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Exploring the Influence of Students' Perceptions of Instructional Message Content Relevance and Experienced Cognitive Load on Students' Cognitive Learning

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EXPLORING THE INFLUENCE OF STUDENTS' PERCEPTIONS OF
INSTRUCTIONAL MESSAGE CONTENT RELEVANCE AND EXPERIENCED
COGNITIVE LOAD ON STUDENTS' COGNITIVE LEARNING

DISSERTATION

A dissertation submitted in partial fulfillment of the
requirements for the degree of Doctor of Philosophy in the
College of Communication and Information Studies
at the University of Kentucky

By
Benson Travis Sexton

Lexington, Kentucky

Director: Dr. Derek Lane, Associate Professor of Communication

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2017

ABSTRACT OF DISSERTATION

EXPLORING THE INFLUENCE OF STUDENTS' PERCEPTIONS OF INSTRUCTIONAL MESSAGE CONTENT RELEVANCE AND EXPERIENCED COGNITIVE LOAD ON STUDENTS' COGNITIVE LEARNING

Connecting the relevance of course content to students' lives has been a learning strategy for decades. In educational psychology, Keller (1983) suggested content relevance to be a component within the ARCS model to motivate students toward learning behaviors. Within instructional communication research, Frymier and Shulman (1995) argued that students enter classrooms with the expectation that they will understand the connection between the content and their lives. Specifically, students want to know why they are taking a course and how it impacts their interests, needs, and professional goals (Frymier, 2001). In both education and instructional communication literature, teacher content relevance strategies are known to influence students' learning behaviors. However, the influence of content relevance messages on students' cognitive learning has been a missing link in extant research. Building upon previous theoretical framework, this dissertation extends the content relevance research agenda by investigating the extent to which students' perceptions of instructional message content relevance and students' experienced cognitive load predicts students' cognitive learning. Data was collected from 559 undergraduate statistics students who completed an online survey about their perceptions of message content relevance, affect toward the instructor and the class, experienced cognitive load (intrinsic, extraneous, and germane), academic performance, and perceived cognitive learning. Results revealed a regression model explaining 11.1% of the total variance in students' academic performance and 63.8% of the total variance in students' perceptions of cognitive learning. Further, the full sample ($N = 559$) was divided by a median split to determine how low ($n = 277$) and high ($n = 282$) categories of content relevance interact with cognitive load, students' affective behaviors, and learning strategies to predict academic performance and perceived cognitive learning. Analyses revealed significant models for low message content relevance regressed on academic performance explaining 18.2% of the total variance, and for high content relevance regressed on academic performance explaining 7.9% of the total variance. For low and high content relevance categories regressed on perceived

cognitive learning, analyses revealed significant models accounting for 61% (low) and 40.3% (high) of the total variance. Implications of the results are presented in the discussion and conclusion.

KEYWORDS: Instructional Communication, Content Relevance, Cognitive Load, Cognitive Learning

Benson Travis Sexton

March 9, 2017

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March 9, 2017

In memory of my father, Rev. Thomas B. Sexton, who instilled a drive in me to become the best version of myself. And, to my firstborn son, Luke Aaron, whose 12 days on this earth truly taught me that *nothing is impossible with God*.

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Chapter 1: Introduction

Communication is the very essence of human interaction. Individuals interact with one another through message exchange, both verbally and nonverbally, to co-create meaning and understanding. As a result, scholars within the communication discipline focus their research on the messages that are exchanged and how those messages influence the environments for which they are enacted (e.g., Frisby, Slone, & Bengu, 2016; Frymier & Houser, 2016; Johnson & LaBelle, 2015). One context for which messages are the central focus of research is instructional communication.

Instructional environments are complex situations for which message exchanges are constantly occurring between all individuals. The instructor is responsible for facilitating the communication exchanges, but due to the diversity of classrooms, managing effective communication exchanges can often be difficult. Therefore, instructional communication scholars seek to explore communicative acts in instructional environments that can potentially influence the learning process, both positively and negatively.

Booth-Butterfield (1992) argued that there are three interrelated goals that college instructors should seek to accomplish in the classroom: to inform, to relate, and to influence others. Making course content relevant has long been considered a strategy for instructors' to link the impact of the course material to the lives of their students (Keller, 1983). When students believe course content to be relevant, they are motivated to engage in more learning behaviors (Frymier & Shulman, 1995; Keller, 1983). It is important to note that empirical research on content relevance has been primarily related to exploring the construct as a teacher strategy. While this research focus is important, content

relevance as an instructional communication construct can be explored in a novel way. The primary focus of instructional communication research is centered around messages that are exchanged between and among teachers and students (Myers, 2010). All messages exchanged in the classroom are not solely content focused, but the central messages to learning are content focused. Therefore, it is important to explore how content relevance embedded within the instructional messages influence student learning.

The primary purpose of this dissertation is to explore the extent to which students' perceptions of instructional message content relevance impacts cognitive load and, in turn, how the two influence students' cognitive learning. First, in order to better understand the instructional communication research discipline, the remainder of chapter one will review the instructional communication research context and address three current criticisms of instructional communication research.

Instructional Communication

Instructional communication research is at the intersection of the instructor, student, and meanings exchanged between and among the instructor and the student (Myers, 2010). Therefore, instructional communication can be identified as the study of communication processes that occur in instructional settings. Those instructional settings are not limited to academic classrooms. In fact, instructional communication represents an applied social scientific body of research that can manifest in communication related training contexts such as teaching employees an organizational system or policies related to the organization, assisting the public with instruction during a crisis situation, helping patients and medical professionals communicate more efficiently in healthcare situations, and assisting teachers with the identification and understanding of communicative

behaviors that influence the classroom. As a result, instructional communication research focuses on the communication factors in teaching and learning processes across all grade levels (i.e., K-12), instructional settings (i.e., classroom, organizational, healthcare), and subject matters (Friedrich, 1987; Staton, 1989). Lashbrook and Wheelless (1978) conceptualized instructional communication as the body of research representing the study of communication variables, strategies, processes, technologies, and/or systems as they relate to formal instruction and the acquisition and modification of learning outcomes. Learning is central to instructional contexts and, therefore, the concentration of how communication influences learning is central to the body of research. For this study, the influence of students' perceptions of instructional message content relevance is the communication variable of study on students' learning.

Instructional communication is not communication education. Communication education focuses on the teaching of communication (i.e., skills, processes) to learners (Sprague, 1993; Sorensen & Christophel, 1992), while instructional communication focuses on the messages, verbal and nonverbal, that are exchanged among and between all individuals involved in the instructional context (Sprague, 1993). Communication education research in post-secondary undergraduate education takes, for example, the form of teaching public speaking or interpersonal communication skills to students within a communication program, while instructional communication research in post-secondary undergraduate education focuses on the communication behaviors of both the instructor and students in the learning context. Instructional communication research, then, focuses on how those communication variables influence learning outcomes in the teaching of all subjects, in all contexts, at all levels (Sprague, 1992, 1993). Arguably, relevance of

course content is not isolated to the study of communication as all students in all courses in all subjects are curious as to the relevance of the content to their lives and/or goals.

Instructional communication research explores message effects at the intersection of three different disciplines: educational psychology, pedagogy, and communication.

Educational Psychology, Pedagogy, & Communication

Instructional communication is a multidisciplinary research context with influences from educational psychology, pedagogy, and communication. Educational psychology provides a context for better understanding the cognitive, affective, and behavioral processes of learners who are affected by communicative acts. The instructional communication focus from the educational psychology perspective is on the learner. As stated in Lashbrook and Wheelless' (1978) definition of instructional communication, a central premise for inquiry is to investigate how messages affect the acquisition and modification of learning outcomes. Primarily, instructional communication research has focused on ways in which communicative acts affect cognitive and affective domains of learning. Cognitive learning refers to the acquisition and development of intellectual abilities and skills, while affective learning refers to students' interests, attitudes, and values (Bloom, Englehart, Furt, Hill, & Krathwohl, 1956). Of the two domains, affective learning has been given the most attention among instructional communication scholars. In fact, Richmond and McCroskey (1992) argued, in terms of instructional effectiveness, affective learning to be a more valid indicator than cognitive learning. Teacher nonverbal immediacy, teacher credibility, teacher use of humor, and teacher communicator style (Nussbaum, 1992) have been argued as having positive relationships to student affective learning. Cognitive learning, however, when

thinking in terms of learning outcomes, is critical in the study of communication in instruction. Instructional communication research has, for example, linked teacher clarity, student motivation, and content relevance to cognitive learning behaviors (Comadena, Hunt, & Simonds, 2007; Frymier & Shulman, 1995; Frymier, Shulman, & Houser, 1996; Frymier & Houser, 1998, Nussbaum, 1992). Specifically, the study of content relevance within instructional environments began in educational psychology. While content relevance has often been viewed as an obvious component of instruction, it received little research attention prior to Keller's ARCS model (Frymier, 2002). Keller's (1983) ARCS model represents an approach to student motivation and engagement in the classroom. Within the model, gaining students' attention is followed by making relevant course connections, instilling confidence in students' self-perceived abilities, and praising their accomplishments in order to encourage self-satisfaction (Keller, 1987a, 1987b). This model of instructional design positions content relevance within a strategic process of motivating students to become engaged in the learning process.

The second multidisciplinary influence is pedagogy. Here, the focus is on the teacher. Areas of research include the history of teaching, theories of teaching, development of assessment, design of instruction, and ways in which teachers use communication to influence learners (Myers, 2010). Instructional communication research from a pedagogical perspective focuses on instructors' communication techniques and behaviors, for example, the communicator style of the instructor, teacher confirmation, and strategies for which instructional messages are delivered (Mottet & Beebe, 2006). Specifically, teacher content relevance strategies has been an area of research focus over the past two decades. Frymier and Shulman (1995) argued that

higher rates for which teachers use content relevance strategies (i.e., using personal experiences to introduce or demonstrate concepts) increase students' perceived value of a course and their motivation to study for a course. Research on teacher content relevance strategies leads to pedagogical best practices and effective approaches to instructional design.

Further, two specific areas of pedagogical focus in instructional communication research are centered on teacher self-efficacy and teacher satisfaction. Teacher self-efficacy is related to the how the teacher perceives he or she is effective in instruction, and teacher satisfaction is related to how teachers feel about their role (Mottet & Beebe, 2006). Ultimately, research from a pedagogical perspective can assist instructors to find ways to effectively communicate course content to their students, for example, implementing content relevance strategies into the instructional environment. Although teachers are not educational bankers, instructional communication research focused on pedagogical practices helps teachers better understand how they can be dispensers of information that ultimately influence learning outcomes for students.

The third multidisciplinary influence is communication. Mottet and Beebe (2006) argued that communication is at the heart of the teaching and learning process and described how and why communication works in instructional settings. This is one of the main reasons why instructional communication is important to the overall discipline of communication. As mentioned above, instructional communication is not limited to classrooms, but instead applies to all instructional contexts (organization, public crisis, healthcare, etc.). The influence of the communication discipline helps instructional communication researchers explore the processes by which instructors and learners

stimulate meanings in the minds of each other. Historically, instructional communication has been studied through the lens of two communication perspectives, rhetorical and relational. From the rhetorical perspective, teachers are viewed as persuaders, or influencers (McCroskey & Richmond, 1996). This perspective lies within Aristotle's rhetoric where instructors use logical (logos), emotional (pathos), and credible (ethos) appeals to persuade and/or influence the learner (Mottet & Beebe, 2006). In terms of communication processes, the rhetorical perspective is action, or linear, oriented as instructors represent the message source and the learners represent the receivers. More recently, 21st century instructional communication research has been influenced from the relational perspective of communication research. Specifically, this perspective views messages and meaning as co-creations of the individuals involved in the communication situation (McCroskey & Richmond, 1996). Research from a relational perspective focuses, for example, on communication variables such as teacher and student self-disclosures, classroom humor, instructor misbehaviors, and power dynamics in the classroom (Mottet & Beebe, 2006). This line of communication research helps explain how communication affects the overall classroom and how instructors can manage the communication climate. In the current study, the focus is on the communicative messages in the classroom that influence students' perceptions of the relevance of the course content. It is important to note that content relevance has been studied as a communication variable but primarily as a motivational factor to engage students (Keller, 1983, 1987a, 1987b) and/or as a teacher strategy (Frymier & Shulman, 1995). The current study explored the extent to which students' perceptions of instructional message content relevance influence students' cognitive processes and, ultimately, learning.

As noted above, instructional communication is a multidisciplinary research context, yet it is very distinct. Theoretical influences from educational psychology, pedagogy, and communication interact to move the instructional communication research agenda forward with messages as the variable of study. Therefore, understanding the influence of each multidisciplinary focus on the study of content relevance is particularly important. However, there are several criticisms to address within instructional communication research prior to reviewing extant literature that will help frame the argument for this study.

Criticisms of Instructional Communication Research

Over the past four decades, instructional communication research has made a significant impact on understanding classroom interactions. However, several criticisms infiltrate the discipline. The following discussion addresses three primary criticisms specifically related to the study of instructional message content relevance.

First, it is evidenced in the aforementioned discussion of instructional communication research that results and practical implications of this multidisciplinary research focus can enhance student learning. Unfortunately, though, one of the main criticisms of instructional communication is that it does not have a far reach or outside influence to other disciplines or lines of research (Nussbaum & Friedrich, 2005; Nussbaum & Scott, 1980; Sprague, 1992; Sprague, 2002). Perhaps this is due to instructional communication scholars' lack of promotion, but it is believed to be deeper than that. The measurement of cognitive learning, as discussed previously and addressed specifically in chapter 2, could have a significant influence on this criticism. Although frequently discussed in research articles, cognitive learning is often reported

solely based on student self-report surveys and, often, addresses affective learning instead of cognitive learning. Nisbett and Ross (1980) criticized self-report learning by positing that subjects don't know themselves well and always guess what, in this case instructors, want from them. As argued by Lane (2016), while it is not possible to read the minds of students to measure exact learning, it is important that instructional communication scholars measure learning accurately. By doing so, instructional communication can begin to reconnect with its applied mission and allow the greater academy to see the impact and importance of instructional communication research (Sprague, 2016). In order to do so, it is critical that instructional communication scholars focus on the impact of communication in instructional settings on students' cognitive learning. An exploration of extant cognitive learning measurements in instructional communication research in the next chapter identifies a recent self-report cognitive learning survey (Cognitive Learning Measure) that is a better theoretical fit than previous surveys, and proposes to combine the Cognitive Learning Measure (Frisby & Martin, 2010) with students' exam grades as a more sophisticated measure of students' cognitive learning. This approach to assessing cognitive learning as a result of students' perceptions of instructional content relevance will provide a robust measurement of students' cognitive learning.

A second criticism is that instructional communication is often viewed as atheoretical and variable analytic. Waldeck, Plax, and Kearney (2001) argued that the early stages of instructional communication research was propelled by energy more than specific focus and that instructional communication scholars must begin to focus on establishing parsimonious theory. The nature of this criticism has historically been a

focal point as Staton-Spicer and Wulff (1984) posited that an important area of research doesn't lie in isolated research findings, but in the relationship among findings across studies. Instructional communication scholars seem to have interests in the different ways communication impacts instructional contexts, therefore reducing the number of scholars that spend their lifework focusing on one specific area and/or theory. However, there are lines of research within instructional communication that contend this criticism. Myers (2010) identified nonverbal immediacy, credibility, and communication apprehension as three extensive bodies of instructional communication research. Further, research on teacher and message clarity has garnered a strong research focus as findings continue to point to an increase in learning when teachers and course content are clear. The communication variable of the current study, content relevance, has garnered attention from several communication scholars over the past two decades, but a well grounded program of research related to the influence of content relevance on student learning outcomes is warranted. By doing so, the theoretical model tested in the current study extends the efforts toward a future theory of instructional message content relevance.

A third criticism of instructional communication research is the nature of data collection. Chesebro and McCroskey (2000) argued that one reason it is difficult to extend the reach of instructional communication research is because the samples from most studies are too much alike. Data collection has historically resulted from homogenous higher education communication classrooms composed of primarily sophomores. Additionally, much of the research relies on self-report survey designs that have students reflect on a previous class as measurements for student cognitive learning

(Sprague, 2016). This method, established by Plax, Kearney, McCroskey, and Richmond (1986), has been the accepted method of data collection in instructional communication research for nearly three decades. The generalizability of research findings, though, is often too narrow and it is difficult to control for communicative acts when surveying student reports on multiple teachers and instructional environments. To better understand, specifically, the influence of communication on students' cognitive learning, it is more appropriate to collect data from intact courses, which for this study was introductory statistics courses, where students are subjected to the same instructional messages and processes. This approach to data collection helps to contextualize the learning environment and assure that students are subjected to the same instructors and instructional messages related to the same instructional topics rather than an array of instructors and courses from multiple disciplines. The program of research for content relevance has often been linked to student learning, therefore, to extend the program, collecting data from students within a specific higher education classroom with specific teachers will help to overcome the current criticism of data collection.

As evidenced, the most important focus for future instructional communication research should be on student learning outcomes, specifically students' cognitive learning. As mentioned previously, cognitive learning refers to the acquisition, retention, and recollection of knowledge (Bloom, 1956; King & Witt, 2009). Instructional communication research has focused more energy on how communication in instructional contexts leads to student affective learning, or how communication changes students' interests, attitudes, and values toward teachers and courses (Bloom, 1956), than on cognitive learning. Although cognitive learning is often mentioned in instructional

research articles, future research needs to better conceptualize and operationalize, or measure, cognitive learning. Most often, cognitive learning has been measured by asking students to self-report how much information they learned (Clark, 2002; Sprague, 2016). Instruments such as the Learning Loss Scale (Richmond, McCroskey, Kearney, & Plax, 1987) are often used but only measure learning by asking students a couple questions based on how much they learned and how much they would have learned with the ideal instructor. Therefore, it is important that researchers continue to develop better measurements for cognitive learning. Frisby and Martin (2010) developed the Cognitive Learning Measure (CLM), which is considered a reliable measurement of perceived cognitive learning (Frisby, Mansson, & Kaufmann, 2014; Mansson, 2014). Using Frisby and Martin's CLM and student exam grades, then, is a way to explore communicative acts, such as message content relevance, that influences cognitive learning through academic achievement performance, the standard measurement of learning accepted in academia (King & Witt, 2009), and students' perception of their cognitive learning. A more in-depth argument for this approach to measuring student cognitive learning will be presented in chapter 2.

The future of instructional communication research is presented with many opportunities. Researchers have the opportunity to identify important communication factors, strategies, behaviors, and systems in many settings in order to better understand the nature of communication and the impact it has on learner knowledge acquisition. One area of research that is ripe for exploration, as evidenced in the previous sections of this chapter, is students' perceptions of course content relevance and the impact those perceptions have on cognitive learning. Teacher content relevance strategies are known

to influence student motivation and learning behaviors (Frymier & Shulman, 1995; Keller, 1983), but the influence of students' perceptions of course content relevance on cognition has not been extensively explored. Specifically, students' perceptions of content relevance will likely influence, positively or negatively, students' experienced cognitive load. Cognitive load represents how messages and information are processed in the three dimensions (intrinsic, extraneous, and germane) of working memory capacity (Chandler & Sweller, 1991). In turn, students' perceptions of message content relevance and experienced cognitive load will likely influence students' cognitive learning. Therefore, this dissertation addresses the aforementioned criticisms of the influence of communication in instruction on student cognitive learning by exploring the extent to which students' perceptions of message content relevance and the influence those perceptions have on their cognitive load interact to predict cognitive learning.

Organization

This dissertation is organized into five chapters. The first chapter conceptualized instructional communication, addressed three current criticisms of instructional communication research, and provided a brief rationale for studying message content relevance. Chapter 2 provides a literature review of instructional content relevance, cognitive load theory, and student cognitive learning leading to a proposed hypothesis and five research questions. Chapter 3 reviews the methods that guided data collection for the study, while Chapter 4 presents the results of the data analyses. Finally, Chapter 5 offers a discussion of the implications of the results, limitations of the study, and future research recommendations.

Chapter 2: Literature Review

Learning is the goal of education. All strategies, behaviors, instructional designs, and communication utterances should focus on the end product of students' knowledge of the course material. Engaging students in the learning process can often be difficult, but through instructional design techniques and calculated delivery and presentation, instructors can discover ways to motivate students to learn the material. Chesebro (2002) argued that teachers should approach each classroom with a mindset of thinking of their students' needs, interests, and goals and then teach accordingly. Consequently, instructors must understand the student population for which they teach and employ communication behaviors and instructional design strategies that increase students' motivation and willingness to learn the course content. Building upon the interdisciplinary foundation of educational psychology, pedagogy, and communication, instructional communication scholars seek to discover communicative processes, in this case content relevance, that influences student acquisition of knowledge and learning. Therefore, to better understand the interactions of content relevance, cognitive load, and cognitive learning in instructional settings, a review of extant literature is warranted.

Content Relevance

Questioning the usefulness or relevance of the content of a course is not uncommon for students. Frymier and Shulman (1995) argued that students' enter the classroom asking the question, "What's in it for me?" As information and content is presented in a course, it is likely that student's want to know the impact of the information and content on their lives. This notion is considered content relevance. Frymier and Shulman noted that content relevance represents the learner's perspective as

to how the information or content relates to their needs, interests, and educational and professional goals. As a result, it is likely that students continue to ask the question "What's in it for me?" throughout the progression of a course.

Content relevance has been argued for decades in educational disciplines as a motivating factor to engage students in learning behaviors, most often referred to as a teacher strategy. The construct emerged in Keller's (1987) ARCS model, where attention, relevance, confidence, and satisfaction represent a step-by-step process to motivate students. According to Keller, an instructor must gain the attention of the student, make the content relevant to their lives (i.e., interests, needs, goals), instill confidence within the student that they are capable of learning the material, and share in the student's satisfaction with the outcomes of their effort. Keller argued that the sequential conditions of the ARCS model are necessary for student motivation.

More recently, instructional communication scholars have argued content relevance to be a communication issue in the classroom (Frymier & Shulman, 1995). Frymier and Shulman (1995) posed that teachers communicate the relevance of course content to students in different ways in order to generally relate the content to, potentially, all students. It is important to note, though, that content relevance is a perception and ultimately deemed relevant by a student when they believe the course content to satisfy their personal needs, interests, and goals (Keller, 1983). Therefore, instructional strategies to make the content relevant to each student has become an important area of instructional communication research.

Instructional communication research has focused on identifying ways in which instructors can use instructional content relevance strategies as a part of communication

in the classroom. Extant instructional communication research argues content relevance strategies to have a positive relationship with students' state motivation to study (Frymier & Shulman, 1995) and students' willingness to actively participate in class (Cayanus, Martin, & Goodboy, 2009). Further, content relevance through instructor self-disclosures help facilitate student clarity and understanding of the content (Cayanus, 2003), as well as motivation for students to attend class (Cayanus & Martin, 2008). Frymier (2002) also argued that content relevance has a positive relationship with students' valuing the content and engaging in learning behaviors. Primarily, content relevance in the aforementioned studies motivate students to engage in learning behaviors.

Content relevance has also been associated with students' affect toward the teacher. Ryan and Deci (2000) argued that content relevance motivates students' affect for the teacher, and Schrodt (2013) found students' perceptions of instructor credibility and their evaluations of instructors' disclosures are influenced by their perceptions of content relevance. Affect, then, leads to students feeling closer to their instructor because of the relatedness and connections made within the content. Students, then, likely value content more and engage in more learning behaviors when they like the teacher (Roberson, 2013). Frymier, Shulman, and Houser (1996) found teacher content relevance strategies to be positively related to students' affect and learning behaviors.

Although extant content relevance research in instructional communication has produced significant and practical results, content relevance has been primarily explored as an instructional strategy and has been loosely, at best, connected to student cognitive learning. Both limitations represent major gaps in content relevance research and needs to be addressed. Understanding the impact of instructional message content relevance in

instructional environments is critical for instructors as they engage in intentional instructional design. Instructional design is a model of classroom instruction created and implemented by an instructor. Through strategic preparation, instructors can plan specific content relevance links within a class session. Therefore, exploring the influence of instructional message content relevance on students' cognitive learning is warranted. By doing so, the research focuses on students' perceptions of message content relevance. The following section will review the rationale for examining instructional message content relevance.

Rationale for Examining Instructional Message Content Relevance

Frymier and Shulman (1995) argued that students want to know how course content relates to them and why they should attend to the content the instructor communicates in class. Two decades later, this argument appears more relevant than ever before as students live in a globalized world that has been flattened by technology and access to limitless sources of information. In order for instructors to maintain students' interest in the classroom and increase students' motivation to learn, they must communicate connections to the content in a way that is meaningful to all students. Attempting to do so presents a challenge as students' needs and interests vary (Frymier, 2002). However, it is likely that students will understand how the content relates to their lives when the course content is delivered in instructional messages. Frymier (2002) argued that it is evident that teacher content relevance strategies positively influence instructional environments, but that future research needs to address message characteristics of content relevance.

Another challenge for instructors might be determining what aspects of the content to relate to students' lives. Frymier (2002) argued a similar statement based on the fact that relevance is actually a perception. Roberson (2013) articulated that content relevance, then, is a perception that individual's believe something to be interesting and worth knowing. Instructors that have spent years of research devoted to a discipline and/or research program likely believes that all course content is relevant, while students don't understand the connections unless they are explicitly made. As discussed by Lane (2009), "content relevance is influenced by teacher characteristics (e.g., credibility, competence, immediacy), message characteristics (e.g., clarity, structure), and by individual student characteristics (e.g., aptitude, interests, etc.)" (p. 225).

As a result, it is likely that perceptual differences of the instructor as the source of information and students as the receivers of information may indeed create a barrier to content relevance. Kember, Ho, and Hong (2008) argued that, "if teachers wish to motivate their students' learning they need to find ways to show the relevance of topics included in their courses" (p. 255). Further, Chesebro (2002) argued that teachers should approach each classroom with a mindset of thinking of their students' needs, interests, and goals and then teach accordingly. Frymier (2002) positioned that it is easy for instructors to avoid thinking about making content relevant to students' lives, but that students are more satisfied when they see a class as really important to their lives. Therefore, it is vital for instructors to understand the importance of instructional message content relevance and intentionally make an effort to communicate the relevance of course content in the classroom environment in order to increase the likelihood of the goal of student cognitive learning.

Content relevance was long considered an important aspect of the classroom with little research focus. Frymier and Shulman (1995) suggested that one reason why communication researchers have spent little time investigating content relevance as a teacher strategy in the classroom might be because the concept was overlooked. Further, in education and communication disciplines, the importance of the relevance of content has often been, generally, assumed (Frymier, 2002). Roberson (2013) also made this argument by indicating that content relevance is often mentioned in education literature, but mostly in passing and rarely discussed in terms of the constructs nature and/or structure. Within instructional communication research the literature on the construct has increased, although research has seemingly avoided investigating the relationship between instructors' content relevance strategies and learning outcomes (Frymier, 2002), let alone the extent to which students' perceptions of the relevance of course content influences cognitive learning.

Reflecting on one of the major criticisms of instructional communication research mentioned in chapter one, the relationship between content relevance and learning is fuzzy. Frymier and Shulman (1995) found that content relevance increases students' motivation to learn and Frymier Shulman, and Houser (1996) argued that content relevance empowers students to learn and motivates them to use more learning behaviors. However, the measurement of learning in content relevance studies primarily involves students' perceptions of affective learning. It is likely, though, that content relevance has a greater influence on cognitive learning than what has been reported as evidenced in psycholinguistic research. In the study of psycholinguistics, Wilson and Sperber (2002) argued that "relevance is a basic feature of human cognition" (p. 251). As a basic

premise of the argument, when relevant information is processed, it yields a positive cognitive effect, meaning it is deemed as worthwhile to attend to (Wilson and Sperber, 2002). Therefore, Wilson and Sperber argued that receivers of messages in communicative situations expect the stimulus to be at least relevant enough to be processed. This notion increases the argument that instructional message content relevance may have a deeper relationship to student cognitive learning beyond believing it to be an important teacher strategy. Educational psychology and instructional communication have neglected in-depth research of this communication influence in the instructional environment because of its assuming nature (Frymier, 2002). The results of this study seek to fill that gap in the literature.

At this point, it is important to explore how content relevance has been measured in instructional communication research and propose an alternative measurement to measure instructional message content relevance instead of teacher content relevance strategies.

Measurement of Content Relevance in Instructional Communication

Relevance in classrooms has been an assuming construct for decades. In fact, Frymier and Shulman (1995) argued that it has relatively been neglected in empirical research. Most of the research for content relevance involves informal observations (Sass, 1989) and application of content relevance strategies to employ in classroom settings (Visser & Keller, 1990). Specifically, Newby (1991) conducted an empirical investigation linking content relevance to student motivation with elementary school students. Newby's research added value to the research program, but the generalization of the findings was questionable. To better measure content relevance as a

communication construct, Frymier and Shulman developed the Relevance Scale.

The 12-item Likert-type Relevance Scale with anchors of 0 (*never*) and 4 (*very often*) was developed to measure teacher content relevance strategies. For example, participants respond to statements like: Uses examples to make the content relevant to me; Gives assignments that involve the application of the content to my career interests; Explicitly states how the material relates to my career goals or to my life in general. Frymier and Shulman's (1995) Relevance Scale has been the primary measurement for the content relevance construct in instructional communication research over the past two decades. However, again, the Relevance Scale is intended to measure teacher content relevance strategies and not students' perceptions of content relevance. Frymier and Shulman noted this distinction and suggested that future research be designed to "measure the degree to which students believes the content is relevant" (p. 45). Therefore, expanding the empirical measurement of content relevance using a scale created to measure instructional message content relevance is important. The Message Content Relevance Scale (MCRS) is not intended to replace Frymier and Shulman's Relevance Scale, but instead measure perceived message content relevance as opposed to teacher content relevance strategies. Both scales hold heuristic value for future instructional communication research.

The MCRS is an 8-item Likert-type scale with anchors of 1 (*strongly disagree*) and 5 (*strongly agree*). The items are theory driven with influence from educational psychology (Keller, 1985) and instructional communication (Frymier & Shulman, 1995) research. An example item states: I believe the content from the course directly impacts my career goals. The MCRS can be found in Table 2.1 (p. 30). Each item has been

assessed for face validity and considered as having acceptable conceptual and operational fit. The MCRS holds scale content validity as a number of communication researchers have reviewed the scale items and have confirmed face validity, or that the items appear to measure what they are intended to measure (Frey, Botan, & Kreps, 2000). The scale holds construct validity based on theory-driven research. The number of items are proportionate to instructional communication scales (Chesebro & McCroskey, 1998).

Table 2.1 Message Content Relevance Scale

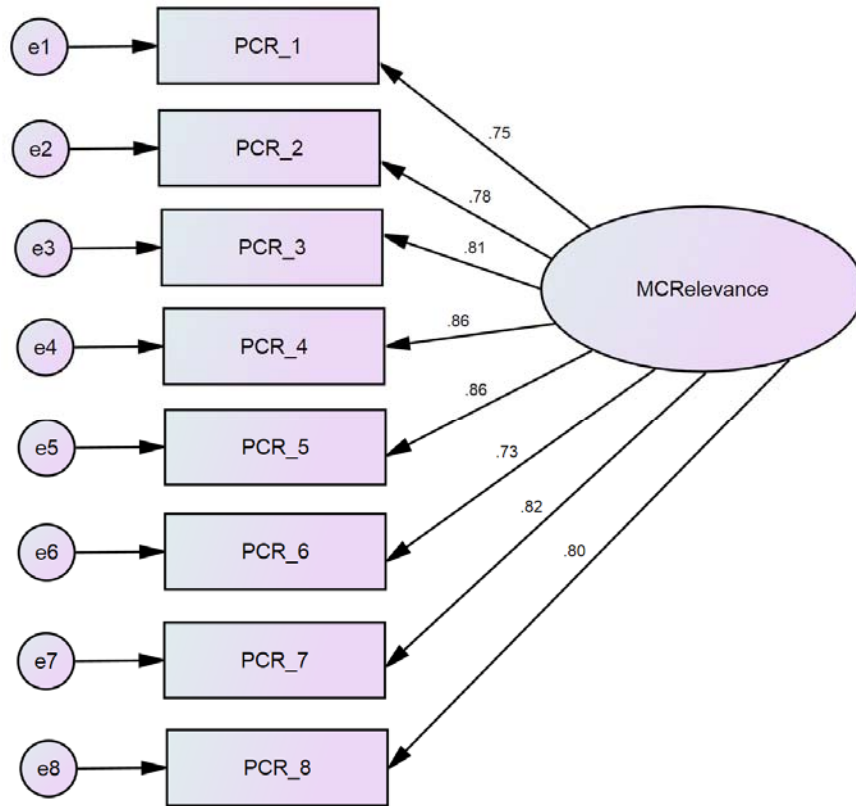
	1 (strong disagree)	2 (disagree)	3 (neutral)	4 (agree)	5 (strongly agree)
1. I believe the content from this course directly impacts my personal interests.	1	2	3	4	5
2. I believe the content from this course directly impacts my educational needs.	1	2	3	4	5
3. I believe the content from this course directly impacts my career goals.	1	2	3	4	5
4. I believe the content of this course is valuable to my life.	1	2	3	4	5
5. I believe this course in general is valuable to my life.	1	2	3	4	5
6. I am able to make connections of the course content to my life.	1	2	3	4	5
7. I believe I will use the content of this course in my future professional life.	1	2	3	4	5
8. I believe this course as a whole is relevant for my development as a well-rounded individual.	1	2	3	4	5

In two previously unpublished pilot studies, the MCRS was subjected to two exploratory principle components factor analyses (EFA) with varimax rotation. Criteria for the EFA's were an eigenvalue > 1 and a factor loading for each item on > .60 on a primary factor and < .40 on secondary factors (DeVellis, 2011). These factorial solutions provided statistical analyses for the underlying structure of the scale, which was

developed as a univariate measurement of instructional message content relevance. The first study in fall 2015 ($N = 118$) revealed a one factor solution with all items loading on one factor at .79 and higher, and accounted for 75% of the total variance. The second study in spring 2016 ($N = 99$) revealed a one factor solution as well with all items loading on one factor at .87 and higher, accounting for 79% of the total variance. Both pilot studies revealed a univariate scale for instructional message content relevance. For the current study, the Message Content Relevance Scale was subjected to a Confirmatory Factor Analysis (CFA) to validate the factorial structure of the scale.

Results of the CFA, using AMOS 24, indicated that the proposed measurement model, containing eight indicators and one latent variable, fit the data well, $\chi^2 (20, n = 559) = 159.28, p < .01$. All goodness-of-fit indices exceeded the recommended levels. Specifically, the two indices that are insensitive to sample size, the Non-Normed Fit Index (NNFI) and the Comparative Fit Index (CFI), were .95 and .93, respectively. The Goodness-of-Fit Index (GFI) was .93, suggesting that 93% of the variance in the covariance matrix could be explained by the model. As Figure 2.1 (p. 32) indicates, the loadings of all indicators onto the single latent variable was significant and relatively large in magnitude, ranging from .73 to .86. While the RMSEA of .112 was out of range for a strong fit (generally RMSEA of $< .05$ signals a good fit), the standardized Root Mean Square Residual (SRMR) of .03, taken together with the other fit indices and the results of the Exploratory Factor Analysis, confirms the unidimensional factor structure of the eight-item Message Content Relevance scale.

Figure 2.1: *Message Content Relevance Confirmatory Factor Analysis Measurement Model*



By using the MCRS, it is beneficial to investigate the relationship between instructional message content relevance as a communication construct and the impact it has on students' cognition. Therefore, the following section grounds the objectives of this study through the lens of cognitive load theory.

Cognitive Load Theory

The human mind is complex and operates based upon interacting systems within it. Birted out of the curiosity to want to know more about the complexity of how information is dealt with in the mind and working memory, Sweller (1988, 1989) developed Cognitive Load Theory (CLT). Cognitive load theory concentrates on the

limited working memory of an individual where information is processed, stored, and retrieve in/from their long-term memory repository (Pass et al., 2013; Van Merriënboer & Sweller, 2005). Prior to CLT, Information Processing Theory (IPT) was the dominant working memory theory. The scope of IPT was broad and failed to concentrate on how information impacts working memory capacity prior to storing the information in long-term memory. CLT, on the other hand, accounted for this gap in the research.

Chandler and Sweller (1991) positioned that CLT's primary concern is with the way cognitive resources are focused and used in learning and problem solving situations. According to CLT, information is, or is not, stored in long-term memory based upon the cognitive load imposed by the difficulty of the information, the presentation of the information, and/or the individual's effort to deeply process the information (Paas, Renkl, & Sweller, 2003). Cognitive load theory was created with the intentions to better understand instructional contexts and to use research findings to enhance instructional application (Chandler & Sweller, 1991; Pass & van Merriënboer, 1993; Pass, van Merriënboer, & Adams, 1994; Pass & Sweller, 2003). Through this theoretical lens, Paas, Renkl, and Sweller (2003) argued that researchers have made great strides in better understanding the impact of instructional processes on learners' cognitive load and the implications those influences have on learning.

Cognitive load is a multidimensional construct that consists of three types of load: intrinsic load, extraneous load, and germane load (Deleeuw & Mayer, 2008). As a basic premise, the three dimensions of load represent the extent of the difficulty of information (intrinsic), the way information is delivered during instruction (extraneous), and the mental resources students' allot (germane) in order to process the information (Sweller,

Ayers, & Kalyuga, 2011). Intrinsic load and extraneous load are identified as negative cognitive loads that, when high, decrease the ability for learners' to deeply process and learn the information (Jong, 2010). Germane load is deemed as positive cognitive load. When intrinsic and extraneous loads are decreased, a learner has more capacity and mental resources available to engage in deeper processing and learning of the information (Jong, 2010). Prior to identifying how cognitive load theory informs instructional communication research, each of the three loads will be clearly conceptualized.

Intrinsic Cognitive Load

Intrinsic load represents the difficulty of the information and/or task that a learner is presented with. According to Pass, Tuoveinen, Tabbers, and Van Gerven (2003), intrinsic cognitive load is the result of the complexity of the material itself, or from the previous experience and/or knowledge of the learner. As a result, the two functions of intrinsic load are represented by the difficulty of the material as well as the previous knowledge of the learner (Jong, 2010). If the learner has previous knowledge of the information, the easier he/she will be able mentally integrate the information. Hailikari, Katajavuori, and Lindblom-Ylänne (2007) argued that “purposeful integration of knowledge from previous courses should be attempted whenever possible in order to help students form an integrated knowledge base” (p. 6). Therefore, a learner’s previous experience and/or knowledge with/of a topic either increases or decreases the intrinsic load imposed by the information.

Element interactivity, or the number and nature of interacting elements involved with the information, plays an important role in the processing of information. Element interactivity refers to “the extent to which relevant elements interact” (Pass, Renkl, &

Sweller, 2003, p. 1), and is considered the driving force of intrinsic load. Element interactivity is not only based on the difficulty of the material, but also the prior knowledge of the student. According to Jong (2010), “low interactivity material consists of single, simple, elements that can be learned in isolation, whereas, high interactivity material individual elements can only be well understood in relation to other elements” (p. 106). The more difficult the content and less experience of the learner, the higher the degree of interacting elements. High element interactivity is cognitively taxing on a student while low element interactivity will not, necessarily, hamper learning because the tasks or content are deemed, at least relatively, easy. Therefore, element interactivity operates on a continuum for each individual. For example, a student with prior experience in a content area will likely have lower intrinsic cognitive load due to less mental integration and element interactivity than a student with little to no prior experience in a content area. Ultimately, the more interacting elements, the more difficult the information and/or task (Jong, 2010).

Originally, Sweller (1988) argued that intrinsic load is fixed and cannot be changed. As such, the inherent nature of intrinsic load was determined as “just there” without the possibility of being reduced. Content and/or tasks have a certain degree of complexity and the difficulty does not inherently change. Further, Jong (2010) indicated that a major premise of cognitive load theory is that intrinsic load cannot be changed by instructional treatments. However, advancements in the theory suggests intrinsic load may be altered.

A counterargument consists of the notion that intrinsic load can, at the very least, be altered. Van Merriënboer, Kirschner, and Kester (2003) argued that one can control

intrinsic load by scaffolding more complex information. For example, an instructor can introduce the simple elements first and move to more complex elements, simple-to-complex learning, as the learners begin to gain understanding (van Merriënboer et al., 2003). Another example is structuring the information through a technique called isolated-followed-by-interacting-elements. The isolated-followed-by-interacting-elements approach suggests that when dealing with complex information, the intrinsic cognitive load of the material should be reduced by laminating the interaction among the information elements (Pollock, Chandler, & Sweller, 2002). This counterargument to the original theoretical construct of intrinsic load has been adopted by several scholars, yet criticized by others. One can argue that criticism of the recent studies is warranted as the two examples above represent strategies that the instructor can use in delivering the material or task rather than the inherent difficulty of the material or task itself. This thought allows for the transition to better understanding the second type of cognitive load, extraneous load.

Extraneous Cognitive Load

Extraneous load is derived from the way instructional information or materials are presented. Instructors have the ability to reduce extraneous cognitive load through effective instruction, or increase extraneous cognitive load through ineffective/poor instruction. Sweller (1988) described this load as not necessary for learning to occur; however it greatly impacts the way students' process information. If students' cognitive load increases due to poor instruction, the mental resources they have available to deeply process and ultimately learn information are reduced.

Extraneous load is imposed by irrelevant instructional activities that negatively

affect skill acquisition and schema acquisition (Jong, 2010; Chandler & Sweller, 1991). Extraneous load is under the direct control and influence of the instructor as he or she presents the information. One of the basic premises of CLT indicates that reduction in extraneous load allows for better processing of the intrinsic load, or difficult nature of the material. Therefore, if the complexity of the information and/or task imposes a high intrinsic cognitive load, instructors can help students free up mental processing capacity through effective instruction. Instructors, then, can remedy unnecessary extraneous load by presenting information in an integrated way (Chandler & Sweller, 1991). Bolkan, Goodboy, and Kelsey (2016) argued that “it is crucial for instructors to remember that simply providing information is not enough to ensure that students have engaged with the material in ways that promote deep learning and lasting memory” (p. 130). Therefore, it is important that instructors seek ways to design instruction in order to reduce the negative extraneous load.

Students can be presented difficult/complex information in unique ways that helps reduce the imposed extraneous load. Research in educational psychology indicates that goal free problems, worked out problems, and completion problems represent alternatives to the assignment of traditional problems (Jong, 2010; Renkl & Atkinson, 2010; Sweller, van Merriënboer, & Pass, 1998; Ayers, 1993). Problems of this type are partially completed to help navigate learners in the completion process and/or fully completed for the learners to study and process. Another instructional design approach to help reduce extraneous cognitive load includes using both auditory and visual representations of the information and/or task (Jong, 2010). By combining auditory and visual representations of the information, learners will be able to better process the information in their working

memory (Baddeley, 2001; Sweller et al., 1998). Finally, another instructional design technique to reduce extraneous load consists of removing redundant information from the instructional materials (Jong, 2010). Sweller (1994) and Sweller et al. (1998) identified this load reducing technique as the redundancy principle. Once learners are presented with the same information in multiple forms it reduces their capacity in working memory to process other information. Therefore, it is important for instructors to reduce multiple sources of the same information and make sure that they cover the initial source clearly and in-depth. It is obvious that extraneous cognitive load can be greatly reduced when an instructor intentionally designs the presentation/delivery of the material. Complex information should be designed carefully so as to not increase negative load on the learner's working memory capacity. It is important to note, though, that if the difficulty of the material is not high (intrinsic load), poor instruction doesn't matter as much (Sweller, 1988, 1989). Sweller (1988) argued that the two loads, intrinsic and extraneous, then, can be additive in order to measure a learner's total cognitive load.

From an instructional communication perspective, instructors' communicative acts and behaviors, then, should have a significant influence on students' extraneous cognitive load. Jong (2010) identified extraneous load as the focus of the majority cognitive load studies. It is likely due to the fact that instruction/delivery is easy to manipulate and measure in research settings. For example, Mayer and Moreno (2003, 2010) proposed several methods for instructors to reduce extraneous load including segmenting course content/information, signaling key ideas/concepts, providing concise and uncluttered information (i.e., clarity), and removing redundant and/or unnecessary course information/materials. Subsequently, instructional communication research is

primed to identify potential load imposing communicative acts that occur in learning situations. Specifically, teacher clarity research reveals that as instructors engage in more clarity strategies (i.e., reviews, examples, transitions) students' extraneous cognitive load decreases (Bolkan, 2015; Bolkan, Goodboy, & Kelsey, 2016). The decrease in extraneous load allows for students to allocate more working memory resources to process the information. Instructional message content relevance should have a similar effect on extraneous load. Content relevance strategies have been positively linked to affective learning, student motivation to study, class attendance, and affect toward the instructor and/or class (Cayanus, Martin, & Goodboy, 2009; Frymier, 2002; Cayanus, 2003; Frymier & Shulman, 1995). Therefore, as students perceive the content of the course delivered by the instructor as relevant to their lives (i.e., goals, needs, interests), the load imposed by instructors' presentation of the material should be relatively low.

Intrinsic load and extraneous load, when high, are considered to have negative effects on learners' abilities to process information. However, when intrinsic and extraneous loads are reduced, learners' have "freed up" space in their working memory to deeply process the content that is presented. This understanding of cognitive load theory leads to the third dimension of cognitive load, germane load.

Germane Cognitive Load

The third type of load, germane, was an added dimension of working memory to the original theory (Jong, 2010). Germane load represents the load that is left over from the total cognitive load that a learner has in order to invest mental effort to learning material (Sweller, VanMerriënboer, & Pass, 1998). Learners' that are motivated to invest mental effort in those processing behaviors are likely to increase their ability to

understand, store, and retrieve the information. Park, Moreno, Seufert, and Brunken (2011) argued, though, that students do not automatically engage in learning behaviors when low load learning environments are presented and need to find a reason, or be presented a reason, to be motivated to deeply process the information. As such, germane cognitive load is similar to central route processing in the Elaboration Likelihood Model where receivers are motivated to consciously process stimuli (Petty & Cacioppo, 1986).

It is within the germane cognitive load dimension of working memory that learning occurs through the construction and automation of schemas (Paas, Renkl, & Sweller, 2003). In fact, Jong (2010) argued that “cognitive load theory sees the construction and subsequent automation of schemas as the main goal of learning” (p. 109). Therefore, an increase in germane load represents positive cognitive load that, likely, leads to better understanding and learning. Mayer (1996) identified interpreting, exemplifying, classifying, inferring, differentiating, and organizing as processes that influence the construction of schemas. Jong (2010) noted, then, that “instructional design should, of course, try to stimulate and guide students to engage in schema construction and automation and in this way increase germane cognitive load” (p. 109).

Since germane load is greatly determined by the investment of mental effort by the learner, instructional message content relevance should have a considerable effect on the learner’s germane load. Keller (1983) argued that relevance increases students’ state motivation in the classroom. Within instructional communication research, content relevance is known to influence students’ state motivation to study (Frymier & Shulman, 1995), willingness to actively participate in class (Cyanus, Martin, & Goodboy, 2009), understanding (Cyanus, 2003), and engaging in learning behaviors (Frymier & Houser,

1999). Therefore, it is likely that learners will invest more mental effort to deeply process complex information and tasks when they believe the content is relevant to their lives (i.e., needs, interests, goals). As a result, load imposed by the intrinsic nature of the material and the presentation of the material can be compensated for when learners' invest more mental effort to deeply process the material. Instructional practices, then, should seek to reduce intrinsic and extraneous loads, and increase germane load in order to positively influence cognitive learning. It is likely that students' perceptions of content relevance will influence this aspect of germane load.

CLT is a prominent theory in educational psychology and is becoming more prominent in instructional communication research as scholars seek to explore the influence of communication in instructional contexts on learners' cognitive load. The ability to explain, predict, and understand instructional message effects on the cognitive load of students allows for instructors to better prepare instructional packages and classroom, or virtual, activities. With learning as the goal of education, cognitive load theory helps better understand communicative acts that help individuals develop automated schemas for novel information and enhance prior sets of automated schemas to account for more complex knowledge/information. Instructional message content relevance, as a communicative act, likely has a resounding influence on learners' cognitive load.

Theoretically, the interaction of instructional message content relevance and the three dimensions of cognitive load (intrinsic, extraneous, germane) should interact to influence, to some degree, students' cognitive learning. It is important, then, to explore extant cognitive learning research in instructional communication.

Cognitive Learning

As previously stated, learning is the goal of education, and all strategies, behaviors, instructional designs, and communication utterances should focus on the end product of students' knowledge of the course material. Engaging students in the learning process can often be difficult, but through instructional design techniques and calculated delivery and presentation, instructors can discover ways to motivate students to learn the material. Bolkan, Goodboy, & Kelsey (2016) argued that instructors and students can create optimal learning conditions by working together. Specifically, they pointed to humor (Bolkan & Goodboy, 2015), clear lectures (Chesebro, 2003; Seidel, Rimmele, & Prenzel, 2005), and making content relevant to students' lives (Frymier & Shulman, 1995; Kember, Ho, & Hong, 2008) as behaviors that teachers can use that have been known to associate with student learning. Again, Chesebro (2002) argued that teachers should approach each classroom with a mindset of thinking of their students' needs, interests, and goals and then teach accordingly. Consequently, instructors must understand the student population for which they teach and employ communication behaviors and instructional design strategies that increase students' motivation and willingness to learn the course content. Additional research focus in instructional communication explores the influence of teacher immediacy on cognitive learning (McCroskey, Sallinen, Fayer, Richmond, & Barraclough, 1996; Rodriguez, Plax, & Kearney, 1996; Chesebro & McCroskey, 2001; Titsworth; Witt, Wheelless, & Allen, 2004). Building upon the interdisciplinary foundation of educational psychology, pedagogy, and communication, instructional communication scholars seek to discover communicative processes that influence student acquisition of knowledge and learning.

Clark (2002) argued that one of the greatest challenges, and disappointments, in instructional communication has been the absence to discover ways in which communication effects learning outcomes. Instructional communication has made great strides to discover ways that communication affects the learning environment, but a significant gap exists in measuring learning outcomes. Therefore, if learning is the goal of education, instructional communication scholars must enhance the measure of the influence of communication on student learning outcomes.

While Clark's (2002) argument is warranted, it is important to note that instructional communication literature is ripe with studies that connect communication in instructional settings to student affective learning. Affective learning, as defined by Krathwol, Bloom, and Masia (1964), represents the interests, attitudes, appreciations, values, and emotional biases students' feel in the instructional environment. Affect, then, is more about an internalization of feelings (Myers & Goodboy, 2015) associated within the instructional communication context. It is important, though, to expand the focus on higher order learning to move the discipline forward. Therefore, measuring the influence of communication in instruction on cognitive learning is critical.

Cognitive learning is associated with the acquisition and retention of knowledge, as well as the ability to recall and use it in particular situations. Specifically, considering Bloom's (1956) conceptualization, Flora-Wei, Wang, and Klausner (2012) defined learning as a "hierarchical order of instructional objectives comprising knowledge, comprehension, application, analysis, synthesis, and evaluation" (p. 190). Several links between communication variables and cognitive learning have been reported, but the measurement of cognitive learning has often been under criticism.

Instructional communication research, nearly exclusively, has relied on student self-report measures to measure cognitive learning (Chesebro & McCroskey, 2000). Most often, the Learning Loss Measure has been employed in research settings. This measurement consists of two items asking (a) how much the student learned, and (b) how much they could have learned with the ideal instructor. The use of only two items and the question as to the ability for students to report their own learning are two standard criticisms of the measurement (Frisby, Mansson, & Kaufmann, (2014). Revisions to the original scale and attempts to measure learning indicators and/or behaviors have been a point of focus over the past decade. For example, Frymier and Housers (1999) Revised Learning Indicators Scale measures behaviors enacted by students indicative of their involvement in the learning process and their understanding of the course content. Further, King and Witt (2009) employed confidence testing where students were asked to rate how confident they were in the answer they provided to specific questions. Although these new measures have been created, criticism over the measurement of cognitive learning in instructional communication continued. Fortunately, the recent development of the Cognitive Learning Measure (CLM; Frisby, Mansson, & Kaufmann, 2014; Frisby & Martin, 2010) has advanced the way students' perceived cognitive learning can be measured in instructional communication. Frisby and Martin (2010) constructed the CLM using language based on theoretically grounded cognitive learning research. Specifically, the scale items focus on students' acquisition, recall, and application, all of which are significant outcomes within the cognitive learning domain. Although it is a self-report scale, the CLM, considered to have both strong conceptual and operational fit, is a better measurement than its predecessors.

In addition to the difficulty of measuring perceived cognitive learning, using students' grades on assignments and/or a class to measure cognitive learning in instructional communication has received criticism as well. McCroskey and Richmond (1992) argued that scores on an exam do not necessarily guarantee that knowledge was gained in class, instead that knowledge was gained somewhere. Further, Frisby, Mansson, and Kaufmann (2014) argued additional limitations for using students' exam scores for measuring cognitive learning. Those limitations include measuring only one aspect of learning (recall), no control for the research to assure test objectivity, and not accounting for additional behaviors that might affect the grade (Frisby et al., 2014). Additional behaviors affecting the exam grades might include the wording of the exam, student attendance, student motivation, procrastination, cheating, extra credit opportunities, sensitization toward the content and/or instructor, and students' test-taking abilities. Ultimately, though, there is no gold standard for measuring cognitive learning. Therefore, it is important that instructional communication researchers utilize the most valid approach possible in order to measure changes in students' knowledge, attitudes, and/or skills. Without a pre-test, it is difficult to measure changes in knowledge as students may have learned information outside of exposure to the instructional messages in the classroom. Therefore, controlling for outside influences (e.g., previous coursework, number of times enrolled in current course) is important. Ultimately, King and Witt (2009) argued that although criticisms of using students' exam grades to measure cognitive learning exist, grades are the nationally accepted measure of learning in education. It is important, then, to acknowledge and account for as many outside factors to academic performance as possible, but still recognize that academic

performance is an accepted measurement of cognitive learning.

In order to advance cognitive learning measurement in instructional communication research, it is important to consider combining self-report perceptions of cognitive learning and academic performance. Therefore, instead of measuring perceived cognitive learning or academic performance in isolated studies, combining the two cognitive learning measurements provides the opportunity for comparison of what students believed they learned and what they scored on an exam as a result of their perceptions of instructional message content relevance. This approach is both conceptually and operationally appropriate for instructional communication research. Based on the review of literature, both cognitive learning outcomes are likely influenced by students' perceptions of message content relevance and their experienced cognitive load (intrinsic, extraneous, and germane). Therefore, the following hypothesis and research questions guided the exploration.

Hypothesis and Research Questions

As evidenced in the literature review, cognitive learning may be influenced by students' attitudes and/or behaviors beyond content relevance and/or cognitive load. Therefore, it is important to account for specific attitudes and behaviors that may be potential covariates influencing students' cognitive learning (Martin, Mottet, & Myers, 2000). First, students' reasons for taking a course will likely be related to students' perceptions of message content relevance. Secondly, studies show that students' affect toward the instructor and/or class is related to teacher content relevance strategies (Ryan & Deci, 2000). As teachers use more content relevance strategies, students perceive the teacher and class more favorably. Further, content relevance is a motivation factor in the

instructional setting (Keller, 1987). Specifically, content relevance strategies motivate students to study (Frymier & Shulman, 1995) and attend class (Cayanus & Martin, 2008). Similarly, it is expected that students will develop the same attitudes and learning strategies when they perceive instructional message content relevance in their courses. As a result, the following hypothesis is posed:

H₁ Students' perceptions of content relevance will be positively related with students' (a) reason for taking the course, (b) affect toward the class, (c) affect toward to the instructor, (d) time spent studying for class, and (e) class attendance.

It is evident that content relevance research has yielded important findings in instruction communication research, however, there is much more to be discovered. As a result of the review of content relevance and cognitive load theory, content relevance likely has an impact on students' intrinsic, extraneous, and germane loads. Students' that perceive course content to be relevant will likely experience decreased extraneous (negative) load, managed intrinsic (negative) load, and develop schema as a result of germane (good) load (Shadiey, Hwang, Huang, & Liu, 2015). While some literature exists, there is little evidence to support this assumption. Therefore, the following research question is proposed:

RQ₁ How does students' perceptions of instructional message content relevance predict (a) intrinsic cognitive load, (b) extraneous cognitive load, and (c) germane cognitive load?

In order to address criticisms of and advance the instructional content relevance research program, it is important to investigate whether or not students' perceptions of message content relevance predict academic performance and perceived cognitive learning. This is an assumption that has been made in both educational psychology and instructional communication research, yet has too often been neglected to be empirically measured. By measuring the influence of instructional content relevance on cognitive learning, a better understanding of the impact of classroom communication on student learning outcomes can be examined. Therefore, the following research question asks:

RQ₂ To what extent do students' perceptions of instructional message content relevance predict cognitive learning through students' (a) academic performance and (b) perceived cognitive learning?

Clark (2002) argued that instructional communication scholars should focus on the impact of instructional communication on student learning outcomes. Although the existing literature on content relevance in instructional communication indicates that content relevance strategies have a positive relationship with students' empowerment to learn (Frymier, Schulman, & Houser, 1996) and learning behaviors (Frymier & Houser, 1999), evidence that content relevance has an actual effect on cognitive learning is absent. Frymier (2002) argued that researchers have invested little time on the nature of content relevance or its relationship to learning, yet frequently discuss the communicative behavior as an important aspect of teaching. Wilson and Sperber's (2004) psycholinguist study of content relevance and cognition provided one of the only arguments that it is likely that instructional message content relevance indeed influences students' cognitive learning. Therefore, based on the review of cognitive load theory, the interactions

between content relevance and the dimensions of cognitive load may, very well, predict students' cognitive learning through academic performance. As a result, the following research question is proposed:

RQ₃ To what extent do students' perceptions of content relevance, intrinsic cognitive load, extraneous cognitive load, and germane cognitive load predict students' academic performance?

Often, in instructional communication literature, students' perceptions of learning is reported as cognitive learning. While this represents what students believe they learned, it does not represent actual measured cognitive learning (Lane, 2016). However, theoretically grounded instruments, like the Cognitive Learning Measure, have advanced the measurement of student self-reports of cognitive learning (Frisby & Martin, 2010).

Therefore, the following research question asks:

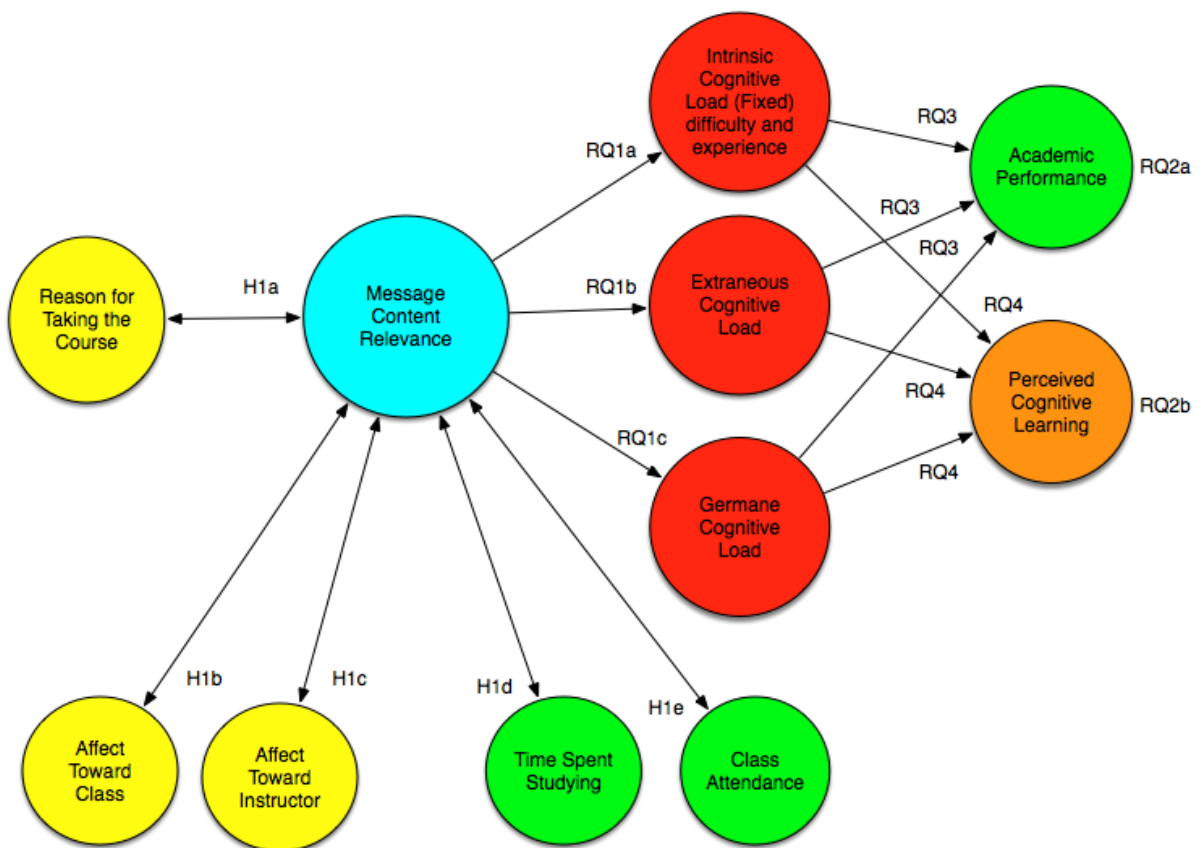
RQ₄ To what extent do students' perceptions of content relevance, intrinsic cognitive load, extraneous cognitive load, and germane cognitive load predict students' perceived cognitive learning?

The proposed theoretical model of H₁ and RQ's 1 through 4 can be found in Figure 2.2 (p. 50). The double arrows represent expectant positive correlations associated with H₁ and the one-way arrows represent predictive relationships among the variables.

Although students' perceptions of message content relevance and their reported intrinsic, extraneous, and germane loads likely predict cognitive learning, more complexities exist. For example, students may report high perceptions of message content relevance and high investment of mental effort (germane load), yet their

perceptions of cognitive learning and/or academic performance scores are low. Therefore, identifying students with high perceptions of message content relevance and low perceptions of message content relevance is important to understanding the influence of message content relevance on cognitive processing and learning. Further, students' attitudes and behaviors previously mentioned could have significant influence on message content relevance within the instructional environment.

Figure 2.2 *Proposed Model of Message Content Relevance and Cognitive Load as Predictors of Cognitive Learning*



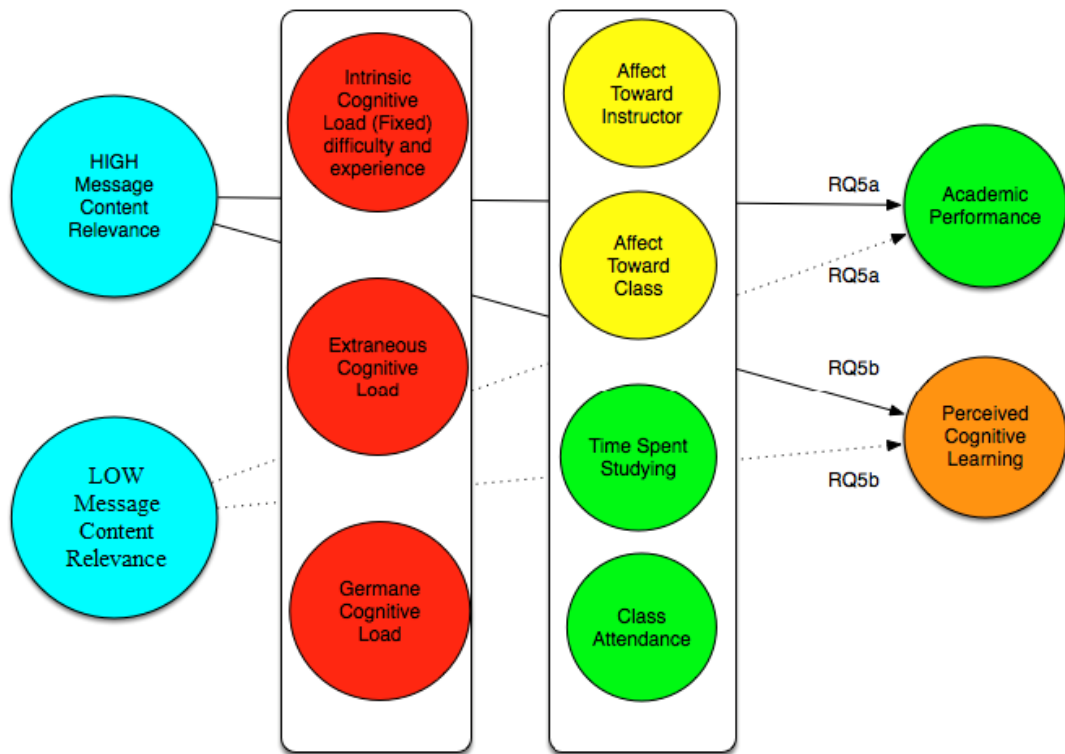
Again, it is important to measure those variables that may influence students' perceptions of content relevance, the three dimensions of students' cognitive load, and/or students' perceptions of cognitive learning and academic performance. The potential variables accounted for in the current study are students' reason for taking the course, students' affect toward the teacher, students' affect toward the class, students' time spent studying for the class, and students' class attendance. Based on instructional communication research, each variable should have a positive interaction with students' perceptions of content relevance. However, it is important to also identify which variables potentially influence cognitive learning when included in the full theoretical model. Therefore, the following research question is proposed:

RQ₅ How does students' perception of message content relevance (when categorized as high or low) interact with cognitive load, students' affective behaviors and learning strategies to predict (a) academic performance and (b) perceived cognitive learning?

The proposed theoretical model of RQ₅ can be found in Figure 2.2 (p. 51).

The hypothesis and research questions posed above represent an extension to the content relevance program of research. For over two decades instructional communication scholars have argued the positive influence of content relevance on student learning with minimal focus on actually measuring students' cognitive learning (Frymier, 2001). The purpose of this dissertation was to test the proposed model to determine the extent of the influence of instructional message content relevance on students' cognition. Therefore, given the hypothesis and research questions, chapter three will present the methods that navigated the exploration.

Figure 2.3 *Proposed Students' Perceptions of Message Content Relevance on Cognitive Learning Model: A Causal Process Model*



Chapter 3: Methods

The purpose of this study was to test a predictive theoretical model that explains the extent to which students' perceptions of instructional message content relevance influences students' cognitive load (intrinsic, extraneous, and germane), which, in turn, influences students' cognitive learning (perceived cognitive learning and academic achievement). Presented in this chapter are the details explaining the participants, research procedures, and survey instruments.

Research Participants

Participants ($N = 559$) were recruited through introductory statistics courses at a public university in the Southeastern United States. An a priori power analysis recommended an approximate sample size of 320 given the proposed theoretical model. Therefore, 559 participants represented a powerful sample size.

The demographic makeup of the participants included males ($n = 166$), females ($n = 392$), and one participant that reported their gender as other, ranging in age from 18-48 years old. Participants' ethnicity included 81.9% Caucasian ($n = 458$), 10.7% African American ($n = 60$), 6.2% Asian ($n = 35$), 3.9% Hispanic ($n = 22$), and 3.2% reported another ethnicity. Further, 6% of participants ($n = 34$) reported multi-ethnicity. The academic classification of participants included 36 first-year students (6.4%), 319 sophomores (57%), 140 juniors (25%), 53 seniors (9.4%), and 11 students that reported other (1.9%). Additionally, participants reported a significant diversity in their academic majors, including, but not limited to, business, communication, education, equine sciences, family consumer sciences, marketing, journalism, and nursing.

Participants were asked to answer additional questions beyond basic demographic

questions to better understand the sample for this research. First, participants were asked to report the reason for taking the statistics course. Responses indicated that students took the course because it was required for their major ($n = 255$, 45.6%), the course was a pre-requisite for a higher-level course ($n = 28$, 5%), to fulfill a general education requirement ($n = 263$, 47%), and as an elective ($n = 13$, 2.3%). Second, participants were asked how many statistics courses they successfully completed prior to their current statistics course. Responses included zero ($n = 451$, 80.7%), one ($n = 98$, 17.5%), two ($n = 8$, 1.4%), and three ($n = 2$, 0.4%).

The final sample ($N = 559$) is a result of cleaning the data from 640 original participants. Participants that did not fully complete the survey ($n = 22$) were removed from the sample, as well as participants that completed the survey under four minutes or over 10 hours ($n = 57$). The duration of completion decisions were made based on the possibility of participants having the ability to complete the survey in four or more minutes on an efficient smart phone or tablet platform. Further, participants that completed the survey in more than 10 hours likely opened the survey and came back to it just to complete it for extra credit in the course without giving full attention to the survey questions. Next, Z-scores, 3.29 standard deviations beyond the mean, were calculated for each scale used in the survey in order to identify participant responses that were deemed outliers. Two participants were removed due to a Z-score of -3.51898 on the Cognitive Learning Measure. Participants' responses were within the Z-score of 3.29 on all other scales. As a result, the aforementioned sample size ($N = 559$) was deemed the final sample for testing the proposed model.

Research Design/Protocol

Upon IRB approval, four introductory statistics instructors (STATS 210) were contacted requesting their students' participation in this cross-sectional research design study. Most often, instructional communication research requests participants to reflect on an instructor they had in the course immediately prior to the one for which they completed a survey (Plax, Kearney, McCroskey, & Richmond, 1986). However, for the current study, participants were asked to report on their current statistics instructor. This method helped to contextualize student learning with the teacher and content in the class. Further, students were not required to have previous experience/coursework in statistics prior to enrolling in this course allowing for a distinct measurement of cognitive load.

After week nine of the semester, to allow for students to become familiar with the course and have had the opportunity to take at least one exam, instructors that volunteered for student participation in their courses were sent a recruitment message. Specifically, data collection opened on Tuesday, October 25th, and ended on Sunday, November 13th. Data collection was open for a total of 20 days. Instructors were asked to read the recruitment message aloud to the students in their courses and post the recruitment message to their web based learning management system (Canvas). The recruitment message directed participants to click on a link to an online self-report survey hosted by Qualtrics. Once participants accessed the survey link, they read a consent form to review their rights as participants in the study and were informed that by clicking on the (*I agree to participate*) button they were providing digital consent. Students that chose not to participate had the option to click on the (*I do not agree to participate*) button and were immediately directed to a page thanking them for their consideration.

After providing their consent, participants were directed to a welcome and instructions page for the survey. They were reminded that they were answering a series of questions composed of six survey instruments and a brief set of demographic questions. Participants were also asked to provide their first name, last name, and section number of the statistics course for which they were enrolled in order to confirm their participation with their instructor. They were assured that their identifying information would be kept separate from the data and would not be distributed to anyone, including their instructor, in conjunction with their survey responses.

Participants were then asked to report on their perceptions of instructional message content relevance, their perceived intrinsic, extraneous, and germane cognitive loads, their affect toward the instructor and the course, how much they perceived to have learned in the class, and their academic achievement. Participants were reminded that they were not providing an evaluation of the instructor or the course, instead reporting on their experiences in the course. They were informed that the survey (Appendix) would take approximately 15-20 minutes to complete and that they should carefully read each question, follow the instructions accurately, and answer all questions truthfully. Participants then clicked on a link in order to begin their response to the survey questions.

After data collection ended, survey responses were collected and a list of participants was generated to distribute to the statistics instructors in order for them to confirm participants for extra credit in their classes. The survey data was downloaded and analyzed using SPSS software. The data file was cleaned under the conditions of the explanation in the previous participant's section and then analyzed according to the statistical tests needed to test the hypothesis and answer the research questions.

This research protocol provides accurate details, a credible protocol, and the potential for replication of the research design (Fowler, 2009). The following section provides descriptions of the survey instruments included in this study.

Instrumentation

The following scales were used to operationalize each variable and collect data from participants in order to test the proposed hypothesis and answer the research questions.

Message Content Relevance. To measure students' perception of instructional message content relevance, the Message Content Relevance Scale (MCRS) was used. The scale was developed by the author of the current study and has been used to measure perceptions of content relevance in two previously unpublished pilot studies. The MCRS consists of eight theory driven questions (i.e., I believe the content from the course directly impacts my career goals.) derived from education (Keller 1987, 1983) and instructional communication (Frymier & Shulman, 1995) literature. The MCRS is a 5-point Likert-type scale with anchors of 1 (*strongly disagree*) to 5 (*strongly agree*). Previous alpha coefficients for the MCRS in the two pilot studies were .95 (fall 2015) and .96 (spring 2016). Cronbach's alpha for the current study was .93. Further, an acceptable reliability was determined for the scale for two groups of low perceptions of content relevance ($\alpha = .86$) and high perceptions of content relevance ($\alpha = .74$).

Cognitive Load. Cognitive load is a three dimensional construct consisting of intrinsic cognitive load, extraneous cognitive load, and germane cognitive load. Leppink, Pass, van Gog, van der Vlueten, and van Merriënboer's (2014) Cognitive Load Questionnaire (CLQ) was designed to measure each of the dimensions of cognitive load.

The scale consists of 13 questions on a 10-point Likert-type scale with anchors of 0 (*not at all the case*) and 10 (*completely the case*) that were adapted to fit the current study (i.e., I invest a very high mental effort during class activities to enhance my knowledge and understanding of the content.). The scale is divided into three subscales with four questions measuring intrinsic cognitive load (i.e., In this course, very complex terms are mentioned.), four questions measuring extraneous cognitive load (i.e., The explanations and instructions in this course are full of unclear language.), and five items measuring germane cognitive load (i.e., The activities really enhance my knowledge and understanding of how to deal with the problems covered.). The instrument has yielded reliable alpha coefficients for each subscale in past studies: intrinsic cognitive load, $\alpha = .87$; extraneous cognitive load, $\alpha = .78$; germane cognitive load, $\alpha = .93$ (Leppink, Pass, van Gog, van der Vlueten, & van Merriënboer, 2014). In the current study, the full scale yielded an acceptable reliability ($\alpha = .85$). The subscales also yielded acceptable reliabilities (intrinsic cognitive load, $\alpha = .93$; extraneous cognitive load, $\alpha = .91$; germane cognitive load, $\alpha = .90$) in the current study.

Students' Perceptions of Cognitive Learning. Students' perceived cognitive learning was measured using Frisby and Martin's (2010) Cognitive Learning Measure (CLM). The CLM consists of 10 items on a 5-point Likert-type scale with anchors of 1 (*strongly disagree*) to 5 (*strongly agree*) that represent students' perceived acquisition, retention, and application of course content (i.e., My knowledge on this class topic has increased since the beginning of the class; I have learned information that I can apply.). Items 5, 6, 8, and 10 were recoded prior to data analysis. Two items, item 2 (I have learned more in other classes than in this class) and item 5 (I would be unable to use the

information from class), were removed from the scale as they decreased the overall reliability of the measure. Previous alpha reliabilities ranged from .85 (Hughes, 2014) to .94 (Frisby & Martin, 2010). For this study, the CLM yielded an acceptable reliability ($\alpha = .87$).

Affect Toward the Instructor and Course. Students' affect toward the instructor and the course were measured using an adaptation of Anderson's (1979) Affective Learning Scale. It is important to note that subscales from the original measurement were used. The subscales that were used measured students' attitudes toward the instructor and the course and may or may not be a consequence of affective learning in the class (Lane, 2016). The subscales of the measure used in this study consisted of four-item semantic differential questions that measured students' attitudes toward the instructor (i.e., Positive/Negative), students' attitudes toward the course (i.e., Bad/Good), students' likelihood of taking a course in the future in the same content area (Unlikely/Likely), and students' likelihood of taking a course in the future with the same instructor (i.e., Would/Would Not). Of the sixteen total items, items 2, 4, 6, 8, 10, 12, 14, and 16 were recoded prior to data analysis. Previous reliability coefficients for the instrument ranged from .83 to .98 (Andersen, 1979; Frisby & Martin, 2010; Teven & McCroskey, 1997). Cronbach's alpha coefficients were reliable for the full scale ($\alpha = .93$) as well as the subscales of affect toward the instructor ($\alpha = .93$) and affect toward the class ($\alpha = .91$).

Academic Performance. To measure students' academic performance, participants responded to three items reflective of their learning in the course. Students were instructed to open a separate tab on their web browser and access their midterm

grade and their most recent exam grade as reported on their course Canvas page. The questions stated: My most recent statistics exam grade was; My statistics grade at midterm was; At the end of the semester, I expect my average grade in my statistics course to be. Students' responded to the following scale for all three questions: 1 (0-59%), 2 (60-69%), 3 (70-79%), 4 (80-89%), 5 (90-100%). All three questions were asked, but the unit of measurement for students' academic performance used in the analyses were students most recent exam scores.

Time Spent Studying. To measure students' reported time studying individually for the course, participants were asked to respond to one item that stated: How much time do you spend studying individually outside of class for your statistics per week? Students were also asked to respond to an item that measured how much time they studied with tutoring help each week (How much time do you spend studying with a tutoring service for your statistics course per week?) Students responded to a 5-point scale: 1 (0-1 hours), 2 (1-2 hours), 3 (3-5 hours), 4 (6-7 hours), 5 (8 or more hours) for both questions. An additional question asked students to report how often they visited their professor's office to discuss course content (How often do you visit your professor's office to discuss content/instruction for your statistics course?). Students responded to a 5-point scale: 1 (never), 2 (once this semester), 3 (once a month throughout the semester), 4 (once every couple of weeks), 5 (once per week) for this question.

Class Attendance. To measure students' reported course attendance, participants responded to one item. The question stated: How many times have you been absent from this class this semester? Students responded using a 5-point scale: 1 (0), 2 (1-2), 3 (3-5), 4 (6-7), 5 (8 or more).

Chapter 4: Results

The purpose of this study was to test a predictive theoretical model of the influence of students' perceptions of message content relevance and cognitive load on cognitive learning. In order to test the model, a series of regression analyses were conducted. Prior to the regression analyses, two correlation matrices were examined.

For the exploration of the relationships among the 13 variables in the study, Table 4.1 (p. 62) displays the correlation matrix for the full sample ($N = 559$) along with descriptive statistics for each variable. To answer the final research question, the full sample was divided into two sub-samples through a median split representing low ($n = 277$, 49.6%) and high ($n = 282$, 50.4%) perceptions of message content relevance. Participants with low perceptions of message content relevance included 60 males (21.7%) and 217 (78.3%) females ranging in age from 19-45 years old. Academic rank of participants included 12 first-year students (4.3%), 169 sophomores (61%), 64 juniors (23.1%), 28 seniors (10.1%), and 4 students that reported other (1.4%). Participants with high perceptions of message content relevance included 106 males (37.6%) and 175 females (62.1%) ranging in age from 18-48 years old. Academic rank of participants included 24 first-year students (8.5%), 150 sophomores (53.2%), 76 juniors (27%), 25 seniors (8.9%), and 7 students that reported other (2.5%). Correlations for the split sample and the 13 variables used in the study were examined. A correlation matrix along with descriptive statistics for each variable can be found in Table 4.2 (p. 63).

Table 4.1 Means, Standard Deviations, Reliabilities, and Zero-Order Correlations for Variables for Full Sample (N = 559)

Variable	M	SD	1	2	3	4	5	6	7	8	9	10	11	12
1. Perceived Content Relevance	2.99	0.90												
2. Perceived Cognitive Learning	3.37	0.58	.698**											
3. Intrinsic Cognitive Load	5.50	2.26	-.023	.017										
4. Extraneous Cognitive Load	4.62	2.52	-.382**	-.456**	.485**									
5. Germane Cognitive Load	5.91	2.10	.529**	.642**	.328**	-.162**								
6. Affect toward Teacher	4.88	1.65	.454**	.505**	.027	-.449**	.412**							
7. Affect toward Class	3.92	1.46	.709**	.613**	-.059	-.454**	.520**	.582**						
8. Academic Performance	3.66	1.26	.182**	.176**	-.275**	-.242**	.096*	.045	.183**					
9. Reason for Taking Course	2.06	1.00	-.064	-.049	-.119**	-.060	-.040	.003	-.029	.063				
10. Time Spent Studying	2.12	0.78	.065	.113**	.397**	.189**	.188**	.065	.044	-.183**	-.059			
11. Class Attendance	1.92	0.80	-.003	-.006	-.010	.071*	.009	-.017	-.033	-.159**	.017	.016		
12. Prior Stats Experience	1.21	0.46	.071*	-.091*	-.045	.102**	-.040	-.040	.050	.023	-.028	.050	.057	
13. Stats Course Attempts	1.03	0.20	-.011	-.027	.068	.061	.003	.042	-.054	-.100**	.017	.067	.038	.083*

** . Correlation is significant at the 0.01 level (1-tailed).

* . Correlation is significant at the 0.05 level (1-tailed).

Table 4.2 Means, Standard Deviations, and Zero-Order Correlations for Variables in Low ($N = 277$) and High ($N = 282$) Perceptions of Message Content Relevance

Variable	Low															High	
	M	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	M	SD
1. Per. Content Relevance	2.26	0.64		.382**	.110*	-.027	.442**	.293**	.401**	.008	.015	.090	.035	.047	.115*	3.71	0.44
2. Per. Cognitive Learning	3.06	0.58	.642**		.067	-.335**	.541**	.391**	.424**	.020	-.003	.118*	.010	-.207**	.108*	3.67	0.41
3. Intrinsic Cognitive Load	5.51	2.43	-.108*	-.001		.433**	.395**	.123*	.005	-.219**	-.115*	.317**	-.002	-.011	.069	5.48	2.09
4. Extraneous Cognitive Load	5.35	2.54	-.414**	-.405**	.560**		-.064	-.322**	-.336**	-.109*	-.097	.063	.106*	.144**	.116*	3.91	2.28
5. Germane Cognitive Load	5.09	1.84	.386**	.603**	.329**	-.054		.401**	.406**	.051	-.005	.175**	-.005	-.065	.106*	6.72	2.05
6. Affect toward Teacher	4.30	1.68	.326**	.418**	-.034	-.440**	.253**		.569**	-.020	.053	.120*	-.012	-.041	.012	5.45	1.41
7. Affect toward Class	3.05	1.07	.603**	.498**	-.145**	-.410**	.376**	.441**		.041	.066	.094	-.004	.029	.008	4.77	1.28
8. Academic Performance	3.51	1.39	.234**	.207**	-.315**	-.301**	.065	.024	.252**		.078	-.117*	-.137*	.028	-.076	3.80	1.11
9. Reason for Taking Course	2.10	0.99	-.095	-.052	-.124*	-.057	-.049	-.011	-.093	.062		-.008	-.068	.033	-.063	2.02	1.02
10. Time Spent Studying	2.09	0.78	.018	.097	.472**	.348**	.196**	-.005	-.071	-.251**	-.110*		.012	.055	-.011	2.16	0.79
11. Class Attendance	1.88	0.75	-.141**	-.069	-.018	.069	-.013	-.056	-.164**	-.195**	.122*	.017		.036	.011	1.95	0.85
12. Prior Stats Experience	1.19	0.42	.042	-.094	-.080	.105*	-.070	-.088	.007	.005	-.098	.038	.080		.153**	1.24	0.50
13. Stats Course Attempts	1.03	0.22	-.106*	-.119*	.067	.031	-.095	.063	-.153**	-.118*	.084	.131*	.063	.019		1.03	0.18

Note: Correlations for students with low perceptions of content relevance appear below the diagonal; correlations for students with high perceptions of content relevance appear above the diagonal.

** . Correlation is significant at the 0.01 level (1-tailed).

* . Correlation is significant at the 0.05 level (1-tailed).

Hypothesis 1: Relevance, Affect, and Learning Strategy Relationships

Hypothesis one predicted a positive relationship between students' perceptions of message content relevance and students' reason for taking the course, affect toward the class, affect toward the instructor, time spent studying for class, and class attendance. Pearson product moment correlations revealed a statistically significant, strong relationship between students' perceptions of message content relevance and affect toward the class ($r = .709, p < .001$) as well as affect toward the instructor ($r = .454, p < .001$). However, there were no statistically significant relationships between students' perceptions of message content relevance and students' reason for taking the statistics course ($r = -.064, n.s.$), time spent studying for class ($r = .065, n.s.$), and class attendance ($r = -.003, n.s.$). Only affect toward the class and affect toward the instructor were significantly related to message content relevance (Figure 4.1, p. 68). Therefore, H_1 was partially supported.

Research Question 1: Relevance on Cognitive Load

The first research question asked how message content relevance predicted (a) intrinsic cognitive load, (b) extraneous cognitive load, and (c) germane cognitive load. Preliminary analyses were conducted to check for violations of the assumptions of normality and linearity. Although the data were found to not be normally distributed, regression analyses were still used despite the violations as it is likely the violations do not pose a threat to the value of the results (e.g., Lix, Keselman, & Keselman, 1996). To answer the first research question, a series of three regression analyses revealed significant findings for both extraneous and germane cognitive loads, but not for intrinsic cognitive load. The model that regressed students' perceptions of message

content relevance on *intrinsic* cognitive load revealed a non-significant result [$F(1, 558) = .290, p = .590$]. The second regression analysis, however, revealed that students' perceptions of message content relevance was a predictor of *extraneous* cognitive load [$\beta = -.382, t(559) = -9.749, p < .001$] explaining 14.4% of the total variance [$F(1, 558) = 95.039, p < .001, R^2_{adj} = .144$]. Further, the third regression analysis revealed that students' perceptions of message content relevance as a predictor of *germane* cognitive load [$\beta = .529, t(559) = 14.706, p < .001$] and explained 27.8% in the total variance of [$F(1, 558) = 216.262, p < .001, R^2_{adj} = .278$]. Taken together, the results of research question one illustrate that statistics students' perceptions of message content relevance predicted the most variance in germane cognitive load (27.8%), followed by extraneous cognitive load (14.4%), while not being a significant predictor of intrinsic cognitive load (Figure 4.1, p. 68).

Research Question 2: Relevance on Cognitive Learning

The second research question focused on determining how students' perceptions of message content relevance predict (a) academic performance, and (b) perceived cognitive learning. Two separate regression analyses answered the question. Preliminary analyses were conducted to check for violations of the assumptions of normality and linearity. The data were found to not be normally distributed, but regression analyses were used as it is likely the violations do not pose a threat to the value of the results (e.g., Lix, Keselman, & Keselman, 1996).

The first regression analysis revealed a significant model, [$F(1, 558) = 19.062, p < .001, R^2_{adj} = .031$] where students' perceived message content relevance [$\beta = .182, t(559) = 4.366, p < .001$] explained 3.1% of the variance in students' academic

performance. It is important to note that academic performance was measured using students' reported range of their most recent exam score. The second regression analysis also revealed a significant model, [$F(1, 558) = 530.493, p < .001, R^2_{adj} = .487$] where students' perceived message content relevance [$\beta = .698, t(559) = 23.032, p < .001$] accounted for 48.7% of the variance in students' perceived cognitive learning. Taken together, statistics students' perceptions of instructional message content relevance predicted both academic performance and students' perceptions of cognitive learning (Figure 4.1, p. 68).

Research Question 3: Relevance and Cognitive Load on Academic Performance

The third research question explored a model that regressed students' perceptions of content relevance, intrinsic cognitive load, extraneous cognitive load, and germane cognitive load on students' academic performance. Preliminary analyses were conducted to check for violations of the assumptions of normality and linearity. The data were not normally distributed, however regression analyses were conducted as it is likely the violations do not threaten the value of the results (e.g., Lix, Keselman, & Keselman, 1996). The regression analysis revealed a significant model [$F(4, 554) = 19.045, p < .001, R^2_{adj} = .115$] and accounted for 11.5% of the variance. However, neither students' perceptions of content relevance ($\beta = .084, t(559) = 1.666, n.s.$) nor students' reported extraneous load ($\beta = -.041, t(559) = -.801, n.s.$) were statistically significant predictors of students' academic performance. Students' reported intrinsic cognitive load ($\beta = -.299, t(559) = -5.783, p < .001$) and students' reported germane cognitive load ($\beta = .142, t(559) = 2.726, p = .007$) were significant predictors of students' academic performance.

As a result, a post hoc regression analysis with both students' perceptions of

content relevance and students' reported extraneous load removed from the analysis revealed a significant model [$F(2, 557) = 35.705, p < .000, R^2_{adj} = .111$] where students' reported intrinsic cognitive load [$\beta = -.342, t(559) = -8.099, p < .001$] and students' reported germane cognitive load [$\beta = .207, t(559) = 4.908, p < .001$] accounted for 11.1% of the total variance in statistics students' academic performance (Figure 4.1, p. 68).

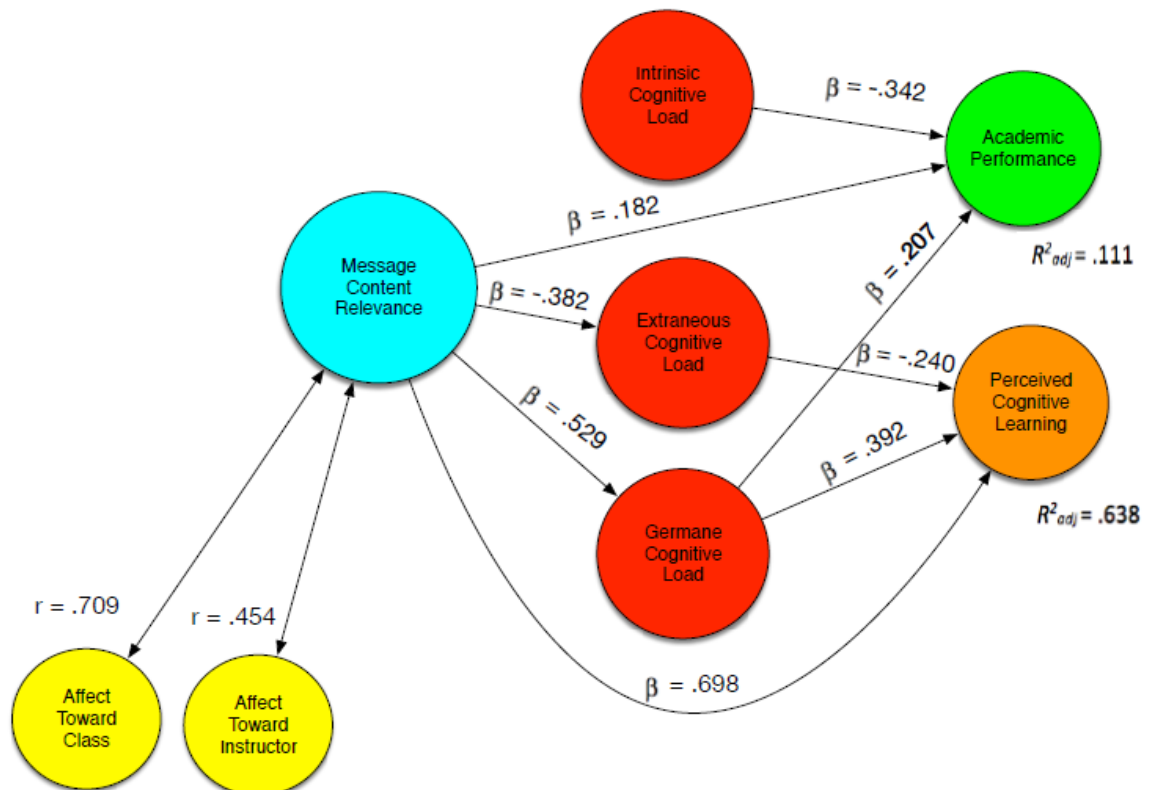
Research Question 4: Relevance and Cognitive Load on Perceived Cognitive Learning

The fourth research question replicated RQ₃ but substituted student's perceived cognitive learning for students' academic performance as the criterion variable and replicated the analysis with students' perceptions of content relevance, intrinsic cognitive load, extraneous cognitive load, and germane cognitive load as the predictor variables. Preliminary analyses were conducted to check for violations of the assumptions of normality and linearity. Although the data were found to not be normally distributed, regression analyses were still used despite the violations as it is likely the violations do not pose a threat to the value of the results (e.g., Lix, Keselman, & Keselman, 1996). The regression revealed a significant model [$F(4, 554) = 246.781, p < .000, R^2_{adj} = .638$] that accounted for 63.8% of the variance. Specifically, students' perceptions of content relevance [$\beta = .401, t(559) = 12.474, p < .001$], students' reported extraneous load [$\beta = -.252, t(559) = -7.691, p < .001$] and students' reported germane cognitive load [$\beta = .382, t(559) = 11.417, p < .001$] predicted students' perceptions of cognitive learning. Since students' reported intrinsic cognitive load [$\beta = .024, t(559) = .720, p = .472$] was not a statistically significant predictor of students' perceptions of cognitive learning a final regression analysis was calculated with intrinsic load removed.

The post-hoc regression, excluding students' reported intrinsic cognitive load, revealed a model where students' perceptions of content relevance [$\beta = .400, t(559) = 12.459, p < .001$], students' reported extraneous load [$\beta = -.240, t(559) = -8.688, p < .001$], and students' reported germane cognitive load [$\beta = .392, t(559) = 13.055, p < .001$] were all significant predictors accounting for 63.8 % of the variance in statistics students' perceptions of cognitive learning [$F(3, 555) = 329.154, p < .000, R^2_{adj} = .638$].

The results of the full model associated with the hypothesis and four research questions can be found in Figure 4.1 (p. 68).

Figure 4.1 *Model of Message Content Relevance and Cognitive Load as Predictors of Cognitive Learning*



Research Question 5: Split Model Test

The fifth research question explored how students' perceptions of message content relevance (when categorized as high or low) interact with experienced cognitive load, students' affective behaviors, and learning strategies to predict (a) academic performance and (b) perceived cognitive learning. To answer this final research question, the sample was split using the median of 3.0 to create two sub-samples corresponding with low perceived content relevance ($M = 2.26, SD = .64$) and high perceived content relevance ($M = 3.71, SD = .44$); see Table 4.2 on page 62 for the correlation matrix for each sub-sample. Preliminary analyses checked for violations of the assumptions of normality and linearity. The data were not normally distributed but regression analyses were used despite the violations as it is likely the violations do not pose a threat to the value of the results (e.g., Lix, Keselman, & Keselman, 1996).

Academic Performance Analyses

The first regression analysis explored how the sub-sample related to low perceptions of message content relevance predicts academic performance with all the variables included in the model.

Low message content relevance on academic performance. For low perceptions of message content relevance, the regression revealed a significant model [$F(8, 267) = 9.185, p < .000, R^2_{\text{adj}} = .192$] explaining 19.2% of the variance. Specifically, students' reported intrinsic cognitive load [$\beta = -.222, t(277) = -2.86, p = .005$], students' reported affect toward the teacher [$\beta = -.142, t(277) = -2.134, p = .034$], students' reported study time [$\beta = -.128, t(277) = -2.037, p = .043$], and students' reported attendance [$\beta = -.168, t(277) = -3.029, p = .003$] predicted students' academic

performance. However, students' reported perceptions of message content relevance [$\beta = .082, t(277) = 1.122, n.s.$], students' reported extraneous cognitive load [$\beta = -.096, t(277) = -1.163, n.s.$], students' reported germane cognitive load [$\beta = .112, t(277) = 1.672, n.s.$], and students' reported affect toward the class [$\beta = .116, t(277) = 1.550, n.s.$] were not statistically significant predictors of students' academic performance.

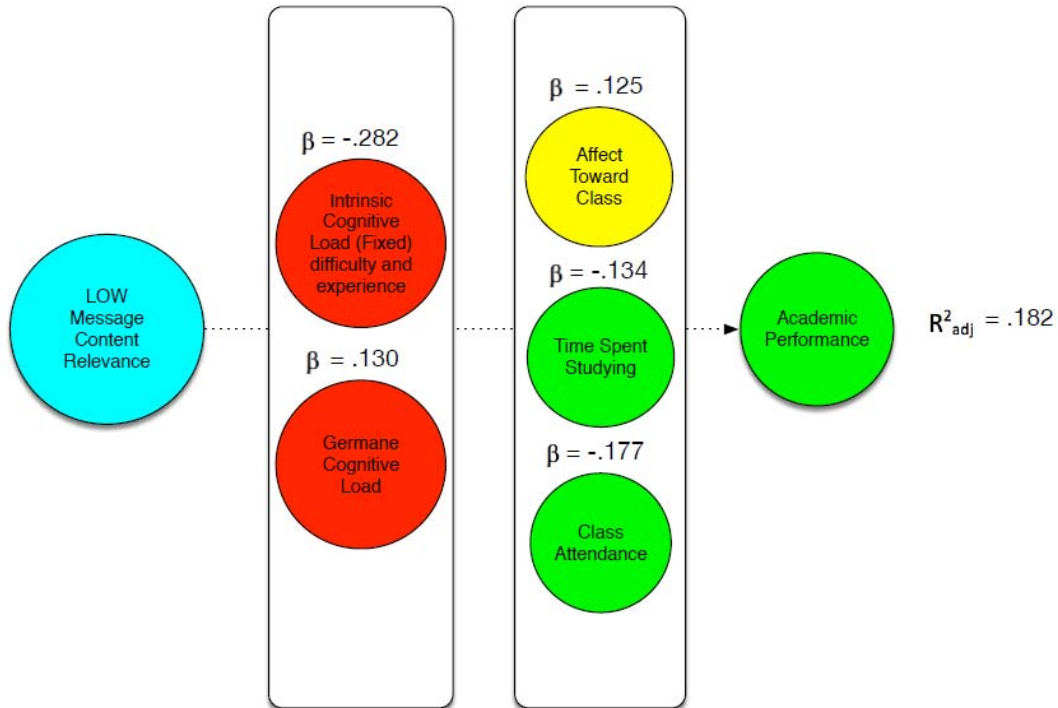
After removing non-significant variables from the model, the final regression for students with low perceptions of message content relevance predicting academic performance revealed a significant model [$F(5, 270) = 13.236, p < .000, R^2_{adj} = .182$] and accounted for 18.2% of the variance. Specifically, students' reported intrinsic cognitive load [$\beta = -.282, t(277) = -4.228, p < .001$], students' reported germane cognitive load [$\beta = .130, t(277) = 2.003, p = .046$], students' reported affect toward the class [$\beta = .125, t(277) = 1.981, p = .049$], students' reported attendance [$\beta = -.177, t(277) = -3.197, p = .002$], and students' reported study time [$\beta = -.134, t(277) = -2.162, p = .032$] predicted students' academic performance (Figure 4.2, p. 71).

High message content relevance on academic performance. For participants with high perceptions of message content relevance, the regression revealed a significant model [$F(8, 273) = 3.652, p < .000, R^2_{adj} = .070$] and accounted for 7% of the variance. Specifically, students' reported intrinsic cognitive load [$\beta = -.288, t(282) = -3.754, p < .000$], students' reported germane cognitive load [$\beta = .203, t(282) = 2.701, p = .007$], and students' reported attendance [$\beta = -.140, t(282) = -2.406, p = .017$] predicted students' academic performance. Students' perceptions of message content relevance [$\beta = -.032, t(282) = -.481, n.s.$], reported extraneous cognitive load [$\beta = .036, t(282) = .493, n.s.$], reported affect toward the teacher [$\beta = -.051, t(282) = -.689, n.s.$], reported affect toward

the class [$\beta = .019, t(282) = .248, n.s.$], and reported study time [$\beta = -.055, t(282) = -.901, n.s.$] were not statistically significant predictors of students' academic performance.

After removing non-significant variables from the model, the final regression for students with high perceptions of message content relevance predicting academic performance revealed a significant model [$F(3, 279) = 9.069, p < .000, R^2_{adj} = .079$] and accounted for 7.9% of the variance. Specifically, students' reported intrinsic cognitive load [$\beta = -.283, t(282) = -4.546, p < .000$], germane cognitive load [$\beta = .162, t(282) = 2.606, p = .010$], and attendance [$\beta = -.137, t(282) = -2.399, p = .017$] predicted

Figure 4.2 Model of Low Perceptions of Message Content Relevance, Cognitive Load, Student Attitudes, and Student Behaviors as Predictors of Cognitive Learning



Perceived Cognitive Learning Analyses

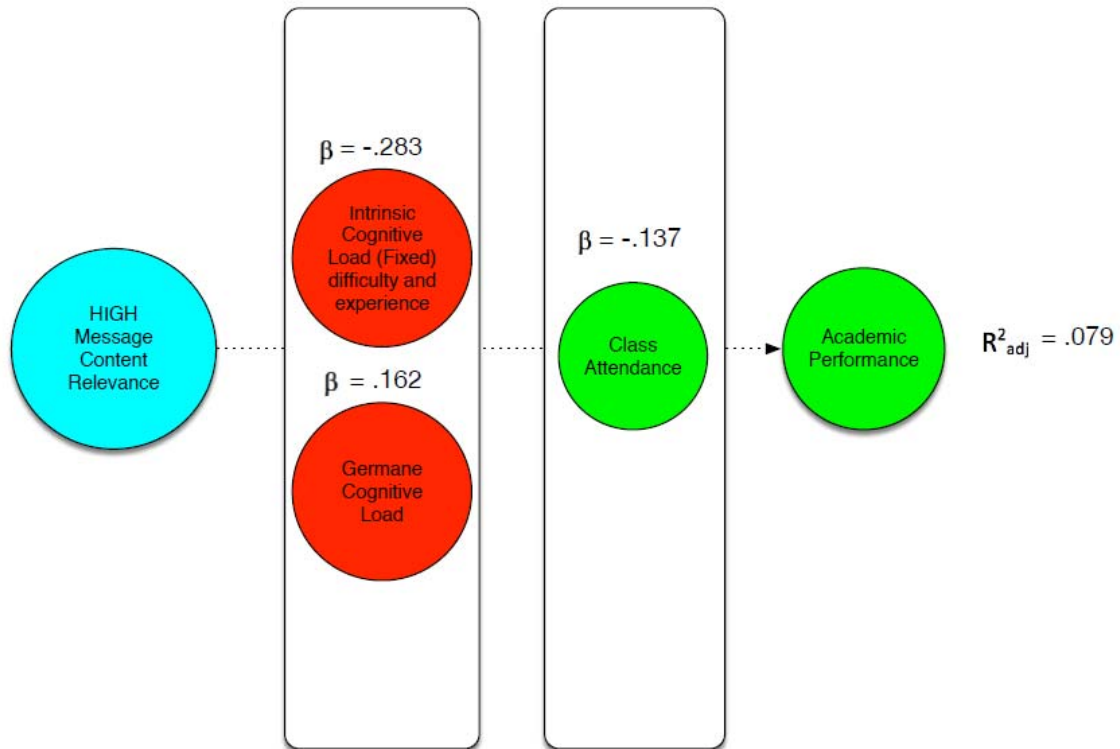
The second regression analyses explored how the sub-samples related to low and high perceptions of message content relevance predict perceived cognitive learning with all the variables included in the model.

Low message content relevance on perceived cognitive learning. For low perceptions of message content relevance, the regression revealed a significant model [$F(8, 268) = 53.962, p < .001, R^2_{adj} = .606$] explaining 60.6% of the variance. Specifically, students' perceptions of message content relevance [$\beta = .358, t(277) = 7.037, p < .001$], extraneous cognitive load [$\beta = -.209, t(277) = -3.651, p < .001$], germane cognitive load [$\beta = .418, t(277) = 8.907, p < .001$], affect toward the teacher [$\beta = .105, t(277) = 2.0265, p = .024$], and study time [$\beta = .093, t(277) = 2.121, p = .035$] predicted students' perceived cognitive learning. Students' reported intrinsic cognitive load [$\beta = -.023, t(277) = -.431, p = .667$], affect toward the class [$\beta = -.003, t(277) = -.061, p = .952$], and attendance [$\beta = .004, t(277) = .114, p = .909$] were not statistically significant predictors of students' perceived cognitive learning.

After removing non-significant variables from the model, the final regression for students with low perceptions of message content relevance revealed a significant model [$F(5, 271) = 87.195, p < .001, R^2_{adj} = .617$] explaining 61.7% of the variance.

Specifically, students' perceptions of message content relevance [$\beta = .357, t(277) = 7.853, p < .001$], germane cognitive load [$\beta = .410, t(277) = 9.670, p < .001$], extraneous cognitive load [$\beta = -.221, t(277) = -4.523, p < .001$], affect toward the teacher [$\beta = .101, t(277) = 2.298, p = .022$], and students' reported study time [$\beta = .088, t(277) = 2.105, p = .036$] predicted statistics students' perceived cognitive learning (Figure 4.4, p. 74).

Figure 4.3 *Model of High Perceptions of Message Content Relevance, Cognitive Load, Student Attitudes, and Student Behaviors as Predictors of Academic Performance*



High message content relevance on perceived cognitive learning. For participants with high perceptions of message content relevance, the regression revealed a significant model [$F(8, 273) = 24.839, p < .001, R^2_{adj} = .404$] explaining 40.4% of the total variance. Specifically, students' perceptions of message content relevance [$\beta = .146, t(282) = 2.699, p = .007$], extraneous cognitive load [$\beta = -.261, t(282) = -4.448, p < .001$], and germane cognitive load [$\beta = .406, t(282) = 6.734, p < .001$] predicted students' perceptions of cognitive learning. However, students' reported intrinsic cognitive load [$\beta = -.016, t(282) = -.263, p = .793$], affect toward the teacher [$\beta = .054, t(282) = .912, p = .363$], affect toward the class [$\beta = .079, t(282) = 1.288, p = .199$], attendance [$\beta = .035,$

$t(282) = .757, p = .449$], and study time [$\beta = .041, t(282) = .839, p = .402$] were not statistically significant predictors of students' perceptions of cognitive learning.

After removing non-significant variables from the model, the final regression for students with high perceptions of message content relevance predicting students' perceived cognitive learning revealed a significant model [$F(3, 278) = 64.164, p < .001, R^2_{adj} = .403$] and accounted for 40.3% of the variance. Specifically, students' perceptions of content relevance [$\beta = .179, t(282) = 3.478, p = .001$], extraneous cognitive load [$\beta = -.302, t(282) = -6.538, p < .001$], and germane cognitive load [$\beta = .443, t(282) = 8.603, p < .001$] predicted statistics students' perceived cognitive learning (Figure 4.5, p. 75).

Figure 4.4 *Model of Low Perceptions of Message Content Relevance, Cognitive Load, Student Attitudes, and Student Behaviors as Predictors of Perceived Cognitive Learning*

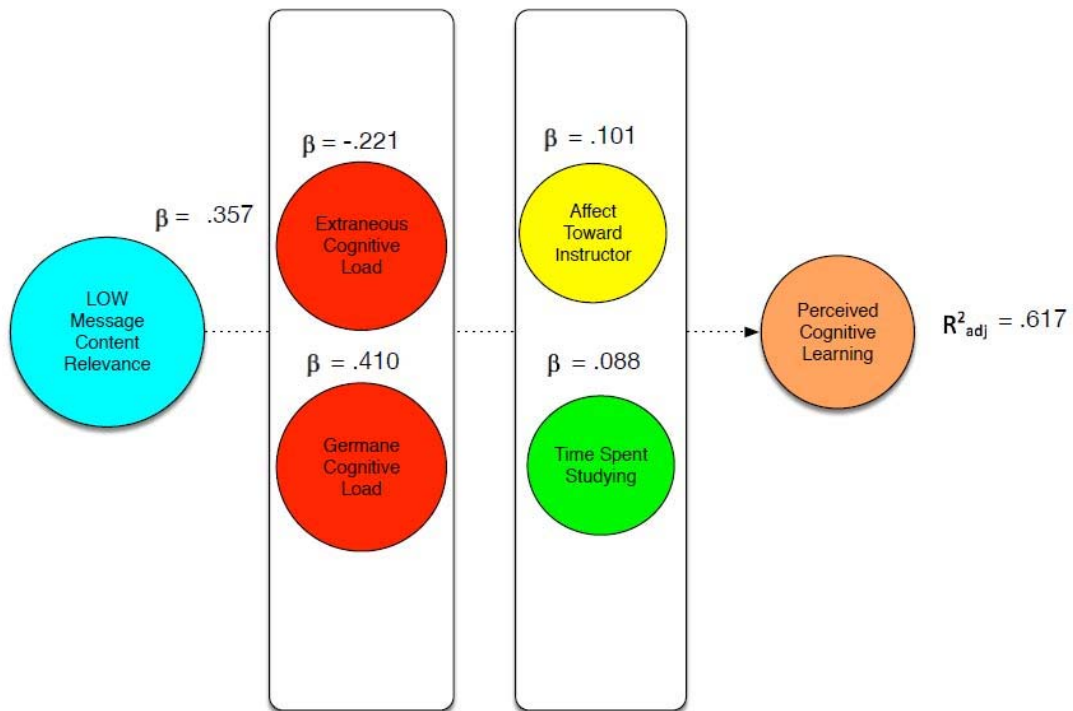
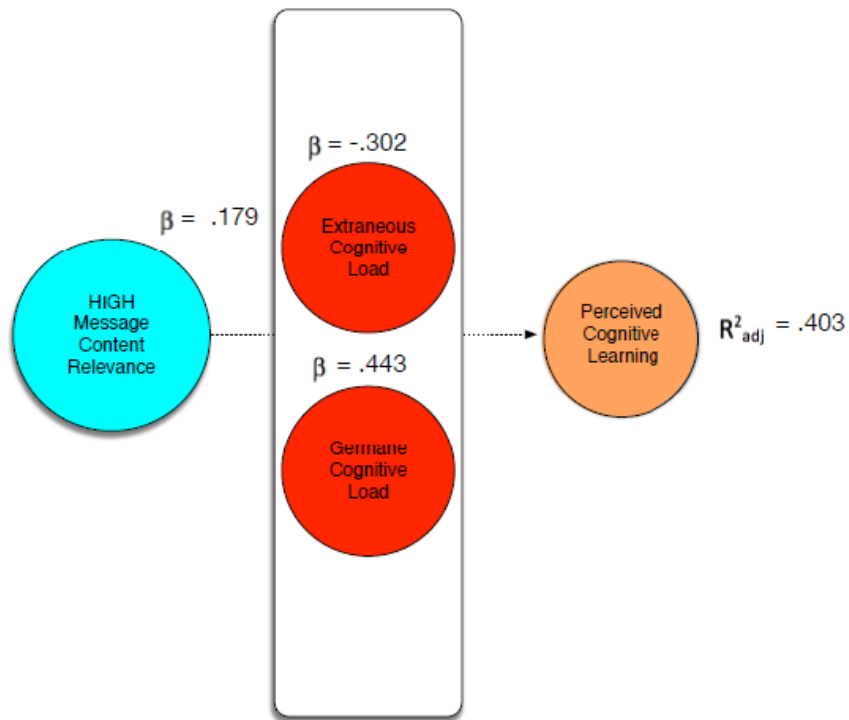


Figure 4.5 *Model of High Perceptions of Message Content Relevance, Cognitive Load, Student Attitudes, and Student Behaviors as Predictors of Perceived Cognitive Learning*



The results found within this chapter represent the testing of the hypothesis and answering of the research questions for the proposed theoretical models. The following chapter provides an in-depth interpretation and implication of the results.

Chapter 5: Discussion

Although an embryonic body of research compared to other programs in the communication discipline, instructional communication research is rich with meaningful findings for instructional settings across many contexts (i.e., classroom, organizations). However, as mentioned in chapter one, several criticisms of instructional communication are often argued, including significant reach beyond instructional communication circles, theory building, and data collection methods. While not overcoming all the criticisms in one isolated study, each of the three concerns were addressed while advancing the instructional communication research program of content relevance. Specifically, the findings are meaningful to communication practitioners as well as education and educational psychology scholars as it is evident that message content relevance influences students' cognitive load, academic performance, and perceived cognitive learning.

Based on the results of the current study, several implications are warranted. By examining the influence of the communication variable of message content relevance on students' cognitive learning through the lens of cognitive load theory, the findings both reinforced and challenged theoretical assumptions of the ARCS Model (Keller, 1983, 1987a, 1987b) and cognitive load theory (Sweller, 1988). Ultimately, the current research findings advanced understanding of the communicative influence of students' perceptions of message content relevance on academic performance and perceived cognitive learning in the classroom. Thus, the following discussion will highlight the significance and implications of the findings.

Implications of Results

The results of the data analyses advance the instructional communication research program. Significant findings illustrate the influence of students' perceptions of message content relevance and experienced cognitive load on students' academic performance and perceived cognitive learning. Beginning with the hypothesis, the following discussion relates the findings to theoretical framework and previous research while discussing their significance and practical application.

Relationships between Message Content Relevance, Learning Behaviors, and Affect

Prior to examining how message content relevance and cognitive load interact to predict academic performance and perceived cognitive learning, the relationship between instructional message content relevance and selected learning behaviors and student affect were examined. Learning behaviors and student affect have been associated with the content relevance construct in past educational psychology and communication research (i.e., Keller, 1988a; Frymier & Shulman, 1995). Therefore, determining whether they were potential covariates influencing cognitive learning in this study was important.

As indicated in Table 4.1 (p. 60) the relationship between students' perceptions of instructional message content relevance and affective behaviors were statistically significant. As predicted in the hypothesis, there was a positive and strong relationship between perceived message content relevance and affect toward the class [$r = .709, p < .001$], as well as a positive and moderately strong relationship between perceived message content relevance and affect toward the teacher [$r = .454, p < .001$]. These relationships suggest that students' affect, or liking, of the teacher and/or course are highly related to their perceptions of the relevance of the content presented in the course.

For this specific sample, statistics students that experienced affect toward the teacher and/or course also perceived the instructional messages of the content to be relevant. It is important to understand that these correlations do not represent a causal process, or a change in affect toward the teacher and/or course caused by a change in perception of message content relevance. Instead, the relationship signifies the strength of affect and perceived message content relevance interacting together. These findings were consistent with previous research as Ryan and Deci (2000) argued that teacher content relevance strategies were positively related to students' affect toward the instructor and/or class. In Ryan and Deci's research, they explored the relationship between content relevance strategies and affect while the current study explored the relationship between message content relevance and affect. The consistency of the findings support continued exploration of how the variables interact to influence students' cognitive learning. Practically, instructors, in statistics and other courses, should understand the relationship between students' perceptions of message content relevance and students' affect toward the instructor and/or course. By doing so, instructors can implement activities such as in-class, low impact assignments asking students to relate what they are studying in the course to their needs, goals, and/or future. This will, likely, positively influence students' perceptions of message content relevance and their affect toward the instructor and/or the course.

While the relationship between students' perceived message content relevance and affect toward the instructor and course supported the hypothesis, students' perceptions of instructional message content relevance were not significantly related to students' reason for taking the course, time spent studying for course, or class attendance.

After examining the demographic makeup of the sample, it is important to note that students' reason for taking the course varied greatly. Students indicated that the statistics course was required for their major ($n = 255$, 45.6%), a pre-requisite for a higher-level course ($n = 28$, 5%), a general education requirement ($n = 263$, 47%), or an elective ($n = 13$, 2.3%). More than half the students included in the sample enrolled in the course without *needing* that specific statistics course. Therefore, it is possible that students *just taking* the course without future implications, other than a passing grade, did not perceive the content to be relevant to their needs, goals, and/or future. Instructors in statistics courses, as well as other courses that may satisfy general education and/or elective requirements, should understand that all students in their courses may not perceive the content of the course to be relevant to their lives and manipulate instructional messages and communication of course content accordingly.

The non-significant relationships between students' perceptions of message content relevance and students' learning behaviors were surprising. Educational psychology (Keller, 1987a, 1987b) and instructional communication (Frymier & Shulman, 1995) literature identify teacher content relevance strategies as motivating factors that influence students' learning behaviors. Specifically, teacher content relevance strategies are deemed as motivating factors to engage students in studying for class (Frymier & Shulman, 1995) and class attendance (Cayanus & Martin, 2008). The findings in this study contradict the previous findings. Perhaps, though, the contradiction exists within the conceptualization and operationalization of the message content relevance construct. Previously, content relevance was measured, almost exclusively, as a teacher strategy without specifically examining students' perceptions of message

content relevance in their courses. The Message Content Relevance Scale (Table 2.1, p. 31) requested students to indicate their perceptions of the relevance of the course content through the instructional messages used in course. These findings may be an anomaly and/or specific to statistics courses. However, further investigation is needed to test these assumptions and draw more specific conclusions beyond this isolated study.

Thus, the hypothesis in this dissertation was partially supported as students' perceptions of message content relevance were significantly and positively related to affect toward the instructor and course, but not significantly related to students' reason for taking the course, time spent studying for the course, or course attendance. With a better understanding of the relationship between students' perceptions of message content relevance and the potential covariates, the implications of the findings for research questions one and two follows.

Message Content Relevance on Cognitive Load and Cognitive Learning

The first two research questions addressed the influence of instructional message content relevance on experienced cognitive load and cognitive learning. As instructors approach the classroom, it is important to have, at minimum, an understanding of how messages about the course content influence students' learning experience. Specifically, for statistics students, understanding the relevance of the content to their needs, goals, and future, no matter the reason for taking the course, significantly influenced their experienced cognitive load and cognitive learning.

Cognitive load. The findings in RQ₁ illustrated that students' perceptions of instructional message content relevance were statistically significant predictors of extraneous and germane cognitive loads. Specifically, students' perceived message

content relevance regressed on extraneous cognitive load [$\beta = -.382, p < .001$] explained 14.4% of the total variance, while students' perceived content relevance regressed on germane cognitive load [$\beta = .529, p < .001$] explained 27.8% of the total variance. Conversely, students' perceptions of message content relevance was not a significant predictor of students' experienced intrinsic cognitive load.

The findings in RQ₁ hold several theoretical implications. First, it is important to note that the insignificance of message content relevance on experienced intrinsic cognitive load is not surprising. Although some scholars have attempted to disprove Sweller's (1988) argument (i.e., vanMerriënboer et al., 2003), the findings in this study support the boundary condition of cognitive load theory that suggests intrinsic cognitive load is fixed and cannot be changed. Ultimately, intrinsic cognitive load represents the degree of difficulty of the course content and the previous knowledge of the learner (Jong, 2010). Statistics courses are not *easy* courses as they challenge students' analytical thinking and abilities. For the current sample, participants' reported how many statistics courses they completed prior to the one in which they were currently enrolled. Participants' answers included zero ($n = 451, 80.7\%$), one ($n = 98, 17.5\%$), two ($n = 8, 1.4\%$), and three ($n = 2, 0.4\%$). Due to an overwhelming majority of students' with no previous coursework in statistics, the findings that message content relevance was not a significant predictor of intrinsic cognitive load aligns with theoretical assumptions about the degree of difficulty of the content. It is critical, then, for instructors to understand students' foundation and/or previous knowledge of course material. By doing so, instructors can scaffold course material to introduce foundational concepts followed by interacting elements to allow students the opportunity to learn complex material in steps

(Tuovinen & Sweller, 1999; Pollock et al, 2002). This approach is considered an instructional modification and does not ultimately reduce the degree of difficulty of the content. However, by introducing interacting elements strategically, the intrinsic nature of an entire concept/construct, for example a statistical equation, may be mediated.

Second, the findings for extraneous cognitive load hold theoretical implications as well. Like intrinsic cognitive load, extraneous cognitive load is considered negative cognitive load and is influenced by, and in direct control of, the instructor (Sweller, 1988). In the case of statistics students in this study, students' perceived message content relevance was negatively related to experienced extraneous cognitive load. This means that as students' perceived message content relevance decreased, experienced extraneous load increased. Practically, the more confounding a student believes the instructor to be, the less they understand the importance of the content. This finding may be linked to the intrinsic nature of the content of the statistics course interacting with students' extraneous load. To support this assumption, the correlation between intrinsic and extraneous cognitive loads in Table 4.1 (p. 60) identifies a moderately strong relationship [$r = .485, p < .001$]. If the material is difficult for the students' to understand, even effective instructional practices may result in an increase in students' extraneous load. Ultimately, an instructors' goal is to decrease students' extraneous cognitive load in order to free up mental working capacity to promote long-term memory (Bolkan, Goodboy, & Kelsey, 2016). By understanding that as students' perceptions of message content relevance increases their experienced extraneous cognitive load decreases, instructors can strategically find ways to have students connect the course material to their interests, needs, and/or goals. Short discussion and/or low-impact writing assignments can

transform students' perceptions of the relevance of the content to free up more mental capacity in order to deeply process the course content.

Finally, germane cognitive load is considered *good load* and should be the targeted experienced load of instructors for each of their students. Germane load is the mental capacity learners have remaining to invest their mental effort after accounting for intrinsic and extraneous loads and is the cognitive processing domain where the development and automation of schemas takes place (Sweller, VanMerriënboer, & Pass, 1998). When intrinsic and extraneous cognitive loads are low, learners have increased capacity to deeply process content, construct schema, and automate information in long-term memory. Still, students need a reason, or be presented with a reason, to invest mental effort and deeply process information (Park, Moreno, Seufert, & Brunken, 2011). The findings in RQ₁ are grounded within this cognitive load theoretical principle. Specifically, as students' perceived messages about the content to be relevant in their statistics course, they were motivated to engage in deeper mental processing of the content. Theoretically, this finding is grounded in Keller's (1988a, 1988b) ARCS Model. Further, this finding is significant to the instructional communication content relevance research program as it advances the understanding of the influence of message content relevance on students' ability, and willingness, to engage in deep processing. Although the results of H₁ did not support a significant correlation between perceived message content relevance and the two selected learning strategies, time spent studying and class attendance, the predictive nature of perceived content relevance on experienced germane cognitive load is significant. As a result, statistics instructors can understand the importance of presenting the content in ways in which students perceive it to be relevant

to their interests, needs, and/or goals in order to motivate them toward schema construction and automation.

In addition to measuring the predictive nature of students' perceived content relevance on experienced cognitive load in RQ₁, the second research question addressed the same predictive nature on students' academic performance and perceived cognitive learning.

Cognitive learning. A major criticism in instructional communication research has been the measurement of cognitive learning. Clark (2002) expressed disappointment in the absence of true measurement of communicative messages on student learning outcomes and issued a call to action for instructional communication scholars to be conceptually intentional when measuring student learning. Further, studies have often claimed the influence of communication on student learning, yet the measurement of learning was limited to affective behaviors (Lane, 2016). The findings within this research question addressed this criticism by measuring student cognitive learning through academic performance. While this measurement has been criticized as well, academic performance is the accepted measure of cognitive learning within the education community (King & Witt, 2009). The disparity between what students in the current study demonstrated they knew through academic performance and what they thought they knew through perceived cognitive learning is, while not shocking, significant.

It is important to note that students' perceptions of instructional message content relevance was a statistically significant predictor for both academic performance and perceived cognitive learning. Specifically, the regression models accounted for 3.1% of the total variance in academic performance, and 48.7% of the total variance in perceived

cognitive learning. While the results suggest that perceived message content relevance predicts both academic performance and perceived cognitive learning, the discrepancy in the variance explained is significant and concerning. Noticeably, the variance explained in the academic performance model (3.1%) is extremely low, meaning that although perceived message content relevance is a predictor of academic performance, it is not a strong predictor. Not surprisingly, the variance explained in the perceived cognitive learning model (48.7%) is significantly higher. As a result, this indicates that when statistics students perceived the content to be relevant, their perception of cognitive learning increased even though their recent exam scores did not illustrate the same strength of connection. As previously discussed in Chapter 2, the measurement of cognitive learning has received much criticism, although the scale used in this study (Cognitive Learning Measure, Frisby & Martin, 2010) has emerged as the most theoretically sound self-report measure of cognitive learning. However, as indicated in Table 4.1 (p. 60), the relationship between academic performance and perceived cognitive learning is weak [$r = .182, p < .001$]. The difference in students' actual academic performance and perceived cognitive learning is concerning and should be an important foci of future instructional communication research. For instructors, it is important to understand the discrepancy between what students' perceived they learned in class and their actual academic performance when they perceived instructional messages about the content to be relevant. Although the findings are promising, there is a wealth of research ripe to explore about the impact of perceived message content relevance on cognitive learning.

RQ₁ and RQ₂ specifically examined instructional message content relevance as a

predictor of experienced cognitive load and cognitive learning. The results advance the content relevance research program but also illustrate the need for continued research. More importantly, the findings offer several implications for practitioners in using instructional messages to relate course content to students' lives as it significantly influences their cognitive processing, academic performance, and perceived cognitive learning. In summary, students' perceptions of instructional message content relevance significantly predicted students' experienced extraneous and germane cognitive loads, as well as academic performance and perceived cognitive learning. The third and fourth RQ's examined the interaction between students' perceived message content relevance and experienced cognitive load on academic performance and perceived cognitive learning.

Message Content Relevance and Cognitive Load on Cognitive Learning

After reviewing the influence of instructional message content relevance on the three dimensions of cognitive load, academic performance, and perceived cognitive learning, RQ₃ and RQ₄ examined the predictive nature of the interaction between perceptions of message content relevance and the dimensions of cognitive load on academic performance and perceived cognitive learning. Until now, previous research has not examined this predictive relationship. In fact, the use of cognitive load theory in instructional communication research is relatively new with primary studies focusing on instructional message clarity (Bolkan, 2015; Bolkan, Goodboy, & Kelsey, 2016). The findings in the current study represent an interesting dynamic in students' cognitive learning through the interaction of perceived message content relevance and cognitive load.

Academic performance. The model to answer RQ₃ regressed students' perceptions of message content relevance, intrinsic cognitive load, extraneous cognitive load, and germane cognitive load on students' academic performance. In that analysis, students' perceptions of message content relevance and extraneous cognitive load were not significant predictors of academic performance. In the post-hoc regression analysis, intrinsic cognitive load [$\beta = -.342, p < .001$] and germane cognitive load [$\beta = .207, p < .001$] predicted students' academic performance explaining 11.1% of the total variance. This finding is quite troubling as it indicates that students' perceptions of message content relevance and instructor teaching strategies do not interact with the difficulty of the course content and/or students' motivation to deeply process the content to predict students' most recent statistics exam scores. Even more, intrinsic load's, or difficulty of the content, negative influence on academic performance is greater than the mental processing load, germane, when interacting together.

Theoretically, this model was expected to include each dimension of cognitive load and explain more of the total variance in academic performance than 11.1%. Extant research suggests that content relevance motivates students to engage in learning behaviors while the dimensions of cognitive load interact to help individual's process information. However, the findings represent the continued criticism of understanding the effect of communication on student learning outcomes within instructional communication research. As noted in the next discussion of RQ₄, students' perceived to know more than their statistics exams scores indicated.

Perceived cognitive learning. In order to answer RQ₄, students' perceptions of message content relevance, intrinsic cognitive load, extraneous cognitive load, and

germane cognitive load were regressed on students' perceptions of cognitive learning. In the analysis of that model, intrinsic cognitive load was not a significant predictor. A post-hoc regression analysis revealed that students' perceptions of message content relevance [$\beta = .400, p < .001$], extraneous cognitive load [$\beta = -.240, p = .001$] and germane cognitive load [$\beta = .392, p < .001$] predicted students' perceived cognitive learning, explaining 63.8% of the total variance. Interestingly, the findings indicate that the degree of difficulty of the material does not influence students' perceptions of cognitive learning while interacting with the other predictor variables. Therefore, students' perceived cognitive learning was based on how they perceived the content to be relevant to their lives, instructors' teaching strategies, and students' motivation to deeply process information.

This regression model explained 63.8% of the total variance, which is a statistically high regression model. However, this finding is not surprising. As Lane (2016) argued, an affective learning paradox exists in instructional communication research where using students' self-report learning measures are contradictory to students' actual learning. Often, students will report they learned the content yet their academic performance scores suggest otherwise. As mentioned earlier, Frisby and colleagues have developed the most conceptually and operationally sound self-report instrument for measuring perceived cognitive learning in instructional communication contexts. However, in the current study, there continues to be a major discrepancy in accounting for the variance explained in students' academic performance versus what students' believe they know. Students' perceived to construct schema while processing the statistics content, yet they were unable to recall the information during their exams.

Taken together, the findings in RQ₃ and RQ₄ illustrate the predictive nature of intrinsic and germane cognitive loads on students' academic performance, and the predictive nature of perceived message content relevance, extraneous cognitive load, and germane cognitive load on students' perceived cognitive learning. The major implication to instructional communication research is the fact that germane cognitive load was significant predictor in both academic performance and perceived cognitive learning. Theoretically, germane cognitive load is the *good* load, or target load, for learners. When communication behaviors in the classroom positively interact with germane load, deeper processing of content occurs and students are likely to learn more, as suggested in the results of these analyses. Practically, these findings can be applied in instructional settings as teachers become aware of the influence of the predictive variables working together to influence cognitive learning. However, these findings continue to challenge instructional communication scholars to explore ways to better measure academic performance. Perhaps using students' most recent exams scores was not the *best* measure of academic performance, but it was a starting point representing the standard measure of learning in educational settings.

The final research question explored how students' perceptions of message content relevance interact with cognitive load, learning strategies, and affect toward the instructor and the course to predict academic performance and perceived cognitive learning when students' perceptions of message content relevance are categorized as low and high. The discussion follows.

Low and High Perceptions of Message Content Relevance

The implications of the results for the hypothesis and first four research questions are significant to instructional communication research. As noted, the findings illustrate the influence of students' perceptions of message content relevance on cognitive load and cognitive learning. To advance the understanding of the degree of influence, the final research question asked the extent to which cognitive learning can be predicted when perceived message content relevance is low and high. Additionally, students' learning strategies and affective behaviors were included in the model. A median split of the sample categorized low and high perceptions of message content relevance and the predictive models were computed.

Academic performance. Low perceptions of message content relevance means that students found the course content to be irrelevant or minimally relevant to their needs, interests, and/or goals. As detailed in the regression analyses, when students' perceptions of message content relevance were low, message content relevance, extraneous cognitive load, affect toward the instructor, and reason for taking the course were not statistically significant predictors of academic performance. The variables that were significant predictors of academic performance included intrinsic cognitive load [$\beta = -.282, p < .001$], germane cognitive load [$\beta = .130, p < .001$], affect toward the class [$\beta = .125, p < .001$], time spent studying [$\beta = -.134, p < .001$], and attendance [$\beta = -.177, p < .001$] and explained 18.2% of the total variance. Further, when students' perceptions of message content relevance were high, message content relevance, extraneous cognitive load, affect toward the instructor, affect for the course, time spent studying, and reason for taking the course were not statistically significant predictors of academic

performance. However, intrinsic cognitive load [$\beta = -.283, p < .001$], germane cognitive load [$\beta = .162, p < .001$], and attendance [$\beta = -.137, p < .001$] were statistically significant predictors of academic performance and explained 7.9% of the total variance.

The results of these findings are significant in that neither low nor high perceptions of message content relevance predicted students' academic performance when interacting with the other variables. Past research suggests that teacher content relevance strategies motivates students to engage in learning behaviors (Frymier & Shulman, 1995). However, Frymier (2002) argued that the influence of content relevance on actual student learning outcomes has historically been avoided. Therefore, this study is the first in instructional communication research to test a causal model with multiple variables interacting with content relevance. While taken alone in the second research question, perceived message content relevance did predict academic performance but only accounted for 3.1% of the total variance. Classrooms, though, are complex environments with many factors interacting together. As a result, students' perceived message content relevance in the statistics courses involved in this study did not influence their academic performance when interacting with the other variables. Instead, the difficulty of the material, their mental effort to process the content, their liking of the course, their time spent studying the content, and their class attendance all interacted to account for 18.2% (low category) of the explained total variance of their most recent exam scores. Additionally, only the difficulty of the content, their mental effort to process the content, and their class attendance explained 7.9% of the variance for the high category.

Perceptions of message content relevance did not interact with cognitive load, learning strategies, and/or affect to predict academic performance. However, in RQ₂, perceived message content relevance acting alone, although minimally, was a significant predictor of academic performance. The current results suggest that the intrinsic nature of the course content, along with extraneous cognitive load, learning strategies, and affective behaviors supersede perceived message content relevance within the statistics course academic performance. The results of the second part of RQ₅ suggest implications when measuring perceived cognitive learning in the predictive theoretical model.

Perceived cognitive learning. Instructional communication research often suggests that teacher content relevance strategies are related to students' reported learning (e.g., Frymier & Shulman, 1995; Frymier, Shulman, & Houser, 1996; Kember, Ho, & Hong, 2008). It is important to highlight the term *reported learning*, as too often reported learning is reported in research articles as actual measured learning (Lane, 2016). However, there is significance in the way communication exchanges in the classroom impacts the way students perceive their learning. In fact, instructional communication research has historically accounted for high percentages of the variance in perceived cognitive learning. The results for the second part of RQ₅ support that trend.

When students' perceptions of message content relevance were low, intrinsic cognitive load, affect toward the course, attendance, and reason for taking the course were not statistically significant predictors of perceived cognitive learning. However, perceived message content relevance [$\beta = .357, p < .001$], extraneous cognitive load [$\beta = -.221, p < .001$], germane cognitive load [$\beta = .410, p < .001$], affect toward the teacher [$\beta = .101, p < .001$], and time spent studying [$\beta = .088, p < .001$], were statistically

significant predictors of academic performance and explained 61.7% of the total variance. When students' perceptions of message content relevance were high, intrinsic cognitive load, affect toward the instructor, affect for the course, time spent studying, attendance, and reason for taking the course were not statistically significant predictors of perceived cognitive learning. However, perceived message content relevance [$\beta = .179$, $p < .001$], extraneous cognitive load [$\beta = -.302$, $p < .001$], and germane cognitive load [$\beta = .443$, $p < .001$] were statistically significant predictors of academic performance and explained 40.3% of the total variance. The high percentages of variance explained in the model represent the significance of the interaction of perceived message content relevance and the other variables on students' perceived learning.

The results of these analyses represent the continuous plague of student learning outcomes and instructional communication research. While it is evident that communication impacts learning contexts, measuring the degree of impact on actual learning continues to be difficult. The findings here seem to be more in-line with the relational-oriented component of communication than the content-oriented component of communication on student learning (Watzlawick, Beavin, & Jackson, 1967). Although, the measure used in the current study for perceived cognitive learning has better conceptual and operational grounding than previous cognitive learning instruments.

It is important to note that findings suggest students' perceptions of message content relevance positively influences, and consistently interacts with, germane cognitive load. Practically, this means that as students perceived instructional messages in their statistics courses to be relevant, they engaged in deeper mental processing of the information/material, which leads to construction and automation of schema. These

findings are substantial contributions to extant instructional communication research in that the gateway to automation of schema and long-term memory is increased germane load. Although the results advance extant instructional communication research, the quest for better explaining how communicative factors, specifically message content relevance, account for more of the variance in students' cognitive learning continues.

Limitations

Implications of the theoretical model put forth extends the content relevance research program in instructional communication. However, like all research, there are several limitations to the study. To begin, the homogenous nature of the sample should be accounted for. Although there was an extensive range in academic disciplines of the participants, data was collected exclusively from one university from an overwhelmingly majority of Caucasian (81.9%) sophomores (57%). Even though the sample size was large ($N = 559$), the generalization of the results to more diverse populations is limited.

Next, data was collected from eight intact statistics courses taught by four instructors without manipulation to instructional methods. All sections were taught in technologically enhanced classrooms, but it is not known whether or not the instructors have similar teaching styles, completed training tailored to the specific statistics course, have extended teaching experienced, or have varying expectations of their students. Therefore, it is likely that students' perceived message content relevance differently depending on the instructional disposition of their teacher. While affect toward the instructor and course were included in the analyses, the causal model did not account for individual teacher differences. Although the sample was contextualized, generalizations of the results to a larger population of students in courses other than statistics are limited.

While contextualizing the environment was important to the current results, more contextualization is warranted. Additional ways to enhance ecological validity are discussed in the future directions.

In addition to the external validity threats, there are limitations due to internal validity threats as well. While the study provided significant results of the influence of message content relevance on cognitive load and cognitive learning, using students' most recent exam grades may not have been the best representative of academic performance. The exams were standard across the eight sections, however it is not known how the intrinsic nature of the reported exam was in comparison to other exams in the course. If the exam was particularly difficult or a student scored an unexpected low score, their perceptions of message content relevance, experienced cognitive load, learning strategies, and affect toward the instructor and course may vary. Therefore, the cross-sectional survey design used in this study likely influenced the internal validity. A longitudinal study, or data collection across different time points throughout the semester, may have allowed for a better understanding of the influence of perceived message content relevance, cognitive load, affective behaviors, and learning strategies on academic performance and/or perceived cognitive learning.

Moreover, the discrepancy between students' academic performance and their perceptions of cognitive learning are concerning. Students report they perceive to learn the content yet their most recent exam scores do not reflect. One limitation may be the time difference between the exam and the survey. This information was not accounted for in the study. Therefore, students' may have not performed well on the exam but gained a better perceived understanding of the content after the fact. To overcome this

limitation, the perceived cognitive learning survey could be distributed prior to the exam to gain a better understanding of students' perceptions of the content they are being tested over.

It is also possible that more covariates beyond the ones included in the current study (reason for taking the course, time spent studying, class attendance, and affect toward the teacher and the course) exists that may indeed interact with message content relevance and cognitive load to better understand the discrepancy and/or explain higher variance in academic performance. For example, students' report of experienced test anxiety was not used in the current study. Test anxiety very likely influences students' academic performance. Therefore, the current limitation of potential covariates should be considered in future research.

Another threat to internal validity could be the way students responded to the survey. Although this criticism of instructional communication research was addressed by measuring the influence of a communication variable on actual learning, the measure of academic performance used was students' self-report. Participants were directed to open a second web browser and accurately report their most recent exam grade; however it is possible that students did not follow directions and/or inaccurately reported their exam grade. Additionally, the amount of time students took to complete the entire survey varied. While all completed surveys under four minutes and beyond ten hours were excluded from the sample, the variance from four minutes to ten hours should be noted. Participants that completed the survey in the shortest amount of time may have quickly responded without fully considering each question. Whereas, participants that completed the survey in the longest amount of time likely started the survey at one point in time and

completed it hours later. This could have caused those participants to have different perceptions in their answers from the start of the survey to the end of the survey.

Finally, as noted in the results for each research question in Chapter Four, data were not normally distributed. In most cases, the abnormality of distribution was low to moderate, but still important to consider. Despite the violations of normality of distribution, regression models were computed for two primary reasons. First, it is reasonable to consider that data would not be normally distributed based on the collection of data from intact courses and only four instructors. Although the sample size was considered large ($N = 559$), the target of students responses were only four. Second, the low to moderate violations of normal distribution were not considered to pose large threats to the value of the results (e.g., Glass, Peckham, & Sanders, 1972; Lix, Keselman, & Keselman, 1996). While normality of distribution is desired for regression models, it is not expected to alter the current findings. However, it is important to note this limitation to the current study.

Even with the stated limitations, the results and subsequent theoretical model are substantially significant to instructional communication research. Acknowledging limitations of studies allows for continued curiosity and sharpening of future research opportunities. Therefore, not only do the findings in this dissertation advance understanding of the influence of message content relevance and experienced cognitive load, but warrant several avenues for future research.

Future Directions

The findings extend extant instructional communication research on students' perceptions of content relevance, cognitive load, and cognitive learning. The study tested a causal process model to determine the extent to which students' perceived message content relevance, experienced cognitive load, select learning strategies, and affect toward the teacher and course interact to predict students' academic performance and perceived cognitive learning. The implications of this study present empirical evidence missing in extant literature related to the way message content relevance influences experienced cognitive load and cognitive learning. As a result, several directions for future research will continue to enhance the richness and theoretical implications of this instructional communication research program.

First, it is important to recognize that a single isolated study does not support definitive conclusions. Therefore, replication of the current study is warranted. Even with the same instructor and same content, no two classrooms are alike. Based on the demographic makeup and collective disposition of the students, each classroom becomes a single context with complex communicative interaction. A more diverse sample of participants and instructors, specifically in disciplines other than statistics, would provide more generalizable results to the larger population. Additionally, while the current study moved beyond asking participants to think about their previous instructor and/or class, and instead requested they report on their specific statistics courses, more contextualization of the environment is warranted in future research.

Teacher, student, and content effects should be considered as possible covariates that influence students' perceptions of message content relevance to better contextualize

the classroom. One area to explore teacher effects would be to consider teacher misbehaviors (i.e., incompetence, indolence, offensiveness). Teachers that return work later than expected (in-class or online), do not provide valuable feedback on assignments, appear unprepared for class, and behave/speak in ways that may be perceived as offensive likely influences students' perceptions of message content relevance and, ultimately, student learning outcomes. Additional teacher effects to consider in order to better understand how the teacher effects the classroom environment includes teacher differences, such as lecture style and approachability, teaching experience, use of technology, availability outside of class, and training received by the instructor for teaching the specific course. Further, classroom size, large versus small, would provide additional insight as to how instructors interact with each student during class.

Several student learning behaviors and students' reported affect toward the instructor/course were included in the current study. However, accounting for additional student effects in future research is warranted. First, factoring in students' time spent with a tutor and meeting with their instructor outside of class would provide a better measurement of overall study time. Next, test anxiety likely influences students' academic performance on exams. Therefore, measuring students' anxiety may help explain the discrepancy in the variance between students' perceived learning and academic performance. Another potential covariate is the time of day the class meets. For the sample in the current study, it would have been interesting to include the time of day of their statistics course. Exploring the influence of morning, early afternoon, and late afternoon classes may provide additional explanation of students' perceived message content relevance and cognitive learning. Additional student effects to account for, but

not limited to, include students' motivation to succeed, expectations of the course/instructor, attitude toward learning outcomes, classroom distraction, course load, familiarity with classroom technology/learning platforms, and learning behaviors during class such as question asking, participation in discussion, and cell phone use.

In addition to teacher and student effects, content effects should be considered in future research as well. Aside from degree of difficulty of the content, accounting for specific instructional materials (i.e., textbooks, handouts, PowerPoint slides, online resources) is important. Specifically, this would allow for better understanding of students' perceptions of message content relevance across different channels of instructional messages. While accounting for additional covariates, variables, and teacher, students, and content effects will better contextualize the learning environment and enhance future exploration of message content relevance on students' learning, additional approaches to research methods should be considered as well.

Empirical support of the influence of students' perceptions of message content relevance and experienced cognitive load on cognitive learning are evident in the results of the current study. However, consistent with previous findings in instructional communication research, the regression models accounted for high percentages of the variance in perceived cognitive learning and very low percentages of the variance in academic performance. While the regression models advance the content relevance research program, further methodological sophistication is warranted in future research. First, an experimental design with manipulation and control should be considered. Specifically, randomized control trials would allow for an experimental research design accounting for experimental and control groups. Further, structural equation modeling

could be used to explore the relationships between message content relevance and latent, predictor, and criterion variables. Finally, hierarchical linear modeling would allow for the nesting of groups (i.e., specific classes, teachers) into more sophisticated regression analyses.

Another area of future research should continue to address the criticism of instructional communication research and student learning outcomes. As discussed in the limitations of this study, students' self-report of the percentage range of their most recent exams scores may not be the most accurate representation of cognitive learning. It is important, then, for future studies to identify additional measures of academic performance. There is a wide range of additional measures of students' academic performance to be considered in future research. First, requesting access to students' exam scores would provide an actual score, instead of percentage range, of their academic performance. Second, comparing students' exam grades throughout the semester would provide longitudinal data of their academic performance. Both measures would provide a more accurate representation of students' academic performance. Further, tapping into psychology research methods would provide advanced measurements of cognitive learning. By doing so, through sophisticated measurements like electromyography, instructional communication scholars may discover ways to get closer to the measurement of actual learning.

Interestingly, academic performance alone may not be the best representation of actual cognitive learning. Students may perform well on exams and assignments but not be able to recall the information after the semester has concluded. Finding more robust ways to measure the influence of message content relevance, and other communication

variables, on different forms of cognitive learning (i.e., acquisition of knowledge, recall, and application of knowledge) are important to the advancement of instructional communication research.

The tested theoretical model builds upon the extant content relevance research program. However, it is important to continue advancing in a direction that moves from atheoretical studies to theory building. Frymier and Shulman (1995) provided the foundation for content relevance research in instructional communication, yet a rich theoretical framework continues to be desirable. The significant findings provide a step in that direction, but additional studies exploring the influence of message content relevance on student learning outcomes is needed.

Theoretically, the significance of understanding how communication influences cognitive learning may indeed begin with how communication influences experienced cognitive load. A few studies grounded in cognitive load theory have recently been published in instructional communication research. Specifically, teacher clarity is believed to have a significant impact on students' experienced cognitive load (Bolkan, 2015; Bolkan, Goodboy, & Kelsey, 2016). The current study expands the use of cognitive load theory in instructional communication research, but more exploration is desired. Specific focus on whether or not instructional messages mediate intrinsic cognitive load, reduce extraneous cognitive load, and increase germane cognitive load will greatly advance understanding of the interaction between communication and the cognitive process. Further, the measurement of experienced cognitive load should be considered in future research as well. The decision to measure cognitive load in this study using Leppink et al.'s (2014) Cognitive Load Questionnaire instead of popular

measurements like the NASA – Task Load Index was due to conceptual and operational fit. However, in future research, additional measures of cognitive load may help explain the influence of message content relevance, and other communication variables, on each dimension of cognitive load and, specifically, schema construction and automation.

Moreover, with the emergence of cognitive load theory as a lens to study the influence of communication on cognitive processing (Bolkan, 2015; Bolkan et al., 2016; Bolkan, Goodboy, & Myers, 2017; King & Finn, 2017), it would be useful for construction and validation of a measurement, unique to instructional communication, that specifically measures message effects on the three dimensions of cognitive load.

Further, instructional communication research is often criticized for lack of theoretical reach beyond the discipline. However, implications of the research can often be applied throughout all disciplines as the purpose of the research is to explore the influence of messages across all contexts. For message content relevance, instructors across all disciplines should understand the impact of connecting course content to students' lives. As students begin to understand the importance of the content to them personally, they will be motivated to engage in more learning behaviors. Further, they will begin to value the content more as they consider the relevance of instructional messages. For instructors, understanding the difference between the use of optimal and essential message orientations in the classroom is important. Instructors' consciously make decisions as to which messages are necessary (essential) to providing a foundation for student learning versus the messages that are more favored (optimal). Content relevance messages are optimal as they are supporting messages to the foundational (essential) content. However, implementing the relevance messages may be what it takes

to draw the attention of the learners to value the essential messages. Future research can continue to build upon the current theoretical model by exploring the interaction of message content relevance, optimal and essential messages, cognitive load, and students' expectancy value.

The theoretical model advanced in this study builds upon and strengthens content relevance research, but the instructional communication research program is primed for continued exploration. Exploring ways to better understand the influence of message content relevance on student learning outcomes continues to be of great importance for scholars but even more important for teachers and learners, for both theoretical and practical reasons.

Conclusion

The theoretical implications of the results of this study offer significant contributions to instructional communication research in several ways. First, cognitive load theory is a proven theoretical framework to help explain cognitive processes and learning in educational settings. Understanding that instructional message content relevance influences the dimensions of extraneous and germane cognitive loads is important for communication and education scholars, as well as teachers. Pragmatically, teachers can gain practical implications from the results of this study to incorporate more opportunities for students to understand the relevance of coursework, in statistics and other courses, to their needs, interests, and goals. Scientifically, as mentioned in the previous section, these results open the door for greater exploration of the influence of the interaction between message content relevance, as well as other communication variables, and experienced cognitive load on students' cognitive learning. In fact,

cognitive load theory may become the lens that instructional communication scholars have been searching for to better assess the impact of communication on student learning outcomes. Measuring students' experienced cognitive load may indeed help instructional communication scholars get closer to students' actual cognitive learning.

Second, until now, content relevance has been measured, primarily, as a teaching strategy. With the validation of the Message Content Relevance Scale, content relevance can now be measured in relation to the message components within instructional settings. The unidimensional scale is conceptually and operationally sound and is primed for future research, reaching beyond communication classrooms and into courses like the statistics course used in this study. As Harwood (2010) argued more for careful, objective, descriptive analyses of the content contained within messages, the MCRS allows for that across instructional settings.

Next, although accounting for small variations, message content relevance acting alone significantly influenced academic performance in the current study. This finding is important as this predictive relationship was missing in extant instructional communication literature. Knowing that message content relevance influences academic performance, instructors should strive to make deeper connections for students. Further, researchers should continue to explore how the messages may account for more variation in students' learning. Importantly, perceived message content relevance significantly interacted with germane cognitive load in most models within this study. These findings provide an important foundation to continue building upon the influence of communication on students' deep processing of information. While not overcoming with a single study, these results are important to the current criticism of the measurement and

influence of communication on student learning outcomes. The goal now is to continue measuring these impacts on different forms of academic performance/achievement as discussed in the previous section.

Chesebro (2002) argued that teachers should enter the classroom with students' interests, needs, and goals in mind and then teach accordingly. The results of this dissertation support this argument. With learning as the end goal, students' desire to first understand the importance, or relevance, of the content to their lives, whether in a statistics course or another discipline, before devoting mental effort to learning the content. The contributions of the tested theoretical model to instructional communication research are significant and pave the way for future research opportunities.

Appendix

Dissertation Data Collection Survey

A1: Message Content Relevance Scale

The next set of questions are about your perceptions of content relevance in your course. Please answer as honestly as possible.

Thinking about your PERCEIVED CONTENT RELEVANCE related to THIS COURSE, please indicate your agreement with each item using the rating scale below.

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
I believe the content from this course directly impacts my personal interests.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I believe the content from this course directly impacts my educational needs.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I believe the content from this course directly impacts my career goals.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I believe the content of this course is valuable to my life.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I believe this course in general is valuable to my life.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I am able to make connections of the course content to my life.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I believe I will use the content of this course in my future professional life.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I believe this course as a whole is relevant for my development as a well-rounded individual.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

A2: Cognitive Learning Measure

Thinking about the content of your course, please indicate your agreement with each item using the rating scale below.

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
I have learned a great deal in this class.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I have learned more in other classes than in this class.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
My knowledge on this class topic has increased since the beginning of class.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I can clearly recall information from this class.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I would be unable to use the information from this class.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I have learned nothing in this class.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I can see clear changes in my understanding of this topic.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I am unable to recall what I have learned in this class.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I have learned information that I can apply.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I did not understand what I learned in this class.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

A3: Academic Performance

Prior to answering the next questions, please use a separate web browsing tab to login to your statistics course Canvas page and access your grades.

Please report your academic performance according to each question.

My statistics grade at midterm was...

- 90-100%
- 80-89%
- 70-79%
- 60-69%
- 59% or below

My most recent statistics exam grade was...

- 90-100%
- 80-89%
- 70-79%
- 60-69%
- 59% or below

At the end of the semester, I expect my average grade in my statistics course to be...

- 90-100%
- 80-89%
- 70-79%
- 60-69%
- 59% or below

A4: Cognitive Load Questionnaire

The next set of questions are about your self-report of the cognitive load imposed by the course content. Please answer as honestly as possible.

Thinking about the content in this course, please indicate your agreement with each item using the rating scale below.

	Rate on a scale of 0 (not at all the case) to (completely the case)
The content of this course is very complex.	0 1 2 3 4 5 6 7 8 9
The problems/assignments covered in this course are very complex.	0 1 2 3 4 5 6 7 8 9
In this course, very complex terms are mentioned.	0 1 2 3 4 5 6 7 8 9
I have invested a very high mental effort in the complexity of this course.	0 1 2 3 4 5 6 7 8 9
The explanations and instructions in the course are very unclear.	0 1 2 3 4 5 6 7 8 9
The explanations and instructions in the course are full of unclear language.	0 1 2 3 4 5 6 7 8 9
The explanations and instructions in this course are, in terms of learning, very ineffective.	0 1 2 3 4 5 6 7 8 9
I have invested a very high mental effort in unclear and ineffective explanations and instructions in this class.	0 1 2 3 4 5 6 7 8 9
This course really enhances my understanding of the content covered.	0 1 2 3 4 5 6 7 8 9
This course really enhances my understanding of the problems/assignments that are covered.	0 1 2 3 4 5 6 7 8 9
This course really enhances my knowledge of the terms that are mentioned.	0 1 2 3 4 5 6 7 8 9
The course really enhances my knowledge and understanding of how to deal with the problems/assignments covered.	0 1 2 3 4 5 6 7 8 9
I invest a very high mental effort during this course to enhance my knowledge and understanding.	0 1 2 3 4 5 6 7 8 9

A5: Affective Learning Measure

The next set of questions are about your feelings toward the course content and the instructor. Please answer as honestly as possible.

Please circle the number that best represents your feelings. The closer a number is to the item/adjective the more you feel that way.

Overall, the instructor I have in the class is:

- | | | |
|-------------|---------------|-----------|
| 1. Bad | 1 2 3 4 5 6 7 | Good |
| 2. Valuable | 1 2 3 4 5 6 7 | Worthless |
| 3. Unfair | 1 2 3 4 5 6 7 | Fair |
| 4. Positive | 1 2 3 4 5 6 7 | Negative |

I feel the class' content is:

- | | | |
|-------------|---------------|-----------|
| 5. Bad | 1 2 3 4 5 6 7 | Good |
| 6. Valuable | 1 2 3 4 5 6 7 | Worthless |
| 7. Unfair | 1 2 3 4 5 6 7 | Fair |
| 8. Positive | 1 2 3 4 5 6 7 | Negative |

My likelihood of taking future courses in this content area is:

- | | | |
|----------------|---------------|------------|
| 9. Unlikely | 1 2 3 4 5 6 7 | Likely |
| 10. Possible | 1 2 3 4 5 6 7 | Impossible |
| 11. Improbable | 1 2 3 4 5 6 7 | Probable |
| 12. Would | 1 2 3 4 5 6 7 | Would Not |

My likelihood of taking future courses with this specific teacher is:

- | | | |
|----------------|---------------|------------|
| 13. Unlikely | 1 2 3 4 5 6 7 | Likely |
| 14. Possible | 1 2 3 4 5 6 7 | Impossible |
| 15. Improbable | 1 2 3 4 5 6 7 | Probable |
| 16. Would | 1 2 3 4 5 6 7 | Would Not |

A6: Additional Questions

Please answer the following questions related to your experience in this class this semester.

What is your reason for taking this course?

- Required for my major
- Pre-requisite for a higher-level course
- General education
- Elective

How many times have you been absent from this class this semester?

- 0
- 1-2
- 3-5
- 6-7
- 8 or more

How much time do you spend studying individually outside of class for your statistics course per week?

- 0-1 hour
- 1-2 hours
- 3-5 hours
- 6-7 hours
- 8 or more hours

How much time do you spend studying with tutoring services outside of class for your statistics course per week?

- 0-1 hour
- 1-2 hours
- 3-5 hours
- 6-7 hours
- 8 or more hours

How often do you visit your professor's office to discuss content/instruction for your statistics course?

- 0-1 hour
- 1-2 hours
- 3-5 hours
- 6-7 hours
- 8 or more hours

How many statistics courses have you successfully completed prior to your current statistics course?

- 0
- 1
- 2
- 3
- 4 or more

Please indicate the number of times you've attempted to complete the statistics course you are currently in.

- This is my first attempt
- This is my second attempt
- This is my third attempt
- I've attempted to complete this course more than three times

Please answer the following question:

I believe that my statistics course is relevant

Strongly disagree	Disagree	Neutral	Agree	Strongly Agree
1	2	3	4	5

Please answer the following question:

What is your comfort level with studying statistics?

Very Uncomfortable	Uncomfortable	Neutral	Comfortable	Very Comfortable
1	2	3	4	5

A7: Demographic Information

The next set of questions are related to your demographics. Please answer as honestly as possible.

What is your gender?

- Male
- Female
- Other

What is your ethnicity? Please check all that apply.

- White/Caucasian
- African American
- Hispanic
- Asian
- Native American
- Arabic
- Other _____

What is your class rank?

- First-year
- Sophomore
- Junior
- Senior
- Other

What is your major?

What is your first and last name (this will be kept separate from the data in order to issue extra credit for completing the survey)?

Which section of Stats 210 are you enrolled in (this will be kept separate from the data in order to issue extra credit for completing the survey)?

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VITA

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EDUCATION

- M.A. Communication, Western Kentucky University, Bowling Green, KY, May 2007
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ACADEMIC EMPLOYMENT

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Lindsey Wilson College, Columbia, KY
- May 2007 – August 2012* **Director of Freshman Year Experience**
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- August 2007 – August 2012* **Adjunct Instructor of Communication**
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- May 2004 – May 2007* **Freshman Advisor**
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SCHOLASTIC & PROFESSIONAL HONORS

- Assistant Faculty Marshal, Lindsey Wilson College (*2015-present*)
- Student Government Association Teacher of the Year, Lindsey Wilson College (*2014 & 2016*)
- Lambda Pi Eta – National Communication Association Honor Society
- Sigma Tau Delta – International English Honor Society
- President's Award, Lindsey Wilson College (*2004*)

SCHOLARLY PRODUCTIVITY

PROFESSIONAL CONFERENCE PRESENTATIONS

Sexton, B. T. (2015). *When students self-disclose in the classroom: Instructor perceptions of student disclosures*. Paper presented at the annual conference of the Eastern States Communication Association, Philadelphia, PA.

Sexton, B. T. (2015). *Clarifying content relevance as an instructional communication construct*. Paper presented at the joint conference of the Kentucky Communication Association and Tennessee Communication Association, Burns, TN.

Sexton, B. T. (2015). *Exploring content relevance in liberal arts general education classrooms*. Paper presented at the annual summit of the Appalachian College Association, Kingsport, TN.

Radford, A., **Sexton, B. T.**, Bickers, E., Bunch, K., & McCutchen, H. (2005). *Intrusive advising for at-risk first-year students: A freshman advising program in action*. Appalachian College Association Annual Summit, Abingdon, VA

PROFESSIONAL CONFERENCE PANEL PRESENTATIONS

McAlpine, T., & **Sexton, B. T.** (2013). *Undergraduate Research Discipline Forum*. Appalachian College Association Annual Summit, Knoxville, TN

BOOK CHAPTERS

Phelps, G. A., & **Sexton, B. T.** (accepted). Reckoning appalachia: Considerations for culturally competent counseling in an appalachian context. In D. S. Sandhu & J. Parsons (Eds.), *Appalachian Americans: Issues and Concerns for Counseling and Psychotherapy*. Huntington, NY: Nova Science Publishers.

INSTRUCTIONAL DESIGN RESEARCH

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BOOK REVIEWS

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Signed: Benson Travis Sexton