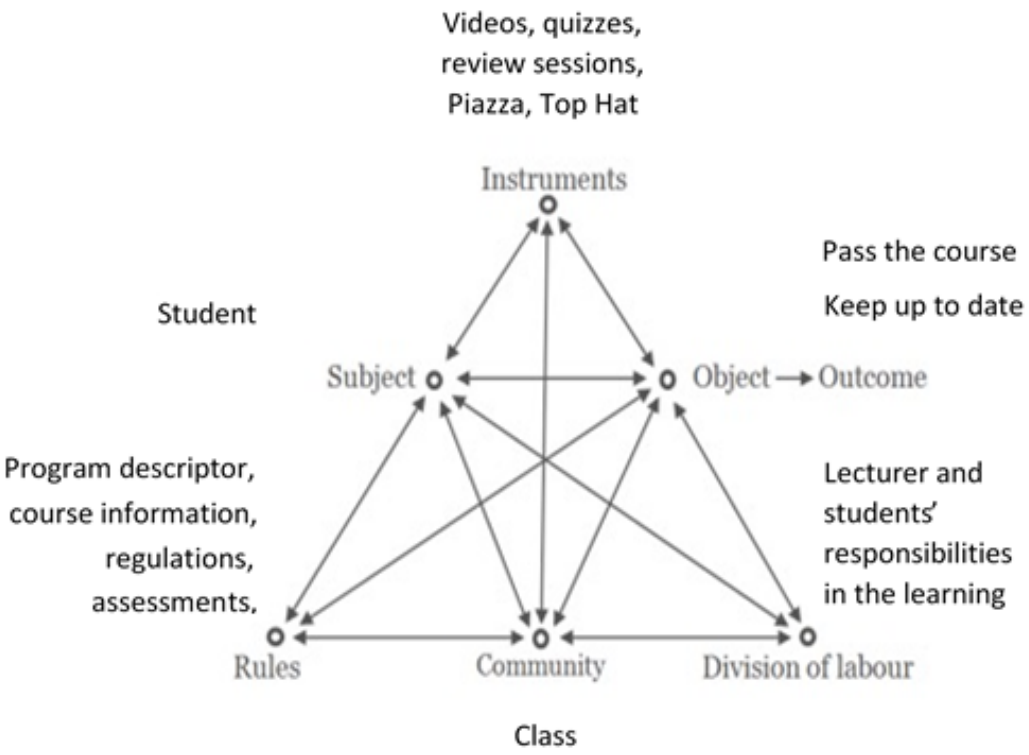

Figure 17: Keeping up-to-date or passing the course

The second goal (i.e., object), which was a shared goal among students, was about simply needing to pass the course. These students were not motivated to get the best score or learn but still needed to use the online tools, including lecture videos, quizzes, and LMS as mediating artefacts. They also had to participate in the review sessions (DoL) to get a participation mark. For these students, this course was not a high priority and, therefore, did not use the tools as expected (DoL). Students talked about the unfair DoL; they said they had a high workload compared to other courses and were reticent to do additional work. The

lecturer performed his role (DoL) by providing all the material online for students. This group did not use the tools as expected. Therefore, participation in the quizzes was sporadic, or they participated without truly concentrating. They did not ask any questions of the community or the lecturer. The rules and community were the same as the previous example above. The outcome was also being able to self-control their study, but the object construct was the only difference between this example and the previous one.

Until now, we have explained the learning process at the activity level. At the action level, the online tools supported the students by providing all the materials online. The listed format of topics in the LMS helped students see what they needed to do for each topic per week. The students had continuous access to them and could engage with the course materials and take notes whenever they desired. At the action level, online tools were visible and comprehensible for the students. All the courses' rules were also given to the students. At the operation level, the tools automated the process of students' accessing the material. In the next sections, we explain the relationship between different constructs and the contradictors we identified using AT.

4.1.5.1.1 Subject - Instruments

Different tools worked as mediators at different times. Participants accessed the materials online; these ranged from lecture videos, course content pages, evaluation tools (quizzes), the forum (Piazza), and email. The lecturer also provided feedback and discussed their problems in the class review sessions. Students used online videos as a mediator for achieving their object. They were able to identify when they needed to use Piazza for a discussion purpose with other students or with their lecturer. They may also refer to other course-related resources provided by their lecturer, e.g., deadlines and other assessment criteria. Table 31 shows the benefits of the BL environment tools from the students' point of view.

4.1.5.2 Problematising Participation in the Online, BL Environment

From an AT perspective, we turn to Engeström (2015) concept of learning by expanding what is understood as widening the students' engagement in online activities. For Engeström, learning goes beyond the linear and temporary dimension of actions and the individual dimension. Engeström (1999) considers learning as the development of a third dimension, which is the development of the activity dimension. Expansion occurs as a result of a transition process in which individuals collaboratively engage in actions together to transit to a new

activity collectively. Engeström (2015) further refers to learning as a "thoughtfully mastered learning activity" (Engeström 2015, p.169) which is realised through the zone of proximal development. Engeström (1999) states, "in activity-theoretical terms, activity systems travel through zones of proximal development …., a terrain of constant ambivalence, struggle, and surprise" (Engeström 1999, p.90).

Instruments	Benefits	Students' quotations
Lecture Videos	Students exercised control over their learning.	*"So, doing it online, I have the accessibility to access it any time I want, anywhere I am, without attending the lectures."*
	Captions help this understanding.	*"On my TV is captions. I like to read, I'm not really a listener."*
	They did not have to commute to the University.	*"I live in Henderson, so every morning I have to go back and forth and spend a lot of time and money on buses. So, and I can just go home and do lectures if I want to."*
	They did not have to carry hard copy books.	"*Especially for me, I bring a laptop to school so it's very accessible to any course content, assignments, reminders.*"
	Students found learning was easier.	*"Lecture recordings … are super helpful because a lot is missed in the physical lectures, sometimes you're not listening or maybe you're tired that day so you just don't hear it. […] they're all online, … so it's just easy, like, when you're at home, … relaxed, … in your environment."*
	Lecturer directly communicated with students.	"*I like how his lectures has a video of him talking to me so I can have … eye contact."*
Quizzes	Quizzes were used as a revision tool.	*"The quizzes I think are great coz it's a great way to, … re-establish knowledge."*
	Students could understand the main concepts of the course.	*"… It reminds me of what I've done before and … [name of the lecturer] doesn't come up with questions that are too sudden. It's questions that you need to know … and I think that's really good, like, you get the main points from the course."*
	Students could reflect on their learning.	*"Yeah, it gives me a better indication of where I'm standing."*
Audience participation tool	Students' answers were anonymised.	*"Because I'm too nervous to put my hand up and say, 'this is what the answer is'. You're able to anonymously submit an answer."*

	Students appreciated revisiting concepts.	*"So after, okay 'A' is the right answer and then let's say like a lot of people didn't get it right he will go to the slide that he has for the lectures. And then he'll be like, this is actually the right answer guys"*
Piazza	The way the lecturer used the tool to affect students' tool use.	*"I think [name of the course]'s last year Piazza was really helpful because the instructors would actually answer and then the students will answer and then the instructor would add more to what the students said. And then I would feel confident in believing the answers."*
	Students did not trust other students' answers.	*"People still don't ask questions on there because usually you'll get a student just answer on it saying something silly and you don't trust a student. They're just like you."*
Review sessions	The environment was engaging and fun.	*"Yeah, I literally came to the review sessions because I knew it wasn't boring … I knew it was very engaging for me and my friend."*
	Opportunity for students to reflect on their learning.	*"I … use the review sessions as a way to test my knowledge. Then, you know, if there's something in there that I don't know then I'll talk to my mates, see if they know it, like try and get the basis behind why I didn't understand that, learn it."*
	Help to understand the most important content.	*"I would say it summarises what I've done for that week."*
Group assignments	Preferred individual assignment, students did not have to manage others in the group.	*"Working by myself is more good because you don't have to manage other people."*
	Blended environments create a lack of trust between classmates.	*"I'm not really sure what type of personality, So it's hard for me to look for people that I don't even know to work with."*

Table 31: Summary of the benefits of instruments

Based on the above premises, the more the students participate in the activities online collectively, it is expected they become more aware of their own learning, which could result in the transition to learning. For learning to expand, one would require the three dimensions of action, individual and collective activity to interact simultaneously. In light of the above, we now refer to the drawbacks that the students experienced, which they thought hampered their learning experience.

4.1.5.3 Drawbacks of BL Environments

Analysis of our interview data showed that not all students liked the blended method of teaching and learning. Students were given the opportunity to participate remotely and in the classroom. Students noted that physically attending classes helped them better communicate with other students, which would help them with their learning. They reported that "with even a small hint from other classmates, they could do better in their studies" (interview data).

Factors	Description	Students' quotations
Sense of community loss	Having the ability to opt-out of physically attending, some students feel they don't have any community to interact with.	*"Because it's all online, you kind of don't really interact with your other members of the cohort as much because it's all online."*
Mental health issues	Staying at home all the time impacted students' wellbeing.	*"I feel really bad mentality come from never going to your lectures. You get lazy, you don't study and I just feel it's not good, even if, because I come in for, I don't actually have that many lectures."*
Less engagement in the blended environment	Face-to-face lectures would have been more helpful.	*"I think because, it's just a click of a button away, that I can just, like, get it down later, it's not as much of a big deal. But because if you're in the lecture, you're actually having to listen to the lecturer and understand what they're saying. When it's just a video, it's just like, I can re-watch it and I can rewind it and it'll still be there. But I think there's just a more sense, a better understanding when you're physically there and having to engage and listen in the class."*
Procrastination	Students needed to have a minimum of self-control to be able to control their learning.	*"Just tell yourself I can do it later, it's no time at all and then you get to the end of the week and go, I haven't done any of my lecture recordings. And then over the weekend you're like, I just, I'll do it later and the next piles up and you end up having, five hours of lecture recordings per subject left."*

Table 32: Drawbacks of blended learning environment

Having constant access to the material and BL method did not help some students manage their time or do better in their studies. They reported that "oh it's just a click of a button away, that I can just, get it down later, it's not as much of a big deal" (interview data). In fact, it caused the students to procrastinate and postpone studying the materials until close to the final examination. Other reported issues are illustrated in Table 32.

4.1.6 Discussion

As we analysed our data with the AT lens, we identified the contradictors. Contradictors have been explained by different scholars. Osono et al. (2008) examined contradictors as considering different priorities simultaneously. In the activity, when the conditions change, the activity is affected. In this way, the object can be achieved or not achieved. It can lead to a break or a contradictor in the system. In the following section, we present examples of the contradictors we identified.

4.1.6.1 Subject- Division of Labour

All the information regarding what students needed to do, the rules, and requirements for passing the course were given to students through the tools. Students required to change their behaviour and learning strategy (DoL) based on their self-evaluation either through the quizzes or based on how they had performed on the internal tests. This blended method of teaching also affected the learners' level of responsibility (DoL). For example, students reported that they had to concentrate on and focus more while watching, take more notes to participate, and learn better. As pointed out by one of the students, he raised an important issue that he would make sure that he would ask questions if he still had problems understanding the concepts when he was in the classroom. However, with the lecture videos, students tended not to use the Piazza forum to raise their questions because they did not trust their peers' knowledge. They were also not sure if the lecturer would regularly participate in the forum to answer them on time.

4.1.6.2 Students- Rules

There were conflicts on the rules; students' perceptions were that it was more practical to ask the lecturer directly instead of posting questions to the online forum. This was because they observed that the lecturer did not regularly participate in Piazza, and they did not trust peers to answer their questions. Students thought peer had the same level of knowledge as themselves. Thus, they did not thoughtfully engage in mastering online activities through the zone of proximal development because there was no engagement.

Nentl et al. (2008) used Bloom's Taxonomy and discussed that for encouraging individuals to explore ideas, question, and construct meaning online, learning needed to be used as a community of inquiry. It was hoped that through discussion, the role of teachers and students

could change, and students could learn from peers. Our analysis shows that even the anonymous interaction did not remove or reduce the teacher's role in learning, and students did not trust peers. Therefore, using Piazza as a discussion tool did not help the subjects to achieve the desired outcome.

4.1.6.3 Division of Labour- Object

The analysis of the data suggests that students' participation in activities affected how they eventually performed. For example, if students simply played the lecture videos in the background and focused on something else, students could not finish their learning and consequently not perform well on their tests and exam.

When the lecturer did not promote using Piazza, for discussion purposes, or when he did not contribute to the forum regularly, students perceived the tool as unhelpful for their objects. Therefore, the students disregarded the rules regarding forum and preferred to interact directly with the lecturer.

4.1.6.4 Rules- Objects

The lecturer set rules for the students. For example, students needed to watch the lecture videos prior to the weekly review session in class, and then they were required to participate in the review session. But for different reasons, this did not always happen. For example, they sometimes had other assignments or commitments; that is why they could not follow the rules. In between, some students tried to catch up later. These students had the goal of achieving their objectives. However, remaining students aimed to get the participation mark by playing the videos in the background, randomly answering the embedded quiz questions, and stacking up the videos for their exam preparation. The way that students followed the rules affected the way they achieved their goals.

Students had two options for participating in weekly review sessions. They could either attend the class physically or watch the session's live streaming and answer the questions remotely. Coming to the university for that review session was costly and time-consuming, particularly if a student had no other on-campus commitments. Still, some students mentioned that they might suffer an Internet connectivity issue when they stayed at home to participate. Thus, it was possible that they could not connect through the tools and would subsequently miss the participation mark.

4.1.6.5 Community- Division of Labour

In the BL environment, students were responsible for watching the lecture videos, participating in the embedded video quizzes, and participating in the review sessions. Thus, they thought they had more responsibilities compared to the traditional method of teaching and learning. Therefore, they needed to make preparations (DoL) for the course while there was no community to interact with.

We understood the tools that the lecturer emphasised (e.g., videos, quizzes, audience participation tools), were used more by the students. Conversely, the tools that the lecturer did not emphasise in class e.g., Piazza that had not been widely used. Students did not consider Piazza as a community. Students did not use the tool since their lecturer did not promote or use it. Therefore, that tool did not mediate their learning. Moreover, for some students emailing the lecturer was the best way of communicating with him. However, some students were shy to ask questions of their lecturer through email. Therefore, they never asked their questions.

As we observed in our analysis of the activity system with different objects, an effective community was not formed. Lack of a community resulted in students not being able to engage in actions and transition to a collective activity. Based on Vygotsky's zone of proximal development, we expected students to improve knowledge through collaboration with more capable peers. Still, we identified that students did not see the community's effect and did not trust their peers online. The activity system from the online interactions, then, could not travel in the zone of proximal development; hence, the learning did not take place the way it was expected to. Therefore, this construct became less important in this teaching experiment. The functionality of the theory may depend on the conditions that govern the use of the activity system. For example, in this case, the lecturers' lack of promotion of and engagement with Piazza could contribute to the students not using this online tool properly. We found that in the activity represented in Figure 18, students could not establish a relationship between themselves and their community in an activity system. By providing the material online, the students did not feel that there was a community, and they felt independent of others and thought they were solely responsible for managing their learning. Therefore, a connection was not established between the individual and community levels.

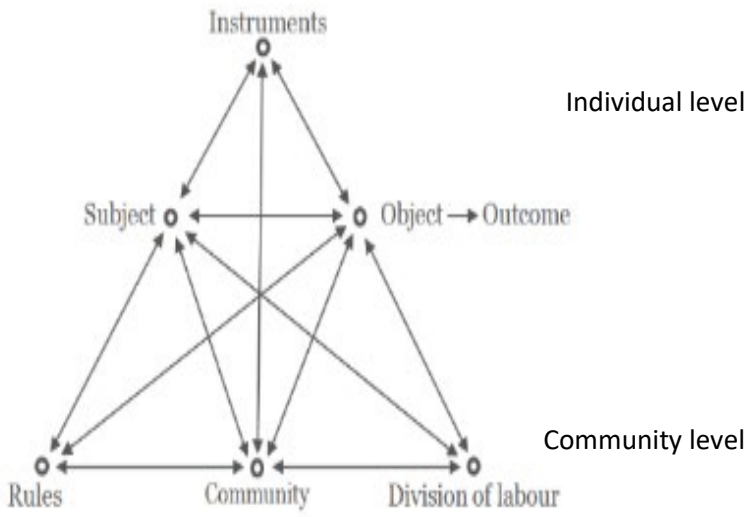

Figure 18 : Factors influencing the level of participation

From an AT perspective, learning is a process in which individuals participate in conjunction with other participants. Their knowledge will be scaffolded by other members of the group who know that activity better. This scaffolding will be mediated through various socio-cultural means. However, in our analysis, students did not feel they belonged to any community to discuss their problems, and they were not learning from their peers. In our analysis, AT helped us to identify the disconnection between the community and the individual. Therefore, it identified the need for future research. We were unable to consider levels of agency and individual preferences. There were some students who had difficulty working with peers. Thus, society and peers did not work as scaffolding for the learner. Since we focused on increasing students' learning through participatory class activities, it was important to consider individuals and their responsibilities in their learning process. Therefore, we connected the AT with SRL (SRL) theory (Winne 2006), enhancing AT by adding another layer to our discussion (Figure 19). We follow Winne (2006) SRL model and will investigate in our future study how the individual used tools to operate on raw materials to construct a product that is evaluated in a formative or summative way with respect to socio-cultural standards.

