

DISSERTATION

INSIGHTS ON LEARNING BEHAVIORS IN UNSUPERVISED ONLINE QUIZZING: THE  
ROLE OF INSTRUCTORS IN INTERLINKING ANALYTICS AND PEDAGOGY

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## ABSTRACT

### INSIGHTS ON LEARNING BEHAVIORS IN UNSUPERVISED ONLINE QUIZZING: THE ROLE OF INSTRUCTORS IN INTERLINKING ANALYTICS AND PEDAGOGY

A major problem faced by instructors post-implementation of unsupervised online assessments is that they may lack real-time access to the students' actual learning behaviors. Limitations in student-feedback, limited know-how of accessing and analyzing log data, and large class sizes could restrict instructors' access to learners' behaviors. This study investigated how learning analytics (LA) can identify learners' actual behaviors within low-stake unsupervised online quizzing, the relationship between behaviors and performance in exams, and how the results can inform pedagogy. To achieve these goals, the present study used LA methods to analyze quiz-logs and qualitative interviews with instructors. Findings show that data-driven methods informed by learning theories can become a valuable tool in providing real-time insights into students' actual learning behaviors. Seven pedagogically meaningful variables related to learners' quiz-taking behaviors were designed and extracted from the quiz-logs. These variables provide evidence that if unsupervised, all students may not self-regulate their learning effectively to engage in productive learning behaviors and hence may need additional guidance from instructors. The instructors were actively involved in the study to interlink the implemented learning design and quiz-log analytics. We conclude that LA methods, when taken into account with instructors' input, may help plan timely pedagogic interventions such as providing the students meaningful and timely feedback, redesigning the existing quizzes, and educating students on the benefits of effective learning strategies.

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## DEDICATION

*To Amma & Achan*

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## DEFINITION OF TERMS

**Effective learning strategies:** Learning strategies which are known from prior research to be linked to superior learning and subsequent performance. Examples include study strategies like active retrieval of information via self-testing and distributed practice of information (Bjork et al., 2013).

**Feedback:** “Information with which a learner can confirm, add to, overwrite, tune, or restructure information in memory, whether that information is domain knowledge, metacognitive knowledge, beliefs about self and tasks, or cognitive tactics and strategies” (Winne & Butler, 1994, p. 5740).

**Formative feedback:** Information communicated to learners with an intent to modify their thinking or behavior with the purpose of improving their learning (Shute, 2008).

**Learning analytics (LA):** “The process of collecting and studying usage data in order to make instructional decisions that will support student success” (Becker, 2013, p. 63).

**LA methods:** Multidisciplinary techniques utilized in LA such as data processing, educational data mining, and visualization.

**Learning design:** The pedagogical intent and sequencing of an instructional technique (Lockyer, Heathcote, & Dawson, 2013).

**Long-term retention:** A sign of robust learning that involves the recall and use of knowledge after a relatively long period of time after instruction. Learning is retained for long periods of time, i.e., for days or even years.

**Low-stake quizzing:** Low-weightage evaluations, which do not heavily impact students’ final grades.

**Massed practice:** A learning strategy wherein study events are close together in time, not distributed into multiple study sessions. Massed practice often leads to better performance when tests are conducted immediately after the study sessions. However, the positive results may not hold good when long-term retention is measured by delayed tests (Karpicke & Roediger, 2007a).

**Pedagogical learning analytics interventions:** Use of LA which has a direct and immediate impact on teaching and learning processes (Wise, 2014).

**Productive learning behaviors:** Learner behaviors that are aligned with the pedagogic intent of the learning design of instructional activity. For example, if the learning activity intends to engage students in practicing an effective learning strategy such as spaced retrieval, evidence of distributed practice from learners' end is considered as a productive learning behavior. In the current study, learners' quiz-taking behaviors are collected, identified, and quantified from Canvas quiz-logs.

**Self-monitoring:** A form of self-observation where one cognitively tracks personal behavior (Zimmerman, 2002).

**Self-testing:** An effective learning strategy to improve memory by actively recalling study materials. Testing enhances learning and later retention when compared to additional study opportunities (Karpicke & Roediger, 2007b; Roediger & Karpicke, 2006b).

**Spaced practice:** An effective learning strategy wherein spacing the study events by distributing the study time into multiple sessions improves long-term retention.

**Unproductive learning behaviors:** Learner behaviors that deviate from the pedagogic intent of the learning design of instructional activity. For example, if the learning activity intends to engage students in practicing an effective learning strategy such as spaced retrieval, evidence of massed practice from learners' end is considered as an unproductive learning behavior.

**Unsupervised online quizzing:** Non-proctored, self-administered web-based quizzes in which the timing, location, and pacing of quiz-taking is the students' choice.

## CHAPTER 1: INTRODUCTION

### 1.1 BACKGROUND

There is robust evidence from cognitive psychology literature which confirms that learning strategies like active retrieval of information via self-testing and spaced retrieval are more effective in enhancing long-term retention when compared to rereading or massed practice of study materials (Carpenter, Pashler, & Cepeda, 2009; Carpenter, Pashler, Wixted, & Vul, 2008; Karpicke & Smith, 2012; McDaniel, Agarwal, Huelser, McDermott, & Roediger, 2011; McDaniel, Thomas, Agarwal, McDermott, & Roediger, 2013; McDaniel, Wildman, & Anderson, 2012; Pashler, Rohrer, Cepeda, & Carpenter, 2007; Roediger, Agarwal, McDaniel, & McDermott, 2011; Sobel, Cepeda, & Kapler, 2011). The Institute of Education Sciences (IES), U.S. Department of Education identifies that the above-mentioned effective learning strategies promote learning among all students, especially with struggling learners, irrespective of grade or subject. However, the majority of students may not practice effective learning strategies since they lack metacognitive awareness regarding the benefits of such strategies (Bjork, Dunlosky, & Kornell, 2013; Karpicke, Butler, & Roediger, 2009).

The metacognitive awareness among learners assumes importance especially in higher education where students have to take up an autonomous and active role in learning outside formal classroom settings (Bjork et al., 2013). Such settings refer to the unsupervised use of online testing and learning tools. Self-monitoring by learners plays an important role in determining successful learning experiences and achievement in self-directed environments where there is less guidance from instructors (Artino, 2008; Dabbagh & Kitsantas, 2004; Sánchez-Alonso & Vovides, 2007; Sun & Rueda, 2012). However, due to subjective differences

in levels of self-monitoring, students often monitor their learning inadequately (Butler & Winne, 1995). High-achieving students self-monitor and evaluate their learning better, while low achievers may misevaluate their performance and use of strategies (Butler & Winne, 1995; Hacker, Bol, Horgan, & Rakow, 2000; Lester, Mott, Robison, Rowe, & Shores, 2013; Zimmerman & Martinez-Pons, 1990). Hence, it is clear that the students who have poor metacognitive awareness may need additional support in the form of feedback from external sources (Garavalia & Ray, 2003; Hattie & Timperley, 2007; Roll, Wiese, Long, Alevan, & Koedinger, 2014). An external source can be computer-mediated feedback or the feedback provided by an instructor. When compared to computer-mediated feedback, instructors may be able to provide students with more meaningful feedback as they can efficiently interpret differences in learners' behaviors in varying learning contexts (Baker, 2016; Clow, 2012; Cui, Jin, & Wise, 2017; Gašević, Dawson, Rogers, & Gasevic, 2016; Koh, 2008; Macfadyen & Dawson, 2010; Scheuer & Zinn, 2007; Wise, 2014). Students highly value the interaction with instructors which encourages them to become self-aware of their learning behaviors in relation to their peers or their own prior activity (Lawton et al., 2012; Tanes, Arnold, King, & Remnet, 2011).

To encourage the use of effective learning strategies among students, instructors can design and implement formative assessments in classrooms and follow-up with meaningful personalized feedback. Most assessments in education are used only to test students' learning or assign grades. When assessments are used to gauge students' learning, only final performances are considered as learning outcomes and instructors usually provide feedback about the accuracy of the assigned task's outcome. The feedback that focuses only on task accuracy provides minimal guidance to the learners to monitor their learning (Butler & Winne, 1995). On the other

hand, formative assessments can act as a guide to improve the learning process as well as future instruction (Baleni, 2015; Black & Wiliam, 1998b, 1998a; Leahy, Lyon, Thompson, & Wiliam, 2005; McTighe & O'Connor, 2005). This is because formative assessments provide instructors with ongoing information about student learning, which allows instructors to follow-up with timely, meaningful feedback and/or pedagogic changes soon enough to impact practice (Black & Wiliam, 1998a; Lawton et al., 2012; Leahy et al., 2005; McTighe & O'Connor, 2005; Tanes et al., 2011).

When formative assessments are implemented with the aid of technology-enhanced learning platforms like a learning management system (LMS), instructors have the opportunity to implement learning designs that can encourage the use of effective learning strategies such as regular and repeated practice via active and spaced retrieval of information (Angus & Watson, 2009; Coates, James, & Baldwin, 2005; Doige, 2012; O'Sullivan & Hargaden, 2014).

Additionally, technology-enhanced learning platforms offer several advantages such as an active role for students in regulating their learning and increased opportunities to track students' actual learning behaviors (as substitutes of their self-reports) to identify patterns related to successful and less successful learning behaviors (Angus & Watson, 2009; Dawson, McWilliam, & Tan, 2008; O'Sullivan & Hargaden, 2014; Pardo, Jovanovic, Dawson, Gašević, & Mirriahi, 2019). In this case, instructors are able to provide timely formative feedback since they have real-time access to students' actual learning behaviors (Aljohani et al., 2019; Shum & Crick, 2012).

Real-time access to actual learning behaviors is facilitated through the analysis of large logs of data accumulated from student activities in technology-enhanced learning platforms. The data reporting options of the built-in dashboards of these platforms are typically limited to simple metrics of student interaction such as first and last login, the history of resources visited, the

number of messages the student has read and posted in discussions, number of downloads of study materials and marks achieved in assignments (Mazza & Dimitrova, 2007). Analysis of unexplored log data could aid in validating learning designs with a specific purpose; i.e., in understanding whether learners' behaviors are productive and in accordance with the pedagogical intent of the design. However, relying solely upon data-driven techniques to extract useful patterns and information from large-scale educational datasets must be dealt with caution (Choi et al., 2016; Rogers, Gašević, & Dawson, 2016; Wise, 2014; Wise & Shaffer, 2015). It is important that theories of learning guide the data-driven research. The variables considered in a study need not necessarily be pedagogically meaningful unless sufficiently informed by theories of learning. When the selection of variables is guided by theory, educators could get hints regarding the underlying causes of unproductive engagement, such as limitations in the learning design, in addition to the identification of students who have less than optimal engagement (Rogers et al., 2016). Thus, a theoretical basis for the selection of the independent variables involved in the study leads to the possibility of planning specific pedagogical interventions that can target shortfalls in teaching, learning, or the learning design (Rogers et al., 2016).

## **1.2 CONTEXT OF THE STUDY**

The instructors of the undergraduate microbiology class - Microbiology, Immunology and Pathology (MIP henceforth) at the Department of Microbiology, Immunology & Pathology, Colorado State University (CSU) had set up online quizzing as a form of formative assessment on Canvas (the LMS at CSU), which were designed based on the findings from educational research such as the benefits of active retrieval and spaced retrieval. The voluntary low-stake online quizzes were to be attempted by the students unsupervised at their own pace and convenience (i.e., the timing and location of

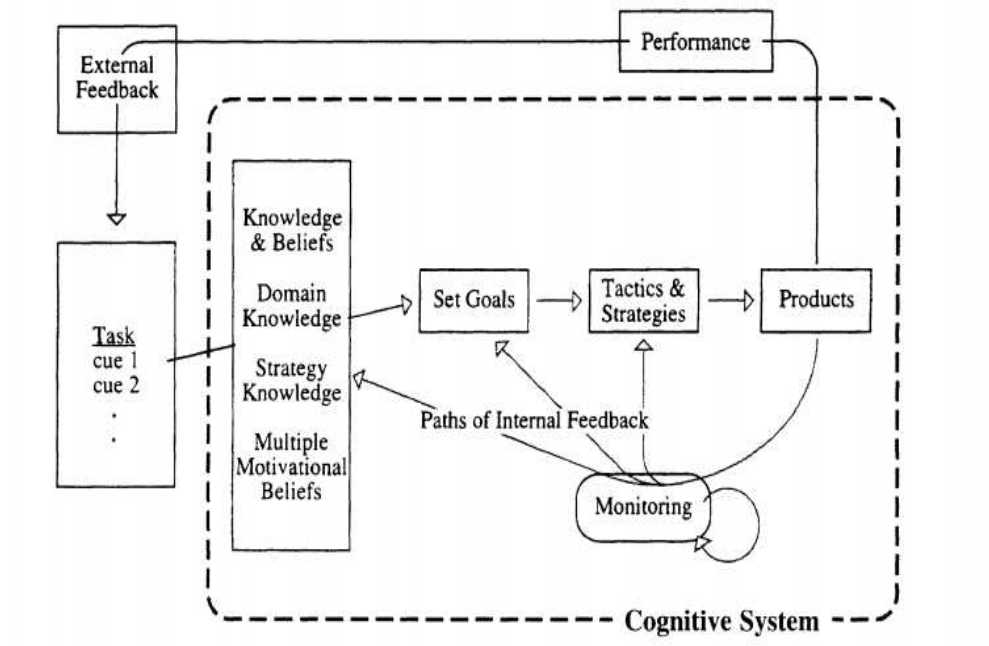
quiz taking was the students' choice). Students could attempt the quizzes multiple times as the intention was to promote learning and mastery among students rather than test their current knowledge. The highest grade among all the attempts was recorded.

The non-proctored, self-administered nature of the quizzes and limited data reporting options of Canvas presented two problems to the instructors. First, the self-regulated quiz-taking behaviors of the students with the low-stake unsupervised online quizzes (referred to as quiz-taking behaviors henceforward) were not readily available to the instructors. Hence, the instructors were not aware of whether students' actual behaviors were in accordance with the pedagogical intent of the implemented design. For example, did students attempt the quizzes just in time before the deadlines only to secure credit? Did students distribute the multiple possible attempts over the period in which the quizzes remained open or did they mass all attempts together? Second, the instructors were unable to provide the students with meaningful and timely external feedback regarding quiz-taking behaviors. Instead, they were able to provide the students with only summative feedback (comparison of an individual's scores with the class averages on exams or comparison to student's own scores in the earlier quizzes).

### **1.3 THEORETICAL FRAMEWORK**

Butler and Winne's model (1995) of self-regulated learning, shown in Figure 1.1 was the theoretical framework chosen for this research. When learners engage in learning tasks, they utilize their prior knowledge and beliefs to develop an interpretation of the requirements of the tasks. Based on these interpretations they set goals and apply tactics and strategies which generate cognitive, emotional, and behavioral products. According to the model, learners' monitoring is a pivotal process in self-regulated learning. Learners could monitor the process of

their engagement themselves. This constitutes the internal feedback, which could aid in modifying one's engagement by re-examining the current tactics and strategies employed and selecting more productive methods. However, students often monitor their engagement with tasks inaccurately and with overconfidence. Under these circumstances, external feedback offered by an instructor could aid in learner's reinterpretations of the task and implementation of strategies. To serve this purpose, the external feedback provided should not be limited to the correctness of the task's outcome and has to guide students in altering their existing knowledge and beliefs. Such formative feedback can mediate subsequent self-regulation among learners and can steer them to engage in more productive learning behaviors.



**Figure 1.1**

*Model of Self-Regulated Learning (Source: Butler & Winne, 1995)*

A primary focus of the current study was to identify learner behaviors with the low-stake unsupervised online quizzing. The study investigated how quiz-log data analytics might help instructors in obtaining hints regarding actual learner behaviors with the quizzes. We

hypothesized that information related to students' quiz-taking behaviors might help instructors in providing formative external feedback to students. Formative feedback from instructors might, in turn, encourage learners to metacognitively monitor their learning behaviors and alter unproductive behaviors (Roll & Winne, 2015).

#### **1.4 STATEMENT OF PROBLEM**

Instructors design and implement unsupervised formative assessments with clear pedagogic intent on technology-enhanced learning platforms to promote students' learning. However, the problem is that post-implementation of unsupervised online assessments, instructors may lack real-time access to information regarding the students' actual behaviors owing to the limitations in data reporting options of such learning platforms. As a result, instructors fail to understand whether learners' behaviors are indeed aligned with the intent of the implemented learning design. Consequently, despite the pedagogical intent of the learning design, instructors are unable to provide the students with timely formative feedback that can act as effective external regulation to improve learning.

#### **1.5 PURPOSE OF THE STUDY**

The purpose of this study was to investigate the pedagogic intent of the MIP instructors in implementing low-stake unsupervised online quizzing in their course and the difficulties they faced in discerning students' quiz-taking behaviors. In addition, this work attempted to explore the actual quiz-taking behaviors of students by parsing the quiz-logs to identify traces of data that could be considered as evidence of productive quiz-taking behaviors. The work attempted to identify common patterns of quiz-taking behaviors among students and the relationship between the behaviors and performance on exams. The findings were shared with the instructors to

understand their views on the usefulness and implications of the results in informing future pedagogical practice.

## **1.6 RESEARCH QUESTIONS**

To meet the purpose of the study the following six research questions were developed.

**Research Question (RQ) 1a:** *What was the pedagogic intent of the MIP instructors in implementing the low-stake unsupervised online quizzes in their classes?*

**RQ 1b:** *What difficulties did the instructors face post-implementation of the quizzes?*

**RQ 2a:** *Are there associations between the variables related to quiz-taking behaviors and the subsequent exam scores?*

**RQ 2b:** *Are there associations between the variables related to quiz-taking behaviors and the final exam scores?*

**RQ 3:** *What common patterns of quiz-taking behaviors can be identified among students in the MIP course?*

**RQ 4a:** *Are there differences between the groups of students, identified based on their quiz-taking behaviors, in regard to the subsequent exam scores?*

**RQ 4b:** *Are there differences between the groups of students, identified based on their quiz-taking behaviors, in regard to the final exam scores?*

**RQ 5:** *According to the instructors of MIP, what is the perceived usefulness and implications of the results of the quiz-log analytics for future pedagogic considerations?*

## **1.7 SIGNIFICANCE OF THE STUDY**

This study was significant for several reasons pertaining to learning and teaching. First, the study explored the actual learning strategies employed by students as they engage with low-stake unsupervised online quizzes and made use of learning analytics (LA) methods to classify

them based on their choice of quiz-taking strategies. The results of quiz-log data analytics were presented to the instructors of the course aiming to improve self-reflection among students who show less metacognitive awareness of their learning. Meaningful feedback from instructors could encourage more effective use of online quizzes among the students so that the quizzes serve as beneficial learning tools, which encourage self-testing and spaced retrieval of information.

Second, many of the existing methods to profile students rely on static variables such as demographics and prior academic records and/or simple metrics related to student engagement level like login frequency, the frequency of course materials accessed, number of discussions posted, and number of downloads of course materials. Static variables cannot be manipulated to implement specific interventions targeting learning and teaching strategies. Simple metrics that track student engagement lack the power to contribute to the understanding of student learning (Lodge & Lewis, 2012). Also, the portability of the results to a different context may not be possible (Wise & Shaffer, 2015). In contrast, the variables considered in this study, which are related to students' quiz-taking behaviors, were malleable, pedagogically meaningful, and closely connected to learning theories and hence addressed the above-mentioned limitations.

Overall, this work offers a possibility to think about the design of pedagogical learning analytics interventions that can improve learning strategies, which students employ within an unsupervised online quizzing platform, thereby moving beyond making mere predictions of exam scores. The focus of the current study was on improving the quality of learning of all students. The approach undertaken in this work may eventually help in making the transition to a learner-centric approach (where the use of study strategies, involvement level, and performance of each student with the unsupervised online quizzing platform is tracked and followed up with

meaningful personalized feedback) from a variable-centric approach (i.e., comparison of class averages on performance).

## **1.8 ASSUMPTIONS**

In the current study, exam scores - midterm examination scores, which immediately followed the low-stake online quizzes and the final comprehensive examination scores - were assumed to be a measure of student learning and used as a proxy measure of learning.

## **1.9 DELIMITATIONS**

The data collection and analyses of this study had to be delimited to the Fall 2019 MIP class for a few reasons. First, the data collection for this study demanded the implementation of a learning design that encouraged the use of effective learning strategies such as active and spaced retrieval among students. The MIP class of Fall 2019 had the desired learning design, quizzes designed and implemented with a pedagogic intent, in place. Second, the collection and extraction of variables related to learners' behaviors from the quiz-logs demanded complex manipulation of hierarchical data (explained in sections 3.5.1 and 3.5.3). The scope of the present study was aptly delimited to a single semester and course so that the study did not exceed the researcher's capacity to deal with the complexities of data collection and analyses.

## **1.10 LIMITATIONS**

In the current study, the data collection occurred in an existing online quizzing platform within Canvas LMS, which was not designed to log variables of interest related to the learning strategies considered in this study (e.g., active retrieval, and spaced practice). Hence, only variables that were logged by Canvas or variables that could be derived by modifying the already logged variables could be considered in this study. This limited the possibility of the design and collection of variables related to the students' learning behaviors.

## CHAPTER 2: LITERATURE REVIEW

The review of the literature is organized into two sections. The first section (2.1–2.7) explores study strategies, which are known to be effective in improving learning and the significance of metacognitive awareness of learners to engage in such strategies while they learn on their own. In addition, this section reviews the role of instructors in encouraging learners' metacognitive awareness. The literature review conducted indicates that instructors can design and implement formative assessments that can encourage productive learning behaviors and provide formative feedback to alter unproductive behaviors. When instructors implement assessments with the aid of technology-enhanced learning platforms, they can obtain ongoing access to the actual behaviors of learners. This would allow intervening at the appropriate time to alter ineffective learning strategies. However, despite the advantages of technology-enhanced learning platforms, pedagogic implementations that can take advantage of the full functionalities of these platforms remain limited. Also, the log data which can be analyzed to understand learners' behavior patterns are often unexplored.

In the second section (2.8–2.11), a review of the importance of the role of learning theories as a guiding framework for data-driven LA approaches are conducted. Meaningful learning behaviors of students which can be extracted from the log data and empirical evidence centered around the relationship between these behaviors and academic achievement are explored. A few existing approaches which attempt to profile students based on behavioral data and limitations of these methods are identified.

## **2.1 EFFECTIVE LEARNING STRATEGIES**

Learning strategies that students adopt in an attempt to master a topic range a wide spectrum such as rereading the study materials, copying notes, underlining or highlighting important topics, creating outlines and diagrams to summarize important ideas, self-testing, studying topics early on or at the last minute before an exam (Dunlosky & Metcalfe, 2008; Kornell & Bjork, 2007). Research confirms that some learning strategies are superior when compared to others in enhancing long-term learning (Broadbent & Poon, 2015). Two such superior strategies, namely self-testing and spaced retrieval of information that are known to have a significant effect on learning are discussed in detail below.

### **2.1.1 *SELF-TESTING***

Self-testing, which aids in the active retrieval of information, is an important study strategy that improves students' learning (Roediger & Karpicke, 2006a). Testing must not be perceived as an approach just to assess learning by measuring the contents of memory. Self-testing helps students to identify gaps in their knowledge, have an accurate assessment of learning, and not to be overconfident in their judgments of learning (Metcalfe & Finn, 2008; Roediger, Putnam, & Smith, 2011; Shaughnessy & Zechmeister, 1992; Son & Kornell, 2008).

Several studies, conducted in the laboratory as well as in classroom settings, have found that active retrieval of information via regular testing enhances learning and long-term retention (Brame & Biel, 2015; Kleitman & Costa, 2014; McDaniel et al., 2011, 2013; F. Rodriguez et al., 2018; Roediger, Agarwal, et al., 2011; Soderstrom & Bjork, 2014). Decades of experiments conducted in cognitive psychology laboratories prove that tests as learning events enhance long-term retention in comparison to additional study opportunities (i.e., restudying the material for an equivalent amount of time) (Carrier & Pashler, 1992; Jacoby, Wahlheim, & Coane, 2010;

Roediger, Agarwal, et al., 2011; Roediger & Butler, 2011; Roediger & Karpicke, 2006a, 2006b; Storm, Friedman, Murayama, & Bjork, 2014). For example, Karpicke and Roediger (2008) found that two groups of students, one which engaged in self-testing and the other in restudying, performed equally well immediately after a study session. However, on delayed testing after a week, the students who tested themselves outperformed the group which restudied the material. Students who tested themselves recalled around 80% of information while the students who restudied recalled 33% - 36%.

