Spring 5-2022

Metacognitive Supports in Online Community College Learners

Bethany L. Emory
Old Dominion University, blemory70@gmail.com

METACOGNITIVE SUPPORTS IN ONLINE COMMUNITY COLLEGE LEARNERS

by

Bethany L. Emory
B.A. May 1992, Central College
M.A December 2004, Marymount University

A Dissertation Submitted to the Faculty of
Old Dominion University in Partial Fulfillment of the
Requirements for the Degree of

DOCTOR OF PHILOSOPHY EDUCATION

WITH A CONCENTRATION IN INSTRUCTIONAL DESIGN AND TECHNOLOGY

OLD DOMINION UNIVERSITY
May 2022

Approved by:

Dr. Tian Luo (Director)

Dr. Linda Bol (Member)

Dr. John Baaki (Member)

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Bethany Emory
Old Dominion University
Director: Dr. Tian Luo

Community colleges provide educational, social and professional lifelines for students. Community college students are often characterized by their need to balance school amidst conflicting life needs, such as employment and family. As a result, many community college students struggle to find time to commit to on campus classes. Asynchronous online courses offer these students flexibility. Without the ability to self-regulate their learning, this mode of learning has been shown to be more challenging, resulting in students who succeed and persist in coursework less consistently.

This quantitative, quasi experimental study involving 92 asynchronous online community college participants from the southeast, explores support structures designed to assist learners in developing effective self-regulation practice. The research combines a two-factor quasi experimental design comparing the use of training that incorporates cognitive modeling, self-reflective prompts and the combination of these elements to evaluate their effect on calibration ability and academic performance. Metacognitive awareness is used as a covariate.

Results of this study showed no significant difference between treatment groups in regard to either calibration ability or academic performance based on the elements of the training intervention. Descriptive statistics combine with these results to both support and challenge existing research, and continued research and updates to heuristic practice are suggested.

Keywords: *calibration, cognitive strategy, and metacognitive strategy*

This dissertation is wholeheartedly and singularly dedicated to my husband, Scott, who always gives me everything I need. He never let me quit, loved me (especially when I wanted to give up), and listened to whatever I needed to work through. In addition to my parents, Ted and Donna who have been lifelong educators of all who have had the pleasure of knowing them. I am also thankful for the support of my two sons Tyler and Cody, and their sometimes-better halves Samara and Dayanne. They supported me in ways that I am not certain they are aware of. As well my two brothers, Ted and Jack who are two of the most dedicated and introspective people I know. I got to be the youngest, so you will always be my role models.

ACKNOWLEDGMENTS

I am thankful for each of my committee members, Dr. Baaki, Dr. Bol and especially Dr. Luo who chaired and guided me throughout this dissertation's development. Dr. Bol, I truly appreciate your work and research surrounding calibration and self-regulated learning, and for agreeing to take this project on. Dr. Baaki, I have always appreciated your fair and direct feedback, and this project was no exception. Dr. Luo, I have appreciated your guidance as I have worked through my coursework, and the development of this document. I appreciate your work and guidance in structuring such a project in a way that I could continue to allow for real life to happen.

Additionally, I would be amiss if I did not thank each and every Instructional Design and Technology student, I have had the pleasure of taking classes with. You have collectively shaped how this old dog sees new tricks and reminded me of the power of thought.

Finally, I must thank the Southwestern Community College administrators, staff, and students for their willingness to help, try many crazy ideas and to support me in ways I could only imagine. This is especially true of Dr. Barbara Putman who helped me code the words of, process the intentions of and learn from the work of each of our students. She is a teacher among teachers, a scholar among scholars, and a pretty great human being above all. I am thankful to work in such a supportive environment.

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CHAPTER I

INTRODUCTION AND LITERATURE REVIEW

Introduction

Community colleges provide educational, social and professional lifelines for students in rural or isolated areas throughout the United States. For students who live in more populated areas, affordability and access have made community colleges equally as effective in supporting students. In the fall of 2019, publicly funded community colleges served 5.4 million students (Community College Research Center, 2019). These students are often characterized by their need to balance school amidst conflicting life needs, such as employment and family (Majer, 2009; Thompson & Verdino, 2018). As a result, many community college students struggle to find time to commit to on campus classes. Students enrolled in at least one online class account for more than 57% of community college enrollment in the researcher's home state of NC (North Carolina Community College System Office, 2020). Asynchronous online courses offer these students flexibility but may also challenge their cognitive and metacognitive processes (Lederman, 2018). Success and completion statistics in online courses lag behind those of non-online instruction, even while pressure on institutions to assist students to complete credentials grows (Community College Research Center, 2019; Lederman, 2018).

When considering the asynchronous online environment - where learning can happen across physical borders and can exist in isolation from immediate learning guidance - novice learners can struggle. Often these students have not yet developed a strong ability to gauge their own expertise, this deficiency can slow attempts to make lasting learning gains. This potential metacognitive insufficiency in learners has the potential to negatively affect enrollment, as well as persistence, in community colleges. From the lens of instructional design, both efficiency and effectiveness of instructional materials, design, and consumption may be affected as well. Researchers have begun to speculate if design, in absence of support for metacognitive monitoring can flourish, especially in non-traditional environments such as asynchronous online learning (Akyol & Garrison, 2011; Bol & Garner, 2011; Broadbent & Poon, 2015; Puzziferro, 2008).

Study Significance

Community colleges, especially those in NC, continue to see rapid growth in the online format, even while broader enrollments have declined. (North Carolina Community College System Office, 2020). At the same time, both persistence and success in those online courses have been plagued by a lack of parity with face to face and hybrid counterparts (North Carolina Community College System Office, 2020). College success or first year seminar courses have been designed and shown to improve persistence and requiring these courses has become best practice (Barefoot, 2004; Crisp & Taggart, 2013; Heller & Cassady, 2017). Like many other college courses, these foundational courses have increasingly moved to an online format. As community colleges focus on student success, improving self-regulation beginning in these introductory courses could prove to be essential to continued growth in enrollment and improving persistence in future courses.

Although much of the research exploring calibration as an essential component of self-regulation has been focused on lab experimentation and traditional classroom environments (Hacker & Bol, 2019), the researcher will expand the burgeoning knowledge base of research focused on the specific population of asynchronous online community college learners. Improving self-regulation through more accurate learning calibration has been explored in both asynchronous online and college environments (Baars et al., 2014; Huff & Nietfeld, 2009;

Kostons et al., 2012; Raaijmakers et al., 2018; Salden et al., 2006). However, this research has rarely included community college populations. In addition, the results of this research have been mixed, indicating a need for further exploration.

Literature Review

Metacognition

Cognition refers to the process the brain uses to move knowledge to its long-term storage (Flavell, 1979; Sweller, 2008). For learning to occur, this information is connected to prior knowledge making it easier to retrieve (Brown et al., 1982; Flavell, 1979; Sweller, 2008). Meta translates from the Greek to indicate about, and cognition encompasses the processes involved in learning, so by inference metacognition can loosely be described as thinking about learning.

Seminal Research

When considering influential research useful in establishing a definition and heuristic practice in developing metacognitive skills, two authors are commonly referenced. Flavell's *Metacognition and Cognitive Monitoring A New Area of Cognitive-Developmental Inquiry A Model of Cognitive Monitoring* (1979) has been cited is excess of 19,000 times. This seminal work began the endeavor of identifying the process of cognitive monitoring using the term metacognition. His work helped to shape the field's characterizations of the component elemental difference between cognition and metacognition.

Soon after, Brown et al. contributed the *Learning, remembering, and understanding. Technical Report No. 244* (1982) Similarly referenced in excess of 8,000 times, the group contributed to the knowledge base by providing a clarity surrounding metacognition's component elements and offering structures for improvement through instructional interventions.

Metacognition's Component Elements

Given the tightly related concepts of cognition and metacognition, research into the control processes of each, often produced ill formed definitions of both (Brown et al., 1982). As a result the two processes and their exploration have overlapped (Brown et al., 1982; Hacker, 1998; Veenman et al., 2006). As stated by Brown (1987), "Confused in the metacognitive literature, even lost in some versions of the concept, is the essential distinction between self-regulation during learning and knowledge of or even mental experimentation with, one's own thoughts (Brown, 1987 in 1982, p. 129)." To clarify the definition of metacognition, Flavell and Brown began categorizing its component elements using broad categories including knowledge, skills, and monitoring or control.

Metacognitive Knowledge

When considering metacognitive process or functions, knowledge refers to a learner's thoughts related to what he or she already knows (Hacker, 1998). This knowledge can be declarative, such as factual knowledge. As well, knowledge can be conditional encompassing the recall of procedures and rules or involving the application of principles and rules / procedures (Flavell, 1979; G. R. Morrison et al., 2019). These pieces of knowledge have been characterized as stable, transmittable, and prone to false estimation (Brown et al., 1982; Flavell, 1979). Brown suggests (1982), when examining one's own learning, knowledge includes what one knows and can explain to another party. In addition, this knowledge of learning potentially is not as reliable as one would expect, as is true for much of our long-term memory. One can think they possess certain understanding even when it may fail to be recovered. (Brown et al., 1982). Lastly, the knowledge of metacognition has been characterized both in seminal works and more recent research as late to develop, and requiring reflection to surface (Bjork, 1999; Brown et al., 1982).

Metacognitive Skills

Metacognitive skills refer to thoughts surrounding the practical learning processes that a learner can do well. For those with higher level metacognitive skills, these tools can also be related to present learning processes (Flavell, 1979; Hacker, 1998). Cognitive skills are about making learning progress while metacognitive skills are about monitoring progress toward learning (Flavell, 1979).

Metacognitive Monitoring or Control

Metacognitive monitoring or control affects a learner's ability to evaluate their own learning and modify learning processes. When involved in metacognition, students may undertake tasks such as planning and prioritizing, gauging and inferring and selecting and evaluating (Brown et al., 1982; Flavell, 1979; Hacker, 1998). This evaluative process can be conscious or automatic (Brown et al., 1982). Automated metacognitive processes can be reflected through cognitive processes, making them hard to isolate (Hacker, 1998). Still, learners make use of evaluative and analytical skills when executing conscious metacognition (Kluwe 1982 in Hacker, 1998). Kluwe (1982 in Hacker, 1998) first termed the process of learners monitoring and selecting knowledge from long term memory to regulate learning processes as executive processes. Through effective use of these processes, later referred to as executive function, learners can better allocate resources, prioritize processes and set an appropriate pace for their learning (Hacker, 1998).

Self-Regulated Learning

From initial work defining the functions of metacognition, self-regulation grew as a dynamic and cyclical process comprised of feedback loops (Panadero, 2017; Winne & Hadwin, 1998; Zimmerman, 2002). Self-regulation is the process students use to plan, complete and monitor their own learning (Hadwin & Webster, 2013; Panadero, 2017; Spruce & Bol, 2015;

Winne, 2004; Zimmerman, 2002, 2008). This systematic process of self-regulation has expanded to include the activation and maintenance of the learning process toward the achievement of goals (Schunk & Greene, 2018). Although throughout its study, a variety of models of self-regulated learning have developed, many follow a consistent cyclical model and build upon the work of Zimmerman (Panadero, 2017; Zimmerman, 1989).

In 1995, Winne and collaborators expanded on the work of Zimmerman through the development of a self-regulation model focused primarily on the metacognitive functions (Panadero, 2017; Winne, 1995). Winne, similar to Zimmerman before him, introduced four phases that focus on clarification of assignments/tasks, organization of learning requirements (including clarifying goals), selection of viable approaches, and adjustment of learning paths (Winne, 1995). Later in conjunction with Hadwin, the COPES architecture was introduced to more clearly define components of the learning process (Winne & Hadwin, 1998).

Pintrich (2000) offered an additional facet of motivation and added much needed empirical evidence to support its impacts (Panadero, 2017; Pintrich, 2000). Pintrich clarified similarities in existing models, including categorizing his model using a similar four component structure like those indicated by Zimmerman (2008) and Winne and Hadwin (1998). Similar to Boekaerts (2005), Pintrich stressed the role of goals on the self-regulation process. This built upon the earlier work of Boekarts (1995) Dual Processing model which emphasized the importance of metacognition in guiding behaviors both positively and negatively.

Theoretical Framework – Zimmerman's Model of Self-Regulated Learning

Based upon its wide acceptance and flexibility, as well as its integration into prior calibration research, Zimmerman's cyclical model of self-regulation will serve as the theoretical framework for this exploration. Throughout his illustrious career, Zimmerman developed three related models of self-regulation – triadic, cyclical, and multi-level (Panadero, 2017). The cyclical is most often cited, and widely accepted. (Panadero, 2017; Schunk & Greene, 2018). Throughout literature surrounding metacognition and self-regulation his work has been cited more than 10,000 times. The cyclical structure formed the foundation for later models of development including its influence on Winne and Hadwin (1998), Pintrich (2000) and Efklides (2011) (Panadero, 2017; Schunk & Greene, 2018). Zimmerman (2008) defined the process as "the degree to which students are metacognitively, motivationally, and behaviorally active participants in their own learning process (p.167)." He classifies the process as including three phases, forethought, performance and self-evaluation. Zimmerman's cyclical model is summarized in Figure 1 below.

Figure 1 Zimmerman's Cyclical Model of Self-Regulation

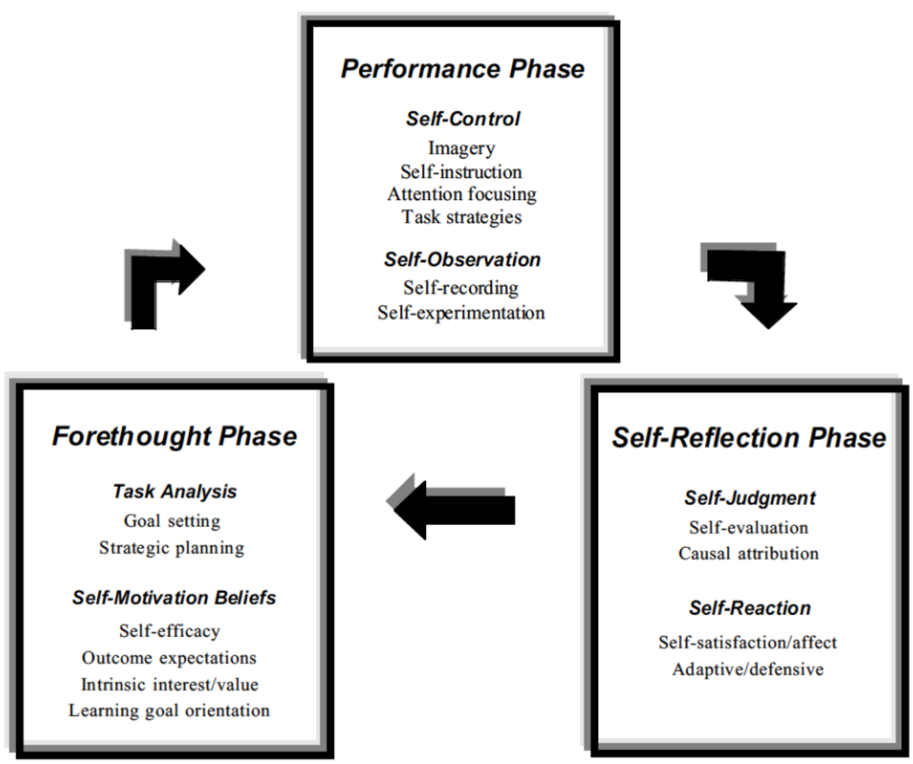


Figure 1. Zimmerman's Self Regulated Learning Model (Zimmerman & Campillo 2003, In J.E. Davidson and Robert Sternberg (Eds.), The Nature of Problem Solving. p.239)

In the forethought phase, students set learning goals or evaluate learning goals established for them (Zimmerman, 1989, 2002, 2008). Research has shown that the ability for students to set goals for themselves, increases their motivation to monitor their learning (Hadwin & Webster, 2013; Wäschle et al., 2014; Zimmerman, 2002).

During performance, learning strategies become essential to mastering content. Through processes of reflection and comparison to established learning goals, learners are able to benefit from effective learning strategies established by the instructor or choose effective strategies while studying in isolation. Research has shown however that many students, both novice and experienced, choose learning strategies that do not align with proven results (Agarwal et al., 2007; Kornell & Son, 2009; McCabe, 2011; Wäschle et al., 2014). By choosing strategies that do not align as effectively as possible with learning to be achieved, many students waste time studying content that has already been mastered or abandoning challenging topics before adequate learning has occurred (Spruce & Bol, 2015; Zimmerman, 2002, 2008).

Finally, self-reflection allows students to evaluate and modify their learning processes. This phase can produce both self-critique and self-protection in novice learners (Zimmerman, 2002). Defensive reactions, common in self-protection, help students shield themselves. For example, should a student focus goals more on the performance of others than specific learning needs during the forethought phase, a defensive action may cause a student to withdraw from class or avoid challenging assignments in order to save face during production (Zimmerman, 2002, 2008). However, as students develop their self-regulation skills, these evaluations become more adaptive, prompting students to evaluate their successes and failures and adapt their regulatory processes to better facilitate their learning (Hadwin & Webster, 2013; Zimmerman, 2002, 2008).

Self-Regulated Learning and Asynchronous Community College Learners

There exists a large number of novice learners in community colleges.(Majer, 2009; Stephens et al., 2014). Learners in this category are more likely to choose to set improper targets, or follow reactive rather than proactive approaches (Stone, 2000; Zimmerman, 2008). Many students either do not possess the skills necessary to self-regulate or choose to apply them ineffectively (Bol & Garner, 2011; McCabe, 2011; Serra & DeMarree, 2016; Thiede & Dunlosky, 1999). It is also common for these students to rely exclusively on due dates to plan their learning (Wäschle et al., 2014). However, self-regulation has been shown in a variety of studies to increase persistence, academic performance and calibration in a community college setting (Bol et al., 2016; Hu & Driscoll, 2013; Liao et al., 2014).

Online learning, especially when conducted in an asynchronous format, can leave learners with primary responsibility for planning and evaluating their learning (Bol & Garner, 2011). Research has shown that the online learning environment presents unique challenges for self-regulation due to its autonomous nature (Bol & Garner, 2011; Hsu et al., 2017). Developing these skills in the online environment becomes harder when students are not provided clear directions, or are challenged to learn on their own time and at their own pace (Bol & Garner, 2011; Schacter & Szpunar, 2015) This failure to prevent distraction can cause a learner to fail to achieve learning goals and complete assigned tasks (Bol et al., 2016).

When focused through a slightly different lens, Barnard-Brak et al (2010), found a correlation between GPA and higher level self-regulation performance in online college learners. And self-regulated learning strategies correlate with success in distance-learning environments

(Bol & Garner, 2011; Hadwin & Webster, 2013; Zimmerman, 2008). Improving students' ability to evaluate their learning has shown to be challenging, and research continues to produce mixed results (Ariel & Dunlosky, 2011; Bol et al., 2016; Gutierrez et al., 2016; Hacker et al., 2008; Hadwin & Webster, 2013; Huff & Nietfeld, 2009; Nietfeld & Schraw, 2002; Reid, 2013; Townsend & Heit, 2011).

Learning Calibration

Determining where a student is on their learning path is essential to self-regulated learning (Hadwin & Webster, 2013; Hattie, 2013; Stone, 2000; Zimmerman, 2002). This process, commonly referred to as calibration, is defined by Stone (2000) as "…a measure of the relationship between confidence in performance and accuracy of performance (p. 467)." Through recognition of their progress in mastering material, learners gain the requisite knowledge to modify their processes and increase efficiency (Boekaerts, 2017; de Bruin & van Merriënboer, 2017; Hadwin & Webster, 2013; Hattie, 2013; Pintrich, 2000; Stone, 2000; Zimmerman, 2002).

Initially calibration was measured in absolute terms. This measurement focused on the distance between student estimation of performance and actual performance. The absolute value of the difference between performance and prediction indicates calibration accuracy (Schraw, 2009). A second measure that is used to evaluate calibration it calibration bias. In this case the indicative sign is included in the measure with negative values representing under confidence and positive values representing over confidence (Schraw, 2009).

Research has shown that the ability to calibrate (both accuracy and bias) improves with age and subject expertise (Bjork, 1999; Finn & Tauber, 2015; Hartwig & Dunlosky, 2012; Hattie, 2013). However, it has also shown that undergraduate students continue to be likely to overestimate their learning, when compared to their faculty's estimates (Finn & Tauber, 2015).

This trend was established as especially true for underperforming students (Bjork, 1999; Hattie, 2013). Research literature highlights several possible causes for this faulty calibration including fluency of information retrieval, difficulty of the learning task, and prior knowledge.

Component Elements of Calibration Error

Fluency

Fluency, or the ease with which information can be retrieved, has been shown as a common cause for calibration error (Finn & Tauber, 2015; Griffin et al., 2009; Hadwin & Webster, 2013; Kornell & Son, 2009; McCabe, 2011). One's confidence in their ability to demonstrate learning (both factual and procedural), is connected to how effectively and quickly one has been able to do it in the past (Bjork, 1999). The more familiar information becomes (often through training) the more likely a student is to assume it has been understood (Bjork, 1999). This belief can be faulty, as learning may occur with no change in performance ability and vice versa (Bjork, 1999). Some research has shown that by spacing the calibration of learning from the learning event, calibration is improved as familiarity lessens (Hadwin & Webster, 2013; Tullis et al., 2013).

Difficulty

In general, if a task feels more difficult, students will tend to underestimate their ability to perform (Bjork, 1999; Finn & Tauber, 2015; Thiede & Dunlosky, 1999). This phenomena has been shown to correlate to students' view of intelligence and its ability to be changed (Finn & Tauber, 2015; Hattie, 2013). Conversely, appropriate challenge in learning is also associated with more long term and effective knowledge acquisition. This is referred to in literature as the theory of desirable difficulty (Bjork, 1999; Tullis et al., 2013). However if a task seems too hard, for many students it becomes unappealing and reduces motivation (Bjork, 1999). This detrimental effect on feelings of self-efficacy in completing complex tasks, can cause students to underestimate their ability to perform.

Prior Knowledge

Prior knowledge has been shown to have a complex influence on students' ability to judge their own learning. As stated above, most research has shown that as students develop mastery in a topic, they are less likely to overestimate their abilities (Bjork, 1999; Finn & Tauber, 2015; Hartwig & Dunlosky, 2012; Hattie, 2013). Research showed that it was more common for developing experts to underestimate when judging their own knowledge, especially when faced with complex tasks (Griffin et al., 2009). However, when tasks were simpler in nature, experts also predicted higher performance than was achieved (Bjork, 1999; Finn & Tauber, 2015; Thiede & Dunlosky, 1999). These results have been related to underestimating the challenge of new learning, and making assumptions that exposure at a broader level will translate into comprehension (Bjork, 1999). As students develop their self-regulation skills, these evaluations become more adaptive, prompting students to evaluate their successes and failures and adapt their regulatory processes to better facilitate their learning (Hadwin & Webster, 2013; Zimmerman, 2002, 2008).

Calibration and Asynchronous Community College Learners

Online text and other forms of hypermedia present choices that can confound the learning process in an online environment especially for those who have difficulty in calibrating learning. (Azevedo, 2009; Greene & Azevedo, 2009) Studies of college students, especially those considered struggling (Bjork, 1999; Hattie, 2013), have shown student propensity to overestimate their progress as compared with faculty estimates (Finn & Tauber, 2015; Zamary et al., 2016). The poor calibration skills of the lowest achieving students have been documented in research (Bol & Hacker, 2001; Hacker et al., 2008). Garner and Tocker (2011) and Heller and Marchant (2015) found that college students with sub-clinical risk factors for executive dysfunction were at risk of poor self-regulatory processes and academic distress.

Training as an Intervention to Improve Calibration and Academic Performance

Training in metacognitive processes has shown to be a reasonable tool to improve learners' calibration ability (Finn & Tauber, 2015; McCabe, 2011; Thiede & Dunlosky, 1999). Examining inclusion of instruction on self-regulation, specifically the monitoring phase, has begun to be explored with positive expectations and mixed results (Baars et al., 2014; Huff & Nietfeld, 2009; Kostons et al., 2012; Raaijmakers et al., 2018; Salden et al., 2006) Heuristic practice suggests that metacognitive training be integrated with other subject specific tasks using an intentional structure and that ample time is included for practice and development (Brown et al., 1982; Collins et al., 1991). As a result, including metacognitive elements in traditional instruction has been seen as challenging to implement by many instructors who find little time to spare in meeting prescribed learning objectives (Brown et al., 1982; Zumbrunn et al., 2011).

In recent studies, effective training in metacognitive monitoring has been explored as a way to improve calibration (Bol et al., 2016; Callender et al., 2016; Emory & Luo, 2020; Huff & Nietfeld, 2009) In their seminal work, Brown et al. (1982) established three broad categories of training and the structures remain useful in categorizing recent research. These categories include blind, informed, and self-control training (Brown et al., 1982).