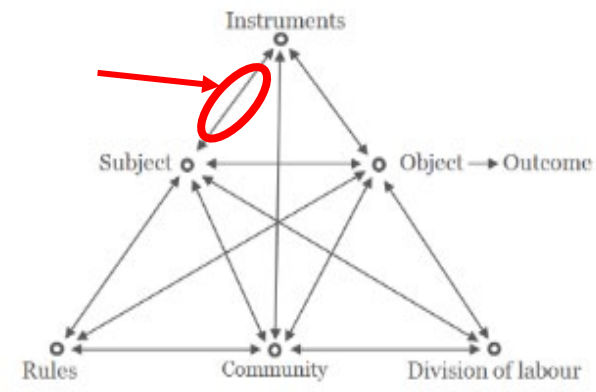

Figure 19: Connecting activity theory with self-regulated learning

4.1.7 Conclusion

We analysed students' perceptions regarding using online tools in three classes. We used the AT to identify students' *perceptions* of what is happening instead of using AT to describe it. Focusing on students' points of view helped us to understand how students' thinking was different from what we thought was happening or intended to happen. This was the best aspect of AT that showed us empirically what needed to be changed. The theory enabled us to consider a range of factors that impacted technology use in a BL environment and understand the obstacles in students' learning process. We firstly focused on the benefits of having access to the materials, but along the way, we identified the contradictors associated with using educational tools in our context. Using AT, we identified the problematic features of the learning and teaching setting. For example, we were unable to ascertain that the community affected students' learning.

From the students' perspective, depending on their individual's characteristics, the tools' usefulness was different. For example, highly motivated students with time management skills could manage their time and be able to self-regulate their learning. Using AT, helped us understand that using educational tools in the learning environment changed the teaching and learning practice, which can be helpful for some groups of students. These findings help us understand the basics of designing and implementing technology-based learning systems. Even though based on the Vygotsky-inspired socio-cultural and AT, we expected to see that learning takes place among students and not on an individual level. Still, in our setting, students did not feel the effect of community on their learning. Only a few students used the discussion forum. Also, the classroom was not used as a discussion place by all the students.

Many students preferred to stay at home and watch the video streaming of a class. We observed that there was no connection between the novice learners and more experienced learners. Therefore, AT helped us identify the disconnection between the community and the individual that will be addressed in future research. This study increased our awareness regarding the challenges in BL environments while different tools were used. For example, the study's implications for the lecturer's practices were the changes that happened to his methodology by identifying the contradictors and more changes that needed to be applied in the next instructional design.

Also, students discussed that they preferred to do assignments alone as they were not sure about the DoL. They could not trust peers as to whether they would contribute to the task or not. They did not know other members well as the community was mostly online, and limited physical. Therefore, social interaction did not foster group learning and group activities. This method of teaching and learning relied on the individual to take control of their learning. We anticipated that all the elements of AT would be involved but observed a disconnection between the individual and community level. We believe that in AT, individuals are manifested by society. Thus personality, motivation, and reasons for engaging with the activity system will not be considered at an individual level. We, therefore, propose the merger of AT with SRL and focusing on the top triangle in AT and looking at how students use the tools to self-regulate their learning. This would be our future path for the study.

(This is the end of paper 6)

4.2 Paper 7- Contradictions Identified through Applying Activity Theory to Perspectives from Students and Lecturers Involved in Blended Learning Courses

(Submitted Journal of Educational Technology & Society)

4.2.1 Abstract

This paper focuses on understanding the contradictions in students' and lecturers' perceptions of educational tool use within three Blended Learning (BL) courses. Using Activity Theory (AT) as an analytical lens, contradictions between and within activity systems were identified. Contradictions were explored to understand the differences in mediating tool uses and discover whether educational tools bridged learning. This study highlights implications for instructional design when using digital learning resources and provides insights into the transformations that occur during the introduction of tools in BL environments. These provide instructive findings to be considered by designers of learning environments in the context of wider educational technology adoption.
Keywords: Students' perceptions**,** lecturers' perceptions, activity theory, contradictions

4.2.2 Introduction

Activity Theory (AT) has been used in different studies in the educational field (Basharina 2007; Berge and Fjuk 2006; Murphy and Rodriguez-Manzanares 2008). AT is not a predictive theory. It is, however, a theory for understanding complicated human activities (Nardi 1996a). When studying technology use, technology is not the focus of interest; however, technology needs to be considered as part of the larger scope of human activities (Kaptelinin and Nardi 2006). Contradiction is an established principle in AT (Engeström 2001). These contradictors are not just conflicts and problems; however, Engeström (2001) stated that they are "historically accumulating structural tensions within and between activity systems" (Engeström 2001, p.137). Engeström (2001) also stated that contradictors generate "disturbances and conflicts, but also innovative attempts to change the activity" (Engeström 2001, p.136).

Based on Nelson (2002) ideas, these contradictors may occasionally inhibit learning. Based on what has been acknowledged and resolved, it enables or disables learning. There are limited studies that have explored contradictors in the educational context using educational tools through the AT lens. But even if they looked at the contradictors, they were primarily focused on technology and not explaining the contradictors in the educational context. Some studies have looked at the contradictors at the post-secondary level (Dippe 2006; Voigt 2006) and a limited number looked at the secondary level (Fahraeus 2004; Murphy and Manzanares 2008).

We are also aware of a few studies (Fredriksen and Hadjerrouit 2020; Gedera 2016) run at the university level which have looked at the contradictors when participants just used for example, the discussion forum. It is evident that there is no longitudinal study that used the third-generation AT that looking at the contradictors between student and lecturer activity systems in a BL environment at a tertiary level using a variety of educational tools and exploring the contradictors among all. To find the contradictors in using educational tools in student learning, we employed AT. Our study focuses on understanding students' and their lecturer's perceptions regarding educational tool use. Aristovnik et al. (2017) stated that when a technology-based teaching method emerged in higher education, the studies focused more on the psychological aspects of learning; however, there is a gap in the understanding of students' perceptions regarding tools' usefulness in BL courses. In accordance with Kaptelinin and Nardi (1997) recommendation to study tool use over time, we observed students throughout their study and interviewed them twice during the course to explore the contradictions, a term used by activity theorists (Kuutti 1996), that emerged during three 12 week courses while students and their lecturers were using educational tools in their classes to understand the changes that happened within the activity system.

This paper, through using AT and its principals of contradictors guided the research in the field of educational technology use in the BL environment at a tertiary level. Specifically focusing on contradictors helps us to understand how teaching practice would change when educational tools were introduced to the classroom. This paper begins with an overview of AT and contradictions, and then outlines the methodology. Subsequently, we present an analysis of the contradictors that we identified. Finally, we present our discussion and conclusion.

4.2.3 Activity Theory and Contradictions

Vygotsky (1980) first coined the idea of socio-cultural approaches to learning and development, arguing that human mental functionalities are mediated processes organised by socio-cultural artefacts. Several socio-cultural theories have been derived from Vygotsky's work (Lantolf et al. 2000; Valsiner 2007; Van Lier 2002). All have one thing in common that all human action is mediated. However, they are different in terms of how the tool mediates human action. Leont'ev (1974) developed AT by using Vygotsky's socio-cultural approaches. AT is a theory that emphasises both historical developments of ideas and the constructive role

of humans. It is a framework for studying human praxis behaviours both at individual and social levels.

Leont'ev explained the "automatic" or unconscious aspects of the activity. In his version of the theory, he explained that those activities were composed of actions and operations. From his perspective, the motive is essential in driving the activity to the object. At the activity level, individuals try to transform the object to the outcome. At the action level, is goal-oriented and contributes to the overall activity. At the operation level, the automatic process contributes to the actions which are associated with the activity (Kuutti 1996).

AT focuses on the context of situated human activities and consciousness, and similarly, on the instructional design. So, it is essential to understand the context of meaningful activity and instructional design when activity analysis is proposed. Engeström (2001) version of AT is depicted in Figure 20. The most important unit of analysis is the activity, which will be accomplished through the top triangle. So, it considers the subject and object of the study and the tool that is used in the activity.

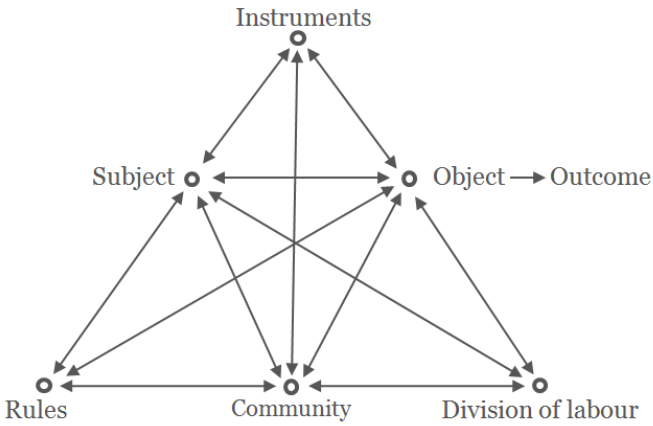

Figure 20: Activity theory (Engeström, 2001)

The seven constructs (subject, instrument, rules, community, division of labour, object, and outcome) used in the context of this study are explained next. The *subject* is the group of students participating in the activities run by their lecturers. The *instrument* is the audience engagement tools. The *lecturers set the rule*s in class. The *community* is the class environment which is guided by rules. *Division of labour* is associated with the students, lecturers, and their responsibilities in class. Students are responsible for their participation and learning. The object of the study is the student's learning while using the tools in the classroom.

Engeström (2001) proposed the third generation of AT for studying the interaction when we have at least two activity systems. Engeström and Sannino (2011) discussed the model of a collective activity system introduced by Engeström (1987) and extended it by considering

multiple interconnected activity systems. Contradictions are frequently occurring within and between activity systems and described by (Kuutti 1996) as "Because activities are not isolated units but are more like nodes in crossing hierarchies and networks, they are influenced by other activities and other changes in their environment. External influences change some elements of activities, causing imbalances between them. AT uses the term contradiction to indicate a misfit within elements, between them, between different activities, or between different developmental phases of a single activity" (Kuutti 1996, p.29).

Osono et al. (2008) considered contradictors as having different priorities at the same time. However, Kuutti (1996) stated that contradictors manifest themselves as "problems, ruptures, breakdowns, clashes" (Kuutti 1996, p.16). But these contradictors or conflicts work as attempts to change the activity. When applied to a BL environment, an AT analysis could help us understand the contradictors in teachers' practice and students' learning in the context of educational technology use activities and the results of that in teaching and learning practice and educational innovation. Next, the methodology, data collection, and analysis are provided.

4.2.4 Methods

In this article, which is part of a larger study, we focus on students' and lecturers' perceptions of using tools in the classroom. Participants were freshmen and upper-level students at a tertiary level. The study investigated three courses in a BL environment over twelve weeks. The core material was developed and delivered through a Learning Management System (LMS). The course lecturers designed student activities before each face-to-face class session. Students were required to watch assigned lecture videos prior to attending weekly class sessions. These videos featured embedded quiz questions that related to the video content. During the courses' weekly 'review sessions', which were held physically in class but also live-streamed via the Internet, the lecturer held quizzes based on student performance for that particular weeks' video quiz. The students were given multiple opportunities to compete with their peers in quiz 'tournaments'. Nicknames of those who provided the promptest correct answers appeared on a leader board displayed to the class.

To understand our participants' motivation, we conducted a Motivated Strategies for Learning Questionnaire (MSLQ) three times during the courses (Pintrich 1991). This gave us some insights into our groups' perceptions, motivation, and strategy use. K-Means clustering algorithm was applied on the data, and students were classified into categories of highly, average, low motivated based on their responses to motivation and strategy use questions. All

students were invited to an interview, and the first four students who accepted the invitation from each cluster were selected for an interview. We interviewed students twice and lecturers once during the course, conducting a total of 42 semi-structured interviews with students and their lecturers to explore their perceptions.

4.2.5 Analysis

We started our analysis by looking at students' and lecturers' objects. Analysing "objects" has been emphasised by activity theorists for the understanding of people and what they do (Kaptelinin and Nardi 2006).

Table 33 shows how tools were helpful at activity, action, and operation levels for the lecturers and students based on Kuutti's framework (Kuutti 1996). At the activity level, we concluded that tools had a different effect on activity, action, and operation levels based on students' different objects. Kuutti (1996) stated that at the action level, the tools supported what he mentioned: "Making tools and procedures visible and comprehensible" (Kuutti 1996, p. 30). These tools supported students by transferring the rules and requirements of the course. In regard to operation level, Kuutti (1996) stated that tools were needed to "automating routines" (Kuutti 1996, p. 30).

		Lecturer	**Students**
Tools	**Activity level**	Teaching the course	Pursuing their objects to pass the course or keep up to date with the materials
	Action level	Preparing all materials such as lecture recordings, assessments, and assignments	Starting to watch, clarifying the materials, and communicating with peers and their lecturers
	Operation level	Distributing materials by uploading them and communicating with the students	Referring to the course content page regularly, checking Piazza for questions other students asked and trying to find answers to their questions

Table 33: Tools support lecturers and students at the activity, action, and operation levels

At the activity level, the lecturers taught the material to the students, and the students pursued their preferred objects. At the action level, the tools supported the teacher. The teacher prepared the teaching material and communicated the rules and requirements of the course to the students. At this point, students started to clarify the instructions and communicated with

classmates. At the operation level, the lecturers distributed material, assignments, tests, and began communicating with the students. At the action level, students regularly checked the webpage and the messages in the discussion forum.

In the process of analysing, we identified contradictors. At the activity level, the activity is affected when conditions change. In this way, the object can be achieved or not achieved, which leads to a break or a contradictor in the system. In the following section, we explore the contradictors we identified.

4.2.5.1 The Unshared Objects Between Students and Their Lecturers

We first started with the contradictions identified due to unshared objects between students and lecturers, as illustrated in Figure 21.

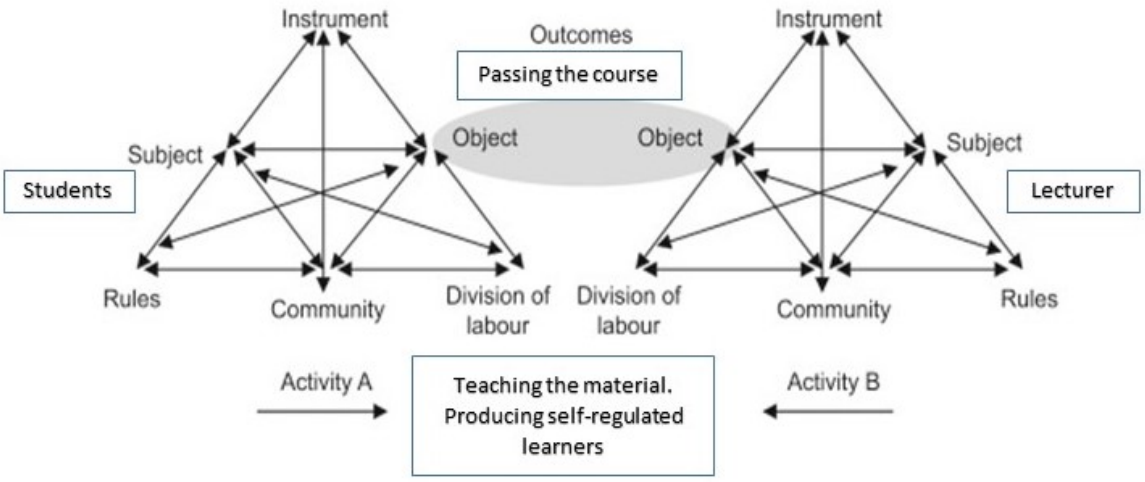

Figure 21: Unshared object between students and lecturers

4.2.5.1.1 Lecturers' Point of View

The lecturers found the tools useful to distribute materials online and facilitated the provision of ubiquitous access to the required resources. The tools facilitated the lecturers at the action level by providing tools to make materials available, set homework, assignment, and quizzes for students. It also provided a platform for the lecturers and students to communicate with each other via discussion forums. The lecturer's objective was to publish the material so that students could read and engage with the course content at their convenience. This action assisted students differently; for example, by reducing photocopying costs or removing the

requirement to commute to the university. At the operation level, the tools were helpful because all the tests and quizzes were run through the system. Therefore, tools helped the lecturers increase their efficiency through the reuse of materials and the automaton of their work which otherwise would have to be done manually. The lecturers were also concerned about balancing time between teaching and research. The lecturers wanted students to use tools as a support to self-regulation or self-study of the materials. However, the students' motivations were different. It was important for a group of students to pass the course, and for some, getting good scores was important. Therefore, based on their objectives and motivation, they used the tools differently.

From the lecturers' point of view, they prepared everything for the students' learning and perceived that the online worked fine and facilitated students' achievement. However, there were students who believed that they were not that helpful. Students expected more from the course and felt that they only received exposure to the material, which was not enough. The lecturers noted that initially, they spent some additional time preparing material, but after that work such as the distribution of materials, communications with students, assessment marking, and understanding students' weaknesses were more efficient. The lecturers also believed that communication was easy for the students as they could easily send an email to their lecturer and get the answer to their questions instead of waiting a couple of days until the physical class to see the lecturer. However, being online is not the same as a physical classroom, and the students noted that they did not feel close enough to their lecturer to ask questions of them.

The lecturers expected students to have ongoing online discussions among themselves. But in reality, the rapport was not established. Students did not know their peers in class and did not trust them to share their knowledge or ask them questions. The lecturers expected students to participate in the forum and ask them questions, but in reality, students preferred to ask questions through emails directly. We identified that the communication mode changes and limited physical communication were two contradictors we identified in this section.

By understanding students' behaviour towards tool usage, the lecturers changed their teaching style from that of controlling to motivating the students to participate by providing material for students, requesting participation in activities, and encouraging them to regulate their learning. The lecturers used different techniques; for example, they awarded students with weekly participation marks to keep up with the course content and participate during the weekly face-to-face 'review sessions'. Furthermore, students who physically attended had an

opportunity to win individually wrapped chocolates based on their quiz tournaments' performance. This is consistent with Engeström (2001)'s claims that contradictions are a cause of change and innovation in teaching practices. The lecturers, all the way through the teaching process, identified issues raised due to using technology and introduced corrective innovations accordingly to their teaching.

4.2.5.1.2 Students' Point of Views

In this section, we concentrate and explain the contradictors identified in students' interviews.

4.2.5.1.2.1 Videos

We identified the first group of contradictors when students discussed the importance of videos in their learning process. When the lecturers created the videos to help students, they were not considered helpful by all the students. Some students could not manage their own time and learning process. Students stated that when watching the videos at home, they faced mental health challenges as there was no socialisation. One of the lecturers' objectives was to help students financially. The lecturers thought it was cheaper for students to watch the videos at home since they did not need to commute. However, the students felt separated from society.

Students reported that they learned differently when they attended the physical classroom compared to when they watch videos. Some mentioned that they could not concentrate when watching video recordings at home. They reported that they were motivated to write notes when they were in class and could not fall asleep in class compared with home. Some students reported that they multitasked when they watched videos, they did not write notes, and because no one was watching them, some reported that they got bored and fell asleep. Some students also were unable to self-regulate their learning and did not watch the videos weekly, letting the content accumulate until the exam. Therefore, students were unable to follow the rules, which was another contradictor between the division of labour and the object.

4.2.5.1.2.2 Tournament

Having access to the tests that have been run as a tournament by the lecturers in class, some students used them for practice. It was helpful for students measuring their understanding of the materials taught in the class. This, however, was not the case for all students, as some were

not able to self-discipline themselves to do the tests. The lecturers used tournaments to increase student motivation. However, the activity impacted students differently; this is contradictory between subject and mediating artefact. Tournaments demotivated some students because they felt that they were not as fast as others, for example, mature students. Students also reported technological issues such as Wi-Fi or phone speeds, which meant that they felt that they could not compete, and therefore, the system was unfair. Again, contradictors between the subject and the mediating artefact were identified where students felt the tool was unhelpful. Therefore, they did not use the tools, and they did not mediate their learning. If the students did not use the tools properly, then there would be a contradiction between the subjects with the mediating artefact. But when the learner did not have knowledge or experience using the tool, it is a contradiction between the subjects and the rules. Consequently, the student also could not achieve the objective, which was a contradiction between the mediating artefact and the object.

4.2.5.1.2.3 Contradictors among Students

When students worked on a group assignment, there was a contradiction between students' objects. These contradictions and the different perspectives regarding the course led to a significant change in the educational process. There were two activity systems among the students. Some wanted to pass the course; some wanted to get a good score. One of the students who just wanted a passing score expected other students to respect her object and not expect her to change her objective. Students also had different experiences, but they did not know about other classmates' experiences. Therefore, they could not choose other group members by chance. If group members did not do their part, the other members would get a low grade. As a result, most students chose to do the project individually. In a group assignment, the community and subject did not share the same object. There was a contradiction between the subject and the community with an object. It may affect the division of labour. There is a body of research about what temporary team group assignments need to be considered a temporary team. Goodman and Goodman (1976) define temporary teams as "a set of diversely skilled people working together on a complex task over a limited period of time" (Goodman and Goodman 1976, p. 2). But because students did not know each other in our case, they could not trust each other and could not form a team. Engeström et al. (2007) emphasised the importance of teamwork, but in our study, teamwork was not chosen by students as there was no trust.

4.2.5.1.2.4 Community

The lecturers encouraged all students to use Piazza (i.e., a loosely structured discussion forum) for their learning and clarifying the concepts among themselves. The connection between the lecture as a subject and community is loose because from the students' point of view the lecturers did not contribute to the online discussions to the extent of students' expectations, but in contrast, attending the review sessions was very helpful from the students' perspective. Student satisfaction and use of tools all depended on the way the lecturers performed and used the tools. The lecturers thought the online environment for discussion could replace the physical classroom, but as we identified in our interviews, students did not trust other students and their knowledge. For clarification, students mostly saw their lecturers or emailed them. They did not use online discussions for class discussion purposes. They did not construct knowledge based on trust. Engeström et al. (2007) discussed the challenge of mistrust on the network partner's competence and its effect on knowledge construction. This contradictor showed itself when the students did not effectively communicate with other members of the class. This contradictor between the subject and community affected their object. It also caused another contradictor between the subject, rules, and division of labour. All these contradictors affected how students achieve the outcome they were seeking.

Another issue identified through using the forum related to uncertainty and fear that students felt about posting materials online. They were not sure about others' judgment of them; that is why they did not want to expose themselves to the class. It was a contradictor we found in using the forum. When the community was available and students still did not want to participate, there was a contradiction between the community and the division of labour.

In our study, we observed that students did the things they were required to do. The students were required to watch the videos to get participation marks; therefore, they watched them or at least attempted to do so. But they did not use the tools when they were not mandatory. When the lecturers did not emphasise using Piazza, students also disregarded this, which was a contradiction between the division of labour and the object. In this regard, Montoro (2016) reported that learners would only use the learning centre if they were forced to attend and pay a significant amount for it. The lecturers believed that by exposing the students to the materials and community activities, the students would be able to address the gap in their knowledge, but it did not happen. Yamazumi (2006) mentioned exposing the learners to community activities could help them learn better. Through this exposure, the learners were able to learn the concepts that were the aim of the activity. Contrary to the study run by Hattinger and

Eriksson (2018), we did not see collaboration among peers in the community. In our study, students did not know each other and therefore, the co-construction of knowledge did not happen through the online environment. Paré et al. (2006) emphasised the importance of active engagement in co-constructing knowledge. With regard to active engagement, what happened in the review sessions was very important for students. In the review sessions, the lecturers were actively engaged in the activities with the students, tried to get the students involved, and made them participate in the questions in class. That is why students were very satisfied and thought they were learning in the review sessions.

4.2.6 Discussion

We explained the complex contradictors we identified in the students' interactions with the educational tools, the lecturers, the community, and the lecturers using and observing students using the tools. We had contradictors within an activity system (when the students used the tools) and contradictions among activity systems (when we considered students' and lecturers' activity systems and unshared objectives). In the first group of contradictors within an activity system, contradictions are among elements of a single activity system. In the contradictions among the activity systems, contradictors are among the two interacting activity systems (lecturer and students activity systems).

The lecturers provided students with educational tools for their learning so that they could take responsibility for their learning by watching the videos, taking part in quizzes in a comfortable place, and participating in the review sessions from their own place or physically attending the class. The lecturers trusted that students would watch the videos. But at the same time, they would have checked the duration of students' watching time to make sure that students did not fast forward the videos without genuinely watching them. They also checked students' responses to the quizzes at the end of each video to find out the level of understanding of the materials provided. Based on that, the lecturers made mini-lectures for the review sessions.

Even though studies such as Dabbagh and Kitsantas (2005) argued that different categories of web-based technologies (e.g., collaborative and communication tools, content creation, and delivery tools) supported or facilitated the enactment of different SRL processes in distributed courses, we were interested in investigating and understanding students' perceptions in this regard. Research suggests that when a new technology is introduced to the activity, it clashes with older elements, and contradictors will be the results of those clashes. This reflects

Engeström (2001) and Thorne (2003b) views regarding contradictors within the activity system. Therefore, it was important for us to identify the socio-cultural contradictors that emerged in our study using educational tools in classes.

From the lecturers' points of view, we understood the contradictors, which led to the changes in their teaching and additional changes they needed to apply, to address the issues identified in their class. Issues included students not having a close relationship with the lecturer, students not using the forum appropriately and using emails instead of online discussions, students not having communication with each other, and time and workload contradictors for the lecturers.

Edwards and Mackenzie (2005) defined relational agency as someone's ability to get support or offer help to others, engage with them, and enhance the work alongside others. We wanted the Piazza to act as an open system so that relational agency could emerge. We wanted individuals to work with others. However, they did not feel they needed to work with others. The relational agency did not emerge. One of the reasons was the lack of trust among students. Edwards and Mackenzie (2005) also discussed the concept of relational agency, which is the understanding of individuals by others. This is a capability that someone can have to be able to align their thoughts with those of others in the group. In the example of group work in our study, the students could not accommodate other group members' objects because they were contradictory to their objects.

4.2.6.1 Lesson Learned

After carefully investigating students' points of view, we identified that it is necessary to make some course design changes. This is consistent with Engeström (2001) claim that contradictions are a source of change in practice. First, we know that it is necessary to make students familiar with other classmates through some mechanism so that they can trust each other and have a social connection with each other prior to the start of a project. We also could familiarise them with the tools and the benefit of using them. We should also find a solution for making students motivated and more involved.

When the students do not participate in the forum despite our expectations, perhaps the lecturers can inform students about the most popular topics in the discussion forum so that students join the online discussion. In this way, the presence of the lecturers would also be more evident for the students. The students may also feel hesitant to post in the forum for different reasons, or they may not believe that the lecturer would look at the material online.

Therefore, awareness is needed to make sure that students feel safe to participate. We also understood that we do not have to underestimate the value of these review sessions. Students all came to the review sessions to get the most critical points. The lecturers can help students by making things clear for them in the review sessions because they are all online either physically attending the course or online so that they can answer the lecturer's questions and get participation marks.

4.2.6.2 Implications

This study increases awareness regarding the challenges of using BL environments. We note several implications for lecturers' and students' practices. Lecturers identified issues when teaching in a blended environment and recognised the changes to their pedagogy and instructional design necessary to facilitate successful learning. As part of this, instructors need to clearly articulate the merits of electronic tool usage, outline student participation goals, give regular updates and remind students about issues concerning their study to avoid procrastination. It is essential that the instructors facilitate student to student engagement to enable successful peer interaction and learning. Students may be encouraged from each of these elements, increase their objects, and have successful outcomes to their courses.

4.2.6.3 Pedagogical Implications

From an activity perspective, there were differences between students' and lecturers' motives, objects, rules of activity, and educational tool use for the purpose of teaching and learning. Even though the lecturers wanted students to use the tools fully, the students were confused or did not comply in the manner the lecturers expected. The lecturers were able to explain the importance of their participation in their learning so that the culture of tool usage could take shape among them. Additionally, it was important that students understand there were some tools that are useful for information transference, such as videos. Some tools are helpful for self-evaluation, and also for lecturers' evaluation of themselves, and finally for communication purposes.

4.2.7 Conclusion

This study was about adopting educational tools in BL environments in three undergraduate courses at a tertiary level. The lecturers provided students with different tools. We used AT

to see how different tools mediated the learning process. We interviewed students and their lecturers to understand their perceptions. We identified contradictors within an activity and between activity systems. When we investigated the lecturers' points of view, we understood the contradictors, which led to their teaching changes. The lecturers understood that students did not have a close relationship with the lecturers (visual indications contradictions). They also understood that students did not use the forum appropriately, and instead, they used emails (direct message contradictions). Students also did not communicate with peers because rapport did not happen. Also, the lecturers had the contradictor between the time they could allocate and the workload they had. We also identified contradictors in the students' points of view. Contradictions in the students' data included technology-related issues and unequal contribution to participating or not in the forum. We understood the way the lecturers used the tools affected how students used them. Therefore, the instructional design needs to be updated. In Russell (2003) view, it is important to understand people's perceptions of what is happening through using AT. This perception could be different from what was actually happening or what we thought would happen. This is the strength of AT, which helped us to understand what needs to be changed in the system as we saw the potential of help through using tools. The students believed that through the tools, they could remove the barrier for participating in activities. However, we did not see the magic in students' learning by using tools. The tools worked for some groups and not for others. Perhaps in the future, we can come up with a way of measuring the effectiveness of these interventions. It is also possible that we may not have understood properly how the students' learning processes happened, that is why we are not targeting things in the right way. Understanding the students' learning processes and the individual agency level is important in the effectiveness of these tools in their learning.

We also identified our limitations in our study. In this study, we just used qualitative data from three classes. Even though its results inform the educators and students, we cannot extend and generalise it to other learning settings. We also had a limitation of considering two different activity systems; however, we need to consider other perspectives such as the institutions' perspective and the changes affecting them in the future.

(This is the end of paper 7)

4.3 Paper 8- Students' Use of Educational Tools: an SRL Focused Longitudinal Study

(Published- Pacific Asia Conference on Information Systems)

4.3.1 Abstract

Electronic educational tools are generally recognised for their usefulness in the classroom, especially in the area of gamification. However, there is little evidence that considers their effectiveness. In our research, we explored students' perceptions of the utilisation of classroom tools and their effect on learning. In doing so the effects of features, such as competition and gamification, on their perceptions and motivation were examined. We interviewed a number of students and analysed their perceptions of tool usage through the lens of self-regulated learning. Our qualitative findings indicated that the tools' gamification and competition features facilitated and motivated the students. In addition, increased participation highlights that students' positive or negative perceptions of the usefulness of the tools and how they used them depended on their own motivation and preferences.
Keywords: Electronic educational tools, competition, gamification, students' perceptions

4.3.2 Introduction

Electronic educational tools are popular and regularly deployed in higher education. Such electronic tools are sometimes distributed through Learning Management Systems (LMS) for fully online learning or partly in a BL course (Dabbagh and Kitsantas 2005). Instructors are free to choose which tools to deploy as either a primary source of information or as replication (e.g. videos or online quizzes). Here sometimes some part or core concept will be recorded and provided as supplementary materials for students (O'Bannon et al. 2011). These tools enable the instructor to deliver material in an active learning form to large numbers of students, therefore increasing student engagement and promoting deeper learning. Dabbagh and Kitsantas (2005) stated that providing various toolsets help students choose the tool that supported their learning and stimulated self-regulated learning (SRL). Thus, from the SRL perspective, students have an agency and choose for themselves whether or not to use tools (Winne 2006). SRL focuses on the students as agents, bringing our attention to the importance of their views about these tools. Shuell and Farber (2001) identified student perception as an important factor in understanding the relationship between technology and the learning process. We postulate that perception is under-examined in the educational tool use literature frequently employing quantitative methods to gain insights. Using the qualitative method of time sequenced interviews we have explored these characteristics. By interviewing each

participant twice, (before and after substantial tool experience) we hope to remove any bias associated with "technology novelty".

The following research questions guide our study:

"What is the perception of students regarding the use of an electronic educational tool in their classes?" We analysed students' perception through the lens of SRL (Winne and Hadwin 1998). Even though the importance of perception in using tools in their learning has been emphasised, not enough studies looked at this from a SRL perspective. Several studies have investigated tool use from the Technology Acceptance Model perspective (Davis 1993), but we explore this further to understand why students neglected tool use or have not been used as we expected them to use by interviewing students (Almarashdeh et al. 2010; Mun and Hwang 2003; Sánchez and Hueros 2010). We seek to understand the effect of tool use in SRL. Even though studies show the usefulness of technology tools in the SRL environment (Winne and Hadwin 2013; Winne et al. 2006), we seek to enable improvements in SRL environments for students. Previous studies explored students' self-reported evidence of tool usage activities we endeavour to add more depth to the existing research through a series of interviews.

By answering this question, we contribute to both practice and theory. Understanding students' perceptions of tool use and functionality help both tool and instructional designers. The former can develop tools which will be more adaptive to students' needs. Instructional designers can understand how to embed the tools in their course and which tools are helpful for which category of students. In an environment which has the goal of producing lifelong learners, we can, by providing tools for students and looking at their tool usage and their decisions to continue using tools, contribute to SRL theory. By considering the perception and usage of tools over time, we are also able, within this SRL process, to validate behavioural decision making. Up until now, we have explained the topic we are investigating and its contribution to the field of instructional design. In the next sections, we review extant literature; our methods, findings, conclusions, and limitations.

4.3.3 Literature Review

In the educational setting, it is essential to increase students' engagement in class to enhance their learning experience. It is suggested that students learn more when they engage in class activities rather than staying passive in the course. Draper and Brown (2004) mentioned that if students do not get engaged in activities, they are less likely to work hard and less likely to perform well. Vygotsky (1978) also notes through human interaction; knowledge construction

will enhance. There are different techniques that teachers use to increase the participation of students in class activities (McKeachie 1990; Saroyan and Snell 1997). One of these is using technology tools to improve the participation of students in the class. Researchers used technologies in the classroom environment to improve the participation and engagement of students and consequently their learning (Park and Farag 2015; Ravishankar et al. 2014). Even though the studies showed the importance of using tools on students' learning, it is students' choice to choose which tool to use and decide on how much to use the tool (Scheiter and Gerjets 2007). Perkins (1985) stated that students do not always use the opportunities that are presented to them.

There are different studies (Esnaashari et al. 2018; Esnashari et al. 2018) which investigate how students use the available tools. The findings revealed that students differ in terms of the amount of tool use. Winne (2004) further stated that a student's perception of the functionality of the tool implies a relationship as to whether a student will use the tool (the intervention) or not. The importance of perception has also been investigated by Salomon (1984). He showed that the students who perceive the environment as more a gaming environment would allocate less mental effort. In contrast, those who perceive the environment as more learning environment invest more cognitive efforts. Struyven et al. (2008) also mentioned that the way students perceive the learning environment would affect the learning activities they employed. Even though the importance of perception in using tools in their learning has been emphasised, unfortunately, few studies have explored this from a SRL perspective.

4.3.3.1 Self-Regulated Learning

We adopt our definition of SRL from that defined by Pintrich (2000) 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). There are different variations of SRL which has been categorised into two groups; goal oriented and meta-cognitively weighted.

While there are different versions of SRL available, all the versions of SRL follow the same three phases of preparatory, performance, and appraisal. Among all the variations of SRL, we focus on Winne's work which has the most heterogeneous theoretical background. Winne's model has been influenced by Bandura (1986a) and Zimmermann (2000) which present a social cognitive theory. In contrast to what other authors have defined as SRL, Winne looks

at SRL as a recursive process. In the metacognitive monitoring, the feedback can be given in any phase. In other words, monitoring happens in the performance phase and feedback in the appraisal phase.

Winne's work is more strategy oriented so it is helpful to assess the effectiveness of different strategies used by the students to be compared with each other. For this reason, the students' self-report has frequently been used to understand the strategies that students used and is considered as an effective lens to investigate contemporary e-learning. Winne (1996) looks at SRL as an inherent part of learning. He defines SRL as meta-cognitively guided behaviour which could enable students to adaptively regulate their use of cognitive tactics and strategies in the face of a task. Winne and Hadwin (1998) define SRL in a four-stage process. 1) task definition which is the perception of students about the task. 2) goal setting and planning 3) enacting tactics and strategies planned in the previous stage, 4) adopting study techniques meta-cognitively.

4.3.4 Methods

In this course, the core material was available on the course LMS, and review sessions were conducted in the classroom for discussion purposes. The students were required to watch all the videos and participate in the quizzes at the end of videos before coming to the review sessions. There was a review session conducted weekly for students. Students had the option of going to class in person or watch the review session online when it was streaming and participate in the quizzes run by the lecturer in class. The lecturer used an audience participation tool to engage the students in class activities. The lecturer used educational tools to run tournaments in class. The students needed to beat other peers in class so that their name appeared on the leaderboard. The students had access to Piazza (forum) in case they needed to clarify anything among themselves or with their lecturer.

Our research here is part of a larger mix method study where we aim to understand students' perceptions from a qualitative and quantitative perspective, we report here on the qualitative interviews. In order to select our participant firstly we conducted a questionnaire survey using the MSLQ tool (Pintrich 1991). 189 first-year students from a university in New Zealand participated in the survey. The students were surveyed from one program which was taught through BL and ran for 12 weeks. This paper focuses on student perceptions of using tools in the classroom. Students were invited for interviews based on the results of the MSLQ questionnaire. In our analysis of students' motivation and strategy use in our full study, we

observed a large standard deviation (SD) among students, therefore, we explored it further to see if we could identify different groups and subgroups of students based on their level of motivation in the classroom (Heirweg et al. 2019; Linnenbrink-Garcia et al. 2018; Regueiro et al. 2018). We applied the K-Means clustering algorithm on students' motivational data collected clustering into three groups (Magnusson and Stattin 1996; Zusho et al. 2003). We invited students from each cluster to attend interviews. The first four students from each cluster who responded to the invitation were chosen to participate in the interviews. We interviewed 12 students twice in the course. We interviewed high, medium, and low motivated students to see how different their perceptions were. These three levels of motivation were selected in order to compare our study findings with earlier work in this field. In accordance with standard interview protocols, we conducted semi-structured interviews, during which we asked about the students' perceptions regarding using tools and understanding the factors that affect their personal tool use. In this study, we investigate the perception of students and in our other study, we used the quantitative data to draw parallels to our qualitative data. With our qualitative method we are able to contextualise and understand more deeply the data from our quantitative survey data.

4.3.5 Findings

In this analysis, we follow Winne's framework which outlines the four critical points that are required for SRL. Different stages of SRL, what teachers and students do and what the tool does to serve each stage of the process is depicted in Table 34.

Providing the materials online is the first step in the SRL process. Therefore, the lecturer by providing the materials online contributed to the SRL of students. The students can access the material anytime and can use them based on their time availability. The tools accelerate the process of accessing the materials. Based on students' self-interpretation, the student defines the task for themselves. Based on the motivation and metacognition that they had, they set the goal and plan for their learning. For example, student 15 mentioned "I allocate time. I reward myself when I do the task".

In the process, they constantly judge their learning. Through the quizzes at the end of videos, the students will check what they know? How much could they remember? This will activate prior knowledge and the strategies they used. In this case, they metacognitively take control of their learning, and they choose study time and content for themselves.

Self-regulated learning theory	Teacher	Student	Tool
Comprehending-Goal setting	The teacher puts all the required sources, sets all the activities, gives all the directions, and the criteria for marking	Comprehending the task, setting personal goals	Videos, audios, instructions, activities
Planning/ Strategies	The teacher puts the timeline there, asks students to watch and take the test before they come to the class	Managing their time, taking part in the quizzes, getting help from the peers and teacher	Online videos, Communicating, Discussion
Evaluating	Review students work, Redirect them if needed	Determining the progress of herself comparing it with the goal, revising strategies	Grades, tracking progress, quizzes

Table 34: Mapping between the stages of SRL and learning process of students

In this study, the lecturer provided students with electronic educational tools and encouraged students to design their own learning environment. Depending on the environment that students prepared for themselves, they had a different learning experience. We asked students about their feelings regarding their learning environment. Students in their own words talked about their process of learning. How tools helped them to self-regulate their learning, what strategies they used to make that happen. For example, student 17 mentioned that:

"So the way I learn, I used to be quite a graphical learner, like I liked to see diagrams and images and stuff. But for me, the way that I learn now the most would probably be just like writing it out, as opposed to typing. Like physical writing's a lot better, I feel that I have to think about it more than just sort of pushing buttons, so it gets ingrained in my memory. And the way that I sort of evaluate my learning is a lot of papers have learning outcomes and stuff like that at the end of each week. I won't necessarily do that each week, maybe like two weeks, and stuff like that, and I'll go over those and I'll double check that I like know all of that. And then if I don't I'll go back, I'll try and learn it, and I'll find things that I don't understand and I'll go to my group and see if they know it. And if not then I'll go to the lecturer. So I'll sort of like, I don't break it up into sort of weekly schedules, I'll sort of break it up into, I sort of like time how many weeks I've got until the next test and then I'll break up how many topics I have to learn. And then I'll set like, you know, maybe like three days to learn a topic, and I'll

go over that and make sure I know everything, that kind of stuff. Yeah, sort of break it up into little windows of need to know this by then. (S17)"

Referring to SRL, through reflection and thinking about his own learning process, Student 17 reported that he is a graphical person. He knows that the best way for him to learn is to use pen and paper and create words and symbols. So, for him, he first sets a goal to learn something he does not know. To master the new learning, he first needs to make it concrete using signs and symbols to make the new information part of himself. Using the physical act of writing creates a thinking space for him that again involves reflection. The ability to produce the written content also is a way to evaluate whether or not he has learned the new information. Through writing, he embodies the new information and self regulates his behaviour. To self-evaluate his learning, he also uses the learning outcomes and double checks whether he has acquired the new learning every fortnight.

4.3.5.1 Students' Perceptions through Self-Regulated Learning

In this section, the reflection of SRL will be given. In this framework, the perception of students is reflected in the use of the tool in their process of learning.

4.3.5.1.1.1 Comprehending the Task (Providing the Required Material)

Comprehending the task is the first and foremost element in SRL. The student must understand what he /she needs to do so that it shows the learning and completion of the tasks. When the students understand the learning environment and task requirements, the first turning point occurs. To accomplish this stage students need to understand the factors such as time requirements and environmental opportunities and constraints which affect the academic success of the students. In a traditional learning environment, the teacher provides the curriculum material through instructional procedures. In new online learning, the materials will be available through the tools for the students who have the potential to facilitate the SRL by providing accurate, meaningful and accessible information.

Darabi et al. (2004) emphasised that teachers, by providing direction and assistance in the description of the problem or the required learning task, can promote the first stage of SRL which is comprehending the task for students. In this study, the teacher supports the comprehending task of students by providing directions and instruction online for the students. The teacher provides online lectures, quizzes, and instructional design for the students. The teacher who is an expert in teaching provides different activities which can help learning of

students and explain the importance of participation in the activities for their learning to the students. In this study the teacher explains the activity and states it is timed.

Students appreciated the learning environment that their lecturers provided them with and they believed in the functionality and usefulness of each of these tools in their learning process, but they used the tools differently. This is inconsistent with the study of Dabbagh and Kitsantas (2005) that mentioned providing diverse toolset would give students the opportunity to choose the tool that support their learning. Dabbagh and Kitsantas (2005) stated that this would stimulate, self-regulate and motivate learning. However, students in our study mentioned that they used the tools based on their level of motivation, their perceived usefulness, other assignments, and responsibilities they had.

Evans (2008) showed that irrespective of the way a podcast has been used as a preparatory, or supplementary material, students just watched the web-lecture for a short period of time (Green et al. 2003; Taylor 2009). In contrast to Evans (2008), our study showed that students mostly watched the video materials which acted as preparatory material for them. However, Scutter et al. (2010) identified that when the web lectures were provided as the duplication of the original lectures, only half of the students would watch them. We asked students about their feelings regarding their learning environment. Student 13 mentioned,

"I feel I'd choose the online one because it's more flexible towards a way of learning. So, like, some people don't learn as well when they go to lecturers, but sometimes if they have online stuff, it's much more helpful. Yeah, and like, the way its been presented is really good. It's new, fun, but like, it's really nice." (S13)

And Student 12 mentioned,

"It was quite useful because I don't, coz I live around South Auckland so if I can't make it on, like, in my classes I tend to use the online. (S12)"

Students thought that their course was their best course, as such, they indicated that the competitive electronic environment using tools made learning more fun. It also made the learning independent of the location.

Referring to the SRL cycle, the first stage is providing all the material so that students understand the task in order to be able to regulate their learning. The teacher helps the students by putting all the materials online on the tool and gives them permission to do the activities at their own pace. The tool provides them with the facility to have access to the material in their own time. By providing the material to students, they will understand the required learning activities, they set the goal for themselves, and they can do the activities anywhere that is more

convenient to them. This is consistent with other studies in SRL (for example Darabi et al. (2004) which showed the importance of providing direction and assistance in the process of learning the task in SRL through an implemented software.

Even though the majority of the students in our study felt that the blended method of teaching was very beneficial, there were a few students who thought that they were not as useful as going to the physical classroom (Different method of learning). Those who were not satisfied with the tools had different reasons. These students mentioned that when they attended classes, they were forced to attend to the material and take things more seriously. They thought the class made them more attentive, therefore, they would listen and learn. But having been provided content online, some students reported that they would leave their work until before the exam, did not learn anything during the course, and some found themselves unable to do it all at the end. Having access to this option is more controversial because it acted differently for the students. One of the students (S1) reported that if he attends the classroom, he will write more notes and he is inclined to listen. While being at home, he "might lose control of learning and end up taking a nap. However, many students the availability of the electronic tools made studying better, as noted by (e.g. S6),

"Yeah, I think that, like, if you're actually going to the lectures, you're more motivated to engage in the lectures. Like, you can't have a nap in class. If you're watching it at home, then you're more tempted to be distracted and do other things. You'll be like, 'oh I'm bored of this, I'll pause it and go do something else'. Like I feel that actually in the class, you have to focus in on the class and what you're learning."(S1)

"Yeah, to more actively engage and to more learn the content. Whereas with, like, just having a recording, it's kind of like, well there's no class, I'm just gonna watch a recording. It's not big deal, I can just chuck it up and then it'll be there. "(S6)

Also, having the option to watch the lectures online and being able to see the lecturer just once a week made it harder for students (e.g. S 7) to build a rapport with the lecturer, feel comfortable to go to him and ask questions of him in person.

"I guess that's one of the negatives of, like, having it all online. Because, like, sometimes when you have three lectures a week, after every lecture you and go and see the lecturer. But there's only one lecture a week. But then again, he has office hours, I'm pretty sure, and we can go to office hours and email him or something like that."(S7)

Bhattacherjee (2001) mentioned that users set their expectations before usage which influences their tool adoption. However, during usage, user develops the perceptions which

influence whether the user decides whether or not to continue the usage. Having been very excited about using audience participation tool could have come from the 'novelty effect' (Clark 1983). Therefore, we asked students about their perceptions in the middle of and towards the end of the course to see if their feeling has changed. We did not want our findings to be affected by the initial tool use. Therefore, we looked at how they continued using the tool and their perceptions were after using the tool for a while. In the second round of the interviews, students (e.g. S 4), mostly mentioned that they had the same feeling and that the tools were very helpful, and they continued using the tools as shown below.

"I think at the start I thought, oh, like the video recordings, oh it's really a cool idea. It'll be like, it'll be more helpful. But I think as I've progressed, it's kind of like, am I actually learning the content or am I kind of, like, putting the video on, watching the video, not really, like, focusing in on the video instead of actually being able to, like, sit through a lecture, like actively engaged kind of stuff. I think it was a cool idea."(S4)

However, other students mentioned that their perceptions have changed as the course progressed when they become aware of the importance of tool use in their learning process. At the beginning, they (e.g. S 3), thought there were too many activities, or it was more like "childish" stuff to do for each week" but when they understood the effect of the activities on their learning, they engaged with it.

"Yeah, and then I think with, like, Top Hat, at first I thought, oh this will just be something really simple, childish, and then, 'cos, as it progresses, kind of like, oh this is a really helpful tool that, like, it's helping us learn and all this kind of stuff. "(S3)

4.3.5.1.1.2 Goal Setting

To accomplish this stage, the students need to identify the learning task and start to set the goal for their learning. This is the conclusion from comprehending the task in the SRL process. The students in this study set the goal based on, for example, what average passing rate was for the course. The teacher can help the student for setting the goal or achieving the goal. For student achieving their goal, the teacher runs the activity and asks students to participate in activities through the tool. The teacher allocates a mark for participation so that students have enough motivation to participate in activities. This stage is the setting of goal and participation in the activities that is the second stage in SRL. When students understand what they need to do in order to accomplish the task, they start to set the goal and start to do planning.

Students had different goals for accomplishing the task. Students 10 mentioned

"I wanted to get all participation marks." (S10)

Student 12 mentioned

"Wanted to learn the topic for my future work."(S12)

Student 1 mentioned

"I reward myself to keep myself on the track by weekly reading catch ups."(S1)

Referring to the SRL cycle, the second stage is for the leaner to set the goal. Based on the explanation of the teacher, the students wanted to be the best student in the class. The teacher helps the student to set the goal and help them by providing the material and also monitor them to make sure students can achieve their goals. Students use the available videos and readings, based on their time and other limitation that they have. They participate in activities set for the students.

4.3.5.1.1.3 Applying Strategies

Setting the strategies is the third step in SRL. Having determined the material and the activities that students need to do, they develop the plan and strategies to perform the required task. Providing the material online and letting the students do the activities in their own time enabled the student to promote self-regulation by planning and doing self-paced and self-management. Providing the material online on audience participation tool and giving students the facility to access them all the time. Students # 6 and 5 mentioned audience participation tool helped them to set their strategies.

I think "[Name of the tool] can affect the classroom but in a positive way. Like, it just brings everyone together. But I think it's the best thing for goals because it's a really good tool, like I said, and I think also it becomes a lot of responsibility, it comes a lot down to the student to, to watch every video and take the quiz at the end and take notes if needed. (S6)

"It's hard to catch up on, like, I had to do everything at once. But [Name of the tool] still very useful and I think, for the first, like, eight weeks, I made the most of it, definitely."(S5)

Referring to SRL, students based on the task to do, will set strategies for themselves to achieve their goals. Students are always evaluating their strategies to understand whether they are correct or whether they need to apply any changes in their strategies. The data from our study is consistent with other studies (Banyard et al. 2006) which emphasise the effect of online tools for promoting SRL through setting the strategies, planning and self-management.

To accomplish this stage the students need to develop strategies which could help them achieve their goals. Planning is what students do to tackle the task. Yang (2006) defined

planning as allocating time to satisfy the requirements of the task and choose the strategies which can help to achieve the object of the task. Then the students participate in activities based on the available times and the constraints they have that is choosing strategies which is the third stage in SRL. The teacher can help the process by setting a reminder for the students so that students do not miss the deadlines.