The robust effects of testing on long-term retention in comparison to rereading has been replicated in classrooms as well. For example, quizzing of classroom material had a positive effect on the following exams when compared to additional opportunities to read the material or not being tested at all (Roediger, Agarwal, et al., 2011). For exams which immediately followed the quizzes, a 3 (tested, read, non-tested) x 3 (chapters) ANOVA showed a main effect for testing ( $F(2, 124) = 33.82, h_p^2 = .35$ ). Pairwise comparisons confirmed a significant benefit for testing compared to non-testing,  $t(62) = 7.60, d = .98$ , as well as a significant benefit for testing relative to the items which were reread,  $t(62) = 6.61, d = .83$ .

A few other benefits of testing include allowing students to identify gaps in knowledge thereby, encouraging them to learn better in the following study episodes, better organization of knowledge, transfer of knowledge to new contexts, improved metacognitive monitoring, and providing feedback to instructors about students' learning (Roediger, Putnam, et al., 2011). It is recommended that tests are conducted as no-stakes or low-stakes so that students experience less anxiety and readily seek help from instructors (Brame & Biel, 2015).

### **2.1.2 SPACED RETRIEVAL**

Studies suggest that the benefits of testing are greater when tests are distributed over time (Bahrick, Bahrick, Bahrick, & Bahrick, 1993; Carpenter & DeLosh, 2005; Dempster, 1996; Glenberg, 1979; Kang, 2016; Karpicke & Roediger, 2007a; Khajah, Lindsey, & Mozer, 2014; Pashler & Zarow, 2003). The superiority of distributed practice over massed practice, known as ‘spacing effect,’ in enhancing long-term retention was demonstrated by a meta-analysis performed on 839 assessments (317 experiments and 184 articles) of distributed practice (Cepeda, Pashler, Vul, Rohrer, & Wixted, 2006). This study showed that spaced practice improved the final test performance considerably.

Robust effects of spaced retrieval have been demonstrated in classrooms (Kapler, Weston, & Wiseheart, 2015; Miyamoto et al., 2015; Schutte et al., 2015). For example, a recent study found that the students who distributed their practice in a mathematics classroom outperformed the students who massed their practice, as evident from their performance in tests administered at the end of week one and six (Nazari & Ebersbach, 2019). A similar finding was reported by McDaniel and colleagues (2011). When classroom quizzes were spaced, they found robust effects of spacing, resulting in 13% to 25% gains in students’ performance on unit exams.

From the above discussion, it is clear that effective learning strategies - self-testing and spaced retrieval - have significant effects in improving student learning. However, it is important to point out that students may not use effective learning strategies during unsupervised self-study sessions unless they possess strong metacognitive awareness of the benefits of such strategies (Brown, Roediger, & McDaniel, 2014).

## **2.2 STUDENTS' METACOGNITIVE AWARENESS OF EFFECTIVE LEARNING STRATEGIES**

Metacognitive awareness can be defined as the ability to reflect upon, understand, and control one's learning (Schraw & Dennison, 1994). Strong metacognitive skills help learners monitor and evaluate their learning process via self-reflection and hence is of great value in supporting students' learning and improving achievement (Connell, Carta, & Baer, 1993; Dalton, Martella, & Marchand-Martella, 1999; Jones, Farquhar, & Surry, 1995; McAlpine & Weston, 2000; Vovides, Mitropoulou, & Nickmans, 2007). Learners who self-reflect on the strengths and weaknesses of their learning strategies make constructive and timely decisions to alter their unproductive learning behaviors (Bransford, Brown, & Cocking, 2000; Roll & Winne, 2015). However, self-reflection demands strong metacognitive awareness from learners' end (Sánchez-Alonso & Vovides, 2007; Vovides et al., 2007). Not all students may possess metacognitive awareness regarding the benefits of effective learning strategies. Generally, high achievers engage in more effective learning strategies such as self-testing, spacing, and an early start of study sessions when compared to low achievers (Hartwig & Dunlosky, 2012; Q. Nguyen, Huptych, & Rienties, 2018). Learners who lack metacognitive skills may struggle to self-evaluate and regulate their learning process especially when there is less direct instructional support (Artino, 2008; Lehmann, Hähnlein, & Ifenthaler, 2014).

Lack of metacognitive awareness of effective learning strategies among learners could be mainly because of two main reasons. First, despite the evidence on the positive impact effective learning strategies have on learning, learners are often not educated about the benefits of these strategies (Bjork et al., 2013). Second, effective learning strategies are counterintuitive and could look seemingly unproductive. The use of such strategies initially produces a high number of

errors turning students less confident. On the contrary, ineffective learning strategies often look more productive to students since the use of these strategies creates a metacognitive illusion of fluency. This can be confused by students as signs of mastery over the study topics (Bjork et al., 2013). Many students hold a wrong perception and believe that lesser productive strategies are in fact effective (Bjork et al., 2013). Survey results among students which show that most students believe that rereading is a more effective learning strategy than self-testing or retrieval practice are illustrative of this fact. Similarly, students believe that massed practice is more beneficial than distributing practice time into different sessions (Hartwig & Dunlosky, 2012; Karpicke et al., 2009; Kornell & Bjork, 2007; McCabe, 2011). Experimental studies conducted in the laboratory are also consistent with the survey results (Karpicke, 2009; Kornell & Son, 2009).

It is important to note that learners' metacognitive skills are not static traits. Such skills can be improved by pedagogical interventions wherein the students are trained to consciously implement metacognitive strategies (Bielaczyc, Pirolli, & Brown, 1995; De Corte, Verschaffel, & Op't Eynde, 2000; Kruger & Dunning, 1999; Perels, Gürtler, & Schmitz, 2005; Schunk, 2005; Schunk & Zimmerman, 1998). For example, external feedback from an outside source such as computer-mediated feedback or feedback from an instructor could be effective in enhancing students' metacognitive awareness (Azevedo, Greene, & Moos, 2007; Witherspoon, Azevedo, Greene, Moos, & Baker, 2007).

### **2.3 ROLE OF INSTRUCTORS IN ENCOURAGING PRODUCTIVE LEARNING BEHAVIORS**

Studies show that external regulation facilitated via computer-mediated feedback or an instructor can be as effective as self-monitoring (Agina, 2012; Okita & Schwartz, 2013). For example, an experimental study which had three groups of students (where one group self-

monitored their progress, a second group had an external monitor and the third had no monitoring) showed that the groups which had self and external monitoring reported higher self-efficacy, skills, and persistence compared to the control group (Schunk, 1982). However, concerns about relying solely on computer-mediated feedback exist in the literature (Baker, 2016; Gašević et al., 2016; Macfadyen & Dawson, 2010; Scheuer & Zinn, 2007). Instructors, who are closest to the learning activity after the students, bring in valuable human insight in interpreting the differences in learners' behaviors in varying contexts and provide meaningful feedback (Clow, 2012).

Instructors can play a two-pronged role in encouraging productive learning behaviors among students. First, they can provide meaningful feedback to support metacognitive awareness among learners which can, in turn, encourage the learners to engage in productive learning behaviors/alter unproductive ones (Black & Wiliam, 2009; Govaerts, Verbert, Duval, & Pardo, 2012). Second, they can encourage productive learning behaviors through mindful design and implementation of formative assessments (Knight & Sydney, 2018; Wise & Shaffer, 2015). The two concepts of timely formative feedback and design of formative assessments are discussed below in detail.

### ***2.3.1 FORMATIVE AND TIMELY FEEDBACK***

Several studies point out the pedagogical benefits of feedback from instructors (Cavanaugh, Gillan, Bosnick, Hess, & Scott, 2005; Clow, 2012; Dickson, 2005; Koh, 2008; Liu & Cavanaugh, 2011; Paschal, 2002; Van Horne et al., 2018). Feedback provided by the instructors can improve self-reflection and metacognitive monitoring of students by motivating them to take up an active role in regulating their learning (Chung, Shel, & Kaiser, 2006; Crisp & Ward, 2008; Hattie & Timperley, 2007; Pachler, Daly, Mor, & Mellar, 2010; T. Wang, Wang, &

Huang, 2008; Zimmerman, Moylan, Hudesman, White, & Flugman, 2011). Students, in fact, monitor their learning better and make constructive changes in their learning behaviors when instructors provide feedback to assist them in the process (Arnold, 2010; Black & Wiliam, 2009; Timperley & Parr, 2009). For example, when students received feedback from the instructors, they started planning in advance. Students posting questions regarding the assignments well before the due dates were indicative of a decrease in the otherwise usual last-minute activity (Arnold & Pistilli, 2012; Tanes et al., 2011).

Although feedback plays an important role in improving learning, all types of feedback may not have the same effect on learning (Gordijn & Nijhof, 2002; Owen & Dudley, 2007; Tanes et al., 2011). The type of feedback and the time at which it is provided by instructors are two significant factors that impact students' achievement. Feedback provided to learners could be motivational or formative. Motivational feedback provides learners with positive or negative reinforcement based on the completion and correctness of an assigned task or can focus on learners' innate qualities such as ability or intelligence. On the other hand, the idea of formative feedback is to focus more on the processes of learning, such as effort and strategic behavior, in addition to the learning outcomes (Hattie & Timperley, 2007). Formative feedback is elaborate, meaningful, and provides students with corrective and instructional advice to monitor and optimize their learning behaviors (Black & Wiliam, 1998b; Sadler, 1989). Meaningful learner-centric feedback encourages the development of self-assessment and reflection among learners (Nicol & Macfarlane-Dick, 2006). Formative feedback, when compared to motivational feedback, is associated more with success and is recognized as one of the most important interventions contributing to students' achievement (Tanes et al., 2011).

Learners value the timeliness of feedback provided. This implies that to be effective the feedback has to be provided when the learning activity is ongoing rather than after completion of the task. (Gaytan & McEwen, 2007; Wolsey, 2008). To provide formative feedback at the appropriate time, instructors need to understand learners' actual behaviors when the learning process is ongoing (Jayaprakash, Moody, Lauria, Regan, & Baron, 2014). However, even when instructors implement learning designs with a pedagogical intent, the information related to learners' interaction with the design may not be accessible to instructors. Hence post-implementation of the learning designs, instructors can be challenged to provide timely feedback to students (Lockyer et al., 2013).

### ***2.3.2 DESIGN OF FORMATIVE ASSESSMENTS TO ENCOURAGE PRODUCTIVE LEARNING BEHAVIORS***

To a large extent, learners' behaviors could be dependent on the instructional design and pedagogy adopted by instructors (Garrison & Cleveland-Innes, 2005; Trigwell, Prosser, & Waterhouse, 1999). When instructors design a classroom pedagogy that focuses only on performance, assessed by final outcomes in midterms and final exams it may encourage massed practice among students. On the contrary, instructors can design and implement formative assessments, spanning throughout the academic term, which focus on the learning process in addition to the final performance. Such assessments that provide meaningful feedback could encourage regular practice and learning gains among students (Black & Wiliam, 1998a; Gibbs & Simpson, 2005; Roediger & Karpicke, 2006a). For example, a study conducted by Lawton and colleagues (2012) found that learning outcomes are dependent on the design of the course. They conducted a randomized experiment where the treatment group could have multiple attempts for the assessments and additionally received formative feedback in the form of an explanation of

correct and incorrect responses. The control group had no intervention from the instructors and had only one final summative assessment. The mean on the pretest for the treatment group was 64% correct ( $M = 21.01$ ,  $SD = 4.47$ ) and the posttest, 82% correct ( $M = 65.52$ ,  $SD = 6.66$ ). The mean on the pretest for the control group was 69% correct ( $M = 22.80$ ,  $SD = 2.94$ ) and the posttest, 78% correct ( $M = 62.48$ ,  $SD = 7.28$ ). Multiple linear regression indicated that the treatment group outperformed the control group by an estimated mean of 5.50 points on posttest,  $b = 5.5$ ,  $SE = .83$ ,  $t(38) = 3.31$ ,  $p < .01$ .

Instructors have successfully implemented formative assessments in various disciplines to encourage regular practice among students (Conole & Fill, 2005; Doige, 2012; Horn & Hernick, 2015; O'Sullivan & Hargaden, 2014; Orsmond, Merry, & Reiling, 2005). However, a well-developed design does not guarantee the productive behaviors of students (Wise, 2014). In many cases, students remain unaware of the intent behind the implemented learning designs, what constitutes productive patterns of engagement and how the process might improve their performance in summative examinations (Wise, 2014; Wise, Vytasek, Hausknecht, & Zhao, 2016). Koh (2008) suggests that an instructor has an important role in altering students' perceptions about assessments. If instructors invest time in explaining the pedagogic intent behind formative assessments, it could have positive effects on learners' attitudes and allow students to align their learning with learning goals (Wise, 2014; Wise, Zhao, & Hausknecht, 2013). Therefore, in addition to the design of assessments, which can encourage productive learning behaviors, instructors could play an active role in making the pedagogical intent behind learning activities explicit to the learners.

The information related to students' engagement from assessments could guide instructors to alter subsequent instruction and hence is valuable to the instructors as well (Hattie

& Timperley, 2007; Shute, 2008). When instructors have access to information regarding students' learning behaviors with an existing pedagogic design, they can make better decisions about their classroom pedagogy such as the design and implementation of classroom assessments. Instructors can further refine the design for pedagogical improvement (Hung et al., 2017; C. Romero & Ventura, 2013). For example, a learning analytics tool TUT LA developed at the Tampere University of Technology, provided instructors with information about students' distribution of activity such as last-minute behavior (just in time before the deadlines) in submitting the assignments. This allowed the instructors to redesign the course schedule (Kuosa et al., 2016; Silius, Tervakari, & Kailanto, 2013).

To summarize, a few benefits of formative assessments include:

1. Initiating a conversation between instructors and students
2. Enabling instructors to support students by taking appropriate action such as providing meaningful and timely feedback to students and/or pedagogic redesign of learning activities
3. Encouraging students to be active participants to improve their learning process.

#### **2.4 FORMS OF DELIVERY OF ASSESSMENTS: IN-CLASS ASSESSMENTS AND ASSESSMENTS IN TECHNOLOGY-ENHANCED PLATFORMS**

Instructors can design and implement various forms of formative assessments to encourage the use of effective learning strategies such as active and spaced retrieval among students. Formative assessments could be delivered in class (e.g., pen-paper assessments, clickers) or outside the classrooms with the aid of technology-enhanced platforms like an LMS. Recently in-class assessments are being replaced by assessments in technology-enhanced platforms. This is owing to the several advantages that technology-enhanced platforms offer

including an opportunity for students to work by themselves outside class hours, which saves class time and augmented opportunities to provide timely feedback to students without increasing the workload for instructors. The two forms of delivery of assessments are discussed below.

#### **2.4.1 *IN-CLASS ASSESSMENTS***

Some forms of assessments can be delivered by instructors within classrooms to encourage active and spaced retrieval of information. Pen and paper tests are a traditional form of such assessments. Of late, pen-paper tests are replaced by assessments via electronic response systems called clickers. Clickers provide instructors with immediate information about students' skills and abilities. This helps them understand gaps in students' knowledge and plan their instruction accordingly (Koenig, 2010). The use of clickers could prompt both instructors and students to reflect on their teaching and learning respectively (Brewer, 2004). Disadvantages of clickers include taking up class time, allowing only certain test formats like multiple-choice questions, requiring the compulsory attendance of students, and the initial cost involved in the implementation (Barnett, 2006; Koenig, 2010; Strasser, 2010).

Assessments in-class could be insightful to instructors in getting an overall understanding of students in a topic covered in class. However, to understand the learning strategies students adopt while preparing for assessments outside the classrooms, instructors would have to interact with students or implement surveys to obtain self-reports of students' perception (Sheard, Ceddia, Hurst, & Tuovinen, 2003).

#### **2.4.2 *ASSESSMENTS IN TECHNOLOGY-ENHANCED PLATFORMS***

Studies affirm the value of the use of technology-enhanced platforms like an LMS in managing the learning activities of students (Al-Busaidi, 2013; Chou, Peng, & Chang, 2010;

Dias & Diniz, 2014; Islam, 2013; V. A. Nguyen, 2017; F. H. Wang, 2017). Self-paced, learner-centered activities can be planned outside classrooms with the help of such platforms (Zhang, Zhao, Zhou, & Nunamaker, 2004). For example, pedagogical tools like low-stake quizzes can be effectively delivered via LMSs as learning designs that provide structure and opportunities for regular practice and self-monitoring among learners (Angus & Watson, 2009; Coates et al., 2005; Doige, 2012; O’Sullivan & Hargaden, 2014). Angus and Watson (2009) point out that certain formative aspects of assessments like an opportunity for multiple attempts, timely formative feedback (which facilitates the development of mastery goal orientation and self-reflection respectively among learners), and randomized questions could be attainable only in the online format.

## **2.5 TRACKING LEARNERS’ BEHAVIORS IN TECHNOLOGY-ENHANCED LEARNING PLATFORMS**

Before the advancement in the field of LA and the use of technology-enhanced learning platforms, learners’ reflection on their behaviors was supported mainly by encouraging recollection of their learning activities via questionnaires or think-aloud-protocols. However, researchers point out the inadequacy of using self-reports in understanding learners’ behaviors and the need for tracking data from empirical activities (Fincham, Gasevic, Jovanovic, & Pardo, 2018; Junco, 2014; Winne, 2005; Winne & Perry, 2000). Self-reports about the learners’ study strategies may be inaccurate and unreliable (Winne & Jamieson-Noel, 2002; Winne, Jamieson-Noel, & Muis, 2002). According to Winne and Jamieson-Noel (2002), learners tend to overestimate the use of specific tactics that they implement.

With the onset of technology-enhanced learning platforms more accurate and reliable measures of learners’ behaviors can be tracked and used to effectively support learners’ process

of reflection. For example, Zhou and Winne (2012) found that trace data-based measures of achievement goal orientation had stronger associations with learning outcomes when compared to self-reported ones. According to the authors, this finding points to the difference between the perceived intention and the actual behavior of learners. Self-reported data measure the intentions of students while trace data measure their actual behavior. The authors believe that the inaccuracy in self-reports could be most probably due to poor reflection from the learners' end. Hence they argue log data has less bias and aids in the collection of finer grain data points that are more in accordance with the actual learning behaviors of students. Similar discrepancies in students' self-reported data of study effort and measure of real effort (tracked by an LA technology) were reported in a recent study (Rawson, Stahovich, & Mayer, 2017). Correlation between course grade and actual time spent on homework was  $r(323) = .44$ , but between course grade and self-reported time doing homework was only  $r(323) = -.16$ .

Analysis of log data related to students' activity tracked by technology-enhanced learning environments such as gStudy have uncovered patterns in learners' behavior and provided insights to understanding their self-regulated learning activity (Hadwin, Nesbit, Jamieson-Noel, Code, & Winne, 2007). Data logged by gStudy included details about the frequency, patterns, timing, and sequence of actual activities of students and indicated that students' self-reports did not calibrate to their actual activities. This study demonstrated that the analysis of log data had the potential to inform students and instructors about the patterns related to actual study activity. Following the study by Hadwin and colleagues (2007), recent studies aim to explore and validate the possibility of using log data as a research tool intended for increasing pedagogical effectiveness (Cicchinelli et al., 2018; Fincham et al., 2018; You, 2015). These studies imply that

feedback provided about the analysis of log data collected from technology-enhanced learning platforms could inform students about gaps in their intentions and real behaviors.

## **2.6 ADVANTAGES OF TECHNOLOGY-ENHANCED PLATFORMS**

Technology-enhanced platforms offer several advantages such as an active role for students in their learning process, an opportunity for providing meaningful and timely feedback to students, and reduced workload for instructors. The advantages of technology-assisted platforms are summarized below (sections 2.6.1-2.6.3).

### **2.6.1 ACTIVE ROLE FOR STUDENTS**

Technology-enhanced environments when used effectively can encourage students' autonomy by empowering them to take up an active role in regulating and monitoring their own learning process (Zhang et al., 2004). This is because learners can be more engaged and reflect on their progress better as they work by themselves on these platforms. They can move at their own pace and convenience, determine their learning needs and deficits, and formulate study strategies to meet their needs (Artino, 2008; Spurlock-Johnson, Zhang, & Allen-Haynes, 2004).

### **2.6.2 MEANINGFUL AND TIMELY FEEDBACK TO STUDENTS**

Several studies have found that technology-enhanced learning platforms provide learners more opportunities to receive meaningful and timely feedback from instructors, which can enhance learners' reflection (Crisp & Ward, 2008; Gikandi, Morrow, & Davis, 2011; Sorensen & Takle, 2005; Vonderwell, Liang, & Alderman, 2007). Assessments delivered by electronic means provide opportunities to continuously record and monitor the interaction and understanding of students (Gikandi et al., 2011; Lin, Liu, & Yuan, 2001). Interaction of students with technology-enhanced learning platforms produces large volumes of logged data related to learners' behaviors (Papamitsiou & Economides, 2014). Logged data can often be classified

using computational methods to uncover meaningful patterns of learners' behaviors, which may be otherwise hard to identify (Sabourin, Shores, Mott, & Lester, 2013). Actual student interaction data can be tracked on technology-enhanced platforms instead of learners' perceptions from self-reported measures such as post hoc surveys (Lockyer et al., 2013). When instructors have immediate knowledge about actual patterns of learners' behaviors, they can utilize the information to provide meaningful and timely feedback to learners (Siemens & Baker, 2012).

### **2.6.3 REDUCED WORKLOAD FOR INSTRUCTORS**

Identifying patterns related to successful (or less successful) learning behaviors is important to instructors so that they can provide meaningful formative feedback to the students. However, tracking learning behaviors of individual students especially in classes with large student enrolment could demand additional labor and time from the instructors (Krause, Hartley, James, & McInnis, 2005). Technology-enhanced learning platforms can:

1. tirelessly and patiently access and keep track of a wide range of information including study tactics adopted and performance scores about an individual student
2. be easily scaled to be used by a larger number of learners (McKay, Miller, & Tritz, 2012).

Therefore, such platforms considerably increase the opportunities for instructors to provide feedback to learners, which could have been previously impossible without increasing the workload of instructors particularly in classrooms with low instructor-student ratios (Nicol, 2009).

## **2.7 UNDERUTILIZATION OF TECHNOLOGY-ENHANCED LEARNING PLATFORMS**

Technology-enhanced learning platforms encourage metacognition among learners by supporting self-monitoring, self-reflection, and peer interaction (McMahon, 2002). However, many instructors use such platforms mainly to deliver course materials electronically to the students (Campbell, 2007; Vovides et al., 2007). Despite the potential of platforms like LMSs to encourage effective learning strategies and support learners' metacognitive awareness, the use of these platforms remains limited in two main areas. First, changes in pedagogic practice to take advantage of the functionalities offered by LMSs are often not utilized (Collis & van der Wende, 2002; Mitrovic, Suraweera, Martin, & Weerasinghe, 2004; Sinclair & Aho, 2018). Second, the integrated features, functionalities, and logged data which can be mined for understanding learners' interaction patterns are rarely explored (Milliner & Cote, 2018). Each of these aspects is explained in detail below.

### **2.7.1 LIMITED IMPLEMENTATION OF PEDAGOGIC DESIGNS**

In 2013, 58% of the institutes which used LMSs, used basic components such as course content distribution (Dahlstrom & Bichsel, 2014). In a study conducted among 862 faculty members at 38 institutions in the US, who used the Blackboard LMS in addition to face-to-face instruction, it was found that the instructors primarily used the Blackboard as a course management/administration tool to publish course materials and manage student grades. Very few faculties used the LMS for instructional or assessment purposes which can provide the learners with timely feedback (Woods, Baker, & Hopper, 2004). Similar were the results of a study conducted by the Educause Centre for Applied Research about the extent and purpose of faculty use of LMS. This study looked at the factors on which instructors' decision to use an

LMS was based, and whether the use of the LMS resulted in “pedagogical gains” (Morgan, 2003). The results of this study showed that the rate of use of LMSs is increasing. However, it is noteworthy that the use is focused on the content creation tools and not the interactive features of the LMS. This study also indicated that although the instructors had claimed they utilized the LMS to meet pedagogical needs, the actual use of the system was limited to class management.

The use of technology-based learning environments that focus mainly on the technological aspect rather than the pedagogical perspective limits the possibilities of supporting student learning (Dabbagh, 2004; Swenson & Curtis, 2004). To overcome this limitation, researchers call upon instructors to craft their learning activities by embedding learning design and considering the possibilities of data collection which can verify whether learners’ behavior is in accordance with the expectation of the implemented design (Rodríguez-Triana, Martínez-Monés, Asensio-Pérez, & Dimitriadis, 2015; Wise, 2014).

### ***2.7.2 LIMITED EXPLORATION OF LOG DATA***

Present-day LMSs offer limited data reporting options related to patterns of student interaction with the system (Dawson et al., 2008; Lockyer et al., 2013; Mazza & Dimitrova, 2007). Advanced methodological requirements are required to access and analyze the remaining logged data stored in the backend in complex format (Dietrichson, 2013; Graf, Ives, Rahman, & Ferri, 2011). Although LMSs might report basic measures such as login frequencies and page visits, detecting successful or less successful learning behaviors of students could be difficult without additional analysis of unexplored logged data (Hung & Zhang, 2008). Analysis of logged data, based on sound learning theories, can aid in data generation aimed to test and validate pedagogical designs of instructors (Angus & Watson, 2009; Knight, Wise, & Chen, 2017). Despite the advantages of using log files, the limitations such as tracking simple

behavioral data related to learners' activities instead of meaningful learning activities and not considering the contextual data have to be dealt with caution (C. Romero & Ventura, 2007).

## **2.8 ROLE OF LEARNING THEORIES IN DATA-DRIVEN APPROACHES**

LA studies have been mainly using data-driven discovery models to extract patterns related to learner behaviors from the logged 'big data' (Siemens & Baker, 2012). Many researchers are of the opinion that to advance research and practice in LA, there exists a strong need to interlink analytics with learning theories (Choi et al., 2016; Rogers et al., 2016; Wise, 2014; Wise & Shaffer, 2015).

The most common methods of data analysis make use of students' access log patterns with a learning platform like an LMS, demographic variables (e.g., gender or socio-economic variables), and current and prior performance measures (grades in enrolled courses or standardized test scores) (Rogers et al., 2016). According to some researchers, such variables are static and cannot be considered as true 'causal variables' (i.e., these variables offer no explanation regarding the outcome and cannot be manipulated to rectify the existing problem) (Wise & Shaffer, 2015). A special issue on LA in Computers in Human Behavior point out that relying solely on LA metrics like simple aggregated counts which includes the number of clicks and number of downloads made by a student may, in fact, slow down the advancement of LA research (Conde & Hernández-García, 2015). One of the criticisms of using simple behavioral data measures such as the number of clicks, time spent online, or the number of resources viewed is that these variables lack the power to contribute to the understanding of student learning (Lodge & Lewis, 2012). The authors argue that simple behavioral data cannot differentiate students who engage with the study material in an in-depth and critical way from the rest of the learners. In a study which modeled student interaction with an LMS, more than 30% of the

variance in the final grade of learners could be explained by using variables such as the total number of messages posted in discussion forums, email messages sent, and assessments completed by students (Macfadyen & Dawson, 2010). This model could predict ‘at-risk’ students with 81% accuracy. But criticisms of studies that solely focus on prediction include lack of transferability of predictor variables to a different context and failure to consider variances in learning patterns. For instance, among students who have similar aggregated times spent on learning, some might have massed their study sessions together, while others could have spaced it out (Hung et al., 2017).

Many of the tools used in analytics in education have been adapted from models in marketing and management where the end goal is simply to predict consumer behavior (Baepler & Murdoch, 2010). Within an education setting, the purpose of LA could move beyond predicting the ‘at-risk’ students to enhancing the quality of teaching and learning of all students. Pedagogical learning analytics interventions could be an alternate approach to prediction, wherein personalized advice to use learning tools help all students progress according to their individual needs (Wise, 2014). This will ensure that the same learning tool is useful to both ‘at-risk’ students as well as others. In this approach, the undesired behavior of students could be detected by instructors and kept under check. However, this approach demands the tracking of the quality of student interactions (meaningful learning behaviors) within the LMS rather than the mere quantity of interactions (frequency measures of student activity). To achieve this, data of each student has to be taken into consideration to generate actionable intelligence to provide detailed feedback that can inform and support individual students (McKay et al., 2012).

Some authors emphasize that the influence of technology manifests not by its direct effects but rather through pedagogic changes (Chan, Tam, & Li, 2011; Crook & Lewthwaite,

2010). It is important for the following reasons that learning theories guide the selection of variables considered in a study and the interpretation of results (Wise & Shaffer, 2015). First, the use of theory could help in turning the results of analytics “actionable”. Actionable analytics implies generating usable information using LA with the possibility of planning specific pedagogic interventions by the instructors rather than general interventions (Rogers et al., 2016). For example, if the independent variables considered in a study are not informed by theory, only general remedial measures can be offered to students identified as ‘at-risk’. Such interventions could include referring ‘at-risk’ students to websites with general tips to improve learning and extra information related to the course content (Wright, McKay, Hershock, Miller, & Tritz, 2014), or referring the students to an outreach program (Smith, Lange, & Huston, 2012). Constructive feedback or targeted interventions to address specific drawbacks in learning, teaching, or curriculum which can improve students’ learning behaviors may not be provided. This implies that the findings may not be translated into recommendations that can promote learning. Second, to generalize the findings of one study to a different context, it is important to have a theoretical rationale regarding the independent variables included in the model (Wise & Shaffer, 2015). This would help in explaining the role of contextual variables or contradictory findings between different studies (Gašević et al., 2016).

In LA research informed by learning theory, one of the major challenges could be designing effective variables that are meaningfully linked to the construct of interest. The pedagogical intent and design of learning activities planned will determine the variables that are extracted from the logged data and translated into meaningful indicators of students’ effort (Macfadyen & Dawson, 2010).

## **2.9 DESIGNING VARIABLES FROM BEHAVIORAL DATA FOR ACTIONABLE ANALYTICS**

Previous studies ascertain that there are no sets of identified variables that are suitable to meet the varying purposes of different LA studies (Saqr, Fors, & Tedre, 2017). Variable selection depends on the context of the course, learning design, learning environment, and purpose of the study (Agudo-Peregrina, Iglesias-Pradas, Conde-González, & Hernández-García, 2014; Gašević et al., 2016; Rienties, Borooa, Cross, Kubiak, & Mayles, 2016). The following paragraphs investigate the existing literature on examples of utilizing the log data by extracting variables related to students' learning behaviors.

### **2.9.1 TIME-ON-TASK AND TIME-OFF-TASK**

Carroll's Time-On-Task hypothesis, one of the pioneer works which investigates the relationship between classroom behavior and learning, hypothesizes that a student who spends more time engaging with the study materials has greater opportunities to learn (Carroll, 1989). This hypothesis implies that off-task activities (behaviors not related to learning including disengaging from the study material) reduces learning.

Several studies have looked at the relationship between the time spent by students on-task and academic achievement. A few have found weak correlations with learning. For example, a study which analyzed log data from students enrolled in a blended medical course found total time students spent online engaging with educational material had a weak correlation ( $r(131) = .22, p = .01$ ) with the final grade (Saqr et al., 2017). Similar results were observed among 120 college students enrolled in an online pharmacy course. Time-on-task (defined by "hits" on content pages) of learners correlated weakly ( $r(120) = .257, p = .02$ ) with learning, defined as pre/post-test change score (Wellman & Marcinkiewicz, 2004). Studies conducted on similar note

report weak to medium positive correlations ( $r(122) = .23, p < .05$  and  $r(74) = .31, p < .001$  respectively) between quantity of time spent on studying and performance, measured by GPA (Allen, Lerner, & Hinrichsen, 1972; Wagstaff & Mahmoudi, 1976). A study that reports a negative correlation between the number of hours invested in work and expected grades ( $r = -.23, p < .005$ ) considers the grade leniency effect as a possible reason for deviation from results in the existing literature (Greenwald & Gillmore, 1997).

Researchers have investigated the effects of self-monitoring on altering classroom behaviors and academic achievement. In a study conducted by Sagotsky, Patterson, and Lepper (1978) students were instructed to record and monitor their behaviors in a mathematics classroom, including whether they worked on the appropriate learning materials. There was a significant main effect for the self-monitoring treatment on the students' time-on-task ( $F(1, 63) = 4.70, p < .05$ , effect size = .24) and task accomplishment ( $F(1, 63) = 5.30, p < .025$ , effect size = .26). A longitudinal study which examined the effects of tracking 'time spent on learning' on self-regulated learning among 36 graduate students found positive effects in tracking time on time management skills (measured by the repeated administration of The Online Self-Regulated Learning Questionnaire and the Time Management Questionnaire) (Tabuenca, Kalz, Drachsler, & Specht, 2015).

A few cautions have been raised regarding the appropriateness of using 'time-on-task' as a measure of students' engagement in online learning. It is disputable whether time-on-task measured by 'clicks and hits' is a real reflection of the time the student actively engages with the learning material. This is because the students could log in to the system and engage in tasks not related to learning such as checking e-mail or social networks. But some researchers raise the counterargument that this could be the case in all learning environments, including

face-to-face learning in a classroom (Bjork et al., 2013). Studies in the past provide evidence that measures of student engagement such as time spent on a task exhibit significant positive correlations with learning (Angus & Watson, 2009; Liu & Cavanaugh, 2011). For example, according to the findings of a study performed by Cho & Shen (2013), effort regulation and the amount of time spent on LMS predicted students' academic achievement in an online course. Student achievement (measured by total points received for the course) significantly correlated to effort regulation and login time ( $r(64) = .30, p < .05$ ;  $r(64) = .42, p < .01$ , respectively). However, researchers caution that spending more time online does not usually translate into higher achievement unless that time is spent on activities related to learning (Macfadyen & Dawson, 2010). Certain authors are of the opinion that even in cases where more amount of time spent on the LMS correlates with higher academic performance, "average time spent online" could be a measure which captures only the superficial and strategic engagement of students rather than deep and critical engagement with the learning materials and content (Lodge & Lewis, 2012). Quality of learning time, which is possibly a better indicator of student engagement when compared to the quantity of learning time, need not be accurately captured by such measures (Macfadyen & Dawson, 2012; M. Romero & Barberà, 2011). Therefore, frequency measures related to 'time-on-task' have to be dealt with caution as they could be crude indicators of the time that students invest in learning.

### **2.9.2 SPACING THE STUDY EVENTS**

Robust findings from psychology as well as studies conducted in classrooms support the finding that distributing the study time into multiple sessions is more productive for long-term retention compared to massing the study time into a few sessions (Kapler et al., 2015; Larsen, Butler, & Roediger, 2008; McDaniel et al., 2013; Nazari & Ebersbach, 2019; Roediger &

Karpicke, 2006b; Schutte et al., 2015). This finding is referred to as the “spacing effect.” Retrieval attempts which are spaced (when compared to massed attempts) may produce more errors initially but eventually will lead to increased learning (Bjork & Yue, 2016; Pashler & Zarow, 2003).

Classroom quizzes implemented with repetition, spacing, and feedback are known to have a positive effect on learning (McDaniel et al., 2013). For example, researchers analyzed the log data of students’ learning behaviors from 20 HarvardX courses in a Massive Open Online Course (MOOC) to examine if the well-established finding from the psychology literature holds good in ‘in the wild’ (i.e., a real-time classroom and not in an experiment conducted within a laboratory) (Miyamoto et al., 2015). They examined the relationship between students’ distribution of study sessions in MOOCs and their performance. Controlling for the effect of total time, the number of study sessions the students engaged in correlated with certification rates (i.e., when the students spent equivalent amounts of aggregated time in multiple courses, they performed better in courses where the total study time was divided into multiple study sessions). The finding held good for students in all courses. This study is an indication of the benefit of the spacing effect in an online learning environment.

Despite the benefits of spaced practice, most classrooms do not implement frequent quizzing where previous topics are revisited (Raley, 2016). A few issues in implementing spaced quizzing in a classroom are requirements of advanced planning from both instructors’ and students’ end and students feeling less confident during spaced retrieval attempts when compared to massed study sessions. For example, in a study that exhibited a robust spacing effect (78% of participants performed better in spaced condition) only 22% of the participants believed that they indeed did better in the spaced condition (Kornell & Bjork, 2008). The increased number of

errors that the students make and resulting low performance in the short-term makes spacing techniques look seemingly less productive (Bjork et al., 2013; Kornell & Bjork, 2008; McCabe, 2011). Survey results among students indicate that they do not choose spaced retrieval as a study strategy (Kornell & Bjork, 2007).

### **2.9.3 PROCRASTINATION BEHAVIOR**

Frequent testing is implemented in classrooms with the aim to encourage students to space their study over multiple sessions rather than mass them together before an exam. With less frequent testing, students tend to procrastinate and study just in time before an exam. According to the results of a survey conducted by Kornell and Bjork (2007) 59% of students, give priority to topics that are due immediately or overdue as they plan their schedule for study.

Evidence from both face-to-face and technology-enhanced learning environments support the finding that procrastination as a learning behavior is detrimental to academic achievement (Akinsola, Tella, & Tella, 2007; You, 2015). The findings of a recent study, which investigated the effect of time management on academic achievement in online learning environments confirm this (Cerezo, Esteban, Sánchez-Santillán, & Núñez, 2017). Association rules performed on a sample of 140 undergraduate students who were subjected to a blended learning experience, showed a negative association between procrastination variables and academic performance. Similar results were reported in a study conducted by You (2016) where data from 530 college students in an online course were analyzed. Late submissions of assignments negatively correlated with exam scores ( $r(569) = -.41, p < .01$ ) and were negatively significant in predicting the final course score ( $\beta = -.40, p < .001$ ) (You, 2015). Academic procrastination accounted for 32.5% of the variability in the exam score ( $R^2 = .325, F(2, 567) = 136.66, p < .001$ , effect size = .48). Similarly, in a study conducted on 40 students significant medium negative relationship was

found between procrastination and grades ( $r(40) = .39, p = .03$ ) (Michinov, Brunot, Bohec, Juhel, & Delaval, 2011).

Certain studies consider procrastination as students' failure to self-regulate their learning process (Wolters, 2003). For example, in a study conducted on 170 college students, procrastination scores inversely correlated to the usage of cognitive strategies ( $r(170) = -.35, p < .01$ ) and meta-cognitive strategies ( $r(170) = -.40, p < .001$ ) (Howell & Watson, 2007). A study conducted among 81 students in an online learning environment found that effort regulation ( $r(81) = -.38$ ) and intrinsic goal orientation ( $r(81) = -.36$ ) was negatively associated with procrastination and explained 19.8% of the variance ( $F(2, 78) = 2.751; p < .001$ ) in procrastination with an effect size of .25 (Rakes & Dunn, 2010).

An experimental study that classified students as high and low procrastinators, identified by Tuckman Procrastination Scale (Tuckman, 1991), randomly assigned the students to two sections that covered the same content in a distance learning program. The treatment group implemented motivational supports such as study skills support groups and instructor office hours which motivated the students to stay on task. Procrastinators in the treatment group performed better in comparison with the control group while students who were non-procrastinators performed equally in both groups (Tuckman, 2007). Mean GPA gain scores for high procrastinators were .43 in the group which had motivational supports and .10 in the control group. For low procrastinators, the means were .16 and .19, respectively.

#### **2.9.4 NUMBER OF ATTEMPTS**

Retrieval attempts, even if unsuccessful, can enhance learning (Hays, Kornell, & Bjork, 2013; Kornell, Jensen Hays, & Bjork, 2009; Richland, Kornell, & Kao, 2009). This is because unsuccessful attempts can initiate learning between attempts (McDaniel et al., 2011). Quiz

designs where grades are awarded for the best attempt among multiple possible attempts could encourage subsequent attempts among students (Zimmerman et al., 2011). Certain studies use the number of attempts in practice quizzes as a proxy measure for the time-on-task of students (Wellman, 2005). Wellman & Marcinkiewicz (2004) report a significant moderate correlation ( $r(120) = .401; p < .001$ ) between improvement in change score (posttest % minus pretest %) and greater use of practice quizzes. A study conducted in a biochemistry course, which used optional learning modules to encourage test-enhanced learning, showed that students' performance increased significantly with a greater number of practice attempts (mean scores in the first attempt being 58.3% and mean scores in a high attempt 89.6%;  $p < .0001$ ) (Horn & Hernick, 2015). Path analysis conducted to predict exam scores of students found that the number of attempts a student makes in quizzes positively predicts their marks in exams ( $\beta = .20, p < .01$ ) (Kleitman & Costa, 2014).

## **2.10 REVIEW OF LEARNING ANALYTICS STUDIES THAT TRACK STUDENT BEHAVIORAL DATA**

There is an increasing interest in recent years to take advantage of LA to inform learning design and pedagogy. LA studies that track students' behavioral data to identify different patterns in their learning behaviors help inform instructors whether the behaviors are indeed aligned to the expectations behind the implemented learning design (Dawson, Heathcote, & Poole, 2010; Dyckhoff, Zielke, Bültmann, Chatti, & Schroeder, 2012). Such studies help instructors have an overview of the course activity and identify students who need additional attention. This is usually achieved by keeping track of the time spent on learning, document, and resource use by students as indicators of their effort and use of quizzes or assessments as performance indicators. Instructors can use information related to students' learning behaviors

and performance to provide them with ongoing and meaningful feedback (Doige, 2012).

Additionally, instructors can reflect on their teaching and make necessary changes in instructional techniques (Melero, Hernández-Leo, Sun, Santos, & Blat, 2015).

Student learning behaviors could be tracked via variables such as information related to login trends (e.g., time spent, number of logins), performance results (e.g., grades of exercise, quiz, or assignment), and content usage (e.g., download of resources, accessing learning materials) (Park & Jo, 2015). Table 2.1 summarizes the most frequently used variables in the existing LA literature. Many of the studies reviewed in table 2.1 investigate variables related to the login trends and content usage of students which are malleable to some extent. Malleable variables under consideration in a study can be manipulated, and hence interventions aimed at altering ineffective study strategies can be planned. However, variables such as the number of logins or number of course material downloads although malleable might not be pedagogically meaningful (i.e., higher frequencies of such measures may not always lead to higher performance or learning). These simple metrics may not be indicative of the quality of learning, high-level engagement, learning process, and elements of self-regulation of students in this process; i.e., these variables could be tracking basic engagement of students rather than an in-depth, productive engagement (Gašević et al., 2016; Lockyer et al., 2013).

**Table 2. 1**

*Variables Commonly Considered in LA Studies That Track Students' Behavioral Data*

| Index  | Variables   |
|--|---|
| 1. (Kizilcec, Piech, & Schneider, 2013)        | Content usage (lecture usage data of students)                        |
| 2. (Gašević, Jovanović, Pardo, & Dawson, 2017) | Content usage (lecture usage, access of course materials, completion) |

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|  |  |
|--|--|
|  | of formative assessments and help-seeking behavior for solutions)  |
| 3. (Kuosa et al., 2016; Silius et al., 2013)     | Content usage (access of course materials), performance results  |
| 4. (Arnold & Pistilli, 2012; Tanes et al., 2011) | Login trends (the total number of LMS logins, total frequency of accessing course materials), performance results, content usage (interaction with LMS in comparison to peers) |
| 5. (Ali, Hatala, Gašević, & Jovanović, 2012)     | Login trends, performance results, content usage (interlinking student activity with levels of difficulty of a topic)  |
| 6. (Hung & Zhang, 2008)                          | Login trends, performance result and content usage (the total number of messages posted, messages read, synchronous discussions attended)                                      |
| 7. (Mazza & Dimitrova, 2007)                     | Login trends, performance results, content usage (access of course materials) and social interaction   |
| 8. (Scheuer & Zinn, 2007)                        | Login trends, performance results, content usage (exercises attempted in each topic)   |
| 9. (Merceron & Yacef, 2005)                      | Content usage (number of exercises completed)  |

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## 2.11 SUMMARY OF LITERATURE REVIEW AND IDENTIFIED GAPS

To summarize, the present study aimed to bridge three identified gaps in the literature. First, to understand whether the actual behaviors of students in an unsupervised assessment system implemented within an existing LMS were in accordance with the pedagogical intent of the instructors' design. Second, to explore the possibilities of using a technology-enhanced platform like an LMS to support reflection and metacognitive monitoring among students as they work on unsupervised quizzing. In existing LA studies, pedagogically meaningful variables

related to the quiz-taking behaviors of students are often not identified. This limits the possibility of providing formative feedback to students in unsupervised technology-enhanced platforms.

Third, to incorporate the viewpoints of instructors rather than depend solely on computational methods in understanding students' behaviors with unsupervised quizzing. This approach would allow to interlink LA with the implemented learning design.

## **CHAPTER 3: METHODS**

This chapter describes the methodology of the study in detail including the objectives, settings, participants, and the researcher's perspective. This chapter also reviews the pilot study, research design, data collection methods, procedures for participant recruitment and interviewing, variables, and the data analysis techniques used in the study. The study used a mixed-methods research design where qualitative data were collected via interviews with instructors of MIP and quantitative data via Canvas quiz-log data analytics.

### **3.1 RESEARCH OBJECTIVES**

The study had three main objectives.

1. To understand the pedagogic intent of the MIP instructors in implementing low-stake, unsupervised online quizzes in their classes and identify the difficulties, if any, they faced post-implementation of the learning design.
2. To identify patterns in students' quiz-taking behaviors from Canvas quiz-logs and to examine the relationship between students' behaviors and performance in subsequent examinations and the final exam.
3. To understand the MIP instructors' views related to the perceived usefulness and implications of quiz-log analytics.

### **3.2 CONTEXT OF THE STUDY**

For the current study, understanding the context was important in verifying whether the learners' quiz-taking behaviors were in accordance with the intent behind the implemented learning design. The settings for the study and details about participants are discussed below.

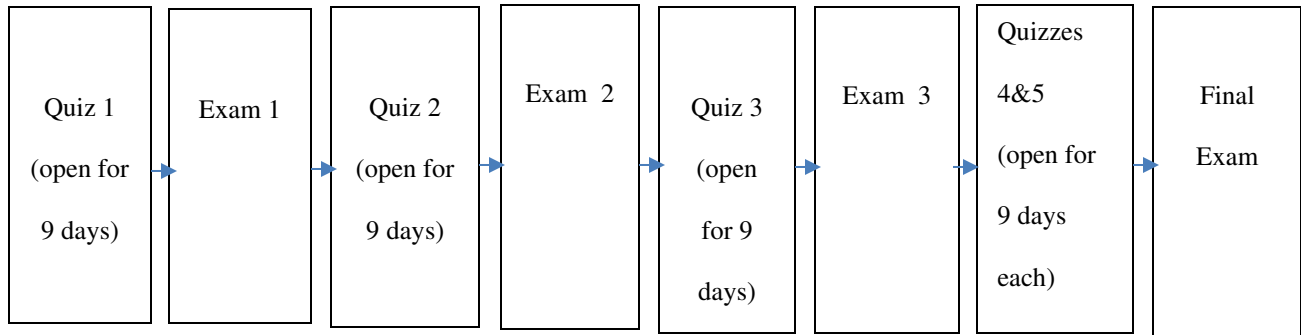
### **3.2.1 SETTINGS**

In summer 2016, the instructors at the Department of Microbiology, Immunology & Pathology at CSU started collaborating with the Center for the Analytics of Learning and Teaching (C-ALT), CSU as they were challenged by a problem in an undergraduate microbiology class: Microbiology, Immunology, and Pathology (MIP). The instructors had set up online quizzing, as a form of formative assessment, within Canvas with the intent to encourage their students to engage in active and spaced retrieval of information. The online quizzes were to be attempted by the students voluntarily and unsupervised at their own pace and convenience (i.e., timing and location of quiz taking was the students' choice).

The students were provided with an option to watch an instructional video as a prerequisite to taking the online quizzes. This video briefly summarized the benefits of active recall on long-term retention and advised the students to learn the material in advance, actively retrieve the information required to complete the problem without looking up any material such as their class notes. Additionally, at the beginning of the semester, the instructors briefly explained to the students how to attempt the quizzes. Students were given the opportunity to practice the quizzes up to ten times over a nine-day period. They could retake the quizzes multiple times in order to achieve mastery of the topic and earn the highest score; the highest score was recorded in the Canvas gradebook. The quizzes were low-stake, contributing to less than 10 percent of the final grade. Every attempt of the quiz had a set of 10 random questions allotted from a question bank. The maximum time available for each attempt was 30 minutes. Each quiz was open for nine

days directly before the following relevant summative examination, allowing students to practice content before being tested.

The timeline sequence of the online quizzes and subsequent examinations (midterms and final exams) is shown in Figure 3.1. As illustrated, each quiz was immediately followed by the relevant summative examination (Quiz 1 by Exam 1, Quiz 2 by Exam 2, Quiz 3 by Exam 3, and Quizzes 4 and 5 by the final comprehensive exam). This quiz structure allowed students to practice content before being tested on the relevant summative exam. In short, this design was implemented as a structure that provided students an opportunity to take part in a flexible, yet focused learning activity.



**Figure 3.1**

*Timeline of the Quizzes and Exams Implemented in the MIP course*

### **3.2.2 PARTICIPANTS**

For the qualitative phase of the study, the participants were the four instructors of the undergraduate microbiology course MIP at CSU, Fall 2019. For the quantitative part of the study, quiz-log data of all students enrolled in the undergraduate MIP at CSU, Fall 2019 who attempted the voluntary low-stake unsupervised online quizzes (Quiz 1 and Quiz 2) were accessed and analyzed. From the three sections of MIP classes, for Quiz 1, data of 276 students and for Quiz 2, data of 278 students were available. The undergraduate microbiology students at CSU typically belonged to the age group 18-20 years.

### **3.3 RESEARCHER'S PERSPECTIVE: MODEL-DEPENDENT REALISM**

Model-dependent realism was chosen as the philosophical framework for the study. Model-dependent realism is an approach wherein the quality of reality or absolute truth is attributed to the model which is successful in explaining events (Hawking & Mlodinow, 2010). According to this approach, it is equally acceptable that the same situation is modeled in multiple ways using different concepts. Rather than raising the question if the model is real, the focus is on whether the model agrees with observation. The present study attempted to model learners' quiz-taking behaviors using LA methods so that the results of analytics might improve the pedagogical design of quizzes and future learning of students.

### **3.4 THE RATIONALE FOR MIXED-METHODS AS A RESEARCH DESIGN**

The study adopted a mixed-methods research design in which qualitative and quantitative data collection and analysis were conducted. The qualitative part of the research comprised interviews with MIP instructors and the quantitative part of the study Canvas quiz-log data analysis. The following sections justify the need for quiz-log analysis and the collection of qualitative data (i.e., the need for mixed-methods as the preferred research design for the study).

### **3.4.1 THE NEED FOR QUIZ-LOG ANALYTICS**

Learners are often not reliable monitors of the learning strategies they deploy and often overestimate the use of a specific tactic (Butler & Winne, 1995; Winne & Jamieson-Noel, 2002; Winne et al., 2002). Therefore, student self-reports about the use of learning strategies may be inaccurate. Providing students with formative feedback about their actual learning behaviors could help students metacognitively monitor their behaviors and hence self-regulate their learning better. Present-day LMSs log large volumes of meta-data related to student activities in online learning platforms. However, the dashboards typically have built-in monitoring features that report only limited data. The remaining logged data are unavailable and incomprehensible to instructors, which makes it difficult to understand students' behavioral patterns. Usually, the information presented in dashboards of LMSs is simple metrics of students' interaction such as first and last login, messages the student has read and posted in discussion threads, number of downloads of study materials, number of pages visited, and scores achieved in assessments. Instructors could make use of this information to monitor the progress of students to a certain extent. However, to provide students with meaningful formative feedback (which can act as pointers to alter any flaws in learning strategies) variables closely related to theories of learning and correlated with academic achievement are to be extracted from the available log data.

In short, the analysis of quiz-log data is important in monitoring students' behaviors for two reasons. First, to obtain an accurate report of strategies that students employ in an online learning platform which could help learners themselves reflect and self-regulate their learning. Second, the results of log analysis can help instructors provide formative feedback to students and act as external monitors to encourage productive learning behaviors. In addition, instructors

could use the information related to learner behaviors to modify the implemented learning design.

### ***3.4.2 THE NEED TO COMMUNICATE THE RESULTS OF ANALYTICS TO THE INSTRUCTORS***

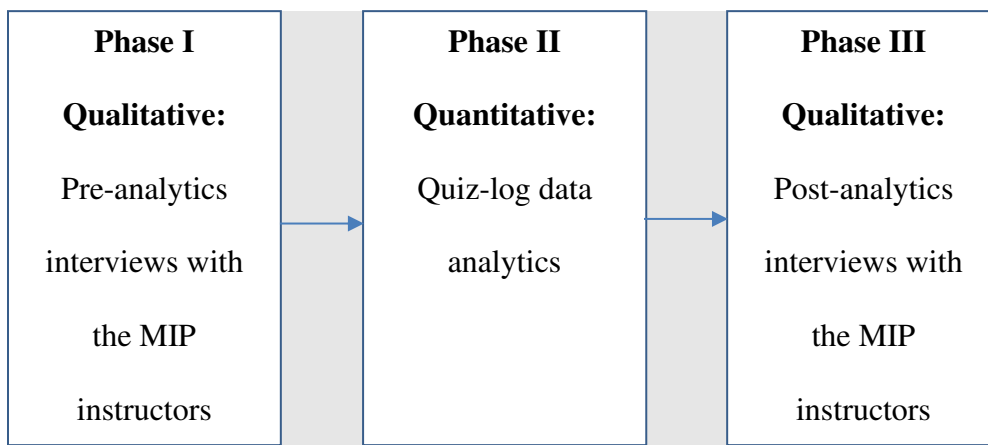
Log-file data related to students' activities on an LMS can be used to improve their learning experience (Gašević, Mirriahi, Dawson, & Joksimović, 2017; Hadwin et al., 2007; Winne, 2018). A formative evaluation (which aims at revising the quality and usefulness of the results) of the analytic methods requires obtaining feedback from the target audience. For example, if results from analytics are presented to instructors, a meaningful interpretation of the learners' activity based on the learning design and context could be possible (Gašević et al., 2016). Therefore, a qualitative interpretation of the findings is considered necessary for a robust analysis intended to improve student learning (Dawson et al., 2010; Fournier, Kop, & Sitlia, 2011). However, Bach (2010) identifies that one of the major limitations of LA studies is in communicating the results of analytics in meaningful ways to users who can understand the data to effect changes.

Two main approaches are identified in making sense of the 'big data' in education, namely automatic processing of the data and presenting data to stakeholders for human judgment (Ruipérez-Valiente, Muñoz-Merino, Leony, & Delgado Kloos, 2015). According to Macfadyen and Dawson (2010, p. 597) "knowledge of actual course design and instructor intentions is critical in determining which variables can meaningfully represent student effort or activity, and which should be excluded". Such an approach will allow the interlinking of LA with the implemented learning design. Taking impetus from this meaningful approach, researchers recently focus on providing results of analytics to instructors and learners (to enable them to

make changes in teaching and learning activities) rather than using automatic interventions (Baker, 2016). This is because, in this approach computer scientists, methodological experts, and educators can work in close association to understand the context in which educational data is collected and analyzed.

### 3.4.3 RESEARCH DESIGN OF THE STUDY

The overall research design for the study was a sequential multi-phase mixed-method design with three phases, which is represented in Figure 3.2.



**Figure 3.2**

*Schematic Diagram of the Multi-Phase Research Design*

In phase I of the study, qualitative data was collected via interviews with instructors of MIP. This was followed up with quantitative quiz-log data analytics in phase II. In order to understand the usefulness and implications of the analytics conducted in phase II, the results were shared with the instructors in phase III of the study. This phase of the study investigated the instructors’ interpretation of the results from Phase II. Each stage of the study is described in detail in section 3.6.1- 3.6.3.

### **3.5 PILOT STUDY**

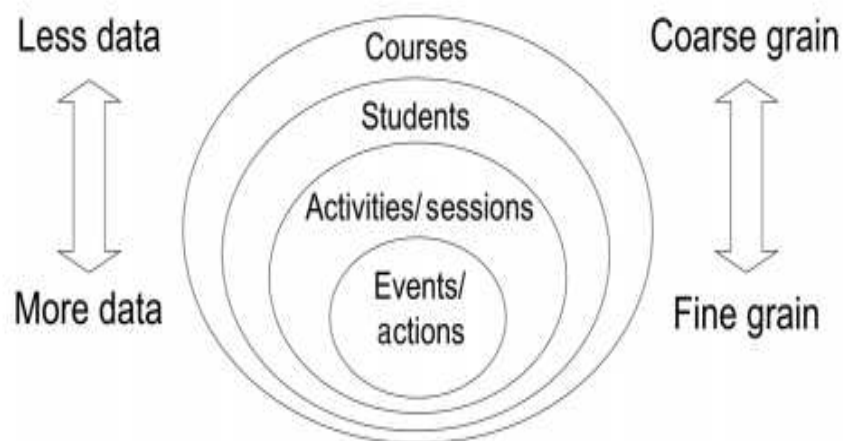
A pilot study was conducted in preparation for Phase II of the study with the quiz-logs collected from 90 students of the MIP class of Fall 2017. The pilot study was necessary because the researchers had to explore the feasibility of a study that could extract meaningful variables from the Canvas quiz-logs related to the quiz-taking behaviors of interest (e.g., spaced practice, massed practice, active retrieval, number of attempts, and procrastination behavior). Exploration of the quiz-log data in relation to spaced practice, massed practice, active retrieval, the number of attempts, and procrastination behaviors was conducted to extract and build variables of interest. Correlations between the identified variables related to learning behaviors and exam scores (both midterm exams, which immediately followed the quiz under consideration and final exams conducted at the end of the semester) were calculated in the pilot study.

The data collection, preprocessing and design, extraction, and normalization of the variables considered in the pilot study are described below in section 3.5.1-3.5.4. Sections 3.5.5-3.5.6 describes the validity and results of the pilot study.

#### **3.5.1 DATA COLLECTION FOR THE PILOT STUDY**

All LMS log data may not be stored in the desired format and therefore educational data mining tasks demand complex manipulation (Merceron & Yacef, 2008). Data from Canvas can be collected for data mining at many levels of granularity ranging from course level to events/actions level. Since these data are heterogeneous and hierarchical in nature, it is crucial to choose the data structures and formats that represent an event under consideration. The nature of the problem to be solved determines the best data structure (C. Romero & Ventura, 2013). Research questions determine the choice of data to be collected (i.e. the collected data have to align with the questions).

For the specific research questions under consideration in the pilot study, it was appropriate to collect quiz-log data from Canvas at the events/actions level (see Figure 3.3). A set of predefined routines and protocols called Application Programming Interface (API) was used to access data from Canvas. Later this data was modified to the desired format using Python scripts. Excerpts of the Python functions written for collecting quiz-logs from Canvas (for accessing the quizzes, submissions, and events) are shown in Appendix A.



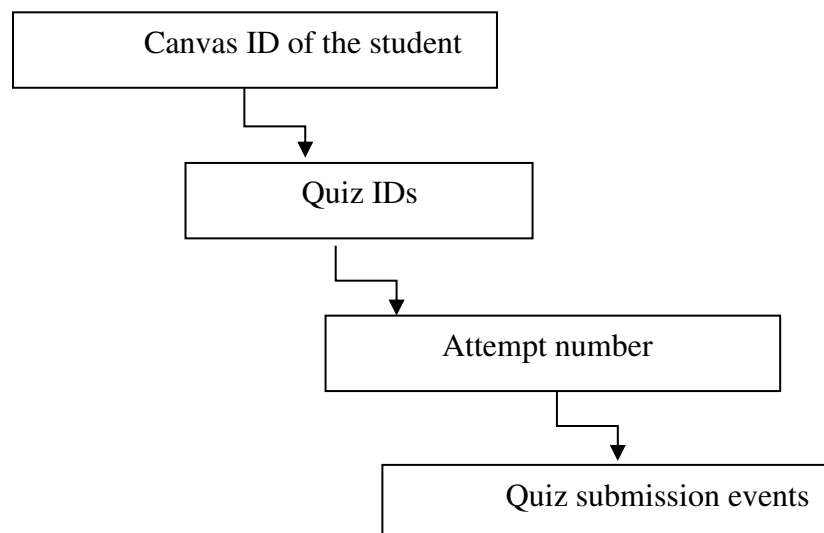
**Figure 3.3**

*Levels of Granularity in Data Collection (Source: C. Romero & Ventura, 2013)*

### **3.5.2 DATA PREPROCESSING (PILOT STUDY)**

In data mining tasks within educational contexts, data preprocessing is an important and complicated task. A great fraction of the total time spent solving the data mining problem is spent on cleaning up the data and modifying it to appropriate forms (Bienkowski, Feng, & Means, 2014). Canvas quiz-logs were stored in a hierarchical form. Data obtained via API responses were in JavaScript Object Notation (JSON) format and hence it was necessary to convert raw data to the desired form (i.e., an event related to the submission of each attempt of a quiz had to correspond to the respective student).

For each quiz, all events related to a single quiz submission was retrieved. Since a student could make multiple attempts for a given quiz, events related to each attempt were to be considered. The summary of each attempt in the quiz-log data consisted of quiz submission events which had information such as the corresponding quiz ID, Canvas ID (for further explanation refer to section 3.8) of the student, the current number of the attempt of a given quiz, remaining number of possible attempts, the total time a student spent on the current attempt, the start time and end time for the attempt, the score for the attempt and number of times the student left the active quiz page (event labeled ‘page blurred’ in Canvas) during the attempt under consideration. The information related to each quiz attempt submission was reorganized to match the corresponding student’s Canvas ID. The hierarchical structure of the data after this reorganization is shown in Figure 3.4.



**Figure 3.4**

*Hierarchical Structure of the Canvas Quiz-Logs*

### **3.5.3 DESIGN AND EXTRACTION OF VARIABLES (PILOT STUDY)**

In the pilot study, we explored the quiz-log data to design and build variables, which reflected the self-regulated quiz-taking behaviors of students with the low-stake unsupervised

online quizzes. Emphasis was given to learning behaviors, which are known to be linked to superior academic achievement, such as total time spent on quizzes, focus on the task, the spacing of study events, procrastination behavior, and the number of attempts. The rationale behind the choice of the variables were the consistent findings from previous studies, which show that learning behaviors indicative of higher engagement such as repeated practice, distributed practice, and quality time spent on learning usually leads to higher performance (de Freitas et al., 2015; Hung & Zhang, 2008; Macfadyen & Dawson, 2010).

The variables were limited intentionally to dynamic measures related to learning behaviors so that instructors would benefit from an opportunity to intervene and provide students with meaningful formative feedback. This would potentially allow the instructors to effect changes in learners' behaviors or make decisions related to future design and implementation of quizzes. Adding static, non-malleable variables like demographic information or prior performance variables of the participants would limit the possibility of planning an intervention (Hung et al., 2017; Tempelaar, Rienties, & Giesbers, 2015).

In the pilot study, an initial exploration of quiz-log data led to the identification of five variables of interest that were related to the learning behaviors of students. A few of the relevant variables were directly logged in Canvas quiz-logs while the rest had to be derived by manipulating the quiz-log data. The details about the design and extraction of variables from the quiz-logs are given below.

**3.5.3.1 Total time spent.** The variable 'total time spent' is a measure of the aggregate time a student spends on all attempts of an individual quiz. The attribute 'time spent', which is recorded in the Canvas log data for each submission of a quiz attempt was extracted. Students

were free to take each quiz up to ten times. 'Total time spent' was obtained by adding up the time a student spends across the multiple attempts they choose to make.

**3.5.3.2 Page blur frequency: a measure of off-task behavior.** Canvas logs a feature called 'page blurred' as an event type for each quiz submission event. The event 'page blurred' is logged when the focus shifts from the current web browser tab during the quizzing activity for a long duration (i.e., the current tab becomes inactive). This could occur when a student leaves the online quizzing system within Canvas and engages in off-task activities such as browsing other tabs or has a period of prolonged inactivity. This feature was considered appropriate to be used as a measure of off-task behavior after preliminary exploration of Canvas quiz-log data. Additionally, a study was conducted to establish the validity of using page blurs as a measure of off-task behavior, which indicated that during proctored testing significantly fewer page blurs were observed in comparison to a non-proctored testing condition (for details see section 3.5.5.1). A variable called 'page blur frequency' was built which is the frequency of page blurs (i.e., the total number of page blurs divided by the total time a student spends on the quizzing system).

**3.5.3.3 Closeness to the due date: a measure of procrastination.** Procrastination in students' quiz-taking was measured as the closeness of the day of the first attempt of a quiz to its due date. For example, if a quiz was due on a given date  $d$  and the day of the first attempt by the student was  $d1$ ,  $d1-d$  was considered as an indication of procrastination behavior. This attribute was termed the 'closeness to the due date'. Canvas logs the date and the start time of each attempt by the student labeled as 'started at'. The attribute 'started at' which is logged in Canvas

corresponding to the first submission of a quiz attempt was extracted to calculate the day of the first attempt.

**3.5.3.4 Number of attempts.** As noted above, students could attempt a quiz up to ten times to allow them to practice concepts until they felt confident in having mastered a concept. In the quiz-log data for each student, each submission associated with quizzes has a feature labeled ‘attempt’ which logs the ordinal number of the attempt. The variable ‘number of attempts’ was calculated as the highest number of attempts (maximum value among the logged number of attempts) a student makes for the given quiz under consideration.

**3.5.3.5 Spacing.** Students were free to choose how to space their attempts across time. The quizzes were open for a window of nine days and the students could distribute their attempts over a period of nine days or mass several attempts together. A score was assigned to the student depending on the number of days across which the attempts were distributed. For example, a student who spaced their practice across three different days would get a score of three, and a student who massed all their attempts in one day a score of one.

In addition to the five variables extracted from the quiz-log data, students’ scores in mid-term and final exams were also considered in the pilot study. Table 3.1 summarizes the variables identified in the pilot study and the details pertaining to the units of measurement of the variables.

**Table 3.1**

*Variables Identified in the Pilot Study*

| Variable            | Units of Measurement |
|---------------------|----------------------|
| Total time spent    | Seconds              |
| Page blur frequency | Count/seconds        |

---

|                           |              |
|---------------------------|--------------|
| Closeness to the due date | Days         |
| Number of attempts        | Count        |
| Spacing                   | Days         |
| Score in midterm exams    | Total points |
| Score in the final exam   | Total points |

---

### **3.5.4 NORMALIZATION OF VARIABLES**

The standard normal distribution model was used to convert all the variables of interest into z- scores (normal distributions of measures). The transformation was considered necessary to allow direct comparisons between different variables under consideration in the study. For example, the variables spacing and closeness to due date were measured in days, the number of attempts as count, the measure of off-task activity as frequency, and total time spent in seconds. The following formula was used to convert the raw scores into normalized scores,  $z = \frac{x - \mu}{\sigma}$ , where z is the calculated z-score, x the raw score value (for an individual),  $\mu$  the mean for the population, and  $\sigma$  the standard deviation of the variable for the population.

### **3.5.5 VALIDITY OF THE STUDY**

Two types of validity were considered in the pilot study - construct validity: a form of measurement validity and ecological validity: an aspect of external validity. The details are as follows.

**3.5.5.1 Construct validity.** The feature ‘page blurred’, logged in the Canvas quiz-log data when the web browser tab during the quizzing activity becomes inactive for a long duration, was used as a proxy measure of students’ off-task behavior. Since off-task behavior was not directly observed, the validity of this construct had to be established. For establishing the construct validity of using page blurs as a measure of off-task, the quiz-logs were collected from

69 students of the Computer Information Systems (CIS) classroom, Spring 2018 at CSU. The CIS course was the chosen setting since the two required test conditions (proctored and non-proctored quizzing) were in place in this class. The same group of students took tests in two conditions, one proctored and the other non-proctored. Page blur frequency, a variable related to students' off-task behavior in quiz-taking was calculated (following the procedure explained in 3.5.3.2). The two conditions (proctored and non-proctored) were compared to see if they differed significantly in page blur frequency. The proctored testing condition showed significantly lesser page blurs when compared to the non-proctored condition in the Wilcoxon Signed-ranks test ( $Z = -7.22, p < .01$ ).

**3.5.5.2 Ecological validity.** This study was conducted in a naturally occurring setting (MIP classroom), which was a less invasive way to explore students' quiz-taking behaviors. This increases the ecological validity of the study compared to a study conducted in an artificial setting like a laboratory. This is because the students are considered to be less self-conscious in a natural setting and hence may tend to use study strategies that they implement on a regular basis (Motz, Carvalho, De Leeuw, & Goldstone, 2018).

### **3.5.6 RESULTS FROM THE PILOT STUDY**

The pilot study examined if there was a relationship between the variables related to quiz-taking behaviors and course grades. Three variables identified from the quiz-log data, page blur frequency, total time and closeness to the due date, exhibited significant correlations with the exam scores. For Quiz 1, correlations between scores in Exam1 and page blur frequency was  $r(90) = -.51, p < .01$ ; scores in final exams and page blur frequency was  $r(90) = -.45, p < .01$ ; scores in Exam1 and closeness to the due date was  $r(90) = -.22, p < .005$ ; scores in final exams and closeness to the due date was  $r(90) = -.21, p < .005$ , scores in Exam1 and total time spent

was  $r(90) = -.40, p < .005$ ; scores in final exams and total time spent was  $r(90) = -.29, p < .005$ . For Quiz 2, correlations between scores in Exam 2 and page blur frequency was  $r(90) = -.30, p < .01$ ; scores in final exams and page blur frequency was  $r(90) = -.30, p < .01$ , scores in final exams and total time spent was  $r(90) = -.22, p < .01$ . For Quiz 3, correlations between scores in Exam 3 and page blur frequency was  $r(90) = -.33, p < .01$ ; scores in final exams and page blur frequency was  $r(90) = -.34, p < .01$ ; scores in Exam 3 and closeness to the due date was  $r(90) = -.35, p < .01$ ; scores in final exams and closeness to the due date was  $r(90) = -.40, p < .01$ .

### **3.6 DATA COLLECTION: PARTICIPANT RECRUITMENT, INTERVIEW GUIDE AND ANALYSIS**

The following sections describe the step-by-step data collection and analysis procedures for phases I, II, and III of the present study.

The inclusionary criteria for the participants in the qualitative phases (I and III) of the study were that they had to be instructors of MIP. Recruitment letters were emailed to all the instructors of MIP (see Appendix B). Signed consent to participate in the study was obtained from the instructors who responded to this (see Appendix C).

During the phases I and III, I conducted individual interviews with the four MIP instructors. I had associated with the instructors of MIP since the summer of 2016 when the project was first conceptualized, which allowed building rapport with them. The interview questions were derived from the research questions and were arranged by topic to follow logically from one topic to the other. An interview guide, which consisted of the broad questions in the questionnaire, was shared with the instructors four days prior to the day of the interview. This was to allow them to reflect on the questions in advance and form some initial thoughts. In-depth semi-structured interviews were conducted by means of open-ended questions. Each

interview was conducted over Skype and scheduled for one hour. The instructors were free to choose a location where they felt comfortable and safe to talk. At the end of the interview, the instructors were given an opportunity to add anything which they considered important but was not discussed during the interview. This allowed having a closure for the interview. Whenever additional information or further clarification from the participant was needed after the interviews, I followed up with emails.

The individual interviews with the four MIP instructors were audio recorded. Later I transcribed the interviews manually, without the help of a software. Transcription was the first step in the preliminary analysis of the data and the first opportunity to immerse in the data. I noted down initial ideas during the transcription phase by relistening to the recordings, reread the transcripts, and developed codes. Thematic analysis was considered suitable to analyze the data as it was more important to understand the verbal content of the interview rather than how the conversation unfolded (Riessman, 2008). The sequences of what participants had to say were not considered important for this study. The case-by-case coding process made use of both inductive and deductive methods. Deductive analysis is driven by the researcher's theoretical and analytical interests (Braun & Clarke, 2006). Therefore, in the deductive analysis phase, I closely followed the research questions in developing the codes. Followed by deductive analysis, I conducted a second round of inductive coding to focus on any unanticipated information the participants had provided. This round of coding was data-driven and did not relate to the specific research questions (Braun & Clarke, 2006). After both rounds of coding was completed, I looked for sub-themes and themes across the dataset. A case-by-case comparison was used to uncover patterns across interviews. I relied on "keyness" as the guideline to develop themes instead of depending on quantifiable measures. This implied that whenever participant interviews consisted

of an important piece of information that could answer the research questions, a theme was developed based on it. Internal homogeneity and external heterogeneity of the themes were considered to establish that the apparent patterns were indeed themes. Internal homogeneity requires that the data organized within each theme adhere together in a meaningful way. External heterogeneity demands clear and identifiable differences across individual themes.

### ***3.6.1 PHASE I: PRE-ANALYTICS INTERVIEWS WITH MIP INSTRUCTORS***

During phase I of the study, qualitative data were collected by conducting individual interviews with the four instructors of MIP. Phase I interviews were conducted before the analysis of quiz-logs from Canvas (phase II of the study). The purpose of the interviews was to understand the instructors' pedagogic intent in implementing low-stake unsupervised online quizzes, how the instructors had ideally wanted the students to behave with the quizzes, what information related to students' quiz-taking behaviors they had access to (prior to having access to the findings from phase II of the study) and any additional information they were seeking. This phase of the study explored the difficulties if any, the instructors faced in understanding the quiz-taking behaviors of students prior to having access to the findings from quiz-log analytics conducted in phase II of the study. The interview questions for phase one of the study (pre-analytics questionnaire) are listed in Appendix D.