Blind Training

Generally speaking, blind training implementations present a metacognitive strategy or activity, yet stop short of involving the learner in the reasoning behind their use (Brown et al., 1982). As a result, the role of the learner is limited. Based on the effects of fluency (Finn &

Tauber, 2015; Griffin et al., 2009; Hadwin & Webster, 2013; Kornell & Son, 2009; McCabe, 2011) and prior knowledge (Bjork, 1999; Finn & Tauber, 2015; Thiede & Dunlosky, 1999) of one's self-regulation and calibration, one could hypothesize that this training could be less effective than training that includes foundational knowledge of metacognitive processes. Some students will recognize the importance and utility of the self-regulation process, while others may not. Still, findings suggest that self-regulation can be improved in students involved in blind training through instructor use of approaches including direct strategy instruction (Callender et al., 2016; Hacker et al., 2008; Zumbrunn et al., 2011).

In addition to a limited role of the student in blind training processes, Brown and her team called into question the ability for students to transfer knowledge of self-regulation skills to novel tasks. The researchers stated, "A second problem is that blind training techniques can, and often do, help people learn a particular set of materials, but existing data suggest that they do not necessarily help people change their general approach to the problem of learning new sets of materials (Brown et al., 1982)."

Blind Training with Asynchronous or Community College Learners

Although research results are scarce in this environment, three recent studies have investigated the effects of this training. Bol et al., (2016) investigated the effects of training on academic performance and self-reported use of metacognitive strategies on community college math students using a computerized intervention, and Hu and Driscoll (Hu & Driscoll, 2013) investigated similar variables in a fully online environment. Emory and Luo (2020) investigated the effect of video based lectures describing metacognitive processes on student learning and calibration.

Bol et al. (2016) provided direct support to developmental math students in a community college environment in hopes of improving academic performance and use of metacognitive practice. The experimental study involved 116 developmental community college students in a traditional classroom setting, however instruction was delivered using a respected online instructional platform. Students were randomly assigned to either a control (no intervention) or treatment (intervention involving blind training and support in self-regulation) group. Students involved in the treatment intervention used training strategies modeled around Zimmerman's (2008) cyclical model and reported self-regulated strategy use using Pintrich at al.'s (1993) Motivated Strategies for Learning Questionnaire (MSLQ) The results indicated that both math performance and self-regulated learning behaviors increased as a result of the intervention.

Hu and Driscoll (Hu & Driscoll, 2013) conducted a study of novice students in a college success course in the southeastern United States. Similar to the current study, a blind instructional model was used. Lecture based instruction was provided online and its effect on academic performance was evaluated. Different from the current study, learner motivation and self-reported use of self-regulated learning strategies, was tracked and evaluated. In Hu and Driscoll's study, a sample of 21 students, with 12 of the 21 being required to take the course as a result of low scores on college entrance exams was studied. A significant difference was similarly shown in academic performance. However, the self-reported strategy usage difference was not significant, with the control group showing a higher average score than those who participated in the intervention.

Emory and Luo (2020) conducted a study of novice students at a rural community college in the southeast. Although external validity results are challenged due to a small sample size, this study did not produce similar findings in relation to academic performance. The study of 22 students enrolled in a required College Student Success course indicated no significant difference in academic performance or calibration as a result of direct instruction.

Informed Training

Informed training involves a conveyance of the importance of monitoring processes to students intentionally during the training process (Brown et al., 1982). Brown et al. (1982) considered it an intermediate level of training in regard to effectiveness in relation to academic performance. The group hypothesized that this format had potential to improve the transfer of learning, but only if initial success in regulating learning is achieved by the learner during the training intervention (Brown et al., 1982). Cognitive modeling has shown to be an effective tool in conveying both the importance and function of cognitive and metacognitive processes (Brown et al., 1982; Collins et al., 1991; Collins & Kapu, 2014).

Cognitive modeling. In early works, Brown et al (1982) characterized the modeling process as involving systematic supports used to guide the learner implemented by caring partners such as parents, teachers, or peers. Later, cognitive modeling was described as an essential practice in the cognitive apprenticeship process (Collins et al., 1991; Collins & Kapu, 2014; Dennen, 2004). In an instructional context, modeling often results in the creation of materials that focus learners on experiencing the process as an expert performs the task rather than observing as an expert describes the task (Wang & Bonk, 2001). In addition to making cognitive processes clearer, the cognitive modeling processes also allow students to recognize how troubleshooting and error correction occurs (Collins & Kapu, 2014; Ghefaili, 2003). The process of observing experts applying their own procedures assists novices in achieving a smooth transfer of similar executive functions in their own work (Brown et al., 1982). Use of the modeling process has been shown to be effective empirically in software development (Mathieu et al., 2000), in improving functions of highly specialized control crews (Waller et al., 2004), and in improving business students' group processes and development of shared mental models (Van den Bossche et al., 2011).

Research has allowed for the development of a set of heuristics for developing cognitive modeling processes and products. When teachers model and explain their own thought processes, students are more apt to understand and begin to use those same processes in developing solutions (Boekaerts & Corno, 2005). This can be especially important to students learning in isolation. When left without guidance, these students may fail to use resources available to them to resolve problems, while experts would not hesitate to seek assistance (Collins et al., 1991; Collins & Kapu, 2014) A common and effective modeling practice involves instructors using a think aloud technique (Dunlap & Grabinger, 2008; Pedersen & Liu, 2002). Modeling should be structured to include the reflective practice inherent in the cognitive apprenticeship model, without it, effectiveness wanes (Cooper et al., 2001; Dennen, 2004). In addition, the work of Dennen (2004) implies the need to avoid an overly directive modeling presence. Finally, Dickey's research (2008) in a web-based technology course indicated that using a conversational style in presentation and tone was preferred in modeling components.

Informed Training using Cognitive Modeling with Asynchronous or Community College Learners

Although many instructional methods have been used to facilitate improvement in learning calibration and academic performance, results highlighted here will focus solely on those using cognitive modeling in an asynchronous online environment or with community college or novice college students. These studies include both quantitative and qualitative research methods, yet their measured variables focus solely on academic performance.

The effects of both training category (blind vs informed) and delivery mode (face to face vs online) on academic performance in Taiwanese college students was studied by Liu (2005). The twenty-four participants in the study were students in the elementary education department. Treatment students participated in an online course facilitated through a cognitive apprenticeship model, with included cognitive modeling. This group was compared to students instructed using the school's traditional model of instructional demonstrations using a face to face delivery. Pre-tests and Posttests of instructional planning (academic performance) were evaluated through a consistent rubric. The rubric evaluated students' ability in regard to planning the activity, setting appropriate goals and objectives, the implemented process, developed material resources and the development of assessment tools. Rubric scores showed significant improvement of performance as evaluated through the posttest were significantly higher, and the researchers attributed this to the inclusion of cognitive modeling. When considering the research design, they inferred that this modeling approach was the only identifiable difference, as assignments and evaluations were constant while only the ability to review expert models varied across groupings. Findings of the study implied that the web-based cognitive apprenticeship model improved pre-service teachers' performance and attitudes on instructional planning more effectively than the traditional training course.

An interpretive case study approach to evaluate the effects of cognitive modeling offered in a variety of formats on college students offered another view into the effects of cognitive modeling (Dickey, 2008). Although the study involved 3 graduate students, its primary participants were undergraduate students (n=39) in a technology-based course. Participants focused on incorporating technology in instruction for pre-kindergarten through 12th grade teachers. Findings revealed that 40 students indicated the cognitive models presented via video through *Over My Shoulder* (OMS) videos were the most influential format. These videos, where experts modeled performance as though students were looking over their shoulders, created the largest magnitude of comments in this qualitative study. In addition, users who referenced these videos submitted fewer questions via email than those who did not (Dickey, 2008).

Alger & Kopcha (2011) found that the use of technology structured cognitive modeling led to shared problem solving (academic performance). Their qualitative case study explored the use of cognitive modeling in the development of student teaching experiences. Their participants included nine triads of two expert mentors and one undergraduate student. Qualitative findings indicated that mental models, offered electronically by the guide teachers were considered essential elements in mastering academic objectives such as lesson planning. Mental scaffolding was also enhanced through technology by the use of templates and discussion tools.

Self-Control Training

Self-control training seeks to develop skills such as planning and evaluation through practice, with a goal of improving executive function. This practice is designed to occur as a supplement to informed training (Brown et al., 1982). Through this more developed approach to training, early research in laboratory environments showed an increase of maintenance metacognitive strategy usage over a one-year period and evidence of the transfer of metacognitive skills (Brown et al., 1982). This transfer of knowledge in the initial research however was directly influenced by student age, and presumably level of metacognitive skills (Brown et al., 1982). One strategy, metacognitive prompting, has been suggested to assist students in developing these essential strategies (Spruce & Bol, 2015; Zumbrunn et al., 2011).

Metacognitive Prompts. Self-reflective prompts have proven beneficial in stimulating metacognitive processes in both the flipped classroom and traditional classroom environments

(Heijltjes et al., 2015; Moos & Bonde, 2016). The use of self-reflective feedback can provide an impetus for students to re-evaluate their progress, often resulting in further learning (Bjork, 1999; Finn & Tauber, 2015; Pashler et al., 2005). These effects have proven most effective in students with knowledge of metacognition, who have forgotten or misuse the process (Bannert & Reimann, 2012).

Heuristic practice has evolved through research and application. When training students to use metacognitive functions, prompts differ from other instructional approaches, as they are designed without an intention to impart new skills or practices. These simple reminders rather are included to support the recall and execution of knowledge and skills (Bannert & Reimann, 2012) Simple questions serve to guide the student toward self-reflection and improved calibration (Ifenthaler, 2012).

Self-Control Training using Metacognitive Prompts with Asynchronous or Community College Learners.

Similar to those strategies available in informed training, many instructional methods have been used to facilitate improvement in learning calibration and academic performance in self-controlled training interventions. Similar to the studies on blind training, the findings included in this work were selected to highlight the use of metacognitive prompts by asynchronous online environments. Unlike the research focused on blind training, studies focused on metacognitive prompts include not only academic performance but also calibration accuracy

Initially, Van den Boom et al. (2004) explored metacognitive prompts and feedback effects on learning in psychology. The experiment was run in an online course with 42 undergraduate participants. Control and treatment groups both received prompts, however control group students received prompts not related to self-regulated learning processes. In addition, half the students in each of the treatment and control groups received corrected feedback from a tutor. The effect of these independent variables and their interactive effects on student academic performance were evaluated. Academic performance, although increased, was not affected either by the independent variables or by their interaction significantly.

Later, Berthold et. al (2007) compared the effects of metacognitive and cognitive prompting, and their interactive effects on academic performance in undergraduate students. Students received the training via video lecture in a face to face classroom setting. Students' ability to ask questions synchronously was restricted. As a result, this environment could be considered similar to an asynchronous learning environment. In addition, 85 undergraduate participants included 64 students who were in their first college semester, aligning closely with the community college population. Findings showed that metacognitive prompts increased self-reported metacognitive strategy use, while cognitive prompts increased both self-reported cognitive and metacognitive strategy use. In addition, both treatments indicated significantly higher scores in academic performance than the control group. However, neither metacognitive prompts (either as a sole intervention or mixed with cognitive prompts) nor cognitive prompts led to better calibration accuracy.

The effects of independent variables of prompting and a combination of prompting and training on dependent variables of academic performance (both short term and long term), learning calibration and effort were explored by Bannert & Reimann (2012). Forty undergraduate psychology and education students participated while completing a course in an online environment. Students in the control group received training via lecture format, where the control group received the same training coupled with metacognitive process prompts before, during, and after the lecture. There were two separate experiments, one where the purpose of the training was not specifically stated (blind), and a second where context and importance were conveyed to the students (informed). In the initial experiment, prompting plus training showed only marginal impact on long term performance yet no impact on short term performance. No significant difference was found in the other variables. In the second experiment, no significant difference was found in short term academic performance, yet a significant change did occur in academic performance over time.

Finally, Daumiller and Dresel (2018) researched the effects of both motivational and metacognitive prompts on valuation of task importance, control of metacognitive processes, learning strategies and performance. The participants consisted of 251 German college students learning in a digital media (online) environment. Metacognitive prompts aligned with increased usage of metacognitive strategies, and the same was true for the relationship between motivational prompts and actions. However non-corresponding effects were not seen. Both types of prompts increased self-reports of application and gains in academic performance (no interaction effect was shown). In addition, both types of prompts produced an effect on self-report of metacognitive control processes, yet the evaluation did not include an assessment of calibration accuracy or bias. The effect of metacognitive prompts was statistically significant, while the effect of motivational prompts was not.

The research base connecting each of these elements, training types, instructional strategies, and novice learners, remains sparse. In addition, exploration of the potentially different effects on community college learners' calibration ability and learning performance bears exploring.