4.3.5.1.1.4 Evaluating the Strategies- Usefulness of Participating in the Quizzes

Students by participating in the quizzes evaluate their learning. They will understand how much they know and whether the strategy they used was helpful for them to achieve their goals. This process helps them for self-evaluation and promote SRL. At the end of each preparatory video there was a quiz that all students needed to complete in order to test their knowledge and get their marks. Students mentioned that quizzes at the end of videos were very helpful for self-evaluation. Students evaluated their learning with quizzes (Step three in SRL- self-evaluation). They checked how much they remembered by counting the number of questions they got them right as it is mentioned by students (e.g. S 9),

"Yeah, so I'd say, like, quizzes and stuff are probably going to be really helpful for the tests, like, we've got and first week back and such. And coz I'm kind of getting the understanding that the questions are gonna be the exact same format. And it's all about, yeah, as I said before, if you've forgotten the answer to one of these questions it kind of just triggers that memory and quite often, coz I guess it's who I am, I'll go and read a little bit around that thing and watch the video again as well." (S9)

The students used the questions to evaluate their learning and applied changes in their strategies (i.e. writing more notes). Even students thought that repetitive questions in the quizzes helped them (deep learning). In this regard one of the students (e.g. S 10), mentioned,

"With the Top Hat I find it useful to an extent though, coz quite often after I watch the videos with the Top Hat, like, you get a set of Top Hat questions on earlier in the week and then by the time it gets to the Top Hat it either, tend to probably remember most of the question, like, answers. " (S10)

The student (e.g. S6), stated that if they did not perform well, they would review her notes again and would participate in the quizzes again. If they got them right, it would be fine. Otherwise, they would re-watch the videos that is they would self-reflect to see if they needed to write more notes. This is changing strategy that is the result of self-reflection.

"And then quizzes I think are great coz it's a great way to, kind of, re-establish knowledge and, you know, from the lecture recordings you do the quizzes." (S6)

The students (e.g. S1), mentioned that quizzes not only helped students to self-evaluate but also helped teachers to evaluate students' learning and his teaching style to see if he needed to repeat the materials.

"It is very useful, and I think [the name of lecturer] uses the quiz results at the end of the videos to identify where we as a group are weak and rehashing the concepts is useful. So propping up and acting as a support layer to the videos, which is fantastic."(S1)

Through participating in the quizzes the student does self-evaluation which is the final stage in SRL. Referring to SRL, through continuous monitoring and checking the accuracy of learned materials helps students to employ strategies and plans which help them to better achieve their goals (Progress monitoring). This is consistent with the other studies (Yang 2006) in SRL which indicate through using WBLE, students do the performance control (self-monitoring) in promoting SRL.

4.3.5.1.1.5 Evaluating the Strategies- Immediate Feedback from the Teacher

When students participate in the activities through audience participation tool, the teacher provides immediate feedback to the students. Providing immediate and informative feedback helps students to learn. This immediate feedback helps and prevents students from wasting time for a look around to find the right approach to deal with the question and absorb the information the teacher provided them with. This immediate feedback could not happen without using the tool. Students mentioned that instant feedback they received helped them as the student (e.g. S7) mentioned,

"Yeah, I like going to the review sessions more, it's better. It's different, like your effort's different, 'cos you're surrounded by people. Yeah. And in, in his, does he give you any feedback, like with the, like, link or something that you have to go or he will just give you the exact answer through the tool." (S7)

Based on the feedback they got, students (e.g. S 13) applied changes in their strategies. For example, writing more notes based on the feedback they received.

"Yeah, so after, like, the Kahoot, like, we'll be like, okay A is the right answer and then, like, let's say like a lot of people didn't get it right he will, like, go to the slide that he has for the lectures. And then he'll be like, this is actually the right answer guys, because blah, blah, blah, yeah and I write down in my notes and more note." (S13)

Referring to SRL, giving timely and immediate feedback is very helpful for scaffolded guidance which helps students to plan for more strategies. This is consistent with other studies (e.g. Denton et al. 2008) which identify the effect of timely and effective feedback in the learning of students in the SRL process.

4.3.5.1.1.6 Regulation- Having Fun through Tournaments and Gamification, Increasing Motivation

Running the quizzes through the tournament was very motivating for students due to providing a fun environment. This environment helps them to participate more and through answering more questions they learned more as reported below by Students #11.

"Yeah, definitely, I reckon the Top Hat and Kahoot helps a lot. Because without that, then I feel like no-one would be motivated to watch the videos, like such a long video and watch it without doing anything else and actually learn. "(S11)

Students (e.g. S 12) mentioned that the tool made the class more interactive so the students would not get bored.

"I need the information to come in, but doing, like, interactive things, like, that makes me awake coz I'm actually doing something." (12)

Students also mentioned that they used the audience participation tool due to its affordances such as competition. Competition was identified as one of the main themes in the students' interview data. Students talked about the fun environment the tool brought to the class through competition. Competition was identified by students as one of the elements which acted as a motivator for students to participate and try more, which consequently affected their course learning outcome.

"Yeah, we do, like, competition ones in Top Hat, like tournaments and stuff and it's kind of, like, it's fun to interact with your other students and be like, oh I can beat you, kind of stuff."

Competition was defined by Alessi and Trollip (2000) as competition between user and computer, competition against oneself, against chance, and against time. Competition has been identified as an element which has a relation with challenge and consequently has a relationship with intrinsic motivation (Malone and Lepper 1987). Cheng et al. (2009) studied the benefit of competition in the level of engagement and active participation. Wu et al. (2010) mentioned that by allocating a score to the game, it is possible to motivate students to put in more efforts which consequently affected their learning. Our study's result was consistent with that of Wu et al. (2010) because in our study, with no extra score, competition alone motivated students to participate.

"you're competing with other people because you do the, so you do Top Hat, like just quizzes. So, what he does is, so he'll just give you, like, three questions and you would answer them by yourself, no leader board. And then we'll do a Kahoot, that's the whole class competing against each other and then we'll do a Top Hat tournament. Which is, like, it's the same thing as the Top Hat quiz but instead you compete with, like, the whole class even without getting extra score" (S17)

Competition comes with a comparison which can have an effect on students' self-efficacy which relates to motivation and performance (Bandura and Locke 2003). As Bandura and Locke (2003) mentioned the way that user looks at the competition can affect self-efficacy, beliefs and consequently the motivation. Competition made the class more attractive, and the students were motivated to participate and enjoy their learning. The students reported that they were very competitive. The students all mentioned that competition worked as a positive motivator for their learning. Students talked about how others actively answered questions that worked as a motivator.

Referring to SRL, through game-like features and environments which have a positive effect on engagement and motivation of students, the tool helps students with their process of learning. Students mentioned, running the quizzes through the gamification aspect of the tool increased the motivation of students. Increasing the motivation of students through gamification is consistent with previous studies (e.g. Kafai 2008). Other studies (E.g. Rowe et al. 2010) show games have been used to teach students different subjects including scientific inquiry which is congruent with our experiment here.

4.3.5.1.1.7 Regulation- Usefulness of Having Discussions – Scaffolding Knowledge

The use of the discussion tool (Piazza) was mixed among the students. Even though Piazza was available for students' communication, the students did not think that there is a place for asking questions and communication.

"I don't really post, I just, most of the time if there's something I don't know how to do it's on there already. So I don't really feel the need to post. I don't really post on Piazza at all, to be honest, yeah, 'cos I don't really need to."(S16)

They just used Piazza as a tool for asking questions about the exam and assignments. Therefore, the tool was not used in a way that it was planned to be by the students.

"I don't use Piazza, I just use it for assignment. But for the other course [Name of the course] we used it a lot."(S12)

Students see Piazza as a tool for getting an update with regards to the exam date, assignments and general enquiries. But not for communication purposes, for example, for information seeking and asking a question of other peers and their lecturers. Most students did not ask other peers in Piazza, they did not trust other peers' knowledge, or they thought their lecturer would not look at their questions in Piazza. Some students trusted the answers based on how many endorsed the answers.

"Yeah, I post in Piazza. I think at the start of the year I asked one of the questions, but yeah, I don't really ask my peers because sometimes they don't really know themselves. So I tend to kind of self-learn everything, or if I don't really get I ask in Piazza.

I don't tend to use Piazza very often. I find that quite often the questions that people are asking on Piazza are questions that you can very easily answer in the course book but some people don't refer to the course book. (S5)

Some students asked questions in Piazza but would seek information themselves and asked others in parallel so that they did not wait for something that might not help them achieve their goals. The quotation below reminded us of the way that students used the tools very much depended on how the lecturer introduced and used the tools in class. Doing the activities and participating in discussions enable students to do peer interaction and self-evaluation which again promote self-regulation. Also, participating in discussion with the teachers and getting guidelines from the teacher will help the scaffolding process of the knowledge for the students which promote SRL. Having access to a better collaboration experience, helps students to understand their weaknesses and think about their knowledge which is all very helpful for promoting SRL. This finding is consistent with other studies (Azevedo et al. 2003). Through scaffolding guideline, the students can be helped in their learning process through SRL.

4.3.6 Discussion

The focus of our study was to understand the perception of students regarding the learning environment prepared by the lecturer for the students. We investigated the students' perception as perception has been identified by different researchers as a factor affecting the amount of tool use (Salomon 1984; Shuell and Farber 2001; Struyven et al. 2008). We asked about students' experience of using tools. How they actually used the tool? When and under what circumstances, what motivates or hinders them to use the tools? Experience of the learners from their own perspective gives us a better understanding of their challenges and strategies they use to overcome them. Knowing about the learners' experiences, issues, and

strategies they employ to overcome their challenges, helps the educators to come up with better ways to facilitate the learning process of students when using online tools such as videos, tests, online discussion forum.

Based on the literature, providing tools help students to self-regulate their learning. In this process in it proposed that they evaluate and reflect on their learning. When we asked about their experience with online materials and tools. We found that students experience with online tools helped them to reflect on their own learning experience and evaluate what tools help them when and under what conditions, so far as students become aware of their abilities. As such students learnt from their reflection what works for them, they became more aware of their learning process and were more confident to be able to independently perform the tasks. In our full study we observed that students just grabbed the cursor and moved it to the end of the video without watching it, we understood that they actually did not want to participate in the activity in a way that was meant to. We investigate this further in the interviews to understand their perceptions. We identified reasons which led students to neglect tool use includes lack of motivation, lack of time, financial problems, etc.

We thought that BL was the best way of learning for students. From our perspective, we thought that we were helping students' SRL process. We believed that all the facilities provided by the lecturer promoted SRL by reading, note-taking, self-management, and time management, help-seeking, visualization for self-monitoring, progress monitoring, and feedback. From our point of view, the most important contribution of the audience participation tool was when there was a lecture theatre with a large number of students, and the students were unable to answer questions. This was very helpful for the teacher to gauge the level of understanding of the students and for example identify students who are at risk. The characteristics of individuals such as motivation, and emotional control, self-efficacy is much easier to control with the audience participation tool compared to the traditional learning environment. What we observed and heard was that students perceived more competence in the environments which was made competitive by the lecturer. They invested more effort and valued the task. To summarize, students in our study believed in the power of the learning environment. They also though competition in the game worked as a motivator by the students.

Most of the students thought the tools are helpful for their learning process. However, there were students who disagreed. Even though the first stage of SRL was providing material and task comprehension, by providing the materials online, not all students could benefit from

that. There were students who were not able to take control of their learning, and they left the material until the last minute. Students thought they were more isolated as they did not have to attend class which did not help them to self-regulate their learning and that actually they did not learn. So contrary to SRL theory (Winne 2006), we provide the material, and we expected to see students can take control of their learning. What we found and could not explain through the theory was when the tools did not allow the student to participate for a number of different reasons be it: internet speed; willingness to cooperate with other students; access to technology; or external pressures or beliefs, the participants chose not to participate in activities.

As we observed, some students were happy, some perceive the environment more like a gaming environment, and some did not benefit at all. Most students reported that they enjoyed the fun learning environment, these students believed that the audience participation tool added the gamification to the learning environment, but we are not sure how much they actually learnt. Some mentioned that the gaming environment and gamification aspects of the tool increased their motivation and consequently help in their process of learning. However, this is a limitation in our study; we would like to connect the perception of students and course outcome to see how different student by different perceptions achieved differently in their final course outcome.

This study has shed light on student learning which will be very helpful for learning scientists. Tool designers and instructional designers will be able to find out about students' preferences in tool use, and the effect of using different tools on the performance. This information would be helpful for developing learning pedagogies to support student-centred learning. Finding reasons behind student tool use differences helps to design more appropriate instructional design, which can help different kinds of students. It provides information for the instructors about how students use the tool differently and what the pattern of students' tool use is. Understanding which tool is more popular will help the tool inventor to improve their learning tools, and it also helps teachers to design the instructional design in a way that desires students' tools use and use the tools more for scaffolding and cognitive help. Understanding the perception of students' regarding tool use and its functionality will help tool designers to invent tools which could help more students and is more adaptive to students' needs.

4.3.7 Conclusion

In a bid to encourage students to take responsibility for their own learning we observed the BL mechanisms deployed by one lecturer in the classroom. As part of a larger mixed method study, we used a cluster analysis grouping of student responses to the MSLQ survey we interviewed 12 students twice in a 12 week period in order to examine their perceptions of electronic tools in the educational setting. We asked students about the competition and motivation aspects of the tools. Through these narratives, we identified different aspects of how the tools helped them to manage their time, taking control of their learning process, and how it helped them to engage with the activities to learn more deeply. We looked at how students' perception changed and whether changes in the perception affect tool usage. In this case, we added to the literature since we were validating a behavioural decision making in the SRL process. Even though several studies examined tool use from the perception of "usefulness or perceived usefulness" (Davis 1989), we examined the motivation of students in a SRL environment. We investigated how the tools helped students in their SRL process. The technology acceptance model (TAM) considers initial attitudes and expectations (Davis 1989). What we investigated was about how students' intentions changed when they understood the helpfulness of the tools in their learning. The prediction of SRL was that providing tools for the students would help them to self-regulate their learning. We found that even though students had a very positive attitude toward the tools and believed in the functionality of them, they used tools differently and their tool use was affected by students' characteristics. Our study showed that the level of motivation was different among students, and motivational and perceptional differences affect tool to use.

4.3.7.1 Limitation

We used the data from a relatively small data set from 189 students from one department and one university. Future research is needed to validate our findings. For us, the webcast was a replacement for the classes. Therefore, students were required to watch all the lecture if they wanted to learn the whole topic. Review session recordings were the only repetitive material for students. In the future, we suggest that the study explores giving students more freedom by replicating the entire class.

(This is the end of paper 8)

Chapter 5

CHAPTER 5

5 Chapter 5- DISCUSSION AND FUTURE RESEARCH

This chapter summarises and discusses the research findings to attempt to answer the overarching research question:

How students' perception, motivation, and learning strategy use inform LA?

In doing so, our discussions are focused on the three sub-questions outlined in the following sections assessing the complementary nature of our use of mixed-method techniques. Our findings and contributions will impact the successful adoption of blended learning techniques. Finally, we present the limitations of the study and the path for future study.

The main focus of this study was to inform LA through understanding students' perceptions, motivation, and learning strategy use, while the lecturers introduced and used different educational tools in their BL courses. We emphasised the importance of our study by recognising that there are increasing numbers of students enrolled in higher education who have various needs and recognising a high rate of non-completion amongst this group. We note the willingness of faculty members to identify the students who are at risk, to apply interventions, and to help them. We also recognised that lecturers who employed BL techniques have fewer interactions with students; therefore, it becomes more challenging to identify these individuals. Consequently, it is necessary to collect and analyse more data from students to provide more insight to the lecturers. LA is an approach that uses educational data and analyses it through learning theories so that proper interventions can be designed to help students' learning processes. This study drew on AT (Engeström 1987) and SRL theory (Winne 2006) and followed a mixed-method approach collecting interview and questionnaire data. In contrast to other studies that looked at students' trace data (Gašević et al. 2016; Strang 2017; You 2016), we employed self-reported data from students as students have a major role in LA; their perceptions are essential to investigate (Pardo and Siemens 2014). Consequentially, we focused on students' perceptions through both interviews and questionnaires.

We chose to investigate motivation and strategy use as studies (i.e. Lonn et al. 2015; Wong et al. 2019a) indicated that the motivational component of SRL is currently not sufficiently considered in the LA field. Li et al. (2020) also stated that SRL is a multidimensional construct that needs to consider metacognition, emotion, and motivation on top of strategic behaviour.

There are many questionnaires available for measuring motivation and strategy use (SRL); we chose the MSLQ as it is one of the most appropriate, it has been widely used in the literature for SRL measurement, and its reliability and validity have been proven in the literature (Roth et al. 2016).

Through running three studies (two quantitative and one qualitative study) based on learning theories, we contributed to LA's theoretical foundation through the three studies based on learning theories by linking LA with SRL and AT. Through choosing motivation and strategy use, the study addressed the gap in lacking motivational research in LA. Moreover, LA lacks empirical evidence (Ferguson and Clow 2017) that we addressed by collecting and analysing longitudinal data from students' motivation and strategy use. Through predictive and cluster analysis, the study contributed to one of the most important aims of LA, identifying at-risk students. By clustering students based on theory and looking at their movement among clusters, we contributed to the SRL literature and addressed the challenge identified by Järvelä et al. (2019) regarding the cyclical nature of SRL. Through analysing students' perceptions with AT, we contributed to the literature in AT by identifying contradictions in students' perceptions regarding tool use in BL environments. Analysing students' perceptions using SRL helped us open the black box mentioned by Winne (1982) through understanding how each tool supported a specific stage of SRL. In what follows, we address and discuss each of the three research questions' findings and their contribution to answering the main research question.