### ***3.6.2 PHASE II: QUIZ-LOG DATA ANALYTICS TO IDENTIFY LEARNING BEHAVIORS***

In phase II of the study, data collection progressed according to procedures explained in the pilot study; i.e., the data (Canvas quiz-log files) collection and variable extraction required the replication of the pilot methods described in sections 3.5.1–3.5.4. The research design of the quantitative part, phase II, of the study was an associational (non-experimental, correlational) design. An associational design was considered appropriate for phase II because the purpose of

the study was to explore quiz-log data to identify variables related to students' quiz-taking behaviors. In addition, the study aimed to examine the relationship between the variables of interest and the performance of students in the subsequent exams. Later quiz-log data was analyzed to understand the patterns of students' quiz-taking behaviors with the low-stake unsupervised online quizzing. Since the manipulation of variables was not the scope of this study, an experimental design was not adopted (Fraenkel, Wallen, & Hyun, 2012). The study was conducted in the context of the MIP classroom, which is an important factor in interpreting the findings and building recommendations for pedagogical improvements (Motz et al., 2018).

In addition to the variables related to learning behaviors identified in the pilot study, two new variables, time spent per attempt and number of page blurs per attempt, were considered in the present study to get additional insight regarding students' quiz-taking behaviors over the multiple possible attempts.

### ***3.6.3 PHASE III: POST-ANALYTICS INTERVIEWS WITH MIP INSTRUCTORS***

In phase III of the study, the instructors of MIP were presented with the results from phase II of the study, which involved quantitative quiz-log analytics. Further, individual follow-up interviews with the four instructors of MIP were conducted to understand the instructors' perspectives related to the perceived usefulness and implications of the findings from phase II of the study. Implications of the findings from phase II, including the possibilities of providing meaningful feedback to students that can alter their unproductive quiz-taking behaviors and pedagogic considerations such as design and implementation of quizzes were investigated. The interview questions for phase III of the study (post-analytics questionnaire) are listed in Appendix E.

### 3.7 RESEARCH QUESTIONS AND DATA ANALYSIS METHODS

**RQ 1a:** *What was the pedagogic intent of the MIP instructors in implementing low-stake unsupervised online quizzing in their classes?*

**RQ 1b:** *What difficulties did the instructors face post-implementation of the quizzes?*

To answer RQ 1a and 1b, thematic analyses of interviews (Phase I pre-analytics) with the instructors of MIP was conducted.

**RQ 2a:** *Are there associations between the variables related to quiz-taking behaviors and the subsequent exam scores?*

**RQ 2b:** *Are there associations between the variables related to quiz-taking behaviors and the final exam scores?*

Non-parametric Spearman's Rho correlation coefficients were used to see if there is an association between the variables of interest, mid-term examination scores, and the final comprehensive examination scores.

**RQ 3:** *What common patterns of quiz-taking behaviors can be identified among students in the MIP course?*

To answer RQ 3, k-means clustering which is an unsupervised classification was performed since no *a priori* knowledge (samples of known classes) of the data set was available.

#### **Clustering**

Clustering was considered as an apt technique to answer RQ 3 since the most common categories within the data set were not known in advance. Clustering techniques have been used in LA studies for grouping similar students based on their interaction patterns (Vellido, Castro, & Nebot, 2010). For example, Amershi & Conati (2009) had used patterns in students' usage of exploratory learning environments to distinguish the effective and not so effective

study strategies students employ. Clustering techniques identify data points that naturally group together, dividing the whole data set into a set of clusters. Groups of instances that are similar are identified by using a distance measure like Euclidean distance. Each data point in a cluster is generally more similar to the other data points in the cluster than to data points belonging to neighboring clusters.

### **k-means Clustering Algorithm**

Studies suggest that the k-means clustering algorithm is intuitive to understand and efficient on large data sets (Amershi, 2007). Hence this algorithm is one among the best-suited ones for identifying patterns within large datasets that are logged in technology-enhanced platforms.

Clustering algorithms such as the k-means have no prior hypotheses about clusters in the data. The algorithm chooses random data points as cluster centroids, and all other instances are assigned to the cluster such that the Euclidean distance between the centroid of that cluster and the given instance is minimized. The centroid for a cluster is then recalculated as the means of the instances assigned to that cluster. This process repeats until the cluster centroids stabilize. In the k-means algorithm, each data point belongs to only one single cluster. The user must specify a value k. A value of three was used in this study as we hypothesized there could be three different groups of quiz-taking patterns when students engage with low-stake unsupervised online quizzes, namely highly productive behaviors, medium, and least productive behaviors.

**RQ 4a:** *Are there differences between the groups of students, identified based on their quiz-taking behaviors, in regard to the subsequent exam scores?*

**RQ 4b:** *Are there differences between the groups of students, identified based on their quiz-taking behaviors, in regard to the final exam scores?*

One-way ANOVA was used to answer RQ 4a and 4b. This was followed up with post hoc analysis as per the indications of the ANOVA results.

**RQ 5:** *According to the instructors of the MIP course, what is the perceived usefulness and implications of the results of the quiz-log analytics for future pedagogic considerations?*

To answer RQ 5, thematic analyses of interviews (Phase III post-analytics) with instructors of MIP was conducted.

### **3.8 ETHICAL CONSIDERATION**

The present study complied with the ethical principles of LA at CSU (*Ethical Principles of Learning Analytics at Colorado State University*, 2017). Specifically, the following principles were cardinal in the design of Phase II of the study.

1. *LA will serve the teaching and learning mission of CSU, which implies that the analytics used in the study will serve to enhance the instructor-student interaction, placing an emphasis on enhancing individual student learning opportunities and student success.* We anticipate the results of the study will initiate a conversation between the instructors and students, wherein instructors provide meaningful formative feedback that encourages learners to metacognitively monitor their learning and potentially change their behaviors to improve their ability to retain the learned information.

2. *LA data will be collected and maintained to understand specific pedagogical questions, which implies that data will be collected based on predetermined pedagogical reasons, used for the purposes of enhancing learning and teaching, and deleted after the specific use.* In the current study, the broad research questions were to identify whether the quiz-taking behaviors of the students were aligned with the pedagogical intent of the quizzing implemented in the MIP course and to determine

whether there was a relationship between students' behaviors and exam performance. Data collection and analyses attempted to answer the preidentified questions.

3. *LA data usage arises from respect for the individual, which implies the use of data in ways that will help all students and faculty pursue excellence in learning and teaching respectively.* In the current study, data analytics was not conducted with the purpose of identifying the 'at-risk' students. We anticipate that all students may equally benefit from the results of the study and be encouraged to use the quizzes effectively as a pedagogic tool to improve their learning. Similarly, the results of the study would allow the instructors to reflect on the design and implementation of quizzing to encourage productive learning behaviors among students.

Approval for the research protocol was obtained from the Institutional Review Board (IRB) at CSU. The data collected from Canvas resided in a machine in the C-ALT office and as password-protected copies in the researchers' computers ensuring the confidentiality of all student participants. Identifying information including the CSU ID and name was not accessed or linked to the quiz-taking behaviors of an individual student. Canvas creates an alternate ID, labeled the 'Canvas ID', for all students corresponding to their CSU ID. Quiz-taking behaviors extracted from the quiz-logs were matched only to the proxy identifier 'Canvas ID' and never to a student's CSU ID. Therefore, while discerning patterns of quiz-taking behaviors or reporting the results of the analysis, an individual student remained unidentified (by the researchers as well as the instructors) at any period of the study. Hence, it was unlikely for any bias to have caused a potential threat to the grades awarded to the students. Similarly, the instructors' identities were not shared while reporting the interview data. Confidentiality of both instructors and students were protected by deidentifying any personal data.

## CHAPTER 4: FINDINGS

The results of the three-phase sequential mixed-methods study are presented in this chapter. The findings are presented in three sections. The results from Phase I of the study, pre-analytics interviews with the MIP instructors, are presented in Section 4.1. The purpose of this phase of the study was to explore the pedagogic intent of the low-stake unsupervised online quizzes implemented in the MIP course and the difficulties the instructors faced in understanding students' behaviors. Section 4.2 discusses the results of Phase II, Canvas quiz-log analytics. Phase II of the study was conducted to identify students' actual quiz-taking behaviors from the Canvas quiz-logs and to examine the relationships between behaviors and exam scores. The results of Phase III of the study, post-analytics interviews with the MIP instructors, are presented in section 4.3. The purpose of Phase III of the study was to explore the MIP instructors' perspectives regarding the usefulness and implications of the findings from Phase II of the study.

### 4.1 PHASE I: PRE-ANALYTICS INTERVIEWS WITH THE MIP INSTRUCTORS

At the end of Phase I of the study, which was conducted to answer RQ 1a and 1b thematic analysis of the pre-analytics interviews was performed. The research questions, which guided the inquiry during the coding process and the themes and sub-themes that emerged during data analyses are discussed below.

**RQ 1a:** *What was the pedagogic intent of the instructors in implementing the low-stake unsupervised online quizzing in the MIP course?*

Two main themes were identified during the data analysis related to RQ 1a. The instructors had implemented the low-stake unsupervised online quizzes in the MIP course for two reasons, namely to encourage students to take advantage of the benefits of testing and to

obtain feedback from students about their learning, quiz-taking behaviors, and content and design of the quizzes. The identified themes and sub-themes are summarized in Table 4.1 and discussed in sections 4.1.1-4.1.2.

**Table 4.1**

*The Pedagogic Intent of the Instructors in Implementing Low-Stake Unsupervised Online Quizzing in the MIP Course*

| Main Themes  | Sub-themes  |
|--|---|
| To encourage students to take advantage of the benefits of testing | <ul style="list-style-type: none"> <li>Repeated practice ahead of exams</li> <li>Recognize gaps in knowledge</li> <li>Application of knowledge</li> <li>Active retrieval of concepts</li> <li>Spaced retrieval of concepts</li> </ul> |
| To obtain feedback from students                                   | <ul style="list-style-type: none"> <li>Feedback on students' learning and quiz-taking behaviors</li> <li>Feedback on the content and design of quizzes</li> </ul>   |

**4.1.1 THEME 1: To Encourage Students to Take Advantage of the Benefits of Testing**

The instructors had implemented low-stake unsupervised online quizzing in MIP so that students could take advantage of the benefits of testing. According to the instructors, the benefits of frequent testing included an opportunity to repeatedly practice concepts well ahead of exams, recognize gaps in knowledge, apply knowledge and engage in effective learning strategies such as active and spaced retrieval of information. The instructors expected that students would use the quizzes as a formative assessment tool to aid learning rather than a form of summative

assessment, which only evaluates their current knowledge. The related sub-themes which emerged are discussed in section 4.1.1.1-4.1.1.5.

**4.1.1.1 REPEATED PRACTICE AHEAD OF EXAMS.** According to the instructors, they implemented the quizzes in the MIP classes to encourage students to study in advance and be prepared for the summative exams which followed the quizzes. All instructors believed that the quizzes gave students an opportunity to practice materials before the subsequent exams. They believed that repeated self-testing would allow students to assess their understanding and get acclimatized to questions similar to what would appear on the following exams. The opportunity to practice content in advance would allow students to be confident to face the exams. The quizzes were low-stakes contributing to only a small proportion of the final grades. The highest grade among the ten possible attempts was recorded, which would allow students to test themselves multiple times and achieve mastery of the topic without a fear of their final grades being affected. Quotes from interviews with the MIP instructors are presented below as evidence to support this sub-theme.

The quizzes would help students practice answering the kind of questions they could expect on the following exams so that they aren't so surprised (during the following exams). I believe that this might give them more confidence in answering the questions we ask (in exams).

The quizzes are not only for students to secure extra points. It is also to encourage them to practice content before the exam. Quizzes are low-stake contributing to less than ten percent of the total grade. The highest grade among all attempts is recorded. So, in the greater scheme of things, students' grades in exams are not going to change much if their grades for one or two attempts are low.

**4.1.1.2 RECOGNIZE GAPS IN KNOWLEDGE.** The instructors regarded the quizzes as an opportunity for students to recognize gaps in their knowledge. They believed that frequent testing would allow students to assess whether they knew a topic well or struggled with it. Self-recognition of weak areas would encourage students to engage in further study sessions in an

attempt to master these topics. An accurate assessment of their current learning might allow students to learn better in the following study sessions and focus more on weak topics. The following quotes illustrate the views of the MIP instructors in this regard.

The students have several attempts (for a single quiz), so they can take the quiz once and if they don't do well in a quiz, we hope they recognize that they have perhaps not understood the material well enough. We would like them to go back to the material, try to study a little bit better. Self-testing helps students identify by themselves the content they might not have understood well.

Some (students) complain that the quizzes are hard, which is okay. I tell them now you are prepared for the exam because you can see what (questions) you missed and what (topics) you are struggling with. There are multiple tries (for a quiz). I would really hope that they take the first try and maybe see they didn't do quite well or realize there is a particular area that they are struggling more with and then they go back, study, and attempt the quizzes again.

**4.1.1.3 APPLICATION OF KNOWLEDGE.** The instructors said that the quizzes consisted of in-depth application-level questions rather than questions that tested students only on a superficial or factual understanding of the material. Application-level questions ensured that students had to think and apply knowledge to get the answers right. According to the instructors, testing students on application-level questions would allow them to demonstrate that they had understood a concept and were not merely recalling blindly memorized facts. The questions in each attempt of a quiz were distributed randomly from a question bank. As evident from the conversations with the instructors cited below, the design of quizzes would ensure that students got a different set of questions during each attempt. Subsequently, this design would make rote memorization of answers or gaming of quizzes (randomly selecting an answer from the available multiple choices) or cheating (e.g., saving screenshots of questions) impossible to some extent.

We don't want students to know things just without any rationale, we want them to grasp the concept, and actually be able to use it, apply knowledge instead of just memorizing the facts. The quizzes are not just testing the student's (factual) knowledge. Students will have to think before they answer each question.

The quizzes are set up on Canvas in such a way that with each try students get a set of different questions that are randomly chosen from a big pool of questions. So, chances are that they probably do not get the same question again (in a new attempt). They actually have to use their knowledge rather than just get lucky or memorize the correct answer.

**4.1.1.4 ACTIVE RETRIEVAL OF CONCEPTS.** The instructors believed that when students actively recall information by self-testing, they learn better than in a passive lecture-based class, which is followed only by summative exams. They stated that their beliefs were based on evidence from education and cognitive psychology research, which supports the claim that active retrieval enables students to retain more information in the long-term when compared to lesser effective strategies such as rereading the material. All instructors said that they had clearly instructed the students to close their notebooks before attempting the quizzes, to attempt the quizzes by themselves, and not to use external help of any form including online resources or help from other students. The following instances highlight the importance of active retrieval from the instructors' viewpoint.

We tell the students to put away their class notes before attempting the quizzes and not to get any other help, say, from other students or online. We want them to attempt the quizzes without looking up the answers. We see in papers (research publications) that trying to actively recollect information is the best way to learn.

Studying to quiz yourself and later taking the quiz without any help is shown to be a much more beneficial study technique than certain other techniques, such as rereading your notes. A lot of research backs this up as well.

**4.1.1.5 SPACED RETRIEVAL OF CONCEPTS.** The instructors said that they wanted students to space their practice over the period the quizzes remained open rather than mass all the attempts together. The instructors were conversant with education research which advocates that distributing the study sessions into multiple sessions, known as the 'spacing effect', is a more advantageous study strategy than massing all the attempts together. Each quiz was open and available to the students for a period of nine days. Instructors believed that the design of quizzes

with an imposed deadline would encourage students to prepare in advance for the following summative exam and avoid intense study for a short period just before the exam. The instructors were aware that although spaced practice was more beneficial to long-term retention, many students might not engage in this. In certain cases, contrary to the expectations, students who engage in last-minute studies might do just as well in exams as those who distribute their practice. The following statements represent the instructors' views in regard to this sub-theme.

I tell my students to spread out their attempts and not to do it all at the last minute. I tell them there is evidence from education research that shows studying for short periods of time, giving yourselves a break in between, is the most beneficial (learning strategy) for long-term memory. The quizzes are not busywork or a means to secure extra points. The design is to encourage them to study. The deadlines are to keep them honest too because the average undergrad tends to cram the night before the exam.

We know that spacing is better (when compared to learning strategies such as massing the study sessions). The quizzes were implemented so that students would space out their practice. You have some students who attempt the quizzes the way you want them to and then you have some who do it the last minute. I know that some students cram everything right before an exam. But they actually do well (in exams).

#### **4.1.2 THEME 2: TO OBTAIN FEEDBACK FROM STUDENTS**

The instructors viewed the quizzes as a possibility to obtain valuable feedback from students.

The instructors were keen on receiving and incorporating feedback from students as the quizzes were a student-centric learning activity. Instructors believed that the quizzes were primarily to encourage learning among students. This implied that students were the principal agents actively involved in the learning activity and hence were closer to the learning activity than the instructors. The feedback obtained from students could be related to their learning and quiz-taking behaviors or the content and design of quizzes. These sub-themes are discussed in sections 4.1.2.1 and 4.1.2.2.

**4.1.2.1 Feedback on students' learning and quiz-taking behaviors.** The instructors used the quizzes as an opportunity to obtain feedback on whether students exhibited an

understanding of the topics covered in class. The following quotes demonstrate that the MIP instructors viewed students' performance in the quizzes as a measure of their learning. It was also an indirect indication of whether students had engaged in self-study sessions prior to testing themselves.

The students' performance in the quizzes helps us understand whether they have understood the material that we taught in class. Students can go through additional study materials or lectures provided at home. Therefore, their performance in the quizzes demonstrates whether they have gone through the study materials and have mastered the content.

Quizzes force the students to actually open their books (in preparation for the quizzes). We ask them questions that pertain directly to the materials covered in the classroom. Unless they come to the class and listen to the lectures, or watch the materials provided at home they won't be able to perform well in the quizzes.

When the online quizzes were implemented in MIP, the instructors had anticipated gaining insights into students' actual quiz-taking behaviors. The instructors were interested in understanding the maximum number of attempts a student made, the duration of each attempt, and whether the students engaged in productive quiz-taking behaviors such as active and spaced retrieval of information. The following excerpts from conversations with the instructors are illustrative of this.

How are the students taking the quizzes? Are they massing or spacing the attempts? Are they taking the quizzes the maximum number of times possible? Are they looking up (the answers)? Do they use their notes while taking the quizzes? Do they take a neighbor's help? How many attempts do they take in one sitting? How much time do they spend before they give up?

I would like to know if the students are taking the quizzes without looking at their phones or finding material elsewhere like an open book. Sometimes students have so many distractions (while taking a quiz) that I do not know how they can think or concentrate.

Despite the instructors' desire to understand several aspects of students' actual quiz-taking behaviors, due to certain inherent limitations of unsupervised quizzing implemented on an LMS,

they were not able to achieve this. Some of the reasons which limited their understanding of students' actual behaviors are described in detail later (see section 4.1.3).

**4.1.2.2 Feedback on the content and design of quizzes.** The instructors said that they viewed quizzes as an opportunity to get feedback from students about the effectiveness of the content and design of quizzes. As evident from the following quote, the instructors were open to making modifications in the quiz content as well as design by incorporating the feedback from the students.

We get students' feedback on quizzes; we do take this feedback into consideration and incorporate their critiques and modify (the content and design of quizzes). We ask the students whether the quizzes as a learning activity helped them understand a topic and what could get better. For example, they let us know whether the quizzes helped them master a concept or not. Students get motivated and really intrigued by the design (of quizzes) and talk to us about how it could improve.

Regarding the design of the quizzes, many students reported that they found various aspects of the quiz design such as multiple attempts and an opportunity to attempt the quizzes at their choice of time and location to be convenient. However, a few students had wanted the quizzes to be open always, which would allow them to practice the quizzes throughout the semester. On the other hand, the instructors considered the deadlines necessary for the students to start preparing in advance for their exams. According to the instructors, the students had to be self-regulated to attempt the quizzes without missing the deadlines. The following quote represents the instructors' viewpoints with respect to the imposed deadlines.

We don't give students all the time in the world to do the quizzes (since there are due dates for each quiz). Some students tell me that they want the quizzes to be open always which will allow them to practice the quizzes anytime. Students have to be extremely organized with their time to successfully engage with the quizzes. They don't have to be always the good students (who score maximum in exams). The ones who are extremely organized tend not to miss the deadlines.

**RQ 1b:** *What difficulties did the instructors face post-implementation of the quizzes?*

Thematic analysis of interviews with the instructors revealed a single main theme related to RQ 1b: the instructors' limited understanding of students' quiz-taking behaviors. Three sub-themes were identified related to the main theme. The identified theme and sub-themes are summarized in Table 4.2 and explored in detail in section 4.1.3.

**Table 4.2**

*Difficulties Faced by the MIP Instructors Post-Implementation of the Quizzes*

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| Main Theme   | Sub-themes  |
|--|---|
| Limited understanding of students' quiz-taking behaviors | Limitations in the usefulness of student-feedback<br>Limitations in the available Canvas reports or limited know-how of using the available Canvas features<br>Large class size |

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**4.1.3 THEME1: LIMITED UNDERSTANDING OF STUDENTS' QUIZ-TAKING BEHAVIORS**

The instructors said that they had limited understanding of the actual quiz-taking behaviors of students. One of the instructors said that they assumed that the students could be taking all possible attempts of the quizzes very close to the deadline instead of distributing the attempts. They suspected that the students could be using their notes or other materials while taking the quizzes. However, they added many of their claims were mere speculations, not backed by evidence. Another instructor who shared similar opinions said that their views were

formed based on their experience as an undergraduate student. According to the instructors three main reasons contributed to their limited understanding of students' quiz-taking behaviors. These were the limitations in the usefulness of feedback obtained from students, limitations in the available Canvas reports, or limited knowledge of using the available Canvas features, and large class sizes (see 4.1.3.1-4.1.3.3).

**4.1.3.1 Limitations in the usefulness of feedback from students.** The instructors said that they had had conversations with students about their quiz-taking behaviors and considered students' self-reports trustworthy. This was because students' grades were not dependent on the effectiveness of their quiz-taking strategies. For example, a few students had admitted that they engaged in ineffective strategies such as massing of all the possible attempts on the deadline.

Students had shared with the instructors that the quizzes were beneficial in testing themselves on a small amount of material, which allowed them to verify that they were doing well up to a particular checkpoint. While most students considered the quizzes to be useful, a few had complained that the quizzes were busywork and got increasingly difficult as the semester progressed. Despite having conversations with students about the quizzes, the instructors did not always consider the student-feedback valuable in obtaining an understanding of quiz-taking behaviors. The instructors pointed out two reasons for this. First, the students' focus was mainly on scoring the maximum points possible in the quizzes rather than practicing effective study strategies. Students used the quizzes to evaluate their performance and approached the instructors mainly when they had answered questions incorrectly. The following quotes from conversations with the instructors indicate that the students were more interested in understanding the correctness of the solution than practicing or developing effective quiz-taking behaviors.

Students approach me during office hours when they are not performing well (in the quizzes). They are more concerned with their score rather than how the quiz-taking process helps them with their learning. They are obsessed with scoring the maximum number of points in the quizzes. They will do whatever it takes them to get the maximum score.

When students see that some of their answers were incorrect and they can't get it right over the multiple possible attempts they approach me during the office hours, frustrated. We work through the questions they got wrong and I help them figure out the correct answer. I tell them the idea was that they had to first study the material, close their notes, and then take the quiz. I've had only a few students who realize this is the best way of taking the quizzes.

Second, according to the instructors, conversations with students were often too late in letting them know about the poor time management and self-regulation at students' end. By the time instructors got insights into the ineffective quiz-taking behaviors, often poor grades from exams would have been recorded. The following quote suggests that the instructors lacked real-time information about students' quiz-taking behaviors.

Students come back to me and say that they just realized the due date for the quizzes were over. They ask if I could open it again for them. From conversations with the students I've learned that towards the end of the semester, they do realize that it is better to attempt the quizzes early on.

**4.1.3.2 Limitations in the available Canvas reports or limited know-how about the available Canvas features.** Two of the MIP instructors said that they had not used any available options on Canvas to understand students' quiz-taking behaviors with respect to the implemented learning design. This was because they lacked the technical know-how to use the available Canvas features. The instructors felt that spending time to figure out details about the available features would substantially increase their workload. The two other instructors who had used the available Canvas features did not consider it to be very useful in the existing form. For example, the design of quizzes in the MIP course was meant to engage students in effective quiz-taking behaviors such as spaced and repeated practice. Hence it was important to understand whether

the students had distributed the multiple possible attempts over the period when the quizzes remained open. However, the existing version of Canvas provided no options to explore the patterns in the distribution of students' attempts. All instructors confirmed that they lacked the technical skills to access and manipulate the Canvas quiz-log data. The following examples represent the instructors' views.

I do not have enough time to figure out by myself the available features in Canvas. Canvas offers workshops to instructors. But I feel that Canvas features are always changing. During a regular busy semester, I'm not sure about dedicating a lot of time to learn the everchanging details.

The kind of information that I'm looking for is related to students' behaviors with the quizzes: Are they massing or spreading the attempts? Are they taking it as many times as they can? Are they looking up answers, say, from other websites? (From) the current way Canvas is set up, I don't think I can get enough useful data to help my students.

**4.1.3.3 Large class size.** Most of the MIP classes had large student enrolment of more than a hundred students. Instructors viewed large class sizes as a hindrance to understanding students' quiz-taking behaviors. According to the instructors, the tedious and time-consuming process involved in deciphering students' behaviors would increase their workload considerably in large classes. Two of the instructors had used the available Canvas features to understand students' behaviors such as the number of attempts and the duration of attempts. The quotes from the interviews with the MIP instructors prove that despite possessing an understanding of the available Canvas features, they hesitated to invest a lot of time in deciphering and keeping track of every student's quiz-taking behaviors.

I would like to know the actual quiz-taking behaviors of my students. However, I have over a hundred students in my class. So, it does make it a little difficult to go into Canvas and see what each student is doing.

If I'm really patient and click through every student's details, I could tell using the available Canvas features how many attempts each student has made and the duration of each attempt. Since I have over a hundred students in my class, I have never done that.

#### 4.2 PHASE II: CANVAS QUIZ-LOG ANALYTICS

Phase II of the study was conducted to explore the actual quiz-taking strategies of the students in MIP to understand whether their behaviors were in accordance with the instructors' pedagogic intent of the implemented learning design. This phase also explored the relationships between quiz-taking behaviors and exam scores.

Seven variables were extracted from Canvas quiz logs, which were related to the quiz-taking behaviors of students. The variables were total time spent, page blur frequency, closeness to the due date, number of attempts, spacing, page blurs per attempt, and time per attempt. For Quiz 1 ( $N = 276$ ) and Quiz 2 ( $N = 278$ ), the descriptive statistics including the maximum, minimum, and median were calculated for all the seven variables identified from the Canvas quiz-logs. The details can be found in Table 4.3. For Quiz 1, the following variables were non-normally distributed: closeness to the due date, with skewness 2.02 ( $SE = .15$ ); page blurs, with skewness 3.28 ( $SE = .15$ ); spacing, with skewness 1.52 ( $SE = .15$ ) and total time, with skewness 1.48 ( $SE = .15$ ). For Quiz 2, the following variables were non-normally distributed: closeness to the due date, with skewness 2.22 ( $SE = .15$ ); page blurs, with skewness 2.07 ( $SE = .15$ ); spacing, with skewness 1.96 ( $SE = .15$ ); total time, with skewness 1.09 ( $SE = .15$ ) and blur per attempt, with skewness 1.88 ( $SE = .15$ ). The frequency distribution of students was calculated for three variables that could be meaningfully divided into bins. These variables were the closeness to the due date, spacing, and the number of attempts. The comparisons of frequency distributions, percentages, and cumulative percentages for the variable closeness to the due date between Quiz 1 and Quiz 2 are summarized in Table 4.4. Similar details for the variables spacing

and number of attempts can be found in Table 4.5 and Table 4.6 respectively. As evident from Table 4.4, around 62% of the students had attempted Quiz 1 and Quiz 2 on the day of the deadline. Around 94% of the students for Quiz 1 and 93% of the students for Quiz 2 had started the quizzes three days or lesser ahead of the deadline. Table 4.5 shows that around 67% of the students for Quiz 1 and around 69% of students for Quiz 2 had massed their practice in a single day. Around 99% of the students for both Quiz 1 and Quiz 2 had distributed their attempts in three days or lesser. The majority of the students had attempted the quizzes three to four times. Around 11% of the students (Quiz 1) and 16% of the students (Quiz 2) had attempted the quizzes the maximum possible times (i.e., nine attempts) (see Table 4.6).

**Table 4.3***Descriptives of the Quiz-Taking Behaviors Identified from Canvas Quiz-Logs: Quiz 1 and Quiz 2*

| Variables Related to Quiz-Taking Behaviors | Minimum Quiz 1 | Maximum Quiz 1 | Mean Quiz 1 | Median Quiz 1 | Minimum Quiz 2 | Maximum Quiz 2 | Mean Quiz 2 | Median Quiz 2 |
|--|----------------|----------------|-------------|---------------|----------------|----------------|-------------|---------------|
| Total time                                 | 320            | 12961          | 3462.74     | 2999          | 390            | 15109          | 4370.60     | 3917.50       |
| Page blurs                                 | 0              | 439            | 42.83       | 28            | 0              | 444            | 66.51       | 45.50         |
| Closeness to the due date                  | 0              | 7              | .80         | 0             | 0              | 9              | .87         | 0             |
| Spacing                                    | 1              | 4              | 1.39        | 1             | 1              | 5              | 1.36        | 1             |
| Number of attempts                         | 1              | 9              | 4.45        | 4             | 1              | 9              | 4.88        | 5             |
| Time per attempt                           | 229            | 1800           | 859.54      | 784           | 223            | 2382           | 946.57      | 903           |

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|                           |   |    |       |   |   |    |       |    |
|---------------------------|---|----|-------|---|---|----|-------|----|
| Page blurs<br>per attempt | 0 | 69 | 10.08 | 7 | 0 | 49 | 12.94 | 11 |
|---------------------------|---|----|-------|---|---|----|-------|----|

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**Table 4.4**

*A Comparison of Frequency, Percentage and Cumulative Percentage of Closeness to the Due Date Between Quiz 1 and Quiz 2*

| Closeness to the Due Date | Frequency Quiz 1 | Percent Quiz 1 | Cumulative Percent Quiz 1 | Frequency Quiz 2 | Percent Quiz 2 | Cumulative Percent Quiz 2 |
|---------------------------|------------------|----------------|---------------------------|------------------|----------------|---------------------------|
| 0                         | 171              | 62.0           | 62.0                      | 171              | 61.5           | 61.5                      |
| 1                         | 47               | 17.0           | 79.0                      | 45               | 16.2           | 77.7                      |
| 2                         | 28               | 10.1           | 89.1                      | 29               | 10.4           | 88.1                      |
| 3                         | 14               | 5.1            | 94.2                      | 14               | 5.0            | 93.2                      |
| 4                         | 9                | 3.3            | 97.5                      | 6                | 2.2            | 95.3                      |
| 5                         | 3                | 1.1            | 98.6                      | 10               | 3.6            | 98.9                      |
| 6                         | 3                | 1.1            | 99.6                      | 2                | .7             | 99.6                      |
| 7                         | 1                | .4             | 100.0                     | 1                | .4             | 100.0                     |
| Total                     | 276              | 100.0          |                           | 278              | 100.0          |                           |

**Table 4.5**

*A Comparison of Frequency, Percentage and Cumulative Percentage of Spacing Between Quiz 1 and Quiz 2*

| Spacing | Frequency<br>Quiz 1 | Percent<br>Quiz 1 | Cumulative<br>Percent<br>Quiz 1 | Frequency<br>Quiz 2 | Percent<br>Quiz 2 | Cumulative<br>Percent<br>Quiz 2 |
|---------|---------------------|-------------------|---------------------------------|---------------------|-------------------|---------------------------------|
| 1       | 186                 | 67.4              | 67.4                            | 191                 | 68.7              | 68.7                            |
| 2       | 73                  | 26.4              | 93.8                            | 77                  | 27.7              | 96.4                            |
| 3       | 15                  | 5.4               | 99.3                            | 8                   | 2.9               | 99.3                            |
| 4       | 2                   | .7                | 100.0                           | 1                   | .4                | 99.6                            |
| 5       | -                   | -                 |                                 | 1                   | .4                | 100.0                           |
| Total   | 276                 | 100.0             |                                 | 278                 | 100.0             |                                 |

**Table 4.6**

*A Comparison of Frequency, Percentage and Cumulative Percentage of Number of Attempts Between Quiz 1 and Quiz 2*

| Number<br>of<br>Attempts | Frequency<br>Quiz 1 | Percent<br>Quiz 1 | Cumulative<br>Percent<br>Quiz 1 | Frequency<br>Quiz 2 | Percent<br>Quiz 2 | Cumulative<br>Percent<br>Quiz 2 |
|--------------------------|---------------------|-------------------|---------------------------------|---------------------|-------------------|---------------------------------|
| 1                        | 27                  | 9.8               | 9.8                             | 24                  | 8.6               | 8.6                             |
| 2                        | 42                  | 15.2              | 25.0                            | 35                  | 12.6              | 21.2                            |
| 3                        | 47                  | 17.0              | 42.0                            | 38                  | 13.7              | 34.9                            |
| 4                        | 45                  | 16.3              | 58.3                            | 38                  | 13.7              | 48.6                            |
| 5                        | 29                  | 10.5              | 68.8                            | 36                  | 12.9              | 61.5                            |
| 6                        | 24                  | 8.7               | 77.5                            | 33                  | 11.9              | 73.4                            |

|       |     |       |       |     |       |       |
|-------|-----|-------|-------|-----|-------|-------|
| 7     | 18  | 6.5   | 84.1  | 18  | 6.5   | 79.9  |
| 8     | 14  | 5.1   | 89.1  | 12  | 4.3   | 84.2  |
| 9     | 30  | 10.9  | 100.0 | 44  | 15.8  | 100.0 |
| Total | 276 | 100.0 |       | 278 | 100.0 |       |

**RQ 2a:** *Are there associations between the variables related to quiz-taking behaviors and the subsequent exam scores?*

**Correlations: Exam 1 Scores and Variables Related to Quiz-Taking Behaviors for Quiz 1**

Four of the variables related to quiz-taking behaviors identified from the log data for Quiz 1, namely page blur frequency, total time spent, blur per attempt, and time per attempt showed significant negative correlations with the scores in Exam 1. Correlations between scores in Exam 1 and page blur frequency was  $r(276) = -.32, p < .01$ ; scores in Exam 1 and total time spent was  $r(276) = -.21, p < .01$ ; scores in Exam 1 and blur per attempt was  $r(276) = -.30, p < .01$ ; scores in Exam 1 and time per attempt was  $r(276) = -.22, p < .01$ .

**Correlations: Exam 2 Scores and Variables Related to Quiz-Taking Behaviors for Quiz 2**

The correlations between Quiz 2 scores and identified variables related to quiz-taking behaviors were similar to that of correlations between Quiz 1 and the identified variables. Four of the variables identified from the log data for Quiz 2, namely page blur frequency, total time spent, blur per attempt, and time per attempt showed significant negative correlations with the scores in Exam 2. Correlations between scores in Exam 2 and page blur frequency was  $r(278) = -.27, p < .01$ ; scores in Exam 2 and total time spent was  $r(278) = -.13, p = .029$ ; scores in Exam 2

and blur per attempt was  $r(278) = -.36, p < .01$ ; scores in Exam 2 and time per attempt was  $r(278) = -.26, p < .01$ .

**RQ 2b:** *Are there associations between the variables related to quiz-taking behaviors and the final exam scores?*

**Correlations: Final Exam Scores and Variables Related to Quiz-Taking Behaviors for Quiz 1**

Four variables related to the quiz-taking behaviors identified from the log data for Quiz 1, namely page blur frequency, total time spent, blur per attempt, and time per attempt showed significant negative correlations with the scores in final exams. Correlations between scores in final exam and page blur frequency was  $r(276) = -.25, p < .01$ ; scores in final exam and total time spent was  $r(276) = -.17, p < .01$ ; scores in final exam and blur per attempt was  $r(276) = -.25, p < .01$ ; scores in final exam and time per attempt was  $r(276) = -.20, p < .01$ .

**Correlations: Final Exam Scores and Variables Related to Quiz-Taking Behaviors for Quiz 2**

Four variables related to the quiz-taking behaviors identified from the log data for Quiz 2, namely closeness to the due date, page blur frequency, blur per attempt, and time per attempt showed significant negative correlations with the scores in final exams. Correlations between scores in final exam and closeness to the due date was  $r(278) = -.18, p < .05$ ; scores in final exam and page blur frequency was  $r(278) = -.21, p < .01$ ; scores in final exam and blur per attempt was  $r(278) = -.32, p < .01$ ; scores in final exam and time per attempt was  $r(278) = -.30, p < .01$ .

**RQ 3:** *What common patterns of quiz-taking behaviors can be identified among students in the MIP course?*

## Quiz 1

A total of 276 students who attempted Quiz 1 were grouped into three by means of k-means clustering, based on the variables identified related to the quiz-taking behaviors. A value of  $k = 3$  was used as we hypothesized there could be three groups of students: a group of students who exhibit highly effective quiz-taking behaviors, a group that exhibits moderately productive behaviors, and another which exhibits the least productive behaviors. Cluster 1 had a total of 64 students, Cluster 2 had 139 students, and Cluster 3 had 73 students. The mean values were calculated for the seven variables related to quiz-taking behaviors, Exam 1, and Final Exams of the students in each group (see Table 4.7). A high mean value for the variables spacing and closeness to the due date, and a low mean value for the variables page blurs and blur per attempt were considered to be productive behaviors since these indicated that the students had distributed the attempt of quizzes, started the quizzes early on and engaged in less off-task behaviors. The variables total time, time per attempt, and the number of attempts were interpreted more cautiously as high values of these variables would not always translate to high performance unless the students had made all the attempts conscientiously. Cluster 1 had the highest mean values for spacing and closeness to the due date but also had the second-highest mean value for page blurs. Cluster 2 had lower mean values for spacing and closeness to the due date when compared to Cluster 1 and the lowest mean value for page blurs. Cluster 3 appeared to exhibit the most ineffective quiz-taking behaviors as they had the highest mean values for page blurs, time per attempt and blur per attempt and the lowest value for mean spacing, and closeness to the due date. This group of students had scored the lowest points for the online Quiz 1, and the following Exam 1 and the Final Exam. A comparison of the normalized exam scores for both

Exam 1 and the Final Exam of the three groups of students are summarized in Figures 4.1a and 4.1b respectively.

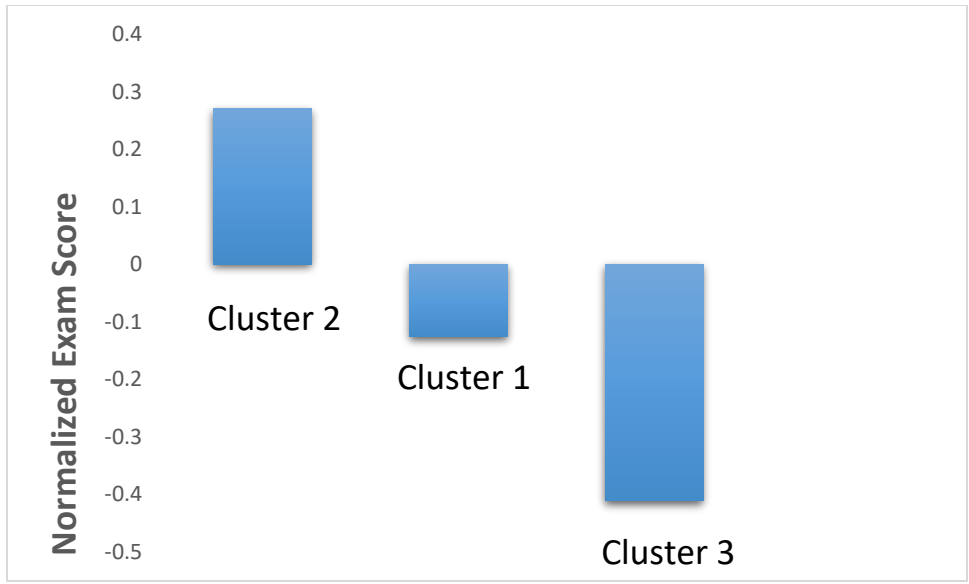
## **Quiz 2**

A total of 278 students who attempted Quiz 2 were grouped into three by means of k-means ( $k = 3$ ) clustering. 39 students belonged to Cluster 1, 150 students to Cluster 2, and 89 students to Cluster 3. The mean values were calculated for the seven variables related to quiz-taking behaviors, Exam 2, and Final Exams of the students (see Table 4.8). Cluster 1 had the highest mean values for spacing and closeness to the due date but also had the second-highest mean value for page blurs. Cluster 2 had lower mean values for spacing and closeness to the due date when compared to Cluster 1 and also the lowest mean value for page blurs. Cluster 3 appeared to exhibit the most ineffective quiz-taking behaviors as they had the highest mean values for page blurs, time per attempt and blur per attempt and the lowest value for mean spacing, and closeness to the due date. This group of students had scored the lowest points for online Quiz 2, and the following Exam 2 and the Final Exam. A comparison of the normalized exam scores for both Exam 2 and the Final Exam of the three groups of students are summarized in Figures 4.2a and 4.2b respectively.

**Table 4.7**

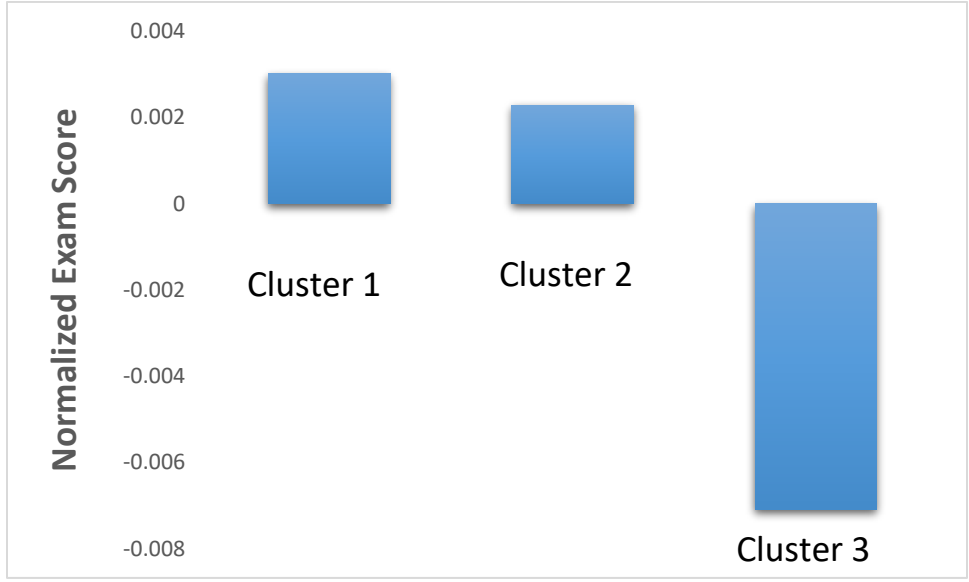
*Mean Values of the Variables Related to Quiz-Taking Behaviors for Quiz 1 and Exam Scores for the Three Identified Groups of Students*

| Cluster   | Spacing | Page Blurs | Closeness to the Due Date | Total Time | Number of Attempts | Time per Attempt | Blur per Attempt | Quiz 1 Score | Exam 1 Score | Final Exam Score |
|-----------|---------|------------|---------------------------|------------|--------------------|------------------|------------------|--------------|--------------|------------------|
| Cluster 1 | 2.2     | 55.81      | 2.3                       | 4693.48    | 6.56               | 717.19           | 8.03             | 9.61         | 79.95        | 74.97            |
| Cluster 2 | 1.15    | 19.29      | .44                       | 2970.67    | 4.04               | 803.98           | 4.46             | 9.49         | 84.58        | 74.96            |
| Cluster 3 | 1.15    | 74.46      | .18                       | 3301.06    | 3.39               | 1083.38          | 22.45            | 9.06         | 76.61        | 74.83            |



**Figure 4.1a**

*Exam 1 Scores of the Three Identified Groups of Students: Quiz 1 Behaviors*



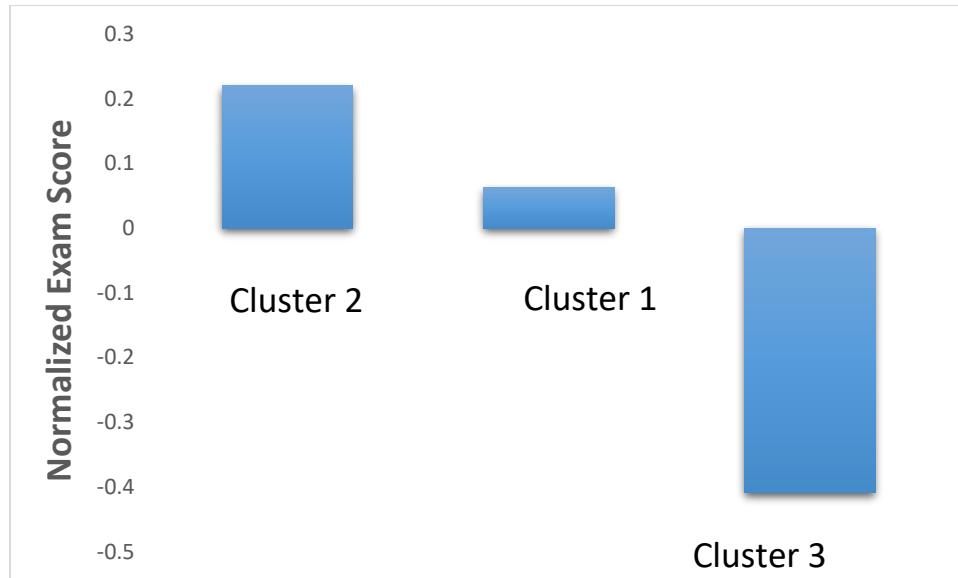
**Figure 4.1b**

*Final Exam Scores of the Three Identified Groups of Students: Quiz 1 Behaviors*

**Table 4.8**

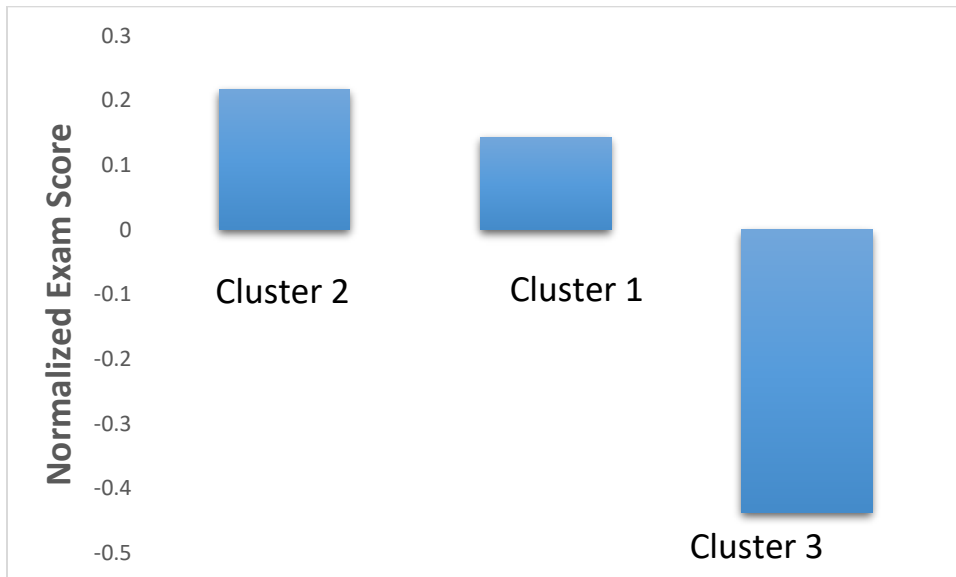
*Mean Values of the Variables Related to Quiz-Taking Behaviors for Quiz 2 and Exam Scores for the Three Identified Groups of Students*

| Cluster   | Spacing | Page Blurs | Closeness to the Due Date | Total Time | Number of Attempts | Time per Attempt | Blur per Attempt | Quiz 2 Score | Exam 2 Score | Final Exam Score |
|-----------|---------|------------|---------------------------|------------|--------------------|------------------|------------------|--------------|--------------|------------------|
| Cluster 1 | 2.23    | 90.82      | 3.62                      | 6184.87    | 6.59               | 976.89           | 13.64            | 9.29         | 76.67        | 82.26            |
| Cluster 2 | 1.22    | 33.70      | .48                       | 3927.57    | 5.00               | 831.19           | 5.85             | 9.29         | 78.50        | 83               |
| Cluster 3 | 1.20    | 100.97     | 0.33                      | 4343.80    | 3.91               | 1133.67          | 24.64            | 8.81         | 71.03        | 76.52            |



**Figure 4.2a**

*Exam 2 Scores of the Three Identified Groups of Students: Quiz 2 Behaviors*



**Figure 4.2b**

*Final Exam Scores of the Three Identified Groups of Students: Quiz 2 Behaviors*

**RQ 4a:** *Are there differences between the three groups of students (identified based on their quiz-taking behaviors) in regard to the subsequent exam scores?*

**Quiz 1**

A one-way ANOVA showed that for Quiz 1 behaviors there was a statistically significant difference in Exam 1 scores between the three different groups of students,  $F(2, 273) = 13.36, p < .0001$ , effect size = .09. See Table 4.9. A follow-up Tukey post hoc multiple comparisons showed that Cluster 2 ( $M = 84.58$ ) significantly differed from Cluster 1 ( $M = 79.95$ ) and Cluster 3 ( $M = 76.61$ ). There were no significant differences between Cluster 1 and Cluster 3.

**Table 4.9**

*One-Way ANOVA of Scores in Exam 1 by Quiz 1 Behaviors*

| Source         | Sum of Squares | <i>df</i> | Mean Square | <i>F</i>             | Partial Eta Squared |
|----------------|----------------|-----------|-------------|----------------------|---------------------|
| Between groups | 3361.38        | 2         | 1680.69     | 13.36<br>$p < .0001$ | .09                 |
| Within groups  | 34334.52       | 273       | 125.77      |                      |                     |
| Total          | 275            | 275       |             |                      |                     |

**Quiz 2**

A one-way ANOVA showed that for Quiz 2 behaviors, there was a statistically significant difference in Exam 2 scores between the three different groups of students,  $F(2, 275) = 13.36, p < .0001$ , effect size = .08. See Table 4.10. A follow-up Tukey post hoc multiple comparisons showed that Cluster 3 ( $M = 71.03$ ) significantly differed from Cluster 1 ( $M = 76.67$ ) and Cluster 2 ( $M = 78.50$ ). There were no significant differences between Cluster 1 and Cluster 2.

**Table 4.10***One-Way ANOVA of Scores in Exam 2 by Quiz 2 Behaviors*

| Source         | Sum of Squares | <i>df</i> | Mean Square | <i>F</i>         | Partial Eta Squared |
|----------------|----------------|-----------|-------------|------------------|---------------------|
| Between groups | 3406.39        | 2         | 1703.19     | 13.36            | .08                 |
|                |                |           |             | <i>p</i> < .0001 |                     |
| Within groups  | 35071.82       | 275       | 127.53      |                  |                     |
| Total          | 38478.21       | 277       |             |                  |                     |

**RQ 4b:** *Are there differences between the three groups of students (identified based on their quiz-taking behaviors) in regard to the final exam scores?*

#### **Quiz 1**

A one-way ANOVA showed that for Quiz 1 behaviors, there was not a statistically significant difference in final exam scores between the three different groups of students.

#### **Quiz 2**

Among 278 students who had attempted Quiz 2, the final exam scores were available for a total of 276 students. A one-way ANOVA showed that for Quiz 2 behaviors, there was a statistically significant difference in final exam scores between the three different groups of students,  $F(2, 273) = 13.36, p < .0001$ , effect size = .09. See Table 4.11. A follow-up Tukey post hoc multiple comparisons showed that Cluster 3 ( $M = 76.52$ ) significantly differed from Cluster 1 ( $M = 82.26$ ) and Cluster 2 ( $M = 83$ ). There were no significant differences between Cluster 1 and Cluster 2.

**Table 4.11***One-Way ANOVA of Scores in Final Exams by Quiz 2 Behaviors*

| Source         | Sum of Squares | <i>df</i> | Mean Square | <i>F</i>         | Partial Eta Squared |
|----------------|----------------|-----------|-------------|------------------|---------------------|
| Between groups | 2398.78        | 2         | 1199.39     | 13.36            | .09                 |
|                |                |           |             | <i>p</i> < .0001 |                     |
| Within groups  | 24508.17       | 273       | 89.77       |                  |                     |
| Total          | 26906.95       | 275       |             |                  |                     |

**4.3 PHASE III: POST-ANALYTICS INTERVIEWS WITH THE MIP INSTRUCTORS**

At the end of Phase II of the study, the MIP instructors were presented with the results of the quiz-log data analytics. In the following Phase III, individual interviews were conducted with all four MIP instructors to understand their perspectives about the usefulness and implications of the results.

**RQ 5:** *According to the instructors of MIP, what is the perceived usefulness and implications of the results of the quiz-log analytics for future pedagogic considerations?*

The instructors said that the results of Phase II analytics were useful in understanding the actual quiz-taking strategies of students including just in time behavior, massed practice, and off-task behaviors. According to the instructors, the possible implications of the findings included providing the students with meaningful and real-time feedback, considering modifications in the current design of quizzes, and educating the students more on the benefits of effective learning strategies. The two main themes and the corresponding sub-themes which emerged from

thematic analysis of the interviews in Phase III are summarized in Table 4.12. The themes and sub-themes are discussed in detail in the following sections (4.3.1-4.3.2).

**Table 4.12**

*Usefulness and Implications of Quiz-Log Analytics*

| Main Themes   | Sub-themes  |
|---|---|
| To understand students' actual quiz-taking behaviors        | Just in time behavior<br>Massed practice<br>Off-task behaviors  |
| To encourage effective quiz-taking behaviors among students | Meaningful and real-time feedback to students<br>Modifications in the existing quiz design<br>Educate students on the benefits of effective learning strategies |

**4.3.1 THEME 1: TO UNDERSTAND STUDENTS' ACTUAL QUIZ-TAKING BEHAVIORS**

According to the instructors, Phase II analytics revealed the actual quiz-taking behaviors of students. For example, the instructors were disappointed that many students had not engaged in productive quiz-taking behaviors despite the intent of quizzing, which was to encourage the use of effective strategies. The results of Phase II analytics indicated that the students had not used the quizzes as a tool to learn and perhaps their focus was only on scoring the maximum possible scores in the quizzes. However, the instructors added that the results were not surprising and were consistent with their hunches from the earlier semesters. The results of the analytics provided evidence-based support to a lot of their earlier assumptions about students' behaviors. The instructors inferred, from the results of Phase II analytics, (see Tables 4.3, 4.4, 4.5, and 4.6) that the quiz-taking behaviors were similar between Quiz 1 and Quiz 2, which indicated that the

students' behaviors had not changed much during the course of the semester. The instructors' views regarding the utility of the quiz-log analytics are presented below.

The variables extracted from quiz-logs are very telling, informative, about the students' quiz-taking behaviors. When I looked at the quiz-data I was disappointed (to see) how badly they were utilizing the quizzes. The students clearly are not following our directions on how to use the quizzes. They are not engaging in effective quiz-taking strategies.

I am not surprised by the results of the analytics. It is nice to see numbers supporting what we have suspected. The behaviors identified from the quiz-log data seem to be very consistent with what you expect from a typical undergrad's behavior.

**4.3.1.1 Just in time behavior.** The majority of the students had procrastinated quiz-taking. As evident from the Canvas quiz-log analytics, for both Quiz 1 and Quiz 2 about 60% of the students took all possible attempts on the day of the deadline. According to the instructors, the just in time behavior from the students' end was a clear indication that the students had not used the quizzes as a tool to engage in repeated practice and spaced retrieval of concepts. The students' behavior seemed to be indicative of the fact that they were focused only on achieving the maximum possible points. The following quotes indicate that procrastination was seen as an ineffective quiz-taking strategy by the instructors.

Most of the students are taking all possible attempts on the day of the deadline or very close to the deadline. This tendency among students to procrastinate their attempts is not good. The results (of Phase II quiz-log analytics) tell us that we don't have many students practicing the quizzes the way we like them to.

We had asked the students not to cram the night before the exams (on the deadline of the quizzes), but they still do. We tell them quiz-taking is not busywork. Every effort that goes into quiz-taking contributes to their learning and preparing them for the exams.

**4.3.1.2 Massed practice.** The quizzes remained open for a period of nine days and students could attempt each quiz up to a maximum of ten times. The students were free to choose how they distributed their attempts during this period. The design of quizzes ensured that the highest score among all possible attempts was the recorded score. Hence, the students were not

at risk of lowering the grades when they chose to distribute their practice. However, not all students distributed their attempts efficiently over the period when the quizzes remained open. For Quiz 1, about 93% of the students and for Quiz 2, about 96% of the students had distributed their practice into only two days or less. The tendency of the students to start attempting the quizzes on the deadline led to an inevitable consequence—they engaged in the massed practice of all possible attempts instead of distributing the attempts over the period in which the quizzes remained open. Quotes from interviews, which highlight the importance of spaced retrieval from the instructors' perspectives are listed below.

We would have liked the students to engage in spaced retrieval, distribute their attempts, and probably take only the last one or two attempts on the due date. There is no risk in spacing the attempts since the design of quizzes ensures that the highest grade is the kept score.

The instructions that were given to the students (by the instructors at the beginning of the semester as well as via video instructions in Canvas) were to space out their attempts; go to class, take the quiz, see how they did in the first attempt, identify what topics they struggled with, go back and restudy, and to take the quiz again. These instructions seem to be not met by many students.

**4.3.1.3 Off-task behaviors.** The instructors considered page blurs as a likely sign of students' off-task behaviors. The high number of page blurs evident in quiz-log analytics was considered as a possible indication that the students were not preparing as well as they ought to, prior to attempting the quizzes and were instead looking up the answers on websites or class notes. The instructors believed that such attempts would have been futile as the quizzes consisted of application-level questions and it would not have been easy for the students to find the answers elsewhere instantaneously. According to the instructors, active retrieval was imperative for long-term retention of information as well as for the recognition of gaps in knowledge. They reasoned that the negative correlation found between the number of page blurs and exam scores was probably because the students were not engaging in active retrieval. However, it was evident

that the instructors were cautious in making a strong conclusion based on this variable. Instructors made a distinction between productive and unproductive off-task behaviors. According to them looking up answers in an attempt to learn could be considered a productive off-task behavior, while engaging in totally unrelated activities to quiz-taking (e.g., watching videos for entertainment purposes or checking emails or social media) could be unproductive off-task behaviors. The following quotes show that prior to quiz-taking, the instructors had directed the students not to look up answers and to actively recall information.

We had asked the students to attempt the quizzes according to the given directions. The directions were to practice the material as if they were taking a real exam; not to look up the answers on other websites, not to use their notebooks, and not to work in groups. They would not have found the answers to the quizzes on other websites readily since the quizzes consisted of application questions.

Students come to talk to me when their grade is not what they want it to be. I advise them to study and when they think they are prepared, go to the quizzes and try them, without looking up the answers or notes. Practicing active retrieval is important because that's what is going to tell them what areas they are struggling with. It makes sense that the students who leave the quizzing system more often, score lesser than the rest on the following examination. These students are probably not using the quizzes to study ahead of time and are looking up the answers.

#### ***4.3.2 THEME 2: TO ENCOURAGE EFFECTIVE QUIZ-TAKING BEHAVIORS AMONG STUDENTS***

In Phase III interviews, the instructors re-emphasized that they had ideally wanted the students to use the quizzes as a tool to learn, rather than merely a tool to evaluate their current knowledge and score the maximum points possible. Given that many students were engaged in unproductive quiz-taking behaviors, as evident from the quiz-log analytics in Phase II of the study, the instructors were encouraged to think about ways in which they could cultivate effective learning strategies among students. Three sub-themes emerged as possible ways to instill productive quiz-taking behaviors among students. These were to provide the students with meaningful and real-time feedback, consider modifications in the existing design and administration of quizzes, and

educate the students more on the benefits of effective learning strategies so that the students use quizzes as a learning tool. Each sub-theme is discussed below (see sections 4.3.2.1-4.3.2.3)

**4.3.2.1 Meaningful and real-time feedback to students.** The instructors agreed that quiz-log analytics would enable them to provide meaningful and real-time feedback to the students. They believed that having access to the trends in students' actual quiz-taking behaviors early in the semester was a chance to bring about positive changes during the same semester. Real-time data could be more beneficial than post-semester evaluations since the students might pay attention and take actions while presented with current data related to their actual quiz-taking behaviors. This would give students an opportunity to rectify unproductive quiz-taking behaviors before poor grades get recorded. Quiz-log analytics conducted in Phase II of the study provided the instructors with usable information which enabled them to identify ineffective quiz-taking strategies without additional manual labor from their end. According to the instructors, the actionable analytics conducted in Phase II would help them provide targeted, meaningful feedback to the students in place of general or motivational feedback. Instructors said that they would like to consider taking advantage of options such as sending automatic messages to students who were exhibiting ineffective quiz-taking behaviors such as procrastination, massed practice, and off-task behaviors. However, this was not a possibility as the existing version of Canvas had no options to automatically identify such students and send reminders. One of the instructors said that although they believed there could be ways to get students' attention by providing them real-time feedback using computers, they lacked the technical skills to implement such possibilities. The following quotes indicate that the instructors found value in providing meaningful and real-time feedback to the students.

It is good to see what the trend (in students' quiz-taking behaviors) is as the semester progresses. If we can bring a change, it can affect the current students directly. If we get

post results, it is not going to help the students (in the current semester), it will only help future students.

It would be ideal if there was a built-in mechanism that would reach out to the students, say, send automatic messages to students who haven't attempted the quizzes even after a few days have elapsed since the quizzes were opened. If there was a built-in feature (available on Canvas) to achieve this I would definitely use it.

**4.3.2.2 Modifications in the existing quiz design.** The instructors came up with suggestions for possible changes in the current quiz design to help students engage in productive quiz-taking behaviors. The suggestions included reducing the number of available attempts and time available for each quiz attempt, implementing a browser lockdown (to refrain the students from printing, copying, going to another URL, or accessing other applications during the quizzing), and changing the due date of the quizzes. Another suggestion that came up was to reduce the length of quizzes (number of questions in each attempt) and optimize the available time for each attempt accordingly to further reduce off-task behaviors. The instructors believed that these changes might encourage the students to put in more sincere effort in attempting the quizzes. For example, reducing the available number of attempts and time for each attempt might encourage the students to prepare well before taking the quizzes since they have less number of chances available to improve their scores. Changing the due date from a weekend to a weekday might reduce the chance for massed practice and encourage the students to attempt the quizzes early on. The instructors considered providing the students with incentives for engaging in effective quiz-taking behaviors and following the ideal quiz-taking protocol. For example, the instructors said that they would consider the possibility of offering extra credit to students who distributed the quiz attempts effectively. However, the automatic identification of such students was not a possibility in the existing version of Canvas.

Interestingly, the instructors did not consider manually supervised quizzing as an option to enforce effective quiz-taking among students. According to the instructors it was important

that the students in higher education took the responsibility of self-regulated learning.

Additionally, manually proctored in-class quizzing would imply a reduction in the available class time and increased workload for the instructors. Despite their intention to encourage productive behaviors among students, it was clear that some instructors felt a sense of helplessness while thinking about ways to achieve this. They were concerned that they should not overload the students, especially taking into account the other responsibilities the students had. One instructor stated that understanding students' perspectives in this regard were important and hence future studies in this direction were necessary. Representative quotes from interviews with instructors are given below.

I do think unsupervised quizzing is important because in real life the students have to take responsibility for their own learning. We can only hold their hands for so long. I think it is important they take the quizzes on their own time.

A typical undergrad has a lot on their plate, and they tend to attend to tasks as they come up. They have a bunch of other stuff due too (in addition to the quizzes). My only concern is that the demands of the implemented quiz-design shouldn't be overloading the students.

**4.3.2.3 Educate students on the benefits of effective learning strategies.** Instructors said that they would encourage productive behaviors among students by educating them about the benefits of effective learning strategies. To achieve this, the instructors wanted to take help from the learning assistants at the university as well. They wanted the students to use the possible attempts of the quizzes more conscientiously, space their attempts across the period when quizzes remained open, and engage in active retrieval of concepts. Instructors said that they had briefly summarized the benefits of effective learning strategies at the beginning of the semester and have not had similar conversations with the students during the rest of the semester. They believed that additional training and instruction might be useful in enlightening the students about the benefits of effective learning strategies. This would include having more

conversations with the students throughout the semester to reiterate the benefits of effective learning strategies, having additional video instructions on Canvas before each quiz, including reminders at the end of classroom lectures and PowerPoint presentations, and presenting the students with the actual behavioral data from the MIP class. The instructors believed that presenting students with the data related to their actual quiz-taking behaviors might help students understand the deviations in their actual quiz-taking strategies from the expected behaviors. The following quotes illustrate this sub-theme.

I will talk to my students and advise them (to engage in effective quiz-taking behaviors) in addition to the directions provided on Canvas. I will keep reminding them throughout the semester to space their attempts and practice active recall without using their notes. I will tell them that they will be inclined to mass all their attempts on one day, probably on the due date. Their tendency is to stop attempting the quizzes once they have got the scores they want.

This is where I see the importance of real-time data from the MIP class. I could show and tell the students I have got data from your class, not theoretical findings from some other class, but findings based on *this* class.

## **CHAPTER 5: DISCUSSION**

The aim of Phase I of the present study was to investigate the pedagogic intent of the low-stake unsupervised online quizzes implemented in the MIP course and the difficulties faced by the instructors in discerning students' quiz-taking behaviors. This study hypothesized that the analysis of logged data from Canvas might help instructors have a clear picture regarding the self-regulation process of students' quiz-taking behaviors. Therefore, in Phase II of the study Canvas quiz-logs were parsed to explore the actual quiz-taking behaviors of students to identify common patterns and to determine whether there was a relationship between quiz-taking behaviors and performance in exams. The findings were shared with the instructors in Phase III of the study to understand their views on the usefulness of quiz-log analytics in informing future pedagogical practice. This chapter presents a brief discussion and possible interpretations based on the literature and the findings of the present study. It also describes the conclusions of the study and directions for future studies.

### **5.1 IMPORTANCE OF LEARNING ANALYTICS**

The results of the present study confirm the importance of LA in informing the instructors about the extent to which the learners' behaviors are aligned with the implemented learning design. The study, via pre-analytics interviews with MIP instructors in Phase I, revealed an important drawback of unsupervised online quizzing: students' quiz-taking behaviors were not completely understood by the instructors, post-implementation of the quizzing. This was a major restriction for the instructors in providing meaningful and timely feedback to the students. According to the instructors, three main obstacles limited their understanding of students' quiz-taking behaviors. First, conversations with students were not particularly insightful about their

quiz-taking behaviors and happened too late in the semester to bring about changes in practice. Students' focus was mainly on attaining the maximum scores in quizzes rather than developing and practicing effective quiz-taking strategies. Second, despite storing wide-ranging data related to students' quiz-taking behaviors, Canvas offered limited data reporting options related to students' procrastination, spacing, and off-task behaviors. The MIP instructors did not know how to access and manipulate the Canvas backend data and consequently, it remained unexplored by them. Third, all sections of MIP were large student enrolment classes. The instructors could not have deciphered student behaviors without a substantial increase in their workload.

Phase I results align with the reports in the literature that even when instructors design and implement unsupervised learning activities on technology-assisted platforms with a pedagogic intent, they may lack access to relevant information related to students' behavioral data (Rodríguez-Triana et al., 2015). This introduces two major problems for instructors. First, instructors are unable to integrate cyclic research activities such as the evaluation of the effectiveness of the implemented learning design (Er et al., 2019). Second, they are unable to provide timely, meaningful feedback to students, especially to those who need additional support to continually practice effective strategies. Some researchers are of the opinion that evaluating learners' correctness of solutions may be a less demanding task when compared to the evaluation of the quality of their learning strategies (Roll et al., 2014). Results from Phase I of the current study reinforces this view. In the absence of LA methods, instructors have been relying on qualitative methods such as interviews or observations to understand students' learning behaviors (Mor, Ferguson, & Wasson, 2015). Data gathered from technology-enhanced learning platforms, related to students' activities on those platforms, are required to understand students' actual behaviors within the system (Junco, 2014). Discovering useful information related to

students' quiz-taking behaviors manually could be a difficult task because LMSs generate and log a large amount of information related to student interaction (C. Romero & Ventura, 2007). These problems are more pronounced in the case of large student enrolment classes where instructors are under constant pressure to allocate time and resources for providing meaningful and personalized feedback to each student (Jayaprakash et al., 2014; Pardo et al., 2019). Results of the present study support the pivotal role LA can play in providing instructors real-time access to student's actual behaviors, thereby, enhancing their capacity to provide timely formative feedback to large student cohorts. The present work assisted the instructors in exploiting the potential of data-driven evidence to decipher the actual behaviors of students within an LMS (see section 5.3).

## **5.2 INTERLINKING LEARNING ANALYTICS AND THE LEARNING DESIGN: THE ROLE OF INSTRUCTORS**

Feedback provided to students can be either through labor-intensive procedures involving instructors or via fully automated tools. Information provided by fully automated LA tools may not be aligned with instructors' requirements for the management of learning activities (Kennedy et al., 2014; Mor et al., 2015). Interconnecting the learning design with the data collected from technology-enhanced learning tools by means of LA helps in overcoming this obstacle (Lockyer et al., 2013). However, this is a largely unexplored area and hence limits the effective use of analytic data in meaningful ways (Ifenthaler, Gibson, & Dobozy, 2018; Lockyer & Dawson, 2012). Recent LA studies attempt to take advantage of two methods, namely obtaining information about learners' behaviors from log data and involving instructors in this process (Pardo et al., 2019). Active participation of instructors has helped research teams to develop an in-depth understanding of the learning design and build rigorous variables that are aligned to the

pedagogical intent of the learning design (Aljohani et al., 2019; Arriaran Olalde & Ipiña Larrañaga, 2019; Er et al., 2019). Building on evidence from the aforementioned studies, interviews with the MIP instructors were conducted in Phase I of the present study to understand how the pedagogical decisions at the design-level of the learning activity inform the analysis of the quiz-log data. The results of this study imply that meaningful variables need to be identified and collected in order to obtain relevant information related to students' behaviors. Thus, this work highlights the importance of considering meaningful data collection at the time of the design of learning activity as recommended by Martínez-Monés and colleagues (2011).

The results of Phase II quiz-log analytics were presented to the MIP instructors to take further advantage of their knowledge about the context, including the implemented learning design and characteristics of the learners. In Phase III of the study, follow-up interviews with the instructors were conducted to understand their views on the perceived usefulness and implications of the quiz-log analytics for future pedagogic considerations. Instructors' perspectives were considered important as students often lack strong metacognitive skills to interpret the results by themselves to use it for reflection and self-regulation (Butler & Winne, 1995). In particular, the lowest performers often monitor, evaluate and calibrate their learning and performance with overconfidence (Garavalia & Ray, 2003; Hacker et al., 2000; Kruger & Dunning, 1999; Pintrich & De Groot, 1990).

### **5.3 ACTIONABLE ANALYTICS**

In post-analytics interviews conducted in Phase III of the present study, the instructors emphasized that quiz-log analytics (Phase II) contributed to a clear understanding of students' actual quiz-taking behaviors, which they had lacked access to in the previous semesters. Many of the existing LA tools (e.g., analytics reported on LMS dashboards) to understand students'

learning behaviors and their patterns of engagement focus on static data (e.g., student demographics and prior academic records) and/or simple metrics related to student engagement levels such as login frequency, the frequency of course materials accessed, number of discussions posted, and number of downloads of course materials. Such variables cannot be meaningfully manipulated to implement specific interventions that target student learning. Also, these variables do not provide insights for improving teaching strategies and the implemented learning design. Hence, conventional quiz report analysis tools that provide statistics about students and items/questions performance do not give recommendations on how to improve student learning and performance. To address these limitations, seven malleable and pedagogically meaningful variables related to students' quiz-taking behaviors were designed and extracted from the Canvas quiz-logs in this study. The design of the variables, in Phase II of the study, was based on the requirements of the MIP instructors. In Phase I of the study, the instructors had identified the quiz-taking behaviors they were interested in, namely repeated practice ahead of exams, active and spaced retrieval of information. The variables total number of attempts, total time invested in all the attempts, time per attempt, and closeness to the due date were designed to understand whether the learners had engaged in repeated practice of material well in advance of the exams. Since the quizzes were unsupervised, it was not possible to confirm with certainty that the learners had engaged in active retrieval of information. However, the variables page blur frequency and page blurs per attempt were considered to be possible measures of students' off-task behaviors. The variables spacing and closeness to the due date provided an insight into how the learners had distributed their attempts. Table 5.1 lists the quiz-taking behaviors that were sought by the instructors in Phase I of the study and the corresponding variables designed in Phase II to address their needs.

**Table 5.1***Quiz-Taking Behaviors Sought by the MIP Instructors and the Corresponding Variables**Designed*

| Quiz-Taking Behaviors of Instructors' Interest Identified in Phase I | Corresponding Variables Designed in Phase II                                |
|--|---|
| Repeated practice ahead of exams                                     | Number of attempts, total time, time per attempt, closeness to the due date |
| Active retrieval   | Page blur frequency, page blurs per attempt                                 |
| Spaced retrieval   | Spacing, closeness to the due date  |

Phase II of the study provided the MIP instructors a new insight into the students' quiz-taking behaviors. The instructors recognized a drawback of low-stake unsupervised online quizzing implemented in their classes: most of the students' behaviors were not in accordance with the intent of the implemented learning design. About 60% of the students had attempted the quizzes on the day of the deadline and had massed all the possible attempts on this day. The instructors had designed the quizzes as low-stakes to ensure that minimal risk was involved in attempting the quizzes early on, making multiple distributed attempts, and actively recalling the information. However, students' quiz-taking behaviors indicated that despite the low-stake, low-risk nature of the quiz design, the majority of the students had engaged in unproductive behaviors such as massed practice, procrastination, and off-task activities. Of the seven identified variables related to students' quiz-taking, page blur frequency, total time, time per attempt, and blur per attempt consistently showed significant negative correlations with the exam scores. K-means cluster analysis indicated three distinct patterns of student behaviors. The group of

students who exhibited the most ineffective quiz-taking behaviors, namely the highest mean number of page blurs, blur per attempt, the lowest spacing, and closeness to the deadline scored the lowest in exams. For Quiz 2 behaviors, the exam scores of the lowest-performers (who also exhibited the least effective quiz-taking behaviors) significantly differed from the other two groups identified. Considering the results of Phase II analytics and the actionable variables designed therein, the MIP instructors came up with three important suggestions to reduce the unproductive quiz-taking behaviors observed among MIP students, namely procrastination, off-task behaviors, and massed practice. The suggestions were to provide students with meaningful and timely feedback, make modifications to the existing quiz-design, and educate the students about the benefits of effective learning strategies. To summarize, the results of Phase II of the study correlate with two important points discussed in the literature in connection with the real-time, usable information that LA can provide instructors about students' actual quiz-taking behaviors. Instructors could use such information to (i) intervene at the right time by providing meaningful feedback to students who show less than optimal engagement during the course delivery (ii) review, reflect, and refine their future learning designs based on data-driven evidence (Doige, 2012; Lockyer & Dawson, 2012; Melero et al., 2015).

As discussed above, access to learners' actual quiz-taking behaviors led to three potential ideas for interventions to encourage productive behaviors. These were to 1. provide meaningful and timely feedback to students, 2. redesign the existing quizzes and 3. educate students on the benefits of effective learning strategies. The three propositions are discussed with supporting literature in sections 5.3.1-5.3.3.

### **5.3.1 MEANINGFUL AND TIMELY FEEDBACK**

The quiz-log analytics conducted in Phase II of this work facilitated the identification of the actual quiz-taking strategies and patterns of student behaviors in the unsupervised online platform. The instructors confirmed that quiz-log analytics enabled them to identify unproductive quiz-taking behaviors such as off-task behaviors, procrastination, and massed practice of quizzes without a significant increase in their workload. Subsequently, this could aid in providing meaningful feedback to improve self-reflection among students who exhibit less metacognitive awareness of their learning behaviors. For example, the instructors suggested they could reach out to students, identified to be engaged in unproductive behaviors, by means of automatic email reminders.

The aforementioned findings are commensurate with the discussions in the literature which indicate that LA can aid in the identification of students' actual study strategies and in turn an accurate reflection of their behaviors (Knight & Sydney, 2018; Wise, 2014). Students' reflection of their choice of study strategies could encourage the effective use of quizzes as a learning tool, which promotes self-testing and spaced retrieval of information. Recent studies bolster the idea that meaningful feedback can encourage students to alter unproductive learning behaviors (Martin, Edwards, & Shaffer, 2015; J. Rodriguez, Piccoli, & Bartosiak, 2019). Rodriguez and colleagues demonstrated that the students who received feedback to engage in positive behaviors outperformed the students who did not by about 13%. Likewise, Martin and colleagues (2015), who examined the effect of feedback on procrastination found that students who received e-mail alerts ( $M = 4.0$  days,  $SD = 3.9$ ) made significantly earlier first submissions than the control group ( $M = 2.4$  days,  $SD = 3.1$ ). The e-mail treatment group also had the lowest number of late submissions.

The instructors of MIP believed that real-time access to student behaviors from Phase II would prove beneficial in providing timely feedback to the students. The timeliness of feedback plays an important role in raising the students' awareness regarding their use of ineffective strategies. For example, feedback provided to students early in the semester before the grades are recorded can give them ample time to rectify their unproductive learning behaviors (Jayaprakash et al., 2014). This is especially true in the case of students who are less confident about their ability to succeed (Irons, 2007). In the absence of LA methods, indicators related to the effectiveness of learning activities are usually collected after the completion of the learning process in a semester. Such indicators collected from students could be subject to sampling and self-reporting bias and hence may not be useful in implementing timely interventions targeted to impact practice (Q. Nguyen et al., 2018; Shum & Crick, 2012; Wise, 2014).

### ***5.3.2 REDESIGN OF THE EXISTING QUIZZES***

In Phase III of the present study, the MIP instructors suggested several modifications in the design of quizzes to reduce the less than optimal quiz-taking behaviors of their students. The suggestions included implementing a browser lock-down option to reduce the off-task behaviors of students, reducing the number of attempts allocated for a given quiz, reducing the time and length for a single attempt of the quiz, and changes in the due date. The suggestions to modify the quiz-design can be understood in the light of a study that examined the effectiveness of web-based quizzing, which found positive effects for in-class quizzing but not for web-based quizzing (Daniel & Broida, 2004). The authors argued that web-based quizzing did not always positively correlate to exam performance when compared to in-class quizzing because students in a web-based quiz group might use strategies to optimize their quiz performance without mastering the content. For example, the students in the above-mentioned study described that their common

methods to cheat on web-based quizzing were to print and share quizzes and to look up answers in books and websites. To discourage the students from such detrimental strategies, the researchers randomly assigned quizzes from a larger question bank and decreased the time allowed for a 10-item quiz from 15 minutes to 7 minutes. These modifications in the quiz design proved to be effective. Bonferroni post hoc tests indicated significant differences between the no-quiz group and both the web-based quiz group,  $t(81) = 11.47, p < .001$ , and the in-class quiz group,  $t(84) = 10.45, p < .001$ .

Even effective learning strategies such as self-testing, which are known to be positively correlated to GPA can be used ineffectively by students in unsupervised online platforms. Ineffective use of such strategies by the students could result in poor performance in exams. This could happen when students merely evaluate their familiarity with a concept without engaging in the active recall of information or when students do not distribute their practice. The present study supports the claim that quality information obtained about actual learning behaviors not only provides actionable information that helps to improve students' learning but also informs instructors to improvise subsequent instruction. This implies that LA can guide the instructors in the iterative process of improving the effectiveness of their courses by redesigning the implemented learning activities (Dyckhoff et al., 2012; Ghislandi & Raffaghelli, 2015; Melero et al., 2015).

### ***5.3.3 EDUCATING STUDENTS ON THE BENEFITS OF EFFECTIVE LEARNING STRATEGIES***

Phase I of the study, the pre-analytics interviews with MIP instructors, indicated that the quizzes were implemented as a formative assessment to encourage the students' use of effective learning strategies. The instructors had ideally wanted the students to comprehend the benefits of

testing and not consider tests as mere avenues to secure points. It is known that testing can enhance students' learning in subsequent study sessions by encouraging them to pay attention to key concepts and commonly-made mistakes. Periodic and spaced practice helps to strengthen retrieval routes, retain information for long periods, and apply knowledge to new settings. Learners could be susceptible to illusions that can impair their judgment of the current knowledge, which leads them to overestimate their learning. In this context, regular self-testing could recalibrate learners' understanding of what they know and do not know (Brown et al., 2014). Studies reinforce that the regular use of online testing, regardless of the grades obtained, is a positive indicator of final exam performance (Angus & Watson, 2009).

Educational psychologists have developed several effective strategies for learning and instruction that benefit student achievement. Nonetheless, students do not always choose to engage in effective learning strategies and as a consequence, there could be a negative impact on their performance (Karpicke, 2009). Findings from Phase II of the present study revealed that around 60% of the students engaged in unproductive quiz-taking behaviors such as massed practice and procrastination. This finding should be viewed in light of the survey results conducted among 472 college students enrolled in an introductory psychology course at UCLA, in which 80% of the students confirmed that their choice of study strategies was not a result of any coaching received from instructors (Kornell & Bjork, 2007). Four out of five students in this sample had improvised their study strategies based on intuition rather than research. One of the reasons for this behavior could be that the students are not explicitly instructed about the use of effective learning strategies in classrooms (Bjork et al., 2013; Kornell & Bjork, 2007; Son & Kornell, 2008). Study decisions made on the basis of intuition make students subjective to the drawbacks of self-regulated study since many effective learning strategies are counterintuitive.

Phase II results hint that the pedagogical intent of learning activities, including the goals of the activity and productive patterns of engagement, perhaps was not conveyed clearly to the students. Therefore, it is important that instructors communicate to students the importance of productive learning behaviors (Wise, 2014). To this end, instructors can explicitly highlight the intent of learning activities in task description pages and the course syllabi (Er et al., 2019). Declarative instruction of the desired behaviors provided in the classrooms helps students grasp the requirements of a learning activity (White & Frederiksen, 1998). For example, in an experimental study, the group of students provided with explicit suggestions like “Struggling is part of the learning process. You will not learn by guessing or abusing hints, even if you get the answer right” scored better than the control group ( $F(1,31) = 6.5, p < 0.02$ ) (Roll, Alevan, McLaren, & Koedinger, 2007).

For the aforesaid reasons, it could be important that instructors spend time to educate the students about the benefits of effective learning strategies. This could especially assist the struggling learners, who in general practice less effective strategies (Azevedo & Cromley, 2004; Moos & Azevedo, 2008; O’Reilly & McNamara, 2007). The current educational system emphasizes delivering content to students. However, it is equally important to educate students on metacognitive strategies through focused practice, reflection, and feedback (McNamara, 2010). Often, instructors may not spend enough time training students to self-regulate their learning or develop effective techniques. Due to time constraints, students are not given enough opportunities within classrooms to practice effective strategies. These constraints point out the need for automated, technology-assisted tools that can encourage strategy instruction and practice with feedback, outside classrooms. In this connection, it is interesting to note that effective study strategies remain underutilized by many instructors as they are unaware of the

benefits of such strategies. This could be because instructors are most likely to learn about effective learning strategies in teacher training classes and most strategies do not receive adequate coverage in educational-psychology textbooks (Dunlosky, Rawson, Marsh, Nathan, & Willingham, 2013).

## **5.4 CONCLUSION**

The goal of Phase I of this study was to identify the pedagogic intent of the low-stake unsupervised online quizzes implemented in MIP and the difficulties faced by the instructors in deciphering the quiz-taking behaviors. Phase I findings of this work demonstrated that the instructors lacked access to learners' actual quiz-taking behaviors. Phase II of the study tracked students' actual learning strategies with the low-stake unsupervised online quizzing, as the learning process was ongoing. To address the limitation of using static variables to classify students' behaviors, seven pedagogically meaningful variables related to the quiz-taking behaviors were designed and extracted from the Canvas quiz-logs. These variables provided evidence that quiz-taking behaviors were related to performance on exams. Additionally, these variables indicated that many students had not regulated their learning effectively to engage in productive learning behaviors. Such students may benefit from external formative feedback provided by instructors. Based on quiz-log analytics conducted in Phase II of the study, it can be concluded that LA methods can provide valuable real-time insights into learners' actual behaviors, which can augment instructors' capacity to provide meaningful and timely formative feedback to students.

In addition to the LA methods used to understand the students' quiz-taking behaviors, this study allowed the active involvement of instructors in the following ways. The variables related to quiz-taking behaviors were built based on the needs identified by the instructors. Later,

the results from the quiz-log analytics were shared with the MIP instructors to understand how the findings of the present study may inform pedagogical practice. The findings suggest that the instructors considered the quiz-log analytics useful to (i) provide meaningful and timely formative feedback to students, (ii) improve the existing quiz-design to reduce unproductive behaviors, and (iii) educate the students on the benefits of effective learning strategies. Based on the findings of Phase III of the study, it can be concluded that LA methods would help instructors plan timely pedagogic learning analytics interventions.

To enumerate, the major conclusions of the present study are

1. Despite the pedagogic intent of the implemented learning design, instructors had limited access to students' actual learning behaviors within the unsupervised online platform.
2. Data-driven methods informed by learning theories can become a valuable tool in providing real-time insights into students' actual learning behaviors and relationships between behaviors and performance on exams.
3. When unsupervised, the majority of the students had not self-regulated their learning effectively to engage in productive learning behaviors.
4. LA methods can augment instructors' capacity to provide meaningful and timely external feedback to students who engage in unproductive behaviors.
5. LA methods, when taken into consideration with instructors' input, can support critical reflection on the implemented learning design and thereby lead to improved pedagogy.

## 5.5 IMPLICATIONS AND FUTURE DIRECTIONS

Findings of the present study confirm that LA can help gain insights into students' actual learning behaviors. Recent research shows that information related to students' behaviors can be successfully used to inform changes in their approach to learning (Pardo et al., 2019). However, in order to maximize the use of LA data that is available from technology-enhanced learning platforms, instructors may have to design and implement evidence-based reflective instructional activities (Hernández-Leo, Martínez-Maldonado, Pardo, Muñoz-Cristóbal, & Rodríguez-Triana, 2019). To implement successful data-driven practices, instructors may have to keep in mind the possibilities of meaningful data collection as early as the design stages of learning activities. To achieve this goal, institutions should consider providing instructors with additional training regarding the design and implementation of formative learning activities on technology-enhanced learning platforms. The training provided should emphasize the pre-planning required from instructors' end for implementing learning activities with clear pedagogic intent that can aid in meaningful data collection.

LA could be beneficial in enhancing the capacity of instructors to provide personalized feedback to students, especially in large cohorts. Based on the conclusions of this study, institutions and instructors should consider taking advantage of LA methods to scale the formative feedback provided to the students and use the wealth of behavioral data of the students in informing the pedagogical practices. To this end, instructors can be provided with additional tools that collect data from technology-enhanced platforms to monitor learners' behaviors. It is important that multi-disciplinary teams with advanced data analysis skills work in tandem with the instructors, for retrieving and analyzing large amounts of data from technology-enhanced platforms. This may help instructors identify productive and unproductive patterns in students'

learning behaviors, provide meaningful and timely feedback to students, and transform their pedagogical approaches.

The following section discusses a few points that can guide future studies.

1. The current study explored instructors' interpretations of student learning behaviors identified from Canvas quiz-logs. Since it is equally important to understand students' perspectives, future studies should investigate whether students consider the quizzes useful or are overloaded with the demands of the quiz design. Students demonstrate cognitive judgment and choice behavior while reflecting on and evaluating the tasks provided to them. For example, students may not use the quizzes efficiently if they consider the quizzes not challenging or important to learning (Corrin & de Barba, 2014). Interviews with MIP students may help reveal their perspectives regarding the usefulness of the available online quizzes. Combining quiz-log data with other sources of information like student interviews have additional advantages. For example, the triangulation of log-file data with surveys, observations, or interviews with students might help establish the difference between perception and reality of students' quiz-taking behaviors (Ingram, 1999). As Peled and Rashty (1999) suggest, combining log-file data with student demographics, performance, interviews, and survey results will provide a clear insight into students' behaviors.
2. Follow-up on the suggestions which emerged from the post-analytics interviews with MIP instructors may be useful in understanding the effect of interventions to encourage productive quiz-taking behaviors. In the current explorative non-experimental study, instructors came up with three suggestions to encourage effective learning strategies. These were to provide students with meaningful real-time feedback, modify the existing

quiz-design, and educate the students on the benefits of effective strategies. Future experimental studies will help in establishing the effects of the proposed interventions. For example, real-time feedback in the form of pop-ups or email reminders could be provided to nudge students who seem to engage in unproductive quiz-taking behaviors such as procrastination, massed practice, or off-task behaviors. Similarly, the quiz design could be modified by implementing a browser lock-down option, which prevents students from moving to a different website while attempting quizzes. Random experiments could be conducted to examine whether such interventions influence students' behaviors.

3. The present study was limited to an undergraduate microbiology course. Further studies across disciplines are required to understand how the results of the current study apply to other courses.

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## APPENDIX A

### Python Code Excerpts for Collecting Quiz-Logs from Canvas

```
def GetQuizzes(self):
```

```
    self._quizzes = self.canvasReader.get_quizzes(course_id)
```

```
    assert (len(self._quizzes) == 1)
```

```
    quizzes = self._quizzes[0]
```

```
    return quizzes
```

```
def GetSubmissions(self, quizId):
```

```
    self._submissions = self.canvasReader.get_quiz_submissions(course_id, quizId)
```

```
    submissions = []
```

```
    for item in self._submissions:
```

```
        submissions = submissions + item['quiz_submissions']
```

```
def GetEvents (self, quizId, submissionId):
```

```
    self._eventsRaw = self.canvasReader.get_events(course_id, quizId, submissionId)
```

```
    events = []
```

```
    for item in self._eventsRaw:
```

```
        events = events + item['quiz_submission_events']
```

```
    return events
```

## APPENDIX B

### Email Recruit Sent to the MIP Instructors

Hello,

My name is *Priya Harindranathan* and I am a researcher from Colorado State University in the *School of Education*. We are interested in conducting a research study on your perceptions about the students' aggregated usage behaviors in the online quizzing implemented in your class MIP 300. The title of our project is *Insights on Learning Behaviors in Unsupervised Online Quizzing: The Role of Instructors in Interlinking Analytics and Pedagogy*.

The Principal Investigator is Dr. James Folkestad, Professor, School of Education, and I (Priya Harindranathan, Ph.D. candidate, School of Education) am the Co-Principal Investigator.

We would like you to participate in an interview. Participation will take approximately *2 hours (1 hour of interview scheduled over two sessions)*. Your participation in this research is voluntary. If you decide to participate in the study, you may withdraw your consent and stop participation at any time without penalty.

Your interviews will be audio-recorded and transcribed to understand the common themes emerging from interviews. We will not collect your name or personal identifiers unless you agree to do so. If you decide not to share your personal details, when we report and share the data with others, no identifiers will be shared. While there are no direct benefits to you, we hope to gain more knowledge on students' use of learning strategies, the scope of providing meaningful feedback to future generations of students, and designing quizzes to encourage the use of effective strategies among students.

It is not possible to identify all potential risks in research procedures, but the researchers will take reasonable safeguards to minimize any known and potential (but unknown) risks.

To indicate your interest to participate in this research, please contact *James Folkestad*, Professor School of Education [James.Folkestad@colostate.edu](mailto:James.Folkestad@colostate.edu), or *Priya Harindranathan* [Priya.Harindranathan@colostate.edu](mailto:Priya.Harindranathan@colostate.edu).

If you have any questions about the research, please contact *James Folkestad* at [REDACTED] [James.Folkestad@colostate.edu](mailto:James.Folkestad@colostate.edu) or *Priya Harindranathan* [REDACTED] [Priya.Harindranathan@colostate.edu](mailto:Priya.Harindranathan@colostate.edu). If you have any questions about your rights as a volunteer in this research, contact the CSU IRB at [RICRO\\_IRB@mail.colostate.edu](mailto:RICRO_IRB@mail.colostate.edu) or [REDACTED].

James.Folkestad, Ph.D.

Priya Harindranathan

Professor, School of Education

Ph.D. candidate, School of Education

## APPENDIX C

### Consent Form

#### Colorado State University

#### Consent to Participate in Research

*Title of Study* *Insights on Learning Behaviors in Unsupervised Online Quizzing: The Role of Instructors in Interlinking Analytics and Pedagogy*

#### Introduction and Purpose

My name is \_\_\_Priya Harindranathan\_\_\_\_\_. I am a *graduate student* at Colorado State University, *faculty advisor, Professor \_Dr.\_James Folkestad\_\_\_\_\_*, in the School/of \_\_\_\_\_Education\_\_\_\_\_. I would like to invite you to take part in my research study, which looks at *Insights on Learning Behaviors in Unsupervised Online Quizzing: The Role of Instructors in Interlinking Analytics and Pedagogy*

#### Procedures

If you agree to participate in my research, I will conduct an interview with you at the time and location of your choice. The interview will involve questions about *the learning design implemented in your class, your knowledge about students' actual study strategies, and the usefulness and implications of quiz-log analytics*. It should last about 2 hours (*1-hour interview distributed in 2 sessions*). With your permission, I will audiotape and take notes during the interview. The recording is to accurately record the information you provide and will be used for transcription purposes only. If you choose not to be audiotaped, I will take notes instead. If you

agree to be audiotaped but feel uncomfortable or change your mind for any reason during the interview, I can turn off the recorder at your request. Or if you don't wish to continue, you can stop the interview at any time.

I expect to conduct one interview each distributed in two phases of my study; however, follow-ups may be needed for added clarification. If so, I will contact you by mail/phone to request this.

*[I may follow-up if I feel I need further clarification for any information you have provided or need any additional details or information]*

### **Benefits**

There is no direct benefit to you from taking part in this study. It is hoped that the research will benefit the future design and implementation of quizzes and future generations of students in receiving meaningful feedback about their quiz-taking strategies

### **Risks/Discomforts**

*The research questions are expected to be non-personal and non-sensitive. However, you are free to decline to answer any questions you don't wish to or to stop the interview at any time.*

As with all research, there is a chance that confidentiality could be compromised; however, we are taking precautions to minimize this risk.

### **Confidentiality**

Your study data will be handled as confidentially as possible. If the results of this study are published or presented, individual names and other personally identifiable information will not be used.

To minimize the risks to the confidentiality, we will store the data at the office of Center for the Analytics for Learning and Teaching (C-ALT). Only the PI of the project, Dr. James Folkestad

and I (the co-PI, Priya Harindranathan) will have access to the data copies stored in our personal computers, protected by passwords.

We will transcribe the audio recordings as soon as possible after the interview. When the research is completed, I will save the transcriptions and other study data for possible use in future research done by myself or others. I will retain these records for up to 3 years after the study is over and destroy these at the end of the 3-year period. We may be asked to share the research files with the sponsor or the CSU Institutional Review Board ethics committee for auditing purposes.

### **Compensation**

You will not be paid for taking part in this study.

### **Rights**

*Participation in research is completely voluntary.* You are free to decline to take part in the project. You can decline to answer any questions and are free to stop taking part in the project at any time. Whether or not you choose to participate in the research and whether or not you choose to answer any questions or continue participating in the project, there will be no penalty to you or loss of benefits to which you are otherwise entitled.

### **Questions**

If you have any questions about this research, please feel free to contact me at

*Priya.Harindranathan@colostate.edu* or [REDACTED]. You may also contact Dr. *James Folkestad*, [James.Folkestad@colostate.edu](mailto:James.Folkestad@colostate.edu) or [REDACTED]

If you have any questions about your rights or treatment as a research participant in this study, please contact the Colorado State University Institutional Review Board (IRB) at [REDACTED] or e-mail [RICRO\\_IRB@mail.colostate.edu](mailto:RICRO_IRB@mail.colostate.edu).

**CONSENT**

Do you consent for your interview to be audiotaped?

Yes

No

If you wish to participate in this study, please sign and date below. You will be given a copy of this consent form to keep for your own records.

\_\_\_\_\_

Participant's Name (*please print*)

\_\_\_\_\_

Participant's Signature                      Date

*[Optional/If applicable]*

If you agree to allow your name or other identifying information to be included in all final reports, publications, and/or presentations resulting from this research, please sign and date below.

\_\_\_\_\_

Participant's Signature

\_\_\_\_\_

Date

## APPENDIX D

### Interview Questions Phase I: Pre-Analytics Questionnaire

1. *Do you mind if I record our interview?*
  
- 2a. *What was the pedagogic intent in implementing low-stake unsupervised online quizzing in the MIP course?*
  
- b. Was there a learning theory that was the driving factor behind the implemented design?*
  
3. *In what ways would you ideally want your students to engage with the quizzes?*
  
4. *What instructions, if any, do you give your students before using the online quizzes?*
  
5. *In the previous semesters, what did you know about the actual quiz-taking behaviors of your students? How did you know this?*
  
6. *How have you used available Canvas analytics to understand the quiz-taking behaviors of students?*
  
7. *If you could proctor your students while taking the quizzes, what behaviors would you look out for?*
  
8. *Before we conclude, would you like to add anything else related to our conversation?*

## APPENDIX E

### Interview Questions Phase II: Post-Analytics Questionnaire

1. *Do you mind if I record our interview?*
2. *What are your perceptions about the variables extracted from the quiz-log data, which are related to students' quiz-taking behaviors?*
3. *Given the information about learners' quiz-taking behaviors, what is your take on their use of strategies in the low-stake unsupervised online quizzing implemented in the MIP course?*
4. *Given the information about learners' quiz-taking behaviors, how would you encourage your students to behave in a different way?*
5. *Given the information about learners' quiz-taking behaviors, how would you change the design or implementation of quizzing in your class?*
6. *What additional information related to students' quiz-taking behaviors might be useful?*
7. *Before we conclude, would you like to add anything else related to our conversation?*