Purpose Statement and Research Questions

The purpose of this study is to explore the effect of metacognitive training, supported through cognitive modeling and metacognitive prompts on students' ability to estimate their learning and their overall academic performance. This exploration will be framed by the following research questions:

(RQ 1) What are the effects of training in metacognitive practice (i.e. cognitive modeling, metacognitive prompts, combination and control) on learners' ability to calibrate their learning in a community college asynchronous online class?

a. Does viewing of cognitive modeling examples presented in video format affect learners' ability to calibrate their learning in a community college asynchronous online class?
b. Does responding to metacognitive prompts affect learners' ability to calibrate their learning in a community college asynchronous online class?
c. Does the combination of viewing of cognitive modeling examples presented in video format and responding to metacognitive prompts affect learners' ability to calibrate their learning in a community college asynchronous online class?

(RQ 2) What are the effects of training in metacognitive practice (i.e. cognitive modeling, metacognitive prompts, combination) on students' academic performance in a community college asynchronous online class?

a. Does viewing of cognitive modeling examples presented in video format affect students' academic performance in a community college asynchronous online class?

b. Does responding to metacognitive prompts affect students' academic performance in a community college asynchronous online class?

c. Does the combination of viewing of cognitive modeling examples presented in video format and responding to metacognitive prompts affect students' academic performance in a community college asynchronous online class?

Chapter 1 serves to introduce the key concepts and research base that will be built upon throughout this dissertation. Chapter 2 focuses on the study design, sample demographics, treatments, data collection and analysis procedures. Chapter 3 presents the results of these analyses. Chapter 4, interprets and discusses the findings in light of previous literature.

CHAPTER II

METHODOLOGY

This section presents the methods used to explore the effect of specific instructional treatments on calibration accuracy and academic performance among community college students. It continues to describe the quantitative design, study participants, instrumentation, and data analyses procedures.

Design

The research design was quantitative and quasi-experimental. The researcher investigated the effects of different instructional treatments on the dependent variables of calibration accuracy (both absolute and relative) and academic performance. The independent variable consisted of four treatment conditions. Training in metacognitive practice consisted of a) cognitive modeling b) metacognitive prompts, c) a combination of both treatments and d) control.

Participants

Protections

Prior to launching the study, several provisions were put into place to ensure participant privacy protection. Approval was obtained from the Institutional Review Board at both the hosting community college and from the Human Subjects Committee of the Darden College of Education & Professional Studies at Old Dominion University. To ensure all participants were well informed, they were given a one-page summary document and asked to indicate their consent using an electronic informed consent process. This document is included in Appendix A. As the researcher also served as an instructor, informed consent was managed by another college staff member to avoid a conflict of interest.

Student names and email addresses were removed during data analysis. Collected data was stored securely using password protection in digital files whenever extracted from the LMS. Raw course grades and LMS activity was recorded for students in accordance with requirements prescribed by the NC Community College system.

Selection Process

Based on the results of an a priori power analysis using the statistical program G* Power, a minimum sample size of 84 across the one control and three treatment groups was suggested to reach a medium effect size of 0.4 (Cohen, 1988). The study sample was collected from Summer and Fall 2021 semester enrollments in the ACA-111 (College Student Success) course at a medium sized rural community college in western North Carolina where the researcher was employed.

Data was collected from seven separate sections of the asynchronous online ACA-111 – College Student Success course, with a total enrollment of 159 students. Prior to the start of the courses, the students were distributed as equally as possible throughout the seven sections based on a traditional registration process coupled with a redistribution following the registration period if necessary. Each section included only one of the training interventions forming a quasi-experimental two factor design.

Table 1

Summary of section offerings, study participants and instructors

	Control	Modeling	Prompts	Combination
Sections	2	1	2	2
Enrolled Students	45	28	42	44
Consenting participants	22	18	24	28
Instructors	2	1	1	2

Although students received a grade in the course, no other incentives were used to induce participation. In addition, no additional course assignments were added, only the instructional methods were modified.

Context

Although the college was selected at least partially for convenience, it is representative of community colleges within the state of NC. The college serves approximately 3,300 students annually as part of a 58–institution, community-college system. This college, although rural is considered representative of the state population. Its enrollment ranks it 34th of 58 schools in size, and its student age and gender demographics are consistent with the system average. (North Carolina Community College System Office, 2020).

The selected course, ACA-111, is a first-year experience course related to college study and success strategies. It is added to student schedules as early as possible, and its enrollment traditionally represents the most novice students at the college. It is required in 45 out of the 48 associate degree programs at the college, providing a cross section of students. In 2019-2020, approximately 75% of students who enrolled in this course at the college chose to take this course in the asynchronous online format (North Carolina Community College System Office, 2020).

Instruments

Metacognitive Awareness

Although metacognitive awareness was not one of the study variables, this measurement was used as an indicator of prior knowledge and was included as a covariate in the statistical models used to analyze the data. The results also allowed a check on group equivalency to help rule out selection bias.

Students were asked to complete questions aligned with the monitoring subscale from the Metacognitive Awareness Inventory (MAI) (Schraw & Dennison, 1994). This instrument was chosen given its intended use with adults, and ease of administration (Schraw & Dennison, 1994). The use of this instrument had been well established in research (Altiok et al., 2019; Emory & Luo, 2020; Schraw & Dennison, 1994). The complete 52-item inventory showed it as a highly reliable indicator of metacognitive knowledge (i.e. Coefficient alpha = .93 and .88) (Schraw & Dennison, 1994). The monitoring subscale used in this study, indicated a Cronbach Alpha level of 0.91 (Schraw & Dennison, 1994). More recently, Altiok et al. (2019) implemented the survey as an indicator of metacognitive understanding in a study conducted at a state university in Turkey, which indicated a Cronbach Alpha level of 0.95. The inventory subscale items are included in Appendix B.

Academic Performance

Academic performance throughout the course was evaluated using multiple choice quizzes compiled of questions taken from a widely used Open Source textbook. The included questions were evaluated by two subject matter experts, both of whom have taught the course for more than 5 years, for alignment with the course content and research design. For this study, an evaluation using Cronbach's alpha was conducted. Quiz 1, focusing on college terminology consisted of 15 multiple choice and choose all appropriate response questions. The analysis results were $\alpha = .58$. Quiz 2, focused on academic and career planning and also consisted of 15 items. Analysis resulted in a score of $\alpha = .53$. The test questions are included in Appendix C.

Calibration

Students' prediction of performance was established using a simple question to elicit information. This approach had been well established in research on calibration (Bol & Hacker, 2001; J. R. Morrison et al., 2015). For this study, a question similar to those implemented by Morrison, Bol, Ross and Watson (2015) and Emory and Luo (Emory & Luo, 2020) was implemented as follows:

> You will now be asked 15 multiple choice questions based upon your reading. Out of 15 questions, how many would you anticipate answering correctly?

Based on extensive prior research including works of Bol and Hacker (2001), Callender et al. (2016), Dunlosky and Thiede (2013), Huff & Nietfeld (2009), Keren (1991), Nietfeld & Schraw (2002) Schraw (1997), Schraw & Dennison (1994) and Yates (1990), two measurements were used to characterize calibration ability. The first, calibration accuracy, was computed by taking the absolute value of the difference between a student's prediction of learning and their quiz score. These scores were summed for all attempted quizzes and divided by the total number of quizzes. Calibration accuracy scores had potential values of zero (indicating the student was able to calibrate their learning perfectly) to 15 (indicating the student showed no ability to calibrate their learning). For example, if a student predicted on each of the 2 quizzes, they would correctly answer 10 out of 15 questions correctly, but actually answered 8 and 14 questions correctly their calibration accuracy score would be 3 ((2+4)/2).

The use of a second indicator of calibration bias has been used in many similar reseach studies (Dunlosky & Thiede, 2013; Hacker et al., 2000; Keren, 1991; Yates, 1990). This was calculated by using the signed value of the difference between a student's prediction of learning and their quiz score. Again, these scores were averaged based on the number of quizzes attempted and the total of calibration bias scores. Scores for calibration bias ranged from a positive 15 to a negative 15. Positive scores were indicative of overconfidence, where negative scores indicated under confidence. As scores approached zero, calibration ability became less biased. For example, if a student predicted that they would answer 14 of the 15 questions correct on one quiz, but in reality, answered only 10 correct their calibration bias score would be 4. This score indicated that they overestimated the correct questions by 4. If on another quiz they predicted their score to be 10 out of 15, and on that quiz, they actually correctly answered 14, their calibration bias would be -4. This score indicated that they underestimated the correct questions by 4. Similar to calibration accuracy, the average bias score for the entire course was calculated. For example, if a student predicted on each of 2 quizzes, they would correctly answer 10 out of 15 questions correctly, but actually answered 8 and 14 questions correctly their calibration accuracy score would be 1 ((-2+4)/2).

Metacognitive Prompts

The self-reflection questions used in content review quizzes were modelled after those used by Reid et al. (2013) and Moos (2016). These prompts included questions designed to encourage metacognitive processes as students worked to master content. The included questions were also evaluated by two subject matter experts who have completed a minimum education level of a master's degree and have taught ACA-111 for five years or more. The following four questions were used as metacognitive prompts:

1. What questions (if any) do you have about the information presented and/or is there anything that you did not understand in the video or text?
2. Do you need to go back in the video or text and fill any gaps in understanding?
3. How effective were your strategies in learning?
4. What could you have done differently while studying?

Materials

Three instructors were used to facilitate seven individual sections of the course. Variations included only instructor contact information, and designed interventions. Grading, sequencing and course length were consistent across treatments. The course was divided into seven units, each lasting one week. Units topics included study strategies, campus resources, career and degree planning, and personal responsibility. Students were expected to spend 3-4 hours per unit. All common course components were evaluated through the nationally recognized Quality Matters review process (Maryland Online, 2018) and the course was certified as a quality online course prior to the experiment.

Instruction and assessment were conducted via Moodle, the college's Learning Management System (LMS), and video content was presented using the college's Kaltura streaming video service. Students were provided with a required self-paced orientation to the LMS in Unit 1, prior to any interventions. In addition, technical support was available throughout the process from the instructor and the college's e-learning department.

Procedure

Students were assigned to one of seven course sections, each comprised of one of the study intervention categories (Modeling – M, Prompts – P, Combination – MP, and Control – C). Assessments were included consistently in two units of the course, plus all students were asked to complete selected questions from the Metacognitive Awareness Inventory to indicate prior knowledge of metacognitive processes prior to the instructional intervention or any assessments.

Treatments

Modeling (M). Students in the modeling treatment (M) began intervention units by reviewing a model of metacognitive practice in a video format. These modeling videos contained think-alouds where the course instructor set goals, planned activities and reviewed tools available to calibrate their level of learning. Each video lasted between 3-5 minutes in length, and student participants had the opportunity to view a total of two examples within the 8-week course. Then after reviewing unit materials, students in the modeling group (M) were asked to provide a prediction of their learning of the content prior to attempting an evaluation of academic performance, which contained 15 multiple choice questions. The prediction and academic performance assessments were conducted through a Moodle Quiz.

Prompts (P). After reviewing intervention unit materials, students in the prompts treatment (P) completed five open ended prompts to encourage metacognitive reflection prior to completing a prediction of learning of the content. Finally, students in the prompts grouping (P) were asked to complete an evaluation of academic performance, which contained 15 multiple choice questions. Each of these assessments were conducted through a Moodle Quiz.

Combination (MP). Students in the combination treatment (MP) began each unit included in the intervention by reviewing a three to five-minute model of cognitive practice in a video format as described for the modeling group above. After reviewing unit content including the cognitive modeling video, students in the combination treatment (MP) were asked to complete five open ended prompts to encourage metacognitive reflection, then provide a prediction of learning for the content. Finally, students in the combination grouping (MP) completed an evaluation of academic performance, which contained 15 multiple choice questions. Each of these assessments were conducted through a Moodle Quiz.

Control (C). Students in the control group were provided only with the course content as contained in the quality matters certified course shell. This shell contained a short video lecture describing metacognition and suggesting steps useful in accomplishing a self-review of learning. It stopped short of providing any instructor to student interaction based on the lecture. After reviewing unit content in intervention units, students in the control group were asked also asked to provide a prediction of learning of the content. This assessment was followed by an assessment of academic performance, containing 15 multiple choice questions. Each of these assessments were conducted through a Moodle Quiz.

Data Analysis

Demographic Description

Initially, elementary data screening was completed following the procedures outlined by Waal, Pannekoek & Scholtus (2011). Descriptive statistics were used to characterize the study participants.

Research Question 1

The process to evaluate the potential effects of methods of training on metacognitive practice (i.e. cognitive modeling, metacognitive prompts, combination) on asynchronous online community college learners' ability to calibrate their learning involved three steps. Predictions of learning were compared to actual academic performance and were averaged across quiz attempts. Both accuracy of calibration and calibration bias were examined through an analysis of covariance with treatment grouping as the independent variable. The researcher used an analysis of covariance (ANCOVA) to establish if a significant difference was present between the different treatment groups, using metacognitive knowledge as a covariant (Laerd Statistics, 2017).

Research Question 2

When considering the potential effects of training on metacognitive practice (i.e. cognitive modeling, metacognitive prompts, combination) on the academic performance of community college learners, a similar two-step process was implemented using average scores across quizzes. The researcher used an analysis of covariance (ANCOVA) process to establish if a significant difference was present between the treatment groups, using metacognitive knowledge as a covariant (Laerd Statistics, 2017).

CHAPTER III

RESULTS

This chapter presents the results of the analyses conducted for this study. A series of parametric tests (i.e. ANCOVAs) were carried out. These tests were used to evaluate the effect of an independent variable, metacognitive training intervention, on asynchronous community college learners, taking into account the effect of a covariant, metacognitive knowledge. Effects on the dependent variables of calibration ability and academic performance were both evaluated.

The results begin with some key demographic descriptions of the sample and its treatment groups. Results are then are organized according to the study's research questions. Each of the research question sections begin with an analysis of the assumptions of ANCOVA and concludes with the results of this analysis.

Demographic Description

Initially, 159 students enrolled in the ACA-111 - College Student Success course and were assigned to sections based on advisor selection, and registration date. Each section used a different instructional treatment and consent to participate was gathered in the first week of the course. This resulted in varied sample sizes based on willingness to participate and enrollment dates. Of the 99 consenting participants who completed the Metacognitive Awareness Inventory, 18 came from a section using the modeling treatment, 27 the prompt treatment, 30 the combination treatment and 24 the control treatment. All completed the Metacognitive Awareness Inventory, however attrition throughout the experiment resulted in a varying number of scores collected both for calibration accuracy and academic performance. The sociodemographic makeup of the subjects is described in Table 2.

Table 2

Summary of participant demographic statistics

		Control		Modeling		Prompts		Combination		Total	
		n	%	n	%	n	%	n	%	n	%
Gender											
	Female	16	76	11	61	18	78	18	64	63	70
	Male	5	24	7	39	5	22	10	36	27	30
Race											
	No Information Provided			2	11	1	4	1	4	4	4
	American Indian or Alaska Native	6	26	1	6	5	22	7	25	19	25
	Black or African American										
	White	15	71	15	83	17	74	20	71	71	71
Age											
	18-24	8	39	12	67	14	67	12	57	46	51
	25-29	4	19	1	5	5	24	5	24	15	17
	30-39	7	33	5	24	4	19	6	29	22	24
	40-49	1	5					3	14	4	4
	50 or older	1	5					2	10	3	3

In considering the metacognitive awareness of student participants, descriptive statistics were evaluated as an initial step. As summarized in table 3 below, the mean and median measures in all groups were relatively consistent. The combination group has both the highest average and median self-reported scores of metacognitive awareness, while the prompts group reported the lowest scores in both categories.

Table 3

Descriptive statistics of results of Metacognitive Awareness Inventory

Group	*N*	*M*	*Median*	*SD*
Control	23	3.76	3.68	.48

Modeling	18	3.68	3.65	.64
Prompts	23	3.69	3.60	.64
Combination	29	3.96	3.82	.54
Total	92	3.79	3.71	.58

To better ensure that the groups were representative of a consistent population, the results of the Metacognitive Awareness Inventory were also evaluated for distribution normalcy. Initial review of histograms revealed reasonably normal distributions. Skewness and kurtosis values, when divided by the standard error remained within the boundaries of 1.96 and -1.96. The Metacognitive Awareness Inventory Average score was normally distributed, as assessed by Shapiro-Wilk's test ($p > .05$). An analysis of variance (ANOVA) also showed that no significant difference existed on normality indices between treatment levels at the $p = .05$ level [F (3,86) = 1.41, $p = .246$]

Descriptive statistics for calibration accuracy and bias are summarized in Table 4 below. In regard to absolute calibration student predictions were quite close to actual performance, contrary to what literature ay have suggested. Students in the Prompts group were the most accurate calibrators but were next to last in effectiveness when considering calibration bias. Students in the prompts group, were the second-best group in regard to calibration accuracy, and presented the least amount on bias in the learning. This provides a small indicator that both informed and self-control training propelled more effective calibration while the effect was not statistically significant. The combination group were the least effective calibrators both in relation to calibration accuracy and bias. This suggests that the sequencing and choice of interventions may play a role in effectiveness in calibration development.

Table 4

Descriptive statistics of average calibration accuracy and bias

		Calibration Accuracy			*Calibration Bias*		
Group	*N*	*M*	*Median*	*SD*	*M*	*Median*	*SD*
Control	21	2.55	2.00	1.77	-0.05	-0.25	2.42
Modeling	18	2.36	1.91	1.48	-0.03	-0.13	2.45
Prompts	28	2.21	1.50	1.75	-0.13	-0.50	2.77
Combination	23	2.59	2.33	1.42	-0.49	-0.33	2.43
Total	90	2.44	2.00	1.58	-0.20	-0.25	2.49

Academic performance results mimicked those of absolute calibration in many ways. The scores were calculated by taking average student scores on two 15-point quizzes. Scores could range from 0 to 15, and in cases students who failed to complete a quiz, their sole quiz score was used. The students who participated in a combination of intervention techniques performed the lowest in regard to academic performance, similar to calibration. Once again, the prompts group outperformed all others, although the difference was not significant. One slight difference in this analysis is that the control group outperformed the modeling group, suggesting that students who participated in modeling sessions were not as effective in learning performance as calibration. These descriptive statistics are summarized in table 4 below.

Table 5

Descriptive statistics of average academic performance

		Academic Performance		
Group	*N*	*M*	*Median*	*SD*
Control	22	11.63	11.75	1.58
Modeling	18	11.48	11.88	1.73
Prompts	24	11.90	11.67	1.40
Combination	28	11.21	11.13	1.69
Total	92	11.54	11.75	1.60

Research Question 1: Calibration Accuracy

Due to student attrition, data was not available for each quiz from all participants. Data collected resulted in the following distribution of average calibration estimates offered by students in treatment groups as summarized in Table 6. The number of calibration scores and academic performance scores were not consistent, as not all students provided a prediction in a numeric format, instead offering phrases like “about as many as last time”, or “a lot I hope” etc. These inconsistent scores were excluded from the calibration analysis.

Table 6

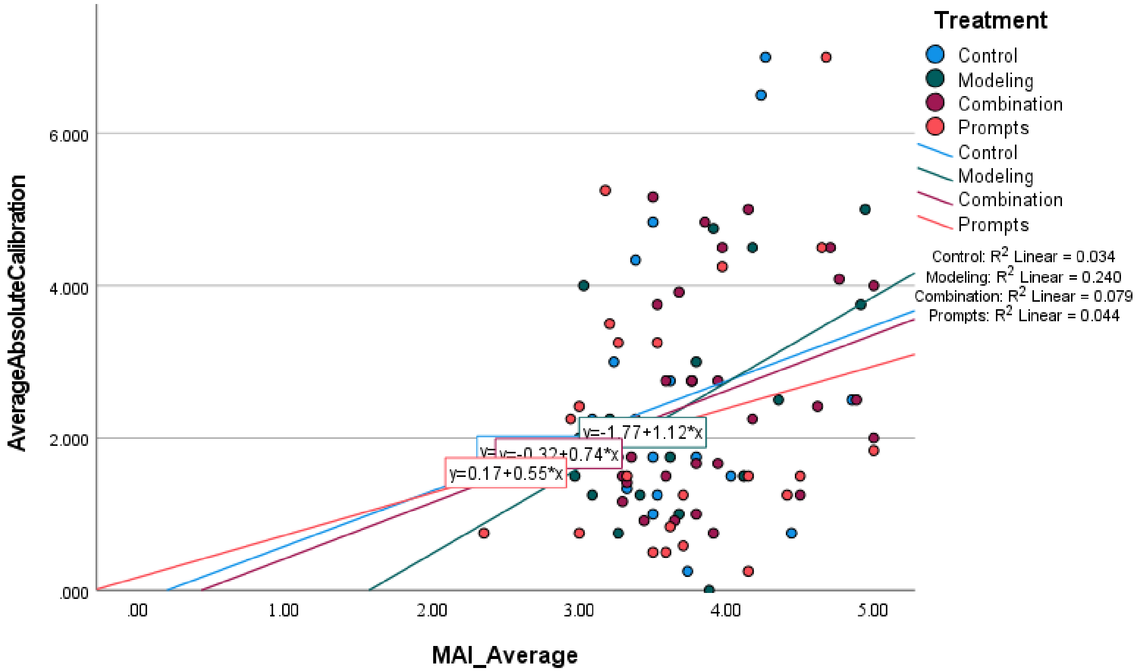
Distribution of calibration estimates cases by assessment

	Quiz 1	Quiz 2	Total
C-Control	21	20	41
M – Modeling	18	17	35
P – Prompts	23	21	43
MP – Combination	28	26	54
Total	90	84	173

Prior to evaluating the effect of the treatments on calibration accuracy, the data was analyzed to ensure the ten assumptions of ANCOVA analysis were met (Laerd Statistics, 2017). One dependent variable (absolute calibration accuracy) and one independent variable (instructional intervention) were included in the analysis. Both were measured using a continuous scale. The independent variable was divided into four categories all of which were measured nominally. The observations were also independent of one another based on the design.

Next, the data was evaluated for linearity of the covariate in relation to the dependent variable using a scatterplot. Figure 2 shows the scatterplot results.

Figure 2 Scatterplot of absolute calibration and metacognitive awareness



The scatterplot showed a reasonably linear relationship across groups. Next the homogeneity of regression slopes was evaluated. There was homogeneity of regression slopes as the interaction term was not statistically significant, F (3, 82) = .181, p = .909. However, standardized residuals for the interventions and for the overall model were not normally distributed, as assessed by Shapiro-Wilk's test (p > .05), with Control (p = .034), Modeling (p = .546), Prompts (p = .036) and Combination (p = .036). Still, the assumptions of homoscedasticity and variance homogeneity were met through an evaluation of a scatterplot and Levene's test of homogeneity of variance (p = .434). Standard residual values ranged from 2.60 to -1.63, indicating no outliers were included in the data. Table 7 shows the means for all treatment groups adjusting for metacognitive awareness.

Table 7

Absolute calibration means adjusting for metacognitive awareness

		Unadjusted		*Adjusted*	
	N	*M*	*SD*	*M*	*SE*
Control	21	2.55	1.77	2.60	.34
Modeling	18	2.37	1.48	2.45	.37
Prompts	23	2.21	1.75	2.23	.33
Combination	28	2.59	1.42	2.45	.30

Finally, the ANCOVA analysis was run and evaluated. After adjustment for metacognitive awareness as indicated through self-report using the MAI, no statistically significant difference in calibration ability between the interventions was indicated, F (3, 85) = .143, p = .934, partial $\eta 2$ = .005.

Research Question 2: Academic Performance

When considering academic performance, student attrition affected the number of quiz attempts available for each student. Scores were summed and divided by the number of quizzes attempted (one or two) to produce the average learning performance score. Data in Table 8, summarizes the number of students attempting each quiz as well as the total student count included in the analysis.

Table 8

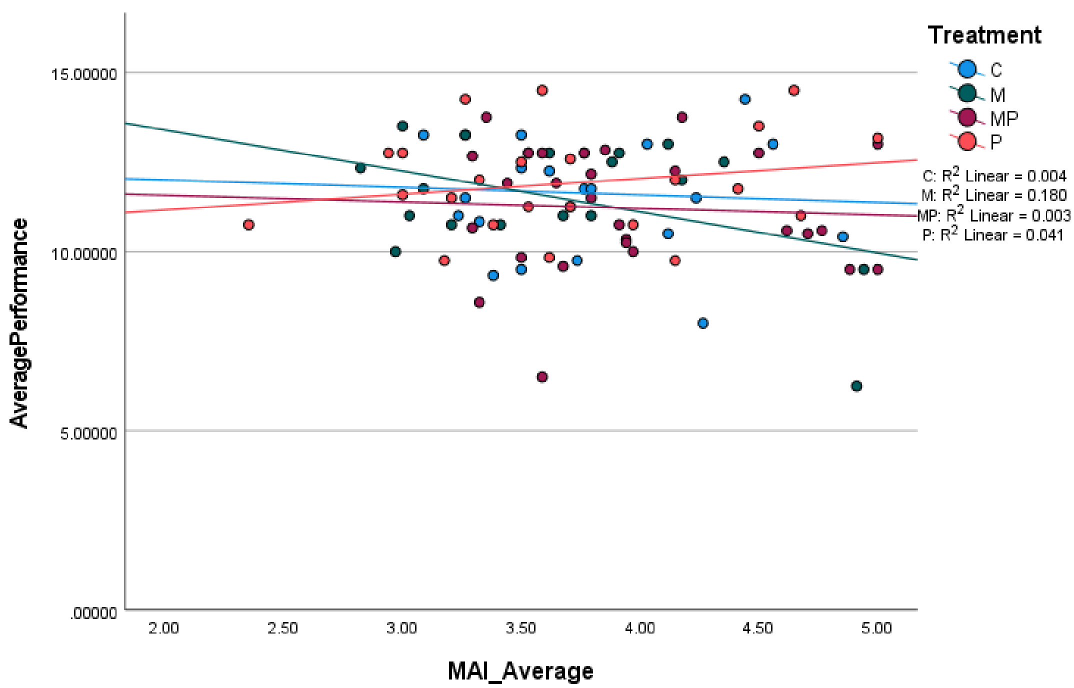
Distribution of cases by assessment

	Quiz 1	Quiz 2	Total
C-Control	22	20	42
M – Modeling	18	17	35

P - Prompts	24	23	47
MP – Combination	28	27	55
Total	92	87	179

Prior to evaluating the effect of the treatments on performance, the data was analyzed to ensure the assumptions of ANCOVA were met (Laerd Statistics, 2017). Similar to calibration, the model included two continuous variables, one dependent variable (performance) and one independent variable (instructional intervention). Four nominal categories described the independent variable, and observations remained independent. Next, the data was evaluated for linearity of the covariate using a scatterplot. Figure 3 shows the scatterplot results. The initial scatterplot showed a clear linear relationship across groups, there was homogeneity of regression slopes as the interaction term was not statistically significant, $F(3, 84) = 1.324$, $p = .272$.

Figure 3 Scatterplot of performance and metacognitive awareness



Initially, the standardized residuals for the interventions and for the overall model were not normally distributed for one group, modeling, as assessed by Shapiro-Wilk's test ($p > .05$), with Control ($p = .510$), Modeling ($p = .014$), Prompts ($p = .394$) and Combination ($p = .151$). The assumptions of homoscedasticity and variance homogeneity were evaluated using a scatterplot and Levene's test of homogeneity of variance ($p = .834$). Standard residual values ranged from 1.74 to -3.08. The one extreme outlier was from the Modeling group. Table 9 shows the academic performance means for all treatment groups adjusting for metacognitive awareness.

Table 9

Academic performance means adjusting for metacognitive awareness

		Unadjusted		*Adjusted*	
	N	*M*	*SD*	*M*	*SE*
Control	24	11.63	1.58	11.63	.34
Modeling	18	11.47	1.73	11.45	.38
Prompts	26	11.90	1.40	11.88	.33
Combination	30	11.21	1.69	11.25	.31

After adjustment for metacognitive awareness as indicated through self-report using the MAI, there wasn't a statistically significant difference in achievement scores between the interventions, F (3, 87) = .684, $p = .564$, partial $\eta 2 = .023$.

CHAPTER IV

DISCUSSION

This study examined the effect of training on asynchronous community college learners' calibration and academic performance. Prior to the study, research findings have varied, and limited statistically significant findings could be noted. This study aligned with some findings, while conflicting with others.

Training to Improve Calibration in Asynchronous Community College Learners

The study explored three types of training interventions as defined in literature: a) blind training, b) informed training, and c) self-control training (Brown et al., 1982; Collins et al., 1991). Blind training, referred to a scenario where students receive lecture based instruction on a topic, but the instruction stops short of providing any reasoning surrounding its use. This group was represented as the control group in the results section. Informed training, where student receive blind training in conjunction with a modeling process to demonstrate how it is used. This group was represented as the modeling group in the results section. Self-control training provides prompts to encourage the development of self-regulation skills. This group was represented as the prompts group in the results section. Finally, a combination of the three training types, represented as the combination group in the results section was included. Based on the literature review one could hypothesize that calibration ability should improve as learners become either more aware (as a result of informed training) or are allowed further practice (as a result of self-control training).

In light of the experiences documented in the works of Händel & Fritzsche (2016) and Serra and DeMarree (2016), it is notable that in comparison this study participants' ability to calibrate their learning appeared strong at face value, while no significant difference was found based on the type of training students received. To better characterize effects fully, the researcher reviewed descriptive statistics for each group.

In regard to the blind training or the control group, participants' average calibration scores lingered close to participants in the other intervention groups, while and exceeding the study average. Overall the average absolute calibration ability for this group was the second highest in the experiment, indicating a lesser ability to calibrate effectively. Their relative calibration ability was slightly negative also indicating their tendency to underestimate their learning. When considering the work of Bol et al (2016) who found that guided instruction based on Zimmerman's cyclical model incorporating metacognitive strategies led to improved usage and academic performance one might see the results of this study as contradictory. It is true that although calibration ability was less pronounced than most intervention groups, the difference remained insignificant statistically. In addition, Hu and Driscoll (2013) looked at a very similar sample (community college students in a college success class) and noted improved learning performance, yet a failure to increase metacognitive practice. The findings of this research partially support the findings, in that calibration is one of the metacognitive strategies that was not significantly affected. Finally the work of Emory and Luo (2020) focused on comparing direct training to no training, and contradicted the results of Bol et al (2016). The results of this experiment would indicate that most forms of training provide some benefit to participants, based on absolute calibration scores. It does however fail to find a method which is significantly more effective than others including blind training.

Similarly, the results of informed training and self-control training also failed to produce a significant difference in calibration accuracy of asynchronous online community college learners. However, the average calibration ability in both these groups fell below that of both the blind and combination training participants, which indicated a stronger ability to calibrate effectively. Based on a review of descriptive statistics, those receiving practice through metacognitive prompts on average calibrated more effectively than any other group, with those receiving informed training including cognitive modeling ranking second. Research thus far in regard to informed and self-control training has been primarily qualitative. (Alger & Kopcha, 2011; Dickey, 2008; Liu, 2005) all explored the use of modeling through student self-reports, which indicated its value in increasing metacognitive process. This research remained indicative of improved calibration or at a minimum described increased strategy usage. The results of this study support the idea that modeling in comparison to lecture based instruction produced more accurate metacognitive behavior yet stopped short of significantly improving calibration ability. The results suggest a need for further exploration and may imply that a purely quantitative approach may not fit as effectively as a mixed method approach.

In addition to the descriptive statistics, a review of the data regarding students' engagement with the modeling videos also provided some insight. This data showed that students in the modeling group watched 73% of the first video and 72.5% of the second. This average was influenced by outliers on both sides. In the case of the first video, 46% of viewers watched the entire video, while less than 12% watched 25% or less. This percentage of disengaged students climbed in the second video with 40% of the students viewing the videos from start to finish, while 15% watched 25% or less. As well student attrition hovered near 12% for the study, indicating a potential lack of engagement in the content.

Finally, the combination of training interventions produced learners with the least effective average calibration score. Although not statistically significant, the descriptive statistics may indicate a need for further study and consideration of the cognitive load placed on students (Boekaerts, 1995; Bol & Garner, 2011).

Training to Improve Academic Performance in Asynchronous Community College Learners

The study also sought to explore the effects of training on the overall academic performance of participants. Similar to student calibration, effects did not show significant differences between training interventions in relation to academic performance.

Similar to calibration ability, the results of this study fail to support disparate effects between blind training, as seen in the control group, and more involved training interventions. Average academic performance scores for the control group ranked third highest in the group. This result may help to clarify the findings of Bol et al. (2016) and Hu and Driscoll (2013) which showed improved performance as a result of instruction. Although these findings were significant, the implication is that although instruction into metacognitive practice is an effective method of improving performance, other methods may prove equally or more effective.

When considering the effect of different training interventions on academic performance, the results were quite similar to that of average calibration ability. One difference is that modeling or informed training resulted in lower average academic performance scores than both self-control (prompts) and blind (control) methods. The results of this research support the findings of Bannert and Reimann (2012) and Van den Boom et al. (2004) who found no significant difference in short term academic performance based on the use of self-reflective prompts in a similar sample. All the while the results contradict those of Daumiller and Dresel (2018) who found a significant increase in academic performance. It is interesting to note that

Bannert and Reimann (2012)'s work was a true experiment in a controlled environment which may have influence the results.

Once again, the combination group scored lower than all other groups, yet not significantly. This supports the idea that further research is required when considering combining effective instructional methods.

Calibration and Academic performance in Asynchronous Community College Learners

Even as the specific results of the study may indicate further research is necessary, the results informed two broader expectations based on the wide base of literature on calibration and academic performance. Based on established research and heuristics, one might hypothesize that calibration in community college learners or novice learners would be poor (Bjork, 1999; Finn & Tauber, 2015; Hartwig & Dunlosky, 2012; Hattie, 2013; Stone, 2000; Zimmerman, 2008). Still at face value of the descriptive statistics collected from this sample, their relative calibration score averages for this set of community college learners hovered close to zero (M = -.20, SD = 2.87). This indicates a relatively strong ability to estimate performance. In addition, the slightly negative skew might suggest that the group erred on average toward underestimation, contradicting what has commonly been expressed in research (Hartwig & Dunlosky, 2012; Serra & DeMarree, 2016).

In addition, much research has shown that regardless of the training intervention used, higher calibration accuracy can be associated with higher academic performance scores (Bol et al., 2016; Callender et al., 2016; Hu & Driscoll, 2013; Huff & Nietfeld, 2009; Liao et al., 2014). Data collected in this research supports this negative relationship between absolute calibration and academic performance r (90) = -.19, p = .077. The findings were however not statistically significant at a .05 level

Potential Limitations

Threats to validity, both internal and external must be addressed when considering quasi experimental research. The researcher sought to identify and control for as many of these limitations as possible as delineated below.

Threats to Internal Validity

Threats to internal validity can call into question the processes and instruments used to make assessments throughout the research. The researcher sought to limit internal validity challenges throughout the research design. Still there are a few factors that may have limited the study's internal validity including instrumentation, treatment diffusion, experimenter effects and experimental attrition.

When considering the instrumentation chosen in this experiment, data from self-reports and multiple choice assessments with low scoring reliability (George & Mallery, 2003) had potential to limit its internal validity. Initially, the Metacognitive Awareness Inventory is a self-report tool and has a potential to induce self-report bias. This self-report bias was mitigated by encouraging students to be as honest as possible when completing the assessment. In addition, course materials included clear instructions about the survey's intent and emphasized that student responses had no effect on overall course grade. As well, the instruments chosen to assess academic performance may not be reliable or valid. While the questions have been evaluated by seasoned instructors and produced consistent results in classes prior to implementation, their overall reliability remains at the lower range of acceptability based on the Cronbach's Alpha. As future studies are approached such assessments should be evaluated for reliability prior to implementation.

Diffusion of treatment is a common threat to internal validity that is hard to completely eliminate in the classroom environment. Training was held with instructors prior to the experiment where they agreed not to discuss the course elements or modify the course in any way throughout the process. Each instructor, with the exception of the researcher, taught sections only associated with one treatment group. In addition, the asynchronous format helped to limit social interactions between treatment student groups. Still an overarching goal of the course is to encourage connection to staff, faculty and other students, and as a result some diffusion could have occurred naturally.

Fidelity of treatments also had potential to limit internal validity. To mitigate, common instructional materials were used across course sections, including the use of a course cartridge that was designed and certified using the Quality Matters Rubric for Higher Education (Maryland Online, 2018). In addition, all instructors received training on the study design and the role of fidelity in the process. Even with these constraints in place, the educators involved in the research are passionate advocates for their students and a potential for unintentional experimenter influence remain.

Attrition occurs when participants fail to complete the experiment. This study indeed felt the effects of this phenomena on its final results. Attrition is often higher in community college courses than in their four-year counterparts and the college success course is no exception. As well the experiment occurred during the COVID-19 Pandemic and a surge of Omicron infections across the south. All of these stressors may have influenced student persistence in the course. Still the researcher took advantage of many college supports and mechanisms to counter the loss of student participants. During the study these included directed outreach from instructors, and established success coaches encouraging participation for at risk students. However, the overall attrition rate for the study hovered at 12% and was dispersed somewhat unequally throughout the treatment groups. Rates were Modeling (6%), Prompts (15%), Combination (10%) and Control (17%). The result of this student attrition must be considered when evaluating the study's internal validity and the relatively lower statistical power to detect group differences.

Threats to External Validity

Threats to external validity can call into question the ability to generalize results to a broader population. Within this study, these challenges fell into three broad categories: the sample, the constructs, and the timeframe.

When considering potential limitation in the selection of and recruitment of the sample for this study the researcher controlled for many potential challenges. For example, the sample mimicked the overall demographic makeup of the college closely. Although the college believes in and fully supports an open-door policy which can result in a broad range of instructional experience (in years) and local environmental factors (such as financial and family supports) the researcher sought to establish a baseline of metacognitive knowledge through evaluation of metacognitive awareness data following sample selection. Still, the sample may have been influenced through a volunteer bias. Initially, one hundred and fifty-nine students enrolled in the course, yet only 99 of them consented to participate. While the researcher offered no incentives for participation, the sample selected may still have been affected by this element.

In addition, still the assignment of students to treatment groups induces a potential for bias. When the study was designed, smaller enrollments were predicted for the college's fall term. Proactively, the college implemented flexible enrollment which kept enrollment levels consistent with prior enrollment levels. This process had an unintentional effect of limiting the researcher's ability to maintain consistency in treatment groups in regard to size and potentially student demographics. Initially, free tuition for all students living in NC caused a rush of last-minute enrollments into the traditional term. As positive cases of infection from the COVID-19 pandemic continued to plague enrollments, sections were also added to allow students flexibility to enter classes after traditional semester start dates. As enrollment in these sections occasionally caused a section not to run based on low enrollments, consistency across treatment groups was again affected. Although the length of the sections and instructional interventions remained consistent, this rolling enrollment process caused class sizes and treatment assignments to vary noticeably, and limited potential statistical analyses.

At a broader scale, the college community's enrollment demographics differ from many others in the community college system. This dissimilarity has potential to limit external validity for other college systems across the country. When reviewing enrollments, students at the college have identified as Black 2% of the time, and American Indian / Alaskan 8% of the time (North Carolina Community College System Office, 2020). Students across the system have identified as Black 21% of the time and American Indian / Alaskan 1% of the time (North Carolina Community College System Office, 2020). These inconsistencies may limit overall external validity across community colleges in North Carolina. Still, for some institutions with similar demographic makeup, external validity may be enhanced.

This quasi experiment occurred during the effects of the COVID-19 pandemic and as a result, situation and history effects must be considered in addition to the internal validity threats as potential threats to external validity. Effects of the COVID-19 pandemic which began in 2020, lingered throughout the research cycle (Jaschik, 2020). Most involved in the research may attest that the environment felt different at the end of the 8-week experiment. In addition the environment would be hard to replicate in future studies. This is simply part of the history of the experiment and although bears noting, offered few options to mitigate its effect.

Implications for Practitioners

It has been shown that those who calibrate effectively as part of a self-regulation process are more successful in online courses (Bol & Hacker, 2001; Hacker et al., 2008). For community college educators and administrators, improving this ability may prove essential not only to continuing to grow online enrollment, but also in improving performance and learning. Practitioners continue to chip away at the goal of establishing the most effective and efficient ways to improve this ability in students, yet it remains a challenging process to master. Some considerations for practitioners (both educators and designers) moving forward include combining the appropriate range of intervention elements, effectively making connections between elements of academic performance and regulation and ensuring appropriate intervention support is available.

This study sought to further develop student supports to enhance student understanding of metacognitive monitoring with the intention of increasing student performance on recall tasks. While its selected elements have been studied separately, their specific combination has been explored only on a limited basis. The results, although not significant did provide insight into the lower performance of students when presented with a combination of designed elements aiming to increase metacognitive self-regulation. Although each of the component parts of the intervention did provide some insignificant gains, when combined the gains were the least significant consistently. In addition, high student attrition, and lower levels of engagement with materials indicate that motivation may as well have been affected. As practitioners continue in the quest to develop heuristic practice in relation to regulatory development, this study suggests that consideration of the cognitive load of included elements is essential as has been suggested in prior literature (Boekaerts, 2017; Kirschner et al., 2011; Kostons et al., 2012; Sentz et al., 2019; Sweller et al., 2019). Practitioners should seek to choose interventions that increase metacognitive monitoring, at a rate which does not cause cognitive overload.

In considering the results in isolation, selection of specific instructional interventions, although important, may be thought of as second to alignment of those elements with a well-developed understanding of the student needs and backgrounds. In the extreme it suggests that a conscious understanding of the role of metacognitive process is not essential to academic performance improvement. The researcher however would suggest that practitioners avoid such extreme conclusions. Many instructional techniques have shown to increase performance, yet the development of effective metacognitive processes is less established. In considering solely the metacognitive monitoring performance, both modeling and self-reflective prompts produced results be them at an insignificant level. Even though the result was not also seen in improved academic performance, the increase in calibration ability may prove more beneficial in longer term studies and those which focus more on transfer of skills across topic areas as has been suggested in prior literature (Spruce & Bol, 2015; Zumbrunn et al., 2011). These results should not be overshadowed.

Finally, in regard to the connection between academic performance and calibration, the insignificant results might suggest that practitioners move toward making the connection between metacognitive monitoring and metacognitive self-control processes more explicit. Students in this study became more acutely aware of their ability to successfully complete a performance task, yet still did not make the jump to correct insufficient or ineffective learning processes. Practitioners may need to better separate the reflective process from performance to allow students an ability to take action. Results from prior studies (Bjork, 1999; Finn & Tauber, 2015; Pashler et al., 2005) in which students used self-reflection prior to performance of a higher-level academic performance task often included this timeline for self-correction which was essential, and the results of this study support such heuristic practice.

Finally, practitioners should remain aware that support in developing tools such as cognitive models although not highlighted is supported indirectly through this research. The old adage that students do not learn exactly the way designers develop, and teachers may not want to teach in the ways they were taught is evident in undertaking practices such as cognitive modeling. Success has been shown from formal process development in educators (Dukerich, 2015; Pedersen & Liu, 2002) and the researcher recognizes her own room for development in this area. Although not yet tested, the development of the ability to clearly convey cognitive and metacognitive processes can reasonably be estimated as a variable of interest in the further development of metacognition in novices.

Recommendations for Future Research

Metacognitive research continues to present a confusing landscape for educators and designers alike. Future research is recommended to improve upon this study's design in hopes of clarifying the role of calibration in learning. For example, improvement of instrumentation, specifically the measures of learning and compound effects of cognitive load may provide more statistically significant results. As well, the inclusion of a larger and more diverse sample size has potential to ameliorate external validity. Finally, many studies in this realm have included qualitative data to support and describe their results. This qualitative data may be helpful in tweezing out those elusive elements which will serve to improve calibration as well as the effectiveness of other metacognitive monitoring elements.

Alternatively, component elements of the design may lend themselves to alternative consideration. Self-regulation and specifically calibration are diverse and deceptively complex tasks. Recent literature has also begun to integrate the study of metacognitive process with cognitive load (Boekaerts, 2017; de Bruin & van Gog, 2012). Even while the results of this study were not statistically significant, their indications would support further development of this connection, in conjunction with exploration of the best combination of instructional elements to aid students. Student engagement also may have played a role in the effect of the intervention as indicated by student interaction with the materials and student attrition. Future research may focus more precisely on the length and design of interactions as well as the amount of time that can be dedicated to student engagement through practice.

Finally, the effects of student-specific factors on their ability to gauge and make appropriate choices about their learning cannot be ignored (Heller & Marchant, 2015; Majer, 2009; Thompson & Verdino, 2018). These factors include the students' lack of prior knowledge, motivation and societal responsibilities, which were too broad to be taken into account in the current study, must also be considered. Further research is essential to make appropriate connections between the training of metacognitive monitoring processes and the most effective ways for students to master these skills in a variety of contexts.

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APPENDICES

Appendix A – Informed Consent Document

INFORMED CONSENT DOCUMENT

OLD DOMINION UNIVERSITY

PROJECT TITLE:

Metacognitive Supports in Online Community College Learners

INTRODUCTION

The purposes of this form are to give you information that may affect your decision whether to say YES or NO to participation in this research, and to record the consent of those who say YES. The name of this study is the Metacognitive Supports in Online Community College Learners.

RESEARCHERS

Principal Investigator: Dr. Tian Luo (Associate Professor, Old Dominion University, STEM Education and Professional Studies)

Investigators: Bethany Emory (Dean of Teaching and Learning Support, Southwestern Community College and Doctoral Student at ODU in STEM Education and Professional Studies)

DESCRIPTION OF RESEARCH STUDY

Metacognition can help students to plan, evaluate and slect appropriate study tactics. This is helpful in becoming what is termed a self-regulated learner. Being able to judge how well you are learning is essential to this process. This ability can be improved through instruction, and we are trying to determine effective ways to do this for community college learners.

If you agree to take part in this study, your participation will consist of:

1. Completing assigned work throughout the course in ACA-111
2. Offering your personal assessment of your abilities as the course progresses.

RISKS AND BENEFITS

RISKS: As with any research, there is a possibility that you may be subject to risks that have not yet been identified. There may be a risk of the release of confidential information. However, any documented information and responses will be secured and confidential. These documents will be destroyed once the data have been aggregated and the study is complete.

BENEFITS: There are no direct benefits for participating in this study. If you decided not to participate, we will not include your data for research and analysis.

COSTS AND PAYMENTS

The researcher is unable to give you any payment for participating in this study.

NEW INFORMATION

If the researcher finds new information during this study that would reasonably change your decision about participating, then they will give it to you.

CONFIDENTIALITY

The researchers will take reasonable steps to keep private information, such as interview responses and analysis, confidential. The researcher will remove any real names or key identifiers from survey and interview responses. The results of this study may be used in reports, presentations, and publications; but the researcher will not identify you. Of course, your records may be subpoenaed by court order or inspected by government bodies with oversight authority.

WITHDRAWAL PRIVILEGE

It is OK for you to say NO. Even if you say YES now, you are free to say NO later, and walk away or withdraw from the study -- at any time. Your decision will not affect your relationship with Old Dominion University, or otherwise cause a loss of benefits to which you might otherwise be entitled.

COMPENSATION FOR ILLNESS AND INJURY

If you say YES, then your consent in this document does not waive any of your legal rights. However, in the event of any physical or mental injuries arising from this study, neither Old Dominion University nor the researchers are able to give you any money, insurance coverage, free medical care, or any other compensation for such injury. In the event that you suffer injury as a result of participation in any research project, you may contact Tian Luo at 757-683-5369, Dr. Laura Chezan, the current IRB chair at at 757-683-7055, or the Old Dominion University Office of Research at 757-683-3460 who will be glad to review the matter with you.

VOLUNTARY CONSENT

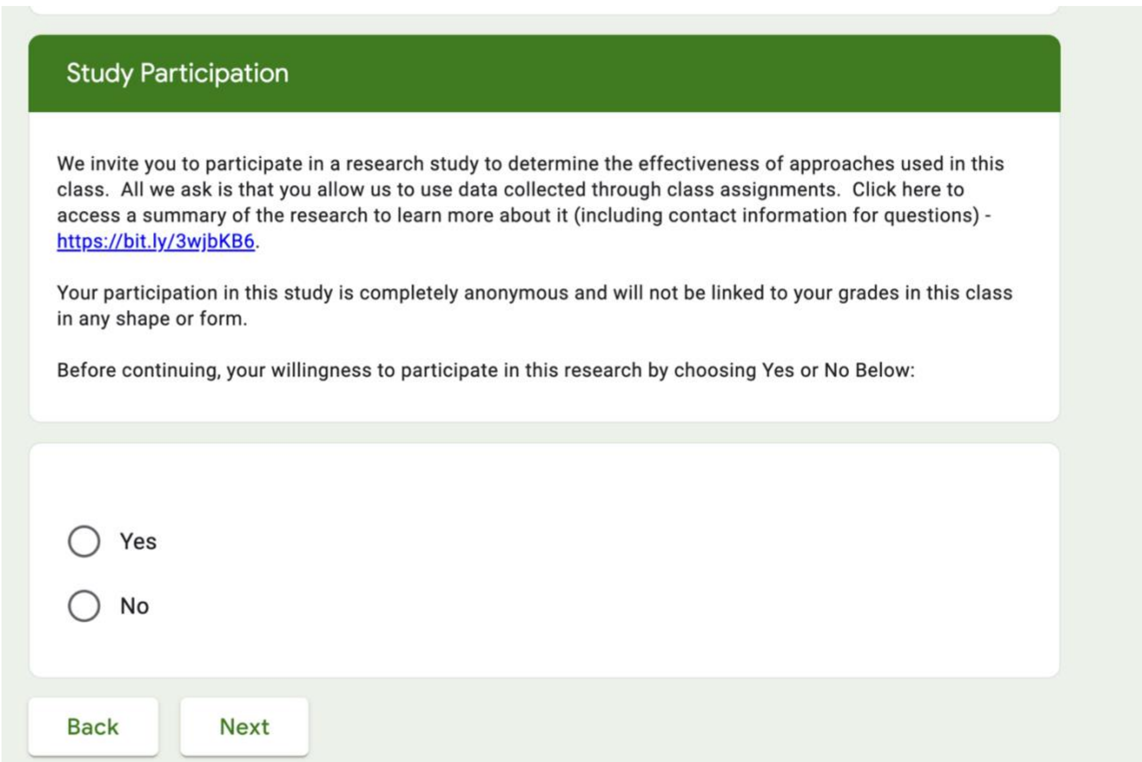
By participating in this process, you are saying that you have read this form or have had it read to you, that you are satisfied that you understand this form, the research study, and its risks and benefits. The researchers should have answered any questions you may have had about the research. If you have any questions later on, then the researchers should be able to answer them:

Principal Investigator: Dr. Tian Luo (757-683-5369 OR tluo@odu.edu)

Ms Bethany Emory (828-339-4261 OR b_emory@southwesterncc.edu)

If at any time you feel pressured to participate, or if you have any questions about your rights or this form, then you should call Dr. Laura Chezan, the current IRB chair, at 757-683-7055, or the Old Dominion University Office of Research, at 757-683-3460.

Electronic Conformation:



Study Participation

We invite you to participate in a research study to determine the effectiveness of approaches used in this class. All we ask is that you allow us to use data collected through class assignments. Click here to access a summary of the research to learn more about it (including contact information for questions) - https://bit.ly/3wjbKB6.

Your participation in this study is completely anonymous and will not be linked to your grades in this class in any shape or form.

Before continuing, your willingness to participate in this research by choosing Yes or No Below:

Yes

No

Back

Next

Appendix B – Selected Questions from Schraw & Dennison Metacognitive Awareness Inventory (1994)

Read each statement carefully then consider how it generally applies to you (when you are in the role of a learner). Rate each using a scale of (1 - Very false to 5 - Very True).

1. I ask myself periodically if I am meeting my goals.
2. I consider several alternatives to a problem before I answer.
3. I pace myself while learning in order to have enough time.
4. I think about what I really need to learn before I begin a task.
5. I know how well I did once I finish a test.
6. I set specific goals before I begin a task.
7. I slow down when I encounter important information.
8. I ask myself if I have considered all options when solving a problem.
9. I consciously focus my attention on important information.
10. I ask myself if there was an easier way to do things after I finish a task.
11. I periodically review to help me understand important relationships.
12. I ask myself questions about the material before I begin.
13. I think of several ways to solve a problem and choose the best one.
14. I summarize what I've learned after I finish.
15. I ask others for help when I don't understand something.
16. I find myself analyzing the usefulness of strategies while I study.
17. I focus on the meaning and significance of new information.
18. I create my own examples to make information more meaningful.
19. I find myself pausing regularly to check my comprehension.
20. I ask myself how well I accomplish my goals once I'm finished.
21. I draw pictures or diagrams to help me understand while learning.
22. I ask myself if I have considered all options after I solve a problem.
23. I try to translate new information into my own words.
24. I change strategies when I fail to understand.
25. I use the organizational structure of the text to help me learn.
26. I read instructions carefully before I begin a task.
27. I ask myself if what I'm reading is related to what I already know.
28. I reevaluate my assumptions when I get confused.
29. I organize my time to best accomplish my goals.
30. I try to break studying down into smaller steps.
31. I focus on overall meaning rather than specifics.
32. I ask myself questions about how well I am doing while I am learning something new.
33. I ask myself if I learned as much as I could have once I finish a task.
34. I stop and go back over new information that is not clear.
35. I stop and reread when I get confused.

Appendix C – Objective questions from ACA-111 Quizzes

Questions from Quiz 1:

1. What GPA is required to be considered making Satisfactory Academic Progress?

    a. 4.0
    b. 3.5
    c. 1.2
    *d. 2.0

2. How is GPA calculated?

    *a. Quality Points multiplied by course credits, divided by hours attempted
    b. Quality Points minus by course credits
    c. Quality Points multiplied by course credits
    d. Quality Points divided by course credits, multiplied by hours attempted

3. If I am taking a Hybrid class

    *a. I will work on class activities online at least 50% of the time
    b. I will attend class in person at least 75% of the time
    c. I will never be required to complete course activities online
    d. I will never be expected to attend class in person.

4. My instructor can withdraw me from a class, if:

    a. I miss assignment deadlines when taking online courses
    b. I miss class when taking in person classes
    c. I fail to communicate
    *d. All of the responses are correct

5. The drop/add period:

    a. Occurs at the end of the semester and allows student to change their schedule with no financial penalty
    *b. Occurs at the beginning of the semester and allows student to change their schedule with limited financial penalty
    c. Occurs in the middle of the semester and allows student to change their schedule with limited financial penalty
    d. Occurs throughout the semester and is used to change a student's GPA

6. What day is Advising Day held in the Fall semester 2021? (Hint you can find this information using the Student Academic calendar found in the calendar pages at the bottom of the SCC Website, or by asking your advisor or a member of the Student Support Services staff.)

    *a. Oct 26,2021
    b. Nov 1,2021

c. Aug 16, 2021
d. Dec 13, 2021

7. What if you are not able to maintain your Satisfactory Academic Progress (SAP)?

a. As soon as you fail to maintain SAP, you will no longer be able to take classes using financial aid
*b. If you fail to maintain SAP, you will be given one semester to improve (called financial aid warning) prior to financial aid being revoked
c. If you fail to maintain SAP, you will be given three semesters to improve (called financial aid warning) prior to financial aid being revoked
d. If you fail to maintain SAP, you will no longer be able to take classes

8. What is a quality point?

*a. Quality points are numeric representations of course letter grades, where 4 quality points are awarded for an "A" grade and zero quality points are awarded for an "F" grade.
b. Quality points are numeric representations of letter grades, where 100 quality points are awarded for an "A" grade and zero quality points are awarded for an "F" grade.
c. Quality points are used to estimate your average in a class.
d. Quality points are assigned by your instructor for assignments in each course.

9. What percentage of your courses must be completed successfully to be considered making Satisfactory Academic Progress?

a. 22%
b. 50%
*c. 67%
d. 100%

10. Which of the following represent plagiarism ***(select all that apply)***:

[50.0000] a. Using information from a website without citation
[-50.0000] b. Using information from a course textbook with proper citation
[50.0000] c. Using information from a course textbook without proper citation
[-50.0000] d. Rewording or paraphrasing an expert, including a citation of where you read/watched the information

11. Which of the following represent a violation of academic integrity ***(select all that apply)***:

[-50.0000] a. Participating in a study group, where all members craft their own homework responses for assignments
[50.0000] b. Using information from a website without citation
[50.0000] c. Using google to search for answers during an online exam
[-50.0000] d. Citing information in a research paper

12. Which of the following are services offered at either the Jackson or Macon Campus Learning Assistance Center? ***(Choose all that apply)***

[50.0000] a. Test proctoring
[-50.0000] b. Advising Support
[-50.0000] c. Scheduling of medical appointments
[50.0000] d. Tutoring

13. Which of the following topics are included in the online library research guides available to students via their My SCC Library page?

a. Climate Action
b. Information Technology
c. Nursing
d. Is it Fake News?
*e. All of the above

14. Withdrawal from a class:

a. Can only be initiated by a student and must occur in the first week of the semester.
b. Can only be initiated by a course instructor and must occur in the first week of the semester.
*c. Can be initiated by either a student or a course instructor and must occur prior to the last few weeks of the semester.
d. Can be initiated by either a student or a course instructor and must occur in the first week of the semester.

15. Withdrawal from a class:

a. Carries no financial penalty
*b. Carries some financial penalty, does not affect GPA, and can affect Satisfactory Academic Progress
c. Carries some financial penalty, and can affect GPA
d. Can affect GPA

Questions from Quiz 2:

1. Associate of applied science degrees (AAS) are ***(check all that apply)***:

[50.0000] a. designed to be completed in approximately two years
[50.0000] b. designed to prepare students to enter directly into the workforce
[-50.0000] c. designed to make transfer to a four-year university seamless
[-50.0000] d. the only credential offered at Southwestern Community college

2. Courses required to complete a credential at SCC are listed:

a. in the student handbook
b. in the college catalog
c. on the college website
*d. on both the college website and in the college catalog

3. _______________ is the shortest of the credentials listed:

*a. Certificate
b. Associate Degree
c. College diploma
d. Bachelor's Degree

4. Juliann has some free time in her schedule. She will soon be graduating with an associate degree in business and wants to use this time to prepare for her upcoming career search. Which of the following activities would you recommend?

*a. Look for internship opportunities in her chosen field
b. Apply for part-time jobs that fall outside of her chosen career path
c. Spend more time having fun with her friends

5. Lolina has joined a student organization, developed relationships with faculty in her major, and is spending time practicing for job interviews. Which of the following would also support Lolina's career preparation?

a. Take a vacation with her friends, at the same time the college career fair is happening
b. Spend hours on social media but never mentioning her academic accomplishments
*c. Explore work-based learning or internship opportunities

6. This credential will take a most full-time students four to five years to complete:

a. Certificate
b. Associate Degree
c. College diploma
*d. Bachelor's Degree

7. What is a co-requisite course?

a. a course that must be taken in high school, prior to attending college
*b. one of two courses that must be taken together
c. a course required to be taken ahead of another course
d. None of the responses are correct.
e. All of the responses are correct.

8. What is a pre-requisite course?

a. a course that must be taken in high school, prior to attending college
b. one of two courses that must be taken together
*c. a college course required to be taken ahead of another college course
d. None of the responses are correct.
e. All of the responses are correct.

9. What is a soft skill?

a. specific technical skills, like using knives safely if you are a chef

*b. skills that can transfer from job to job, like working well in teams
c. None of the responses are correct.
d. All of the responses are correct.

10. What is the best thing to do if you realize that your selected major is no longer aligned with your values and long-term goals?

a. Drop out of college, without asking about other majors that seem like a better fit
*b. Talk to your advisor
c. Just finish the major you started, it really doesn't matter

11. Which of the following degrees could you earn in two years?

a. Master's degree in education
*b. Associate's degree in college transfer
c. Bachelor's degree in art
d. Bachelor's degree in accounting

12. Which of the following are true about getting involved in campus activities?

a. it can help you to grow and develop, especially in regard to soft skills
b. it can help you to develop skills like teamwork and problem-solving
c. it can help you to build connections
d. None of the responses are correct.
*e. All of the responses are correct.

13. Which of the following activities will assist you in building a strong relationship with your advisor ***(check all that apply)***

[33.3333] a. read your email
[33.3333] b. prepare questions and discussion topics prior to meetings
[33.3333] c. when reaching out, try to be specific in requests for information or necessary actions
[-100.0000] d. exhaust all resources available to you prior to reaching out to your advisor for assistance

14. Who is the best person to contact to talk about your grade point average (GPA), educational goals, degree requirements, and institutional policies?

*a. Advisor
b. Financial Aid Office
c. Registrar's office
d. Career Services office

15. You have a meeting with your advisor next week. The goal of the meeting is to discuss your plans for next semester. How would you apply what you have learned to help you create the list of topics to discuss?

*a. Organize my questions around my values, goals, and career plans
b. Identify the classes my friends are taking

c. Determine which professors have the highest pass rates
d. None of the responses are correct.
e. All of the responses are correct.

VITA

Bethany L. Emory

Department of STEM & Professional Studies Old Dominion University, Norfolk, VA

EDUCATIONAL BACKGROUND

Old Dominion University, Ph.D. Instructional Design & Technology, May 2022

Marymount University, Master of Human Performance Systems, December 2004

Central University of Iowa, Bachelor of Arts in International Business and French, May 1992

PROFESSIONAL EXPERIENCE

Southwestern Community College, Sylva, North Carolina Lead Dean of Teaching and Learning Support: August 2014 – Present

Asheville Buncombe Technical Community College, Asheville, North Carolina Director of Instructional Support and Online Learning: March 2003 – August 2014

PUBLICATIONS

Emory, B., & Luo, T. (2020). Metacognitive training and online community college students' learning calibration and performance. *Community College Journal of Research and Practice*. https://doi.org/10.1080/10668926.2020.1841042

Ramlatchan, M., Emory, B., Garcia, D., Spencer, M., Saylor, T., Thull, C., & Dukes, F. (2019). *Instructional Message Design: Theory, Research, and Practice*, Instructional Message Design.

CONFERENCE PRESENTATIONS

Emory, B. and Luo, T (2021, October). Designing to Improve Metacognitive Monitoring in Online Community College Students. Association for Educational Communications and Technology 2021 International Convention, Chicago, IL and Online.

Emory, B. and Putman, B (2018, December). Setting faculty up for success: Continuous improvement of the new faculty orientation program. Southern Association of Colleges and Schools Commission on Colleges Annual Meeting, New Orleans, LA