5.1 Research Question One: How do We Predict Course Outcomes for Two Groups of Students (Upper-Level and Freshmen) Based on Their Motivation and Strategy Use During the Courses?

One of the predominant aims of LA is the prediction of students' learning performance to identify at-risk students (Aldowah et al. 2019; Papamitsiou and Economides 2014). Different studies used different indicators to predict the final score. For example, Zacharis (2015) used reading and posting messages, content creation, quiz efforts, and files viewed as predictors. You (2016) used regular study time, numbers of late submissions, the number of time students accessed online sessions, and reading the course information package as predictors. Strang (2017) used course logins, lesson reading activity, time spent on lesson quizzes, and scores on those quizzes as predictors. However, we used the indicators from theory (motivation and strategy use) for our final score predictions, which would develop LA through learning

theories (Wong et al. 2019b). In this study, we did not just aim to make the best model for predicting final scores from all the variables we could get from the LMS without knowing the importance of the indicators from the LMS for learning. We chose the predictors based on theory (Lerche and Kiel 2018; Rosé et al. 2019).

In Paper 1, we first provided the reliability and validity of our model and predictive analysis of final scores based on three classes of data (N=419). We explored the dynamics of students' motivational belief and learning strategy use as the course progressed. After that, we investigated the constructs that had the highest correlation with the final score. Using three classes of data, we found that, in contrast to other studies, students' levels of motivation and strategy use dropped until midterm but increased again as the course progressed towards the end. By exploring the predictability of the final score, we noted that self-efficacy among the motivational constructs had the highest correlation with the final scores. Test anxiety had the lowest correlation, and time and study environment among the strategy use constructs had the second highest correlation with the final scores. The correlation between critical thinking and the final scores stayed negative throughout the three iterations.

After looking at all three classes together, we repeated the analysis for two groups of students (freshmen and upper-level) separately in Paper 2 and 3 to see how these groups were different. Our sample consisted of 314 students in total (194 freshmen and 120 upper-level students). 850 viable MSLQ surveys were collected from two classes. We found that the dynamics of motivation and strategy use were different as the course progressed. 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. We 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 the new strategies for their learning. 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 same pattern when the course finished (still lower in motivation and higher in strategy use).

We 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. In terms of sub-constructs, self-efficacy for learning and performance and extrinsic goal orientation among the motivational constructs, time and study environment and effort regulation among the strategy use constructs had the highest correlation with the final scores for both freshman and upper-level students.

Subsequently, we examined the predictability of freshmen and upper-level students' final scores 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. We were not sure of the reasons. One of the reasons could be year differences between participants or having different contexts. In this regard, Gašević et al. (2016) state that a course with different instructional design and discipline could have different predictors.

5.1.1 Contribution to Theory

From a theoretical perspective, looking at different motivation and learning strategy use constructs over time could enrich our understanding of students' motivation and strategy use in the online environment and their perceptions regarding their interaction with peers, teachers, and their learning environment.

Our study's findings provide a perspective on tertiary students' psychological needs by investigating their perceived motivational and strategy use in the context of three business school courses. This also contributes theoretically to the debates in SRL theory and identification of the relevant SRL measures and their effectiveness for predictions (Pintrich et al. 1993b; Zusho et al. 2003).

By predicting students' final scores, we could identify at-risk students so that the lecturer could apply proper interventions. This contributes to one of the most important aims of LA - identifying at-risk students (Aldowah et al. 2019). We used variables based on theory and did

not use all the data we could get from the LMS to get the best fit for our model. Researchers (i.e. Lerche and Kiel 2018; Rosé et al. 2019) stated that there are studies that used all the data from the system without understanding whether these data are meaningful concerning LA purposes. We chose the motivation variables for our prediction purposes as it was evident that the use of these variables is missing to a large extent in the extended literature (Lonn et al. 2015; Wong et al. 2019b). Also, different learning theories emphasised the importance of these constructs in students learning. By choosing these variables for the analysis and also bringing empirical evidence, we contributed to LA. Ferguson and Clow (2017) stated that there is still a lack of empirical evidence for LA. This empirical study showed the constructs in motivation and strategy use that were important and impacted the course outcome or helped us predict final scores early in the course.

This study also methodologically contributes by presenting longitudinal empirical data about students' perceptions of their motivation, cognitive, and metacognitive SRL in the classroom environment.

5.1.2 Contribution to Practise

In terms of the study's implication for practice, looking at students' reported motivation and learning strategy use constructs over time in an online environment informs us how students' motivation and strategy use changed and how their test and assignment results affected students' motivation and strategy use. This information is beneficial for instructional design; instructors can update the instructional design to increase students' motivation, teach them strategies, or give them the instructions to better take control of their learning. These insights, which have been given to the lecturers, from analysing students' data are more important in an online environment where the lecturers do not have the opportunity to interact with the students in a physical environment.

We learned that the dynamics of motivation and strategy were different for freshmen and upper-level students throughout the courses. This helped us understand the nature of academic development in our classes and their learning. As this is based on data and discussions with the lecturers, the lecturers understood that they need to work on different constructs in different courses.

We identified the constructs that had the highest correlation with the final scores, which was very informative. It helps the instructors understand that they need to facilitate those adaptive constructs in students' motivational belief or strategy use. Adaptive ones like intrinsic goal

orientation, extrinsic goal orientation, and self-efficacy, which would be good candidates for the lecturer to promote. An example of a non-adaptive one could be anxiety. But this insight would further support students. For example, it was possible to design learning activities and support services to help students. The lecturer can also talk about the role of effort-regulation and strategies as we understood from the analysis that these constructs are effective. The lecturer could teach students the strategies and proper skills to control their learning and become self-regulated learners through different tools and mechanisms. For example, when we know time and study environment, organisation, and effort-regulations have a significant correlation with the final scores, the lecturer can teach students ways to improve them. The lecturers can also talk about the value of the task or update the pedagogy and focus more on task value when its importance is identified in the analysis. It is also important that the lecturer help students by facilitating strategy use. There were strategies and resources available to students, such as critical thinking, peer learning, and help-seeking, which need to be promoted early in a course.

We also identified online teaching and learning issues that teachers first need to be aware of to address in their instructional course design. For example, when in the MSLQ questionnaire, we observed students give a low score to peer learning and help-seeking constructs, and in the interviews, students mentioned that they do not know other students in the class which is why they did not trust other students to get help or learn from them. The lecturer understood that he needs to make students familiar with other classmates to encourage them to get help from peers and learn from each other. He also identified that he needs to encourage students to participate in the discussion forum and try to make more group projects so that students start to know each other.

We identified the most important constructs for predicting the final score through predictive analysis. Understanding the motivational and learning strategy constructs that affect students' course outcomes can inform available support and pedagogies and would be very helpful for designing the learning environment. Through early prediction of students' final scores, we also identified the students who would be at-risk of failure so that the lecturer could apply appropriate interventions to help them.

5.2 Research Question Two: How Can We Understand the Dynamics of Upper-Level and Freshmen Students SRL Profiles that Have an Influence on Students' Course Outcomes?

For answering the second research question, based on the challenges identified by recent studies (Jang et al. 2017; Järvelä et al. 2019) regarding the cyclical nature of SRL, we investigated the SRL profiles of students who shared common motivation and learning strategy use (SRL characteristics) for two groups of students (freshmen and upper-level) in Papers 4 and 5. Further, we investigated how the two groups of students adopted different SRL profiles as the course progressed. We followed a person-centred approach as previous studies mostly used a variable-centred approach.

We identified three distinct student profiles of highly, average, and minimally SRL, based on motivation and strategy use for three different measurements in two BL courses. Profiling students through clustering (identifying a subgroup of students) gives deep insight into students' SRL process and motivation. It helps us comprehend the complex and reciprocal relationships between different SRL behaviours. We presented our findings based on freshmen and upper-level students, and we compared the results between freshmen and upper-level students. We understood SRL profiles are not static. They changed as the course progressed for both freshmen and upper-level students. However, the movement patterns among clusters (SRL unfolding process) were different for the freshmen and upper-level students. We observed that students who had higher levels of motivation and strategy use achieved higher scores at the end, moderate level motivation and strategy use students achieved moderate scores, and low achievers had the lowest levels of motivation and strategy use.

We were also struck by observing the consistency in the profile of freshmen students. Most of the changes for freshmen students were to upper-level SRL. More adaptive clusters had a higher level of motivational belief, cognition, and metacognition. These were students who were active self-regulators. Close to the end of the course, we just had two students in the lowest level of the SRL clusters. We aimed to produce lifelong learners. Considering the number of high and moderate students in the self-report, and based on their final achievement, we were able to produce the learners who were able to control their learning. In terms of movement, upper-level students mostly moved to lower motivation clusters as the course progressed.

We showed that students moved among clusters, but the movement pattern among clusters was different for the two groups. We also understood that not all students were able to self-regulate their learning. Some of them could not reflect on their learning. They did not use the test and assignment as reflective tools on their learning, which is very important for both practice and theory building. Identifying these students is always a challenge for academics in order to help them.

5.2.1 Contributions to the Theory

Understanding different SRL profiles that share the same pattern of motivation and strategy use, identifying their characteristics, and investigating the students unfolding SRL profiles are very important for both practice and theory building. We contributed to the field when we longitudinally clustered students based on well-established SRL theory, not just clustering them based on a lot of data we could collect from the LMS without knowing the real relationship between them. We chose motivation and strategy use based on theory, knowing that these constructs have not been sufficiently studied in LA. This is a contribution to the theoretical foundation of LA.

We contributed to SRL literature by identifying three self-regulated behavioural profiles; highly, average, and minimally SRL and tracking students' profiles and their variations through time. Tracking the changes in SRL profiles is a confirmatory contribution to the challenge identified by Järvelä et al. (2019) regarding the cyclical nature of SRL. We investigated the effect of feedback through exams and assignments on the motivation and level of strategy use. This is an empirical study that brings evidence to prove the existence of the cyclical nature of SRL.

Also, through student clustering, we were able to identify students who were at-risk of failure. This model of prediction also contributed to one of the most important aims of LA (identifying at-risk students). We are also contributing by bringing empirical evidence based on theory for LA which is still lacking.

5.2.2 Contribution to Practise

It enables educators to understand better their SRL sub-groups of students, students' SRL processes, and how they adopted different SRL profiles over time. Thus, the lecturers could employ effective teaching strategies to raise their motivation level or teach them appropriate strategies to adopt appropriate profiles once they are identified.

The other contribution of this study to practise is that students could adopt quite different SRL profiles over time, which helps our understanding of their strategic adaptation through the presence of adaptive SRL.

We mapped how going through different course stages such as receiving test and assignment scores affects the students' motivation and strategy use. In designing a course, this information is very important to consider. Designers need to know how tests and assignments affect students' adaptation of different SRL profiles and what they can do to help them better.

It helps us gain insights into the potential impact of online teaching experience and assessment and assignment results upon learners' interests, motivation, and strategic processing and informs lecturers about the necessary intervention designs for students with different SRL profiles. The lecturer could also update instructional design by giving students proper instructions to target both students' needs with different SRL profiles and the outcome.

5.3 Research Question Three: What Are the Students' Perceptions of Educational Tool Use in a BL Environment?

The use of educational tools has increased worldwide, providing more learning options for students (Hammond-Kaarremaa 1994; Lee 2017; Yadegaridehkordi et al. 2019). However, there remains a lack of evidence on the usefulness of educational tools for helping students' learning.

In LA, students play a major role (Pardo and Siemens 2014); therefore, understanding their perceptions is very important. In LA, we are using student data to give insights to their lecturer; however, we were not sure what the students' perceptions were in this regard (Tsai and Gasevic 2017; West et al. 2020). Therefore, we asked students about their perceptions regarding tool use. As Gašević et al. (2015) mentioned, we have to remind ourselves that LA is about learning and not just collecting student data to make predictions. For this reason, we brought learning theories when we analysed students' perceptions. In Papers 6, 7, and 8, we used AT and SRL to understand students' perceptions of educational tool usefulness in students' learning.

Papers 6 and 7 draw on AT and its principle of contradictions to investigate students' perceptions of educational tool effectiveness to support learning. The AT lens and its contradictions provided a tool for us to investigate the challenges of the BL methodology. We asked students about their perceptions because we know from the literature that having positive attitudes towards technology is a precursor to technology use (Moran et al. 2010). We also asked about their perception of the ease of use and usefulness of tools, which we believed

would affect students' willingness to use them (Venkatesh et al. 2003). Our goal was to motivate students to use the tools and use the tools to self-regulate their learning.

We found that not all students were happy regarding tool use. It showed that students mostly had a positive disposition regarding using tools in class. Students talked about what tool features helped or prevented them from learning. Students mentioned how their motivation increased through gamification, competitions, or throwing chocolate. They also talked about how they got helped through participation in the activities by the tools and receiving instant feedback. However, findings also revealed that learners have several concerns regarding using tools as well. Firstly, we focused on the benefits of having access to the materials, but along the way, we identified the contradictions associated with using educational tools from students' and their lecturers' perspective in our context.

Using AT helped us understand that using educational tools in the learning environment changed the teaching and learning practice, which can help some groups of students and not others. These findings helped us understand the basics of designing and implementing technology-based learning systems. Although based on the Vygotsky-inspired socio-cultural and AT, we expected that learning would take place not only on an individual level, but in our setting, that students would not feel the effect of community on their learning. Only a few students used the discussion forum. Also, the classroom was not used as a discussion venue by all the students. Many students preferred to stay at home and watch the video streaming of a class. We observed that there was no connection between novice learners and more experienced learners. Therefore, AT helped us identify the disconnection between the community and the individual that will be a future research field for us.

We also consider the contradictions between activity systems when we analysed the students' and their lecturer's perceptions regarding using educational tools in the BL environment. Contradictions were explored to understand the differences in mediating tool usage and discover whether educational tools bridged learning. We identified the changes and transformations in the teaching practice as a result of the contradictors in our BL environments by using different educational tools.

There are differences between students' and lecturers' motives, objects, rules of activity, and educational tool use for teaching and learning from an activity perspective. Even though the lecturers wanted students to use the tools fully, the students were confused or did not comply in the manner the lecturers expected. We discovered that students needed to understand that some tools are helpful for information transference, such as videos. Some tools are helpful for

self-evaluation, and also for lecturers' evaluation of themselves, and finally, for communication purposes. These were the issues that teachers first needed to be aware of regarding online teaching and learning so they could address the issues in their instructional course design. For example, they needed to make students familiar with other classmates, make the students familiar with the tools, make the importance of each tool clear for students in their learning (Quizzes, Piazza). Lecturers also needed to inform students about the most popular topics in the discussion and encourage students to participate in the discussion board and try to make more group projects so that students could start to know each other.

This method of teaching and learning relied on the individual taking control of their learning. Therefore, we showed the relationship between subjects, tools, and objects. We anticipated that all AT elements would be involved but observed a disconnection between the individual and community level. Therefore, we propose the merger of AT with SRL focusing on the top triangle in AT and looking at how students use the tools to self-regulate their learning.

Investigating students' perceptions regarding tool use through SRL contributes to opening Winne's (1982) black box and expressing its importance. We explored to understand how tools helped students and, if so, in which stage of SRL. Students explained how each tool helped them to self-regulate their learning or how tools prevented them from learning. They explained the features which could support SRL. We understood that not all tools help them in the SRL process. Each tool may just support a specific stage in SRL. For example, the course content was good for task definition; available videos were good for transferring knowledge, tests were good for recalling material, self-evaluation, and self-reflection (Bannert and Mengelkamp 2013; Bannert et al. 2015). Some students believe that the feedback they got from the lecturer through the tool helped them with quick understanding and deep learning (cognitive and metacognitive feedback) (Pieger and Bannert 2018).

However, having access to the same tools may help students to procrastinate. For example, having access to the videos all the time, students thought they would do it later. We found that even though students had a very positive attitude toward the tools and believed in the functionality of tools, they used those tools differently, and their tool use was affected by their characteristics. For example, students with different levels of motivation reported different levels of tool use and expressed different levels of satisfaction with tool usefulness. It helped to understand better Winne's (1982) black box as tools were not magic. Not all students were happy with the use of tools. Even though the lecturer thought that he prepared everything for students to learn, students could not use them to the lecturer's expectations.

5.3.1 Contribution to the Theory

This study contributed to the theory in applied education, improving participation through the adoption of technical devices and understanding students' perceptions and experience regarding the effect of using these tools in their learning.

Research on understanding students' perceptions about using tools through the AT lens and identifying contradictors in the BL environment contribute to the AT literature and gives further insights into how transformation may occur by introducing educational tools in tertiary education.

Through identifying the disconnection between individual and community levels, we introduced a new conceptual construct (of active SRL) by drawing on AT and SRL. Understanding students' perceptions regarding tool use through an SRL lens also helped open Winne's (1982) black box. We understood not all tools were helpful in students' learning process; this is further discussed in the following section.

5.3.2 Contribution to the Practise

This information sheds light on the students' learning processes, which could influence practice in BL. We identified contradictions in students' and their lecturers' perceptions (two different activity systems) regarding using educational tools in the BL environment, which was important for updating the pedagogy and instructional design.

This study increased our awareness regarding the challenges in BL environments and the use of different tools. It highlights several implications for instructional design when using digital learning resources and provides insights into the transformations that occur during tool introduction within the educational context. Lecturer's instructional design, teaching practice, and assessment changes reflect the recognition of contradictions and the need to modify their methods. As part of this, instructors need to clearly articulate the merits of electronic tool usage, outline student participation goals, and give regular updates and reminders to students about their study issues to avoid procrastination. The lecturers understood they could explain to students the importance of their participation in learning so that the culture of tool usage could take shape among them. Lecturers understood they must facilitate student engagement to enable successful peer interaction and learning. Students may be encouraged from each of these elements, increase their objects, and have successful courses.

We understood that we should also find a solution for motivating students to be more involved. For example, despite our expectations, when students did not participate in the forum,

lecturers could inform students about the most popular topics in the forum so that students are encouraged to join the online discussion. In this way, the presence of the lecturers would also be more evident for the students. The students may also feel hesitant to post in the forum for a number of reasons, they may believe that the lecturer would not look at the online material, students needed to be reassured of the lecturer's presence so that they felt safe to participate, also due to the online setting students had not developed trust in their peers and therefore did not interact.

Students all came to the review sessions to reinforce their understanding of the most critical points, whose value must not be underestimated. Attendance could be either physically in the classroom or online; however, the lecturers are able to help students by clarifying content for them in the review sessions; the students gained participation marks regardless of their mode of participation.

5.4 Understand Self-Regulated Learning Using Students' Reported Perceptions, Motivation, and Learning Strategies

While we separately analysed our qualitative (interview) and quantitative (self-report) data, we compared them to understand if the two sources of data supported each other. We investigated SRL through a mixed-method study. The quantitative survey helped us to measure the constructs separately. Adding qualitative data helped to add context to our study and better understand student self-regulation in a BL environment. Interview data added rich information to the self-report scores. Even though we learned a lot through the student survey due to having knowledge about a lot of students, integrating them with qualitative data helped us to get the bigger picture.

We understood the two sources of data supported each other. We compared what students reported in their interviews with regard to their self-regulatory strategy use and what they reported in the MSLQ. We looked for the congruence between the interviews and surveys. We understood that in our study, surprisingly, both sets of data supported the findings of the other. Lack of peer learning and help-seeking were identified as issues in our study. We also understood that in our method of teaching, students believed that their critical thinking strategy did not improve.

We understood that both lecturers and students acquired new roles and responsibilities in a new online learning environment. In this teaching method, the lecturer's role was mostly as a facilitator and the students were responsible for their own learning. Having said that, some students were complaining about not having the ability to self-control their learning due to

different factors. Studies (e.g., Kim 2009; Macfadyen et al. 2010) have investigated motivational, cognitive, and performance challenges that students and their lecturers face in an online environment and gave their insights into how to enhance the motivational design of self-directed e-learning courses.

The biggest issue we identified in our study was related to the lack of establishing rapport among students. We observed that students believed that there was no community for them to connect with. Even though the lecturer introduced students to their peers in the online environment they could not trust other peers in class and that was why they did not get help from one another. In our study, the students preferred to opt for individual projects instead of a group project. However, studies such as Zimmerman and Schunk (2001) stated that students supported each other to become self-regulated. They mentioned that students monitor other peers' engagements and contributions and they developed strategies to approach the problems. They also recognised the changes they needed to apply to their strategies based on that comparison. Prior studies (e.g., Paris et al. 2001; Pressley 1995) stressed the significance of social learning among peers and teachers, even in an SRL environment. In our study, students could not socialise with other peers yet did not want to ask questions of other peers in the forum because they did not know each other and could not trust their knowledge.

Studies such as Patrick and Middleton (2002) suggested that teachers have the responsibility of facilitating co-regulated learning among students by creating opportunities for collaboration among peers. In our study, even though the lecturer made students work in groups so that they could start to collaborate since they did not know each other, they chose to work individually. McCaslin and Good (1996) discussed the effects of positive interactions in the classroom that could support students to engage cognitively, metacognitively, and motivationally in the tasks set by the lecturer. However, in our study, even though discussion and engagement were between the lecturer and the individual students, no connections were established among peers.

We believed that students' ideas about collaboration also affected how they chose to do their project. For example, regarding group projects, a student reported that "more eyes, more ears; we can do better" (interview data). But when students did not know one another, another reported that "you prefer to do it individually" (interview data). We also interviewed students that see collaboration as a complicated task. For example, one of the students mentioned, "I wanted to get a passing score. Other group members wanted to get a good score. We could not sacrifice our goals and change our strategies and purpose, which was a very complicated

situation for all of us" (interview data). Another student indicated that "I liked to talk to other peers about the project, but when it comes to actually do the project, I prefer to do it by myself" (interview data). In this case, the student used that as a metacognitive awareness but not actually doing the project together with other peers.

Regarding the discussions, one of the students pointed out, "in our course, the lecturer always leads the heated discussion topics in the review session, but the discussion [is] never heated between the students." (interview data). The aim was to observe the discussion among students, so the role of teachers and students could change. However, students were always listening to the discussions between the lecturer and other students. Thus, the construction of knowledge was still between the students and the lecturer whilst other peers were not much engaged in discussions. SRL in our study was a solitary action that was sometimes guided by the lecturer but was rarely promoted by peers.

While we talked about the benefit of using tools in the self-regulation process, we identified the places where provided tools did not help students in their learning processes. We identified the issues in the BL environment compared to the traditional way of teaching and the different strategies that students needed to adapt to this environment compared to the traditional classes. Our quantitative analysis showed that students in a BL environment needed to use different strategies. We understood some of the strategies were not helpful for students to get better scores. The most important change was differences in the community for students and their effect on their behaviour and learning. The pattern of changes in our study's motivational and strategy use constructs was different from traditional classes. Unlike what we expected, rapport was not established among students and they did not get help or learn from their peers. Students also believed that critical thinking was not needed for the course as they just had to listen to the videos and take part in the quizzes at the end of each video. They mostly used rehearsal, elaboration, organisation, and metacognitive strategies.

From this study, we understood that facilities provided by the lecturer promoted SRL by reading, note-taking, self-management, time management, help-seeking, visualisation for self-monitoring, progress monitoring, and feedback but had different effects for different students. We understood that the setting of class, the tools such as tournaments and throwing chocolates at students that the lecturer used in class worked well surprisingly towards the self-regulation learning by motivating students to participate more in the activities. In addition, the setting helped the students to apply a proper strategy for their learning and also enabled students to apply the appropriate changes to their strategies. We also found that students' experiences with

online tools helped them to reflect on their own learning experience and evaluate what tools help them when and under what conditions, so far as students became aware of their abilities. As such, students learned from their reflections what worked for them, they became more aware of their learning processes and were more confident to be able to independently perform the tasks, which were all very important for the self-regulation process.

We also understood the changes that the lecturer needed to apply in his teaching style or in the instructional design so that he could target the issues found in class. For example, the lecturer needed to make students familiar with other classmates through making smaller groups, familiarising them with the tools, and making the significance of each tool clear for students in their learning. A lecturer can also inform students about the most popular topics in the discussion, encourage students to participate in the discussion board, and try to make more group projects so that students start to get to know each other.

Using two sources of data, our study contributes to the practice by identifying the issues in BL environments. We understood the lecturers were responsible for proactively promoting SRL. Teachers first need to be aware of online teaching and learning issues so they can address issues in their instructional course design.

Even though this study contributed to both theory and practice, it is not without limitations. In the next section, we will give an overview of the limitations and will give the direction for future study.

5.5 Limitations and Future Study

We gave limitations of our study in each of the paper we included in the thesis. Here we summarise the limitations in Table 35 and what needs to be done in future to address the limitations.

Data type	Limitation	Future work
Quantitative	Sample size (419 students) from the same department and a single university) - limits generalisation	A larger sample from challenging courses from different departments needed
	Study design - webcast was a replacement for the classes	Give students more freedom by replicating the entire class with online tools and materials and then ask about their perceptions.
	Relying on students' self-reports about their motivation and strategy use	Use different data sources - for example, students actual tool use data (students participation data)

	Not considering the effect of other variables such as instructional design and teaching style	Rerun the study to investigate the effect of different class environments and different teaching methods. Also, do more research on how we can create a learning environment that could convert reluctant students into more focused students or keep students' initial motivation and cross-validate the results
	We became aware of the constructs that affect the final scores	We need to research how we can improve each of these identified constructs
	We identified various patterns of motivation and strategy use through cluster analysis which led to a similar achievement	It is important to understand at what level each construct triggers other constructs or if there is any triggering process?
	We identified three SRL profiles and we looked at how they unfold over time	We need to cross-validate the number of profiles and their unfolding process with new cohorts of students
	We looked at the effect of assignment and test results on the dynamics of SRL unfolding	We need to check the effect of other variables on students' motivation and strategy use and the profiles they adapt
	We used two techniques of regression and clustering analysis	Other techniques such as Structural Equational Modeling can be used to understand the relationship between motivation and strategy use and their effect on each other
Qualitative	Number of interviews - 42	We suggest that it would be appropriate to interview students from different departments to see what different students believe about the usefulness of tools
	Not considering the effect of teaching style and instructional design	Investigate how different teaching styles affect students' perceptions regarding tool use
	Used AT and identified contradictors in students' and lecturers' perceptions	We need to investigate a wider community such as the departments'

		and school's perceptions and identify the contradictors
	We proposed the framework by introducing a concept called active SRL	We need more studies to check the framework we proposed based on two theories of AT and SRL

Table 35: Limitations and Future Study

5.6 Conclusion

This thesis aimed to inform LA by investigating students' perception, motivation, and strategy use through the theoretical lens of AT and SRL, by providing five quantitative and three qualitative papers (Table 1). The results of the analysis contributed to both theory and practice. In this thesis, first, we investigated the dynamics of motivation and strategy use of the two groups of students (freshmen and upper-level) in BL environments, as lecturers do not have that much close contact with students in this environment compared to traditional settings. Therefore, it was essential to give insights to the course lecturers so that they help students. Through investigating student motivation and strategy use (constructs from theory), the study addressed the gaps in LA, including the lack of empirical studies based on learning theories and motivational studies (Ferguson and Clow 2017).

We understood the dynamics of the constructs are different for freshmen and upper-level students. Through correlation analysis, we identified the constructs which affect students' final scores for the two groups. We understood the similarities and differences among these two groups in terms of the constructs that had the highest correlation with the final score. By identifying the constructs, the lecturer could try to promote them in the class.

Through prediction analysis, we identified the constructs from each group that could help us predict students' final scores. Predicting students' final scores helps us identify at-risk students. This way, the lecturers can apply appropriate interventions to help those at-risk students. Identifying at-risk students addressed one of the main aims of LA.

Through cluster analysis, we were able to identify subgroups of students (SRL profiles). The lecturers would be aware of different groups of students to apply different interventions for each group to help them adopt a better profile. Identifying students different SRL profiles and looking at the students' SRL unfolding processes contribute to the literature in SRL. It also addressed the challenge that recent studies identified regarding having the cyclical nature of SRL (Järvelä et al. 2019). In our cases, both groups proved that SRL profiles were dynamic, but the movements among profiles were different. Also, looking at how students unfold their

SRL profiles helps the lecturer understand the nature of class development. The lecturer can understand the effect of his teaching method and the feedback he gave to the students through their assignments and exams. This information is very important for their instructional design. We also asked students about their perceptions regarding tool use in their classes. First, we used AT to understand how tools help students participate in activities and achieve their goals. We understood not all students benefit from introducing tools in their classes. We identified the changes that need to be applied to the teaching methodology and learning setting. We identified the contradictions regarding the use of tools in BL environments. The most important contradiction was the disconnection between individual and community levels through the AT lens, which led us to concentrate on the top triangle in AT and investigate how individuals used the tool to achieve their goals. We used SRL to understand how students use the tools to self-regulate their learning. Investigating students' perceptions regarding educational tool use in their classes through SRL enabled us to open the black box mentioned by Winne (1982). We understood how students used the tools in class, how tools helped or prevented them from learning, and the factors that affected tool use.

To conclude, we have to mention that our study through understanding students' perceptions and the interplay between motivation, strategy use, and final scores contributed to SRL and AT theory, LA, and teaching and learning practice. It gives tips to lecturers in engaging students and helping them achieve their learning outcomes in the courses irrespective of level or content. The importance of this research and our findings have been highlighted and will provide insights to the practitioners of the blended learning in the light of the COVID-19 pandemic. As envisaged in this thesis there are many avenues for research based on this initiative. We advocate for more research to explore the dynamics of students' motivation and strategy use, SRL profiles investigation, and how students unfold their SRL profile which would help us to understand their SRL profile. Also, future studies needed to look at how students use the tools and participate in activities in class and merge it with self-report data to see if they can predict the final score better. The combination of the two sources of data assists them to better understand the students SRL process. Finally, it is also important to understand students' perceptions regarding the usefulness of tools, how different tool use patterns could lead to different achievement, and the effect of students' different characteristics on tool use.

APPENDICES

APPENDICES

6 Appendices:

6.1 Appendix 1: Ethics Approval

Research Office
Post-Award Support Services

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UNIVERSITY OF AUCKLAND HUMAN PARTICIPANTS ETHICS COMMITTEE (UAHPEC)

14-Jun-2018

MEMORANDUM TO:

Assoc Prof Lesley Whitehead
Info Systems & Operations Mgmt

Re: Application for Ethics Approval (Our Ref. 021131): Approved

The Committee considered your application for ethics approval for your study entitled **A learning analytics approach using students' participation and motivation data to understand their impact on students' course outcome.**

We are pleased to inform you that ethics approval has been granted for a period of three years.

The expiry date for this approval is 14-Jun-2021.

If the project changes significantly, you are required to submit a new application to UAHPEC for further consideration.

If you have obtained funding other than from UniServices, send a copy of this approval letter to the Activations team in the Research Office at ro-awards@auckland.ac.nz. For UniServices contracts, send a copy of the approval letter to the Contract Manager, UniServices.

The Chair and the members of UAHPEC would be happy to discuss general matters relating to ethics approvals. If you wish to do so, please contact the UAHPEC Ethics Administrators at ro-ethics@auckland.ac.nz in the first instance.

Please quote Protocol number **021131** on all communication with the UAHPEC regarding this application.

(This is a computer generated letter. No signature required.)

UAHPEC Administrators
University of Auckland Human Participants Ethics Committee

6.2 Appendix 2: Students Information Sheet

THE UNIVERSITY OF AUCKLAND
NEW ZEALAND
Department of Information Systems and
Operations Management

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The University of Auckland
Private Bag 92019
Auckland, New Zealand

Information sheet for students
A learning analytics approach using students' participation and motivation data to understand their impact on students' course outcome

Researcher: Shadi Esnaashari
Researcher Introduction
I am Shadi Esnaashari, a PhD student in the School of Information Systems and Operations Management at University of Auckland, Auckland. To fulfil my PhD degree I would like to conduct the following research study.

Project Description and Invitation
In my research, I am exploring the interaction between teachers and students through an audience participation tool (i.e. Top Hat) and Learning Management System (i.e. Canvas) in order to identify how we can increase the engagement of students in the class through this tools and see whether or not increasing the student engagement relates to the students' course outcome. It is hoped that by conducting this research we can help both students and teachers in the process of learning. I would like to invite you to participate in this research study. There would be no criteria for choosing the students except students need internet enabled devices to participate in this study. We also do not exclude any students from this study unless otherwise stated by the students themselves. There is no payment for the participants in this study. There is no extra time requested from the participants (except for the volunteers to participate in the interview). Study participants will follow the lecturer taking part in the activities.

Project Procedures

I will use the data gathered through Top Hat and Canvas. This data are about your participation in the class, attendance, your scores, assignments and the data from survey questionnaire that you are going to participate for the purposes of this study. Top Hat is safe to use. The data are automatically collected and stored safely in the Top Hat data base. We also use pseudonyms when we are using the students' data. Thus, confidentiality, privacy,

and identity of the students will be maintained. We do not require that you do any extra activity.

Data Management

All the data regarding your participation rate will be gathered through Top Hat and stored securely in Amazon cloud servers. In my reports on this research, I will use pseudonyms to keep your identities and responses confidential. Any audio recordings made will be destroyed after the research is completed. Written materials such as field notes and transcripts will be kept in locked cabinets during conduct of the study and will be destroyed after 6 years. Any publication from this study will ensure that anonymity and confidentiality of participants are maintained.

We will use your data regarding your attendance, and scores to understand the relationship between student engagement in the class and course outcome. After the data are analysed a summary of the findings will be emailed to you. There would not be any conflicts of interest or risks arising from participation in this study. We will anonymize the data and use pseudonym in order to preserve your identity.

If you decide to participate in the interview, the recording will be kept at University of Auckland lock draws. You can ask to delete whatever section of your recording or you can decline to answer any question you dislike.

Participant Identification and Recruitment

Participation in this study is voluntary. To participate, you must have an internet enabled device like mobile phone, computer, iPad etc. If you do not agree to participate, you can contact me or you lecturer, in order for your lecturer to remove your data from this study before the end of data collection for any reason. Any publication from this study will ensure that anonymity and confidentiality of all participants are maintained.

You can choose to withdraw from the study anytime up to two weeks after the end of the data collection. If you do not agree to take part in my study, you do not need to sign the consent form. Even if you choose to use the tool you are not required to participate in the study. You can inform me and I will delete your data from my research study.

I would also like to interview some students to discuss their expectations and how satisfied they are with the tools used in the classroom. I may contact you for the interview through email. The interview is voluntary, and you are in no way obliged to give an interview; however, I can assure you that no questions of a personal nature will be asked. For the interview, the first twelve students who respond to our request will be interviewed. You are free to refuse if you do not wish to be interviewed. The interview will ask about your views in regard to using audience interaction tools (Top Hat) in classroom teaching and will take approximately 15 minutes. The interview will take place in the university premises anywhere that is more comfortable to you. The interview time would be anytime between 9:00 am and 5:00 pm again at your convenience. If you are stressed about any question, you can refuse to answer it. In case of any stress/ discomfort please let me know and I will stop the interview. Also please be aware that University of Auckland Counselling Centre has counselling services available for all students.

Participant's Rights

If you decide to participate, you have the right to:

- decline to answer any questions,
- withdraw from the study until two weeks after the end of data collection,
- ask any questions related to the study,
- be given access to the findings of the research when it comes to concluding.

If you are also willing to participate in the interview, you have the right to ask that the recorder be turned off or ask to delete some part of the interview. In the anonymous survey questionnaire you have the right to not answer any particular questions.

Project Contact

Please be informed that you can contact the researcher and/or supervisors if you have any questions about the project

Researcher's Name: Shadi Esnaashari (PhD student) Date:
Researcher's Email: S.Esnaashari@Auckland.ac.nz

Supervisors:

- Associate Professor Lesley Ann Gardner, department of Information Systems and Operations Management at the University of Auckland, Email: l.gardner@auckland.ac.nz

- Dr Michael Rehm, property department, University of Auckland,
Email: m.rehm@auckland.ac.nz

Committee Approval Statement

This project has been reviewed and approved by the University of Auckland Human Ethics Committee: Application __/__ (insert application number). If you have any concerns about the conduct of this research, please contact

6.3 Appendix 3: Lecturer Information Sheet

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The University of Auckland
Private Bag 92019
Auckland, New Zealand

Information sheet for staff members
A learning analytics approach using students' participation and motivation data to understand their impact on students' course outcome

Researcher: Shadi Esnaashari

Researcher Introduction

I am Shadi Esnaashari, a PhD student in the School of Information Systems and Operations Management at University of Auckland, Auckland. To fulfil my PhD degree I would like to conduct the following research study.

Project Description and Invitation

In my research, I am exploring the interaction between teachers and students through an audience participation tool (i.e. Top Hat) and Learning Management System (i.e. Canvas) in order to identify how we can increase the engagement of students in the class through this tool and see whether or not increasing the student engagement relates to the students' course outcome. It is hoped that by conducting this research we can help both students and teachers in the process of learning. I would like to invite you to participate in this research study. In order to participate in this study you need to use audience participation tool and Canvas in your classes. You also need to teach the whole length of the class. This tool will collect the information regarding student participation in the activities in the class whenever you ask question(s). If you agree to participate in this study, then I will ask you to upload the information sheet on the course website. I will come to visit the class and distribute the information sheet to students and tell them about the tool that the lecturer is going to use in the class. I will also tell them that all their data will be anonymised and this study will look at overall student performances. For further information, I will distribute the information sheets in the class. I will give the student the consent form so that students can sign it if they are willing to participate in the study. Next, at the end of the semester I need to interview six students and you as a lecturer of the class. However, only those students who have an internet enabled devices can participate in this study. I will ask about overall experience in using the tool. Therefore, I will come to the class again and ask for participation of students and if they agree to participate, I will give them a consent form to sign. Then, I will conduct a 15 minute interview with the students and 30 minutes interview with you to gain some understanding on how students felt with the use of real-time audience interaction tools in classrooms.

The students can choose to withdraw from the study anytime until the end of the data collection phases. If the students do not agree to take part in my study, they do not sign the consent form. Even if the student chooses to use the tool he/she is not yet required to participate in the study. Therefore, he/she can inform me and I will delete their data from my study.
I am not requesting any changes to your teaching pedagogy. I only request you to use Top Hat and Canvas alongside your teaching. There would be no criteria for selecting the students. We also do not exclude any students from this study unless otherwise stated by the students themselves. There is no payment for the participants in this study. There is no extra time requested from the participants. Study participants will follow the lecturer taking part in the activities.

Project Procedures

I will use the data gathered through Top Hat and Canvas. This data are about students' participation in the class, attendance, their scores, assignments, and the data from survey questionnaire that students are going to participate at the end of their class for the purposes of this study. Top Hat is safe to use. The data are stored safely in the Top Hat data base. We also use pseudonyms when we are using the students' data. Thus, confidentiality, privacy, and identity of the students will be maintained. At the end of the course I will request you for the final score for students who have given their consent. I will prepare the list of students who gave their consents but I also request you to provide new codes for students to maintain anonymity of students. I also request you to give students an assignment based on the subject thought at the end of each 6 weeks of your teaching. This will not be marked and included in the final grades, rather will help me to understand how the student has progressed.

Data Management

All the data regarding your students' participation rate will be gathered through Top Hat and stored securely in Top Hat servers. In my reports on this research, I will use pseudonyms to keep students' identities and responses confidential. Audio recordings will be destroyed after six years. Written materials such as field notes and transcripts will be kept in locked cabinets during conduct of the study and will be destroyed after six years. Any publication from this study will ensure that anonymity and confidentiality of participants are maintained.
We will use the data regarding your students' attendance, and scores to understand the relationship between student engagement in the class and course outcome. After the data are analysed a summary of the findings will be emailed to you and your students who have participated in this study. There would not be any conflicts of interest or risks arising from participation in this study. We will anonymize the data and use pseudonym in order to preserve your identity.

If you decide to participate in the interview, the recording will be kept at University of Auckland lock drawers. You can ask to delete any section of your recording or you can decline to answer any question(s) you dislike.

Participant Identification and Recruitment

Participation in this study is voluntary. Students must have an internet enabled device in order to participate in this study like mobile phone, computer, tablet, etc. Any publication from this study will ensure that anonymity and confidentiality of participants are maintained.

I would also like to interview you to discuss students' expectations and how satisfied they are with the current tools I used in the classroom. I will contact you for the interview through email, but you are free to refuse if you do not wish to be interviewed. The interview will take approximately 30 minutes. The interview will take place in the university premises anywhere that is more comfortable to you. The interview time would be anytime between 9:00 am and 5:00 pm again at your convenience.

I will request you for an interview in regard to usage of this tool (Top Hat and Canvas) in the classroom. Your participation is voluntary and you are no way obliged to give an interview; however, I assure you no questions of a personal nature will be asked. You can refuse to answer any questions.

Participant's Rights

If you decide to participate, you have the right to:

- decline to answer any questions,
- withdraw from the study until two weeks after the start of data collection,
- ask any questions related to the study,
- access to the findings of the research when it comes to concluding.

If you are also willing to participate in the interview, you have the right to ask that the recorder be turned off or ask to delete some part of the interview. In the anonymous survey questionnaire you have the right to not answer any particular questions.

Project Contact

Please be informed that you can contact the researcher and/or supervisors if you have any questions about the project

Researcher's Name: Shadi Esnaashari (PhD student) Date:
Researcher's Email: S.Esnaashari@Auckland.ac.nz

Supervisors:

- Associate Professor Lesley Ann Gardner, department of Information Systems and Operations Management at the University of Auckland, Email: l.gardner@auckland.ac.nz

- Dr Michael Rehm, property department, University of Auckland,
Email: m.rehm@auckland.ac.nz

Committee Approval Statement

This project has been reviewed and approved by the University of Auckland Human Ethics Committee: Application __/__ (insert application number). If you have any concerns about the conduct of this research, please contact

6.4 Appendix 4: Consent Form – Students

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Auckland, New Zealand

Consent Form for students

A learning analytics approach using students' participation and motivation data to understand their impact on students' course outcome

Name of student: ……..

I have read the information sheet regarding this research and have had an opportunity to ask any questions about the research and have them answered to my satisfaction. I also understand that I may ask further questions at any time.

I understand that:

- I agree to take part in this research.
- My participation in this study is voluntary.
- The information I share will be confidential.
- The information I give will be used to investigate the relationship between engagement of students in the class and their course outcomes.
- No one except the researcher and the supervisors team will have access to the data

I agree to participate in this study under the conditions set out in the Information Sheet.
I agree to take part in this research.

I wish to receive a summary of findings, which can be emailed to me at this email…….

I would like to have the opportunity to edit the interview transcripts and to receive a copy of their recordings within two months of the interview

Researcher: Shadi Esnaashari

PhD student
(Email: S.Esnaashari@auckland.ac.nz)

Signature of student: …… Date:…….

Name and Surname: ……

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NEW ZEALAND

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The University of Auckland
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Auckland, New Zealand

Consent Form for students

A learning analytics approach using students' participation and motivation data to understand their impact on students' course outcome

Name of person: ……..

I have read the information sheet regarding this research and have had an opportunity to ask any questions about the research and have them answered to my satisfaction.
I understand that:

- I agree to take part in this research.
- My participation in this study is voluntary.
- My information will be confidential.
- No one except the researcher (Shadi Esnaashari) and the supervisory team will have access to the data.
- Appropriate pseudonyms will be used to ensure confidentiality is maintained.
- The information I give will be used to investigate the relationship between engagement of students in the class and their course outcomes.
- I can ask for the recording to be turned off at any time of the interview.
- The recordings will be destroyed by the researcher after six years.

Researcher: Shadi Esnaashari
PhD student
(Email: S.Esnaashari@auckland.ac.nz)

I agree to take part in this research.

☐ I wish to receive a summary of findings, which can be emailed to me at this email…….

☐ I would like to have the opportunity to edit the interview transcripts and to receive a copy of their recordings within two months of the interview.

Signature of student……
Date……

6.5 Appendix 5: Consent Form – Lecturer

THE UNIVERSITY OF AUCKLAND
Te Whare Wānanga o Tāmaki Makaurau
NEW ZEALAND

BUSINESS SCHOOL
DEPARTMENT OF INFORMATION SYSTEMS AND OPERATIONS MANAGEMENT

Owen G. Glenn Building
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Telephone 64 9 923 6638
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Private Bag 92019
Auckland 1142
New Zealand

Staff Consent Form

A learning analytics approach using students' participation and motivation data to understand their impact on students' course outcome

Name of staff member: ……..

I have read the information sheet regarding this research and have had an opportunity to ask any questions about the research and have them answered to my satisfaction.

I understand that:

- I agree to take part in this research.
- My participation in this study is voluntary.
- My information will remain confidential.
- No one except the researcher (Shadi Esnaashari) and the supervisory team will have access to the data.
- Appropriate pseudonyms will be used to ensure confidentiality is maintained.
- The information I give will be used to investigate the relationship between engagement of students in class and their course outcomes.
- I can ask for the recording to be turned off at any time of the interview.
- The recordings will be destroyed by the researcher after six years.

Researcher: Shadi Esnaashari (PhD student)
(Email: S.Esnaashari@auckland.ac.nz)

I agree to take part in this research.

☐ I wish to receive a summary of findings, which can be emailed to me at this email…….

☐ I would like to have the opportunity to edit the interview transcripts and to receive a copy of the recording within two months of the interview.

Signature of staff member …… Date: ……

Project Contact
Please be informed that you can contact the researcher and/or supervisors if you have any questions about the project

Researcher's Name: Shadi Esnaashari (PhD student) Date:
Researcher's Email: S.Esnaashari@Auckland.ac.nz

Supervisors:

- Associate Professor Lesley Ann Gardner, department of Information Systems and Operations Management at the University of Auckland, Email: l.gardner@auckland.ac.nz

- Dr Michael Rehm, property department, University of Auckland, Email: m.rehm@auckland.ac.nz

Head of Department

- Professor Tava Olsen, department of Information Systems and Operations Management at the University of Auckland, Email: t.olsen@auckland.ac.nz

Committee Approval Statement
This project has been reviewed and approved by the University of Auckland Human Ethics Committee: Application __/__ (insert application number). If you have any concerns about the conduct of this research, please contact

6.6 Appendix 6: MSLQ Questionnaire

1. In a class like this, I prefer course material that really challenges me so I can learn new things.
2. If I study in inappropriate ways, then I will still be able to learn the main concepts in this course.
3. When I take a test, I think about how poorly I am doing compared with other students.
4. I think I will be able to use what I learn in this course in other courses.
5. I believe that I will receive an excellent grade in this class.
6. I'm certain I can understand the most difficult material presented in this course.
7. Getting a good grade in this class is the most satisfying thing for me right now.
8. When I take a test, I think about items on other parts of the test which I can't answer.
9. It is my own fault if I don't learn the material in this course.
10. It is important for me to learn the course material in this class.
11. The most important thing for me right now is my overall grade point average, therefore my main concern in this class is getting a good grade.
12. I'm confident l can learn the basic concepts taught in this course.
13. If I can, I want to get better grades in this class than most of the other students.
14. When I take tests, I think of the consequences of failing.
15. I'm confident I can understand the most complex material presented in this course.
16. In a class like this, I prefer course material that arouses my curiosity, even if it is difficult to learn.
17. I am very interested in the subject area of this course.
18. If I try hard enough, then I will understand the course material.
19. I have an uneasy, upset feeling when I take a test/exam.
20. I'm confident I can do an excellent job on the assignments and tests in this course.
21. I expect to do well in this course.
22. The most satisfying thing for me in this course is trying to understand the content as thoroughly as possible.
23. I think it is useful for me to learn the course material in this class.
24. When I have the opportunity in this class, I choose course assignments that I can learn from even if they don't guarantee a good grade.
25. If I don't understand the course material, it is because I didn't try hard enough.
26. I like the subject matter of this course.
27. Understanding the subject matter of this course is very important to me.
28. I feel my heart beating fast when I take a test/exam.
29. I'm certain I can master the skills being taught in this class.
30. I want to do well in this class because it is important to show my ability to my family, friends, employer, etc.
31. Considering the difficulty of this course, the lecturer and my skills, I think I will do well in this class.
32. When I revise for this course, I outline the material to help me organize my thoughts.
33. During class time I often miss important points because I'm thinking of or doing other things.
34. When studying for this course, I often try to explain the material to a classmate or friend.
35. I usually study in a place where I can concentrate on my course work.
36. When revising for this course, I make up questions to help focus my studying.

37. I often feel so lazy or bored when I study for this class that I quit before I finish what I planned to do.
38. I often find myself questioning things I hear or read in this course to decide if I find them convincing.
39. When I study for this class, I practice saying the material to myself over and over.
40. Even if I have trouble learning the material in this class, I try to do the work on my own, without help from anyone else.
41. When I become confused about something in this class, I go back and try to figure it out.
42. When I study for this course, I go through the course material and my notes and try to find the most important ideas.
43. I make good use of my study time for this course.
44. If course material is difficult to understand, I change the way I absorb the material.
45. I try to work with other students from this class to complete the course assignments.
46. When studying for this course, I read my notes and the course materials (e.g. PowerPoint slides) over and over again.
47. When a theory, interpretation or conclusion is presented in class, or in the course materials, I try to decide if there is good supporting evidence.
48. I work hard to do well in this class even if I don't like what we are doing.
49. I make simple charts, diagrams or tables to help me organize the course material.
50. When studying for this course, I often set aside time to discuss the course material with a group of students from the class.
51. I treat the course material as a starting point and try to develop my own ideas about it.
52. I find it hard to stick to a study schedule.
53. When I study for this class, I pull together information from different sources, such as lectures, readings and discussions.
54. Before I study new course material thoroughly, I often skim it to see how it is organized.
55. I ask myself questions to make sure I understand the material I have been studying in this class.
56. I try to change the way I study to fit the course structure and the lecturer's teaching style.
57. I often find that I have been studying for this class but still don't know what it was all about.
58. I ask the lecturer to clarify concepts I don't understand well.
59. I memorise key words to remind me of important concepts covered in the course.
60. When course work is difficult, I either give up or only study the easy parts.
61. I try to think through a topic and decide what I am supposed to learn from it rather than just reading it over when studying for this course.
62. I try to relate ideas in this subject to those in other courses whenever possible.
63. When I study for this course, I go over my notes and outline important concepts.
64. When studying for this class, I try to relate the course material to what I already know.
65. I have a regular place set aside for studying.
66. I try to play around with ideas of my own which are related to what I am learning in this course.
67. When I study for this course, I write brief summaries of the main ideas from the course materials and my notes.

68. When I can't understand the material in this course, I ask another student in this class for help.
69. I try to understand the material in this class by making connections between the readings and other written content (slides, etc) and the concepts orally presented in the lectures.
70. I make sure that I keep up with the course schedule and assignments for this course.
71. Whenever I read or hear an assertion or conclusion in this class, I think about possible alternatives.
72. I make lists of important items for this course and memorise the lists.
73. I attend this class regularly.
74. Even when course materials are dull and uninteresting, I manage to keep working until I finish.
75. I try to identify students in this class whom I can ask for help if necessary.
76. When studying for this course, I try to determine which concepts I don't understand well.
77. I often find that I don't spend very much time on this course because of my other activities.
78. When I study for this class, I set goals for myself to direct my activities in each study period.
79. If I get confused taking notes during lectures, I make sure I sort it out afterwards.
80. I rarely find time to review my notes or course materials before a test/exam.
81. I try to apply ideas from course readings in other class activities such as lectures, tutorials and discussions.

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