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INVESTIGATING TEACHERS' COGNITIVE LOAD DURING MATHEMATICS INSTRUCTION AND ITS MOTIVATIONAL AND ATTRITIONAL CONSEQUENCES

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INVESTIGATING TEACHERS' COGNITIVE LOAD DURING MATHEMATICS INSTRUCTION AND ITS MOTIVATIONAL AND ATTRITIONAL CONSEQUENCES

A DISSERTATION APPROVED FOR THE

DEPARTMENT OF EDUCATIONAL PSYCHOLOGY

BY THE COMMITTEE CONSISTING OF

Dr. Alison C. Koenka, Chair

Dr. Rebecca S. Borden

Dr. Benjamin C. Heddy

Dr. Maeghan N. Hennessey

Dr. Revathy Kumar

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Dedication

To my parents who have provided me with the tools and support to pursue my dreams and never once wavered in their confidence in me to achieve them.

And to my sister, who inspired much of this research.

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Abstract

Decades of research have pointed to the central role of cognitive load on an individual's ability to process informational inputs effectively. Despite the pervasiveness of cognitive load, this research has been largely conducted among student populations. In contrast, despite the many inputs that teachers must balance, teachers' cognitive load experiences remain understudied. Moreover, while teachers' motivational experiences have received more attention, no study has yet to explore the interplay between teachers' cognitive load and their (a) motivational experiences and (b) attrition intentions during math instruction. Therefore, the overarching goal of this dissertation was to explore (a) elementary grade level (pre-K-5) teachers' cognitive load experiences during math instruction and its association to their (b) motivation (i.e., self-efficacy, cost perception) and (c) attritional experiences.

To do so, I adopted an explanatory sequential mixed method design (QUAN → qual). During the first, quantitative phase (Phase 1) of this study, I implemented a daily diary design in which $N = 34$ teachers participated in daily surveys following their math instruction over the course of 10 days. The daily surveys measured teachers' experiences of cognitive load, motivation, and attrition intentions during their math instruction. I then selected teachers with high or low levels of cognitive load reported across the daily surveys to participate in the second, qualitative phase (Phase 2) of this study. A total of $N = 10$ teachers participated in semi-structured interviews during Phase 2.

Phase 1 results revealed (a) considerable daily variation among teachers' cognitive load experiences, (b) a non-predictive relation between teachers' experience level and daily cognitive load, (c) predictive relations across all three dimensions of cognitive load (intrinsic, extraneous, and germane) and self-efficacy as well as predictive relations across a variety of combinations of

cognitive load dimensions and cost perception dimensions (task effort, outside effort, emotional, and loss of valued alternatives cost), and (d) few predictive relations between cognitive load and attrition intentions (with the exception of germane load and attrition intentions). Phase 2 results revealed five central themes: (1) The compounding challenges of math instruction; (2) The unpredictable nature of the classroom environment; (3) The cognitive and emotional endurance required of teachers; (4) Experience enables instructional adaptation, and (5) Students as a buffer to teacher attrition. Finally, integrated results revealed key areas of data confirmation, expansion, and discordance across Phase 1 and Phase 2 findings. Theoretical, methodological, and practical implications as well as limitations and future directions that emerged from this study are discussed.

Chapter 1: Introduction

Imagine you are a third-grade teacher, actively introducing a new mathematics concept (e.g., fractions) to your students. While instructing, you must diligently monitor and carefully manage classroom behavior. For example, you are constantly monitoring to ensure your students' safety as well as managing noise and movement disruptions. You are also managing the necessary classroom technology and materials (e.g., math manipulatives like fraction tiles) that are required of you to teach the material effectively. In addition, you are actively processing and answering the numerous student questions that arise. Through all of this you are also regulating your own thoughts and emotions that emerge. You may feel overwhelmed at this moment given all that you are required to process in a short span of time. Moreover, this is likely not your first time feeling overwhelmed while teaching. In fact, the experience described above might be a regular occurrence for you – one that may even occur multiple times daily. How do these recurring experiences impact your instruction? How do these experiences impact you as a teacher? Do they impact your motivation to teach? Are these experiences something you think you could continue to endure on a daily and long-term basis?

The above scenario demonstrates that teachers are expected to regularly process a large number of cognitive inputs to effectively teach, manage their classrooms, and keep their students safe. When considering existing theories of human cognition (e.g., cognitive load theory; Sweller, 1988), the number of processing demands teachers typically receive during instruction likely outweigh the number of processing demands humans can realistically process in an effective manner (Feldon, 2007). However, little research to date has worked to understand the day-to-day processing experiences of teachers. Moreover, research has yet to demonstrate how teachers' day-to-day processing experiences impact important outcomes like their motivational

experiences and attrition intentions – which are all the more pressing to understand and improve in light of the ongoing national teacher shortage (Tan et al., 2024).

In Chapter 1, I expand on the extant literature gaps briefly highlighted above. I specifically outline the gaps within the teacher cognitive load and its motivational and attritional consequences literature. Then, I outline the theoretical frameworks and concepts used to guide this study. Finally, I present the research questions that frame the study.

Problem Statement

The national teacher shortage in the United States has been a persistent and growing concern for at least a decade and has only amplified since the COVID-19 pandemic (IES, 2022; Sutcher et al., 2016). A recent report established that over 400,000 teaching positions across the United States are either vacant or filled by teachers who are underqualified (e.g., through emergency certification; Tan et al., 2024). The dire state of the teaching profession can be attributed to (a) in-service teachers exiting the workforce at a high rate and (b) falling enrollment rates in teacher preparation programs (Saenz-Armstrong, 2023). For instance, according to the U.S. Bureau of Labor Statistics (2018) around 270,000 in-service teachers are expected to leave the field each year between 2016-2026. Further, between the years of 2010 and 2021, teacher preparation enrollment dropped by 30% nationally (Saenz-Armstrong, 2023). A culmination of falling teacher retention and teacher preparation enrollment has led to the *emergency certification* (i.e., the temporary issuance of a teaching certificate to individuals who have not formally undergone traditional state sanctioned teacher preparation requirements; 70 O.S. § 6-187F) of at least 365,044 teachers across the United States (Tan et al., 2024).

In addition, Science, Technology, Engineering, and Mathematics (i.e., STEM) and elementary grade level contexts have particularly felt the ramifications of the national teacher

shortage. For instance, on a national level, school districts consistently report vacant mathematics positions (Feder, 2022) and STEM teacher preparation program completion has decreased by more than 22% (Partelow, 2019). The shortage of teachers in STEM teaching positions paired with the decrease in teachers entering the STEM specific teacher workforce exacerbates current concerns across the United States regarding global competitiveness in STEM (Hutchinson, 2012). Additionally, elementary teachers are at the forefront of many of these ongoing shortages. For example, it was projected that between the years of 2016-2026, 48,300 elementary teachers would exit the labor force annually and 54,000 elementary teachers would annually transfer occupations entirely (U.S. Bureau of Labor Statistics, 2018). Further, the Pew Research Center recently reported that elementary teachers considerably perceive their occupation to be stressful (81%) and overwhelming (75%; Schaeffer, 2024). Taken together, the concerning trends among the teacher workforce – especially among STEM and elementary grade level teachers – underscore the need to better understand the experiences of teachers in today's classrooms and particularly the experiences that may lead them to exit the field.

Existing literature has traditionally pointed to teachers' workload and burnout experiences as reasons for leaving the teaching workforce (Higton et al., 2017; Madigan & Kim, 2021). For example, research commonly points to the number of hours teachers spend outside of the classroom prepping materials, grading, updating parents/guardians on their students, and attending to administration expectations (Higton et al., 2017). A large literature points to motivational processes (e.g., *teacher self-efficacy,* or an educator's beliefs in their capabilities to provide students with effective instruction, Zee & Koomen, 2016) as key mechanisms for explaining burnout. However, less research has explored how the incredibly demanding cognitive processing during instruction teachers are confronted with on a daily basis may impact

their motivation and intentions to remain in the field (Feldon, 2007). In particular, despite decades of research pointing to the central role of cognitive load (i.e., the number of informational inputs an individual must process; Sweller, 1988) on a student's ability to process informational inputs effectively (Paas et al., 2003a), minimal research has investigated cognitive load among the teacher population. Addressing this gap in the literature is crucial given the volume of informational inputs that teachers are required to process during instruction. Therefore, understanding their level of cognitive load (a) provided critical insight into their teaching experiences and (b) contributed to the cognitive load literature by expanding it to the teacher population. In addition, drawing from the small existing teacher cognitive load research (e.g., Moos & Pitton, 2014), very little has explicitly investigated the outcomes of cognitive load among teachers. For instance, research has yet to consider how teachers' cognitive load experiences predict their (a) motivation for teaching and (b) attritional intentions. Therefore, in this study, I aimed to address these gaps.

Purpose Statement

The purpose of this study was to explore (a) elementary grade level (i.e., PreK-5) teachers' cognitive load experiences in mathematics and its association to (b) motivational (i.e., teaching self-efficacy, cost perceptions) and (c) attritional experiences. To do so, I adopted an explanatory sequential mixed methods design. The study occurred in two phases: During Phase 1, I adopted a quantitative, daily diary design to understand teachers' daily experiences with cognitive load, motivation, and attrition. Then, guided by the quantitative results, during Phase 2, I conducted 10 semi-structured qualitative interviews to further gain complementary information on teachers' cognitive load, motivational, and attrition experiences from their own voices.

Brief Theoretical and Conceptual Framework Overview

In this section, I will briefly define and describe relevant constructs and theories that guided this study (Appendix A presents a full list of construct definitions). I begin by describing the three theoretical frameworks I adopt: cognitive load theory, situated expectancy-value theory, and social cognitive theory. In addition, I define constructs central to this work, including cognitive load, self-efficacy, cost perceptions, and attrition intentions. Each of these theories and constructs will be discussed in greater detail in Chapter 2.

Cognitive Load Theory

Cognitive load theory (CLT) is the primary theory guiding this study. CLT is a theory of human processing, which posits that humans have an unlimited *long-term memory* (i.e., is an unconscious, limitless component of the human cognitive architecture where a vast amount of knowledge is stored; Kirschner et al., 2009; Sweller et al., 2011; van Merriënboer & Sweller, 2005) paired with a limited *working memory* (i.e., an aspect of the human cognitive architecture where information is actively processed and interpreted; Paas et al., 2010; Sweller, 1994). Importantly, research has demonstrated that the working memory can only handle about two to four pieces of information for 30 seconds at most (Cowan, 2014; Paas et al., 2003a). Due to the limitations of the working memory, CLT defines the number of demands we receive in our working memory as our *cognitive load* (Sweller, 1988). Moreover, when we receive a greater number of informational inputs at one time than the working memory can handle (i.e., two to four inputs), we experience *cognitive overload* (Feldon, 2007). To date, cognitive load has been overwhelmingly studied among students with the goal of improving instructional design (see Klepsch & Seufert, 2020; Sweller, 1988, 1994). However, very little cognitive load research has focused on a critical population: teachers.

Teachers' Cognitive Load. As aforementioned, teachers are expected to juggle a host of tasks during instruction. For example, on a daily basis, teachers must effectively deliver instruction while managing classroom behavior, differentiating instruction, controlling classroom technology, and managing their personal thoughts and emotions (Higton et al., 2017). The few studies that have investigated teachers' cognitive load have demonstrated that it plays an important role in their everyday experiences. For instance, one study found that pre-service teachers were explicitly aware of their limited cognitive capacity during field placement instruction (see Moos & Pitton, 2014). Another study reported that cognitive overload due to heightened decision-making during instruction prompted adverse emotional reactions from in-service teachers (e.g., passiveness, feeling tired; Blackley et al., 2021). These experiences of cognitive overload among teachers are problematic for several reasons. First, cognitive overload enhances the likelihood of ineffective processing and poor teaching performance (Moos & Pitton, 2014). For teachers, ineffective processing would mean that they are not able to properly and/or effectively teach students necessary mathematics content which, in turn, would negatively influence student achievement. Second, cognitive load can instill suboptimal emotional experiences like frustration and feeling overwhelmed (Brockbank & Feldon, 2024). These types of negative emotional reactions among teachers have been linked to burnout experiences – a strong predictor of teacher attrition (Beymer et al., 2022a; Madigan & Kim, 2021). In the following section, I discuss the third reason cognitive overload among teachers is problematic: its consequences for motivation.

Motivation

Research has hinted towards a link between the cognitive load and motivation literatures (Feldon et al., 2019). In particular, recent findings position motivation as an outcome of

cognitive load in general (e.g., Feldon et al., 2019; Huang, 2017). Given the emerging evidence of a relation between cognitive load and motivation and guided by two prominent theories of motivation: social cognitive theory and situated expectancy-value theory, I investigated how teachers' cognitive load is related to two key motivational constructs: (a) teaching self-efficacy and (b) cost perceptions.

Social Cognitive Theory and Teachers' Self-Efficacy. In this study, I drew from *social cognitive theory (SCT)*, which is a framework that emphasizes the interplay between personal, environmental, and behavioral processes (Schunk & DiBenedetto, 2020). *Self-efficacy,* or an individual's beliefs about competence to successfully complete a given task, is a key construct in this framework (Schunk & DiBenedetto, 2020). According to the model of reciprocal causation subsumed within SCT, personal processes (e.g., self-efficacy) influence and can be influenced by both environmental and behavioral processes (Schunk & DiBenedetto, 2020). A large literature has explored educators' perceptions of self-efficacy towards teaching (e.g., see Klassen & Tze, 2014) which will be discussed next.

It is well documented that *teachers' self-efficacy,* or a teachers' beliefs about their ability to successfully complete relevant teaching tasks, is a powerful precursor to the teaching practices teachers choose to enact and overall student achievement (Skaalvik & Skaalvik, 2007). However, extant research suggests that some teachers are less efficacious for mathematics instruction, which in turn influences their students' mathematics achievement (Althauser, 2018; Zee et al., 2018). Further, low levels of teacher self-efficacy beliefs have been linked to concerning behavioral trends among teachers (e.g., burnout; Skaalvik & Skaalvik, 2007; Zee et al., 2018). Given recent findings suggesting that cognitive load and motivation are linked (Feldon et al., 2019; Huang, 2017), it is likely that cognitive overload during mathematics instruction

exacerbates these already low teacher self-efficacy beliefs (Althauser, 2018; Bjerke & Xenofontos, 2024; Chang, 2015). Despite the importance of cognitive load, teacher self-efficacy, and their outcomes, little research has directly explored cognitive load and its implications for teacher self-efficacy during mathematics instruction.

Situated Expectancy-Value Theory and Teachers' Cost Perceptions. Also guiding the this study was *situated-experctancy value theory (SEVT)*, which proposes that human motivation primarily stems from their perceptions of (a) *expectancies for success* (i.e., "can I do this?") and (b) *task values* ("do I want to do this and why?"; Eccles & Wigfield, 2002, 2020). Moreover, the theory emphasizes that individuals' motivational experiences are situated, meaning that their beliefs about motivation are directly dependent on an array of personal and contextual factors (Eccles & Wigfield, 2020). For the purposes of the present study, *cost perceptions* – a subdimension of the task values component of the theory (Eccles & Wigfield, 2020) – will be of focus. Cost perceptions, or what an individual believes they must sacrifice to engage in a task, is a motivational construct that has received increased attention over the last decade (e.g., see Flake et al., 2015). However, these perceptions were not considered among the teaching population until recently (e.g., see Bergey & Ranellucci, 2021; Beymer et al., 2022a). Research has demonstrated that a high teacher workload is related to high perceived cost for teaching, which in turn elicits greater intentions to leave the profession (Beymer et al., 2022a). Cognitive load, while distinct from workload, is likely to produce similar outcomes given that cognitive overload can trigger frustration and feelings of overwhelm in a similar fashion (Brockbank & Feldon, 2024). However, no known research has investigated how cognitive overload may be related to teachers' cost perceptions – a critical precursor to teachers' attrition intentions (Beymer et al., 2022a).

Methodology and Research Questions

Most of the known empirical research that has focused on teachers' cognitive load has done so via qualitative interviews or retrospective survey instruments (e.g., see Blackley et al., 2021; Moos & Pitton, 2014). Despite the value of these methodological approaches, both require participants to recall their mental state from former experiences. Enduring critiques of retrospective measurements suggest that humans are often unable to accurately recall and represent their former mental states, especially when asked to recall higher order processing (e.g., cognitive load; see Dent & Koenka, 2016; Nisbett & Wilson, 1977). Further, recent calls for increased precision when measuring cognitive load (see Anmarkrud et al., 2019) point to the potential for measuring the construct in or closer to real time. Therefore, in an explanatory sequential mixed methods design (QUAN → qual; Plano Clark & Ivankova, 2016) and to account for (a) issues with retrospective measurement and (b) the need for increased precision when measuring cognitive load, in the quantitative phase, I adopted a daily diary design. Daily diary is the repeated measurement (i.e., typically using short survey instruments) of a construct or constructs as participants engage in their daily lives (Zirkel et al., 2015). In the qualitative phase, I continued to expand on the findings uncovered in the quantitative phase to ascertain how teachers describe their cognitive load and motivational experiences in their own words. Following qualitative data collection and analysis, I integrated the findings using transformation, narrative weaving, and joint displays (DeCuir-Gunby & Schutz, 2017; Fetters et al., 2013; Plano Clark & Ivankova, 2016). Taken together, in an explanatory sequential mixed methods design, I investigated teachers' cognitive load during mathematics instruction and its consequences for their (a) teaching self-efficacy, (b) perceived cost, and (c) attritional intentions. I investigated the following research questions:

1. To what extent does teachers' daily cognitive load during mathematics instruction vary within and between teachers over a two-week period? (*Quantitative*)
    a. To what extent do years of teaching experience predict daily experiences with cognitive load? (*Quantitative*)
2. To what extent does the variation in teachers' daily cognitive load during mathematics instruction predict teachers' daily (a) self-efficacy, (b) cost perceptions, and (c) attrition intentions? (*Quantitative*)
3. How do teachers describe their daily experiences with cognitive load during mathematics instruction? (*Qualitative*)
    a. How do teachers with underrepresented identities within the teaching profession experience cognitive load? (*Qualitative*)
4. How do teachers' qualitative descriptions of their daily experiences with cognitive load during mathematics instruction, motivational beliefs, and attrition intentions map onto the experiences reported on the daily quantitative surveys? (*Mixed*)

Study Significance

Research on teachers' cognitive load during mathematics instruction and its motivational and attritional consequences is essential for improving (a) the instructional and well-being experiences of educators, (b) the quality of mathematics instruction, and (c) teacher retention rates. In addition, it is necessary to understand how these constructs operate across teachers' levels of expertise to determine critical timepoints for intervention. To demonstrate, research suggests that roughly one third of early-career teachers leave within their first five years of teaching (Darling-Hammond et al., 2023). Thus, there is a need to develop a better understanding of how teachers' cognitive load experiences (a) depend on their teaching expertise and (b) relate

to their attrition intentions. Further, understanding teachers' cognitive load across teacher expertise levels could provide necessary insight into how experienced teachers overcome (or are unable to overcome) cognitive overload, which in turn would result in valuable information on strategies to support and aid in teacher retention.

Dissertation Outline

In Chapter 2, I provide a historical account of the cognitive load literature in general and review the extant teacher cognitive load literature. Then, I review the teacher's self-efficacy and cost perception literatures and relate each back to the teacher's cognitive load literature. In doing so, I highlight gaps that emerged from the literature review and the need to address them. The purpose of Chapter 2 is to review relevant literature and justify each research question. In Chapter 3, I present study methods on teachers' cognitive load and its motivational and attritional outcomes using an explanatory sequential mixed methods design. The purpose of Chapter 3 is to outline all the study procedures I adopted to effectively carry out the study. In Chapter 4, I present the results of the study, followed by a detailed explanation and discussion of those results in Chapter 5.

Chapter 2: Review of the Literature

In Chapter 1, I described the (a) extant concerns regarding the ongoing national teacher shortage and (b) dearth of research on teachers experiences of cognitive load in general and in relation to their motivational and attritional experiences. In this chapter, I first provide an overview of the existing cognitive load literature, followed by a detailed account of the history of cognitive load research, its theoretical underpinnings, and how it applies to the teaching profession. I also review the teachers' cognitive load literature within the educational psychology field and relay central themes that emerged. Then, I review two overarching theories of motivation (i.e., situated-expectancy value theory, social cognitive theory) and two of their central constructs (i.e., self-efficacy, cost perceptions) that each centrally influence teachers' experiences in the classroom. I also describe how the cognitive load and motivation literatures intersect. Finally, I describe the remaining literature gaps.

Cognitive Load

Transfer of knowledge to the *long-term memory*, or an aspect of the human cognitive architecture where complex structures of information (i.e., *schemas*) are organized and stored, is the ultimate form of learning (Ayres & Paas, 2009; Baars, 1986; Kalyuga, 2011; Sweller et al., 1998). That is, when information reaches the long-term memory, it means that an individual has successfully learned something new (Ausubel, 2012). Scholars overwhelmingly agree that a key quality of long-term memory is its theoretically unlimited capacity for information storage (Ayres & Paas, 2009; Baars, 1986; Kalyuga, 2011; Sweller et al., 1998). However, before information reaches the long-term memory, it must first be effectively processed in the *working memory*, or where humans actively process the information they receive (Paas et al., 2010; Sweller, 1994). Unlike the long-term memory, the working memory is limited (Cowan, 2014;

Paas et al., 2003a). Research suggests that the working memory can only manage about two to four pieces of information for 30 seconds at most (Cowan, 2014; Paas et al., 2003a).

Given the limitations of the working memory, the human cognitive architecture is easily taxed. For example, *cognitive load*, or the number of inputs an individual receives in their working memory, interferes with how effective an individual is at processing information received (Paas & van Merriënboer, 1994; Sweller, 1988; Sweller et al., 1998). To demonstrate, if an individual were to receive more than the two to four pieces of information their working memory can handle, they would experience a high cognitive load, or *cognitive overload* (Feldon, 2007). Therefore, cognitive load is an antecedent to effective human processing and has inspired decades of research on how to more properly consider the human cognitive architecture in the instructional design of curriculum (Sweller, 1988). In the following section, I describe the historical development and theoretical underpinnings of cognitive load.

The Evolution and Theoretical Underpinnings of Cognitive Load

In this section, I describe how cognitive load and its associated theory, cognitive load theory (CLT), originated. Then, I recount how cognitive load and its dimensions evolved over time, including a discussion on the highly debated dimension: germane load. Next, I discuss the measurement issues that cognitive load has and continues to face. Lastly, I briefly cover the expansion of cognitive load among differing populations and domains.

The Origins of Cognitive Load Theory

In 1988, Australian educational psychologist, John Sweller, critiqued *problem solving* (i.e., problems with unobvious solutions that encourage students to attempt multiple techniques to reach a solution; Dunbar, 1998) instructional design techniques. Framing his work with extant working memory models (e.g., Miller, 1956), Sweller hypothesized that the use of problem-

solving instructional techniques would be ineffective if students do not have the proper background knowledge (i.e., schemas) to solve the problem. Sweller's critiques of and hypotheses about problem solving techniques were unique at the time, as most instructional design research had overwhelmingly considered it as a superior strategy to teach students content – especially mathematics and science content (Bruner, 1961; Dewey, 1910; Sweller, 1988). Regardless of Sweller's divergent take on problem solving, his hypotheses resulted in findings that would alter instructional design and cognition research for good.

In a study of high school mathematics students' use of problem-solving techniques, Sweller (1988) found that the students engaged in problem solving through a *means-ends analysis* approach. Means-ends analysis suggests that student's attention is focused only on obtaining an answer to a problem and not on their strategies used to achieve the answer. That is, students in the study only focused on simply finishing the problem (i.e., a means to an end), and for the most part, failed to expand upon their existing schema structures during the learning process. Because these students were not developing and/or expanding new schemas, they consistently maximized their working memory resources during problem solving tasks. Sweller ultimately concluded that without proper background knowledge or schema structures, problem solving pushed students to use up too much space in their working memory resulting in a high cognitive load.

Sweller's (1988) findings were influential among the educational psychology literature and inspired the subsequent development of a cognitive load theoretical framework: *cognitive load theory* (CLT, Sweller, 1994; Sweller & Chandler, 1991; Sweller et al., 1990). CLT acknowledges several central tenets of human cognition and its influences on learning. First, it acknowledges that humans have an unlimited long-term memory where information is stored

once it successfully passes through the working memory. Second, it emphasizes that the limitations of the working memory can cognitively overload a learner; therefore, the design of curriculum should considerably be informed by these limitations (Sweller, 1988, 1994). Over time, scholars expanded the conceptualization of cognitive load to include three sub-dimensions: intrinsic, extraneous, and germane loads, which are each discussed in the following section.

Breaking Down Cognitive Load: Intrinsic, Extraneous, and Germane Loads

In the years since the development of cognitive load, sub-dimensions of the construct emerged. First, intrinsic and extraneous loads were introduced (see Sweller, 1994), followed by germane load (see Sweller et al., 1998). Scholars have historically debated and continue to debate the validity of germane load. All of which is discussed below.

Intrinsic and Extraneous Loads. Following the development of cognitive load and CLT, Sweller (1994) began considering the potential sub-dimensions of cognitive load. Cognitive load was initially thought to have two dimensions: *intrinsic load* and *extraneous load*. Intrinsic load was initially and continues to be conceptualized today as the cognitive load experienced due to the inherent difficulty of the task and/or information needed to be processed (Chen et al., 2023; Krischner, 2002; Leppink et al., 2013; Sweller, 1994; Sweller et al., 1998). To demonstrate, in elementary grade levels learning fractions is an example of a task that would elicit a high intrinsic load as it requires that students apply the proper background knowledge of multiple operators (e.g., multiplication, division) and visualization skills.

Extraneous load was initially conceptualized as the cognitive load experienced that is unrelated to task and/or information complexity itself (Kalyuga, 2011; Leppink et al., 2013; Paas et al., 2003b; Sweller, 1994). While the conceptualization of intrinsic load has remained consistent since its initial development, extraneous load has expanded. Scholars originally

considered extraneous load as only attributed to poorly designed instructional materials. However, more recent conceptualizations include the physical environment as a contributor to extraneous load (see Choi et al., 2014). Drawing from the fraction example above, not only might confusing instructions contribute to a learner's extraneous load when solving a fraction problem, but a noisy classroom environment could as well (Choi et al., 2014).

Germane Load. Sweller and colleaguesintroduced *germane load* in 1998, four years after intrinsic and extraneous loads. Germane load is defined as the cognitive load experienced due to the effort it takes to transfer information from the working memory to the long-term memory (Kalyuga, 2011; Kirschner, 2002; Paas et al., 2003b; Sweller et al., 1998). In other words, it is the mental effort it takes to construct schemas (Sweller et al., 1998). In the fraction example, this would entail the cognitive load attributed to the strategies learned so that students can easily access and use that knowledge the next time they encounter a fraction problem.

For more than a decade, germane load was relatively accepted by scholars who adopted CLT. However, Kalyuga (2011) strongly challenged germane load, arguing that it could not be distinctly separated from intrinsic load. More specifically, three points of contention against germane load were discussed. First, while intrinsic and extraneous loads were developed from empirical evidence, germane load was not. In addition, attempts to support germane load with empirical evidence had been either unsuccessful or indicated that it was closely aligned with intrinsic load (e.g., see Scheiter et al., 2009). Lastly, it was argued that germane load is unable to be instructionally altered in a similar fashion as intrinsic and extraneous loads and thus challenging to explicitly measure (Kalyuga, 2011).

Following the pushback on germane load, Sweller (2011) published a conceptual review that reconsidered the dimension. Interestingly, Sweller (2011) suggested that it was never

intended for germane load to form as its own cognitive load dimension. Instead, Sweller suggested the term *germane resources* (i.e., "the resources devoted to the load imposed by the nature of the material are germane to learning"; Sweller et al., 2011, p. 57) be used. Despite the critiques of germane load and Sweller's retraction of it himself, scholars have continued to debate the validity of the dimension (see Greenberg & Zheng, 2023; Leppink et al., 2013, 2014). Therefore, today many scholars who adopt CLT as a framework, agree that germane load is not distinct and instead subsumed within intrinsic load (e.g., Jiang & Kalyuga, 2020; Paas & van Merriënboer, 2020; Sweller et al., 2011) while others remain strong advocates of germane load as a distinct dimension (e.g., Choi & Lee, 2022; Klepsch & Seufert, 2020).

Given the (a) measurement inconsistencies and (b) Sweller's own retraction of germane load, I tend to align with scholars who negate germane load as a stand-alone dimension. Despite this, more research needs to be conducted to explicitly determine whether germane load should be positioned as its own dimension or as a sub-component of intrinsic load. Therefore, for the purposes of this study, I continued to frame germane load as its own dimensions and aimed to investigate its validity as a dimension within this research.

Measuring Cognitive Load

The ambiguity associated with the human brain has made it clear that accurately measuring cognitive processes is a challenging feat (Karabenick et al., 2007; Clark, 1988). Cognitive load is not exempt from these cognition-related measurement difficulties (Paas et al., 2003b). Most generally, cognitive load is measured in three ways: (1) task and performance-based measures, (2) physiological measures, and (3) subjective rating scales (Paas et al., 2003b). Below I review each of these measurement techniques.

Task and Performance-Based Measures. Cognitive load is often measured via task and performance-based measures (see Sweller et al., 1990). These forms of measurement often include data in the form of a performance outcome (e.g., grade) or other measurable phenomena (e.g., time to task completion; Bobis et al., 1993; Pillay, 1994; Sweller et al., 1990). Task and performance-based measures can be useful for understanding the outcomes of cognitive load (Paas et al., 2003b). Though, some scholars argue this form of measurement interferes with the task itself and thus adds to cognitive load (Paas et al., 2003b). To demonstrate, when a participant realizes they are under time constraints, that awareness may increase their cognitive load and effectively decrease their task performance – effectively misrepresenting the results.

Physiological Measures. Scholars suggest that cognitive load burdens human physiological functioning (e.g., increased brain activity, heart rate, and eye movement; Paas et al., 2003b; Sweller et al., 1998). Therefore, physiological measures, especially eye tracking, are commonly used to understand fluctuations in cognitive load (e.g., Liu et al., 2022). These forms of measurement provide researchers with the advantage of understanding the trends and patterns of an individual's cognitive load over the course of data collection (Paas et al., 2003b). However, physiological measures are historically unreliable (Paas & van Merriënboer, 1994; Sweller et al., 1998). For example, underlying factors (e.g., participant health) may interfere and ultimately distort findings that are specifically related to the participant's level of cognitive load (Joseph, 2013).

Subjective Rating Scales. Cognitive load is commonly measured using subjective rating scale techniques (e.g., Likert-type scales). Paas and van Merriënboer (1994) were among the first to measure cognitive load using a rating scale. In this measure, participants were asked to rate the amount of mental effort they used on a given task via a nine-point scale. More recently, Leppink

et al. (2013) developed a scale that measured each of the three dimensions of cognitive load (i.e., intrinsic, extraneous, and germane loads) using an 11-point scale. An example intrinsic load item reads: "The topic/topics covered in the activity was/were very complex" (Leppink et al., 2013, p. 1070). While much of the cognitive load research has used subjective rating scales, some scholars have pushed back on its use. Scholars specifically question whether humans can accurately judge their levels of cognitive load – especially in a retroactive manner (Jiang & Kalyuga, 2020; Sweller et al., 1998).

Taken together, while no measurement approach is perfect, new forms or approaches to cognitive load measurement may be needed to more accurately and consistently measure cognitive load. Less used in cognitive load research has been short-term longitudinal designs (e.g., ESM, daily diary) to understand the momentary and daily fluctuations of a participants' experience. Similarly, little research has considered using qualitative techniques to further understand the construct of cognitive load. One aim of this study, discussed in detail in Chapter 3, was to address these measurement gaps.

Cognitive Load across Domains and Populations

Cognitive load is prominently studied among K-20 student populations (e.g., Bobis et al., 1993; Leppink et al., 2014) and mathematics and science domains (e.g., Chandler & Sweller, 1991; Leppink et al., 2013). Despite these trends, research on cognitive load is increasingly far-reaching. For example, cognitive load is researched in domains such as evolutionary biology (see Sweller, 2009) and philosophy (see Gerjets et al., 2009); in addition to, the workplace (e.g., Laarmanen et al., 2018; Young et al., 2016) and among aging populations (e.g., Graves, 2018; Van Gerven et al., 2002).

Cognitive Load in Mathematics. Mathematics as a subject can be complex to learn, often imposing high-element-interactivity (i.e., imposition of intrinsic load) and/or be taught with instructional formats that can lead to ineffective learning (i.e., imposition of extraneous load; Chinnappan & Chandler, 2010). Moreover, at the heart of mathematics instruction is often problem solving – an instructional technique that is commonly viewed as less effective for learning by many cognitive load theorists (Aditomo, 2009; Kirschner et al., 2006).

Given the frequent misalignment of mathematics instruction with the central tenets of CLT, a large literature exists regarding methods for improving mathematics instruction through accounting for key principles of cognitive load theory (Aditomo, 2009). For example, one study demonstrated that mathematics instruction should differ depending on the prior knowledge of the specific student (Gupta & Zheng, 2020). That is, students with less prior knowledge benefitted from mathematics problem examples that had the problem fully worked out whereas students with more prior knowledge benefited more from mathematics problem examples that were only partially worked out – highlighting the importance of scaffolding mathematics problems for individual students to align with their extant schema structured (Gupta & Zheng, 2020). These findings pointing to the importance of mathematics scaffolding to reflect students' individualized schema structures are consistent across the cognitive load literature (see also Ayres, 2006; Clarke et al., 2005; Gerjets et al., 2009). Despite the dearth of existing literature on cognitive load for learning mathematics and improving the design of mathematics instruction, little research exists on the cognitive load associated with delivering instruction (a) generally and (b) in mathematics, both of which will be discussed in the following sections.

Taken together, since their development, cognitive load and CLT have been influential in educational psychology domains. Conceptualization of cognitive load has remained relatively

consistent, apart from ongoing debates regarding the validity of germane load. It is well-documented that measuring cognitive load can be challenging and is typically measured using performance-based, physiological, or rating scale techniques. Finally, cognitive load has expanded its reach to additional domains and populations and may be especially relevant among the domain of math. However, one population that remains understudied at the intersection of the CLT and educational psychology literatures are teachers. Therefore, the extant teacher cognitive load literature will be reviewed in the following sections.

Teachers' Cognitive Load

Research on teachers' cognitive load during instruction is limited within the educational psychology literature. To demonstrate, in a search of the CLT literature, only five articles (see Table 1) explicitly addressed teachers' cognitive load during instruction, and all were published during or after 2014. Teachers' cognitive load studies vary regarding methods used, populations studied, and findings – underscoring the need for the present synthesis. Therefore, in reviewing the CLT guided teacher cognitive load literature, four overarching themes emerged. First, there is evidence that teachers experience cognitive overload during instruction and are aware of it when it occurs. Second, extraneous load may be especially problematic for teachers when compared to intrinsic and germane loads. Third, automaticity plays an important role in decreasing teachers' cognitive load. Fourth, a high cognitive load may introduce or exacerbate other unfavorable states among teachers like negative affect or lowered motivational beliefs. In the next sections, each of these themes is discussed in more detail.

Table 1

Summary of Teacher Cognitive Load Literature

	Ayvaz-Tuncel & Demir (2024)	Blackley et al. (2021)	Hebert (2018)	Kondé et al. (2023)	Moos & Pitton (2014)
Dimensions of Cognitive Load	Intrinsic Extraneous Germane	Not reported or explored	Intrinsic Extraneous Germane	Intrinsic Extraneous	Intrinsic Extraneous Germane
Method	Quantitative	Qualitative	Qualitative	Quantitative	Multi-method
Cognitive Load Measurement	Self-report questionnaire (i.e., Hwang et al., 2013)	Semi-structured interviews; observations	Semi-structured interviews; observations	Working memory assessment (Gronthier et al., 2016)	Self-report questionnaire (i.e., adapted from Paas, 1992; Paas & van Merriënboer, 1994); interviews
Sample Characteristics	*N* = 342 pre-service teachers enrolled in two universities in Turkey	*N* = 8 Australian teachers	*N* = 6 pre-service teachers in the United States	*N* = 70 pre-service teachers enrolled at two Hungarian universities	*N* = 26 pre-service teachers enrolled in a small liberal arts college located in the midwestern United States
Instructional Grade Level	Not reported	Secondary	Elementary (n = 2) Middle (n = 3) High (n = 1)	Secondary (grades 5-12)	Elementary (38%) Middle (23%) High (38%)
Subject Domain	Guidance counseling (17%); math (11.1%);	Not reported or explored	Not reported or explored	Mathematics	Not reported or explored

	Ayvaz-Tuncel & Demir (2024)	Blackley et al. (2021)	Hebert (2018)	Kondé et al. (2023)	Moos & Pitton (2014)
	social studies (11.7%); special education (10.8%); Turkish language (7.3%); science (5.6%); English language (4.1%)				
Teacher expertise	Novice	Novice and experienced teachers (range of 1-27 years of experience)	Novice	Novice	Novice
Findings Related to Cognitive Load	Metacognitive skills perceptions positively predicted cognitive load perceptions. Cognitive load did not mediate metacognition and problem-solving perceptions. Cognitive load and problem-solving skills were not related.	Decision-making demands induce a high cognitive load which can risk negative affect. Praise of appropriate classroom behaviors as opposed to correcting inappropriate classroom behaviors reduced teachers' cognitive load.	High cognitive load was reported when the teachers either did not have the proper mental resources for teaching or the environment was distracting. Teachers were aware of their high cognitive load when it occurred. Teachers described experiencing low self-esteem because of cognitive load.	Increased intrinsic load decreased accuracy and time to task completion. A secondary task increased participants' working memories and therefore increased their time to task completion and errors.	Pre-service teachers' cognitive load decreased during their second placement. The decrease in cognitive load was due to the ability to better manage distractions (i.e., extraneous load). Students also reported increased automaticity.

Conscious Cognitive Load. Of the five articles that emerged from my literature search, several found that teachers are often conscious or aware of their high cognitive load when it occurs. For example, in a qualitative phenomenological study with novice teachers in the United States, it was discovered that teachers were able to distinguish between cognitive actions that were automatic (i.e., did not require conscious processing) and cognitive actions that required significant mental effort (Hebert, 2018). The novice teachers in the study explained that the numerous performances simultaneously demanded of them often made it more challenging to effectively process their "next actions or words" (Hebert, 2018, p. 415). Similarly, in a multi-method study of pre-service teachers, it was found that they were also consciously aware of their limited cognitive capacity (Moos & Pitton, 2014).

The awareness of cognitive load among teachers may be both beneficial and damaging. One study that examined the relationship between pre-service teachers' perceptions of metacognitive skills (i.e., monitoring, evaluating, and controlling learning choices and actions; Greene et al., 2024), perceptions of cognitive load, and problem-solving skills found that pre-service teachers' cognitive load was reduced when they perceived themselves to have sufficient metacognitive skills (see Ayvaz-Tuncel & Demir, 2024). In fact, their findings suggest that an awareness of cognitive load and its potential limitations may even prompt an individual to seek additional metacognitive strategies (e.g., adoption of self-regulation skills) which would in turn improve their instructional skill set. On the other hand, an awareness of cognitive load may add to an individual's load. For instance, a teacher may realize they are experiencing limitations to their processing, thus adding an additional working memory input. The added cognitive load may introduce other unwanted outcomes like negative affect (e.g., frustration), decreased

motivation (e.g., lowered self-efficacy), and/or ineffective instruction – all of which are discussed in the following sections of this chapter.

Teachers' Extraneous Load. There is surmounting evidence from the reviewed articles that extraneous load may be especially problematic for teachers. For example, several articles found that the classroom environment was a substantial contributor to a teacher's cognitive load (Blackley et al., 2021; Hebert, 2018; Kondé et al., 2023; Moos & Pitton, 2014). More specifically, classroom management-related distractions and the need to employ strategies to mediate those distractions were commonly cited types of contributors to a teachers' cognitive load noted during instruction (Blackley et al., 2021; Hebert, 2018; Moos & Pitton, 2014). Along similar lines, unexpected classroom occurrences were also cited as contributors to teachers' cognitive load (Kondé et al., 2023). Events unrelated to the task at hand – including environmental distractions – have long been associated with extraneous load (Choi et al., 2014; Sweller, 1994). Therefore, events associated with the need to employ classroom management strategies lend themselves to experiences of extraneous load among teachers.

Repeated experiences of high extraneous load among teachers are problematic given that the research indicates that teachers who report a high cognitive load can lead to less efficiency in making proper teaching decisions and, thus, inadequate student learning (Hebert, 2018; Kondé et al., 2023). Interestingly, Blackley et al. (2021) found that a high extraneous load could be reduced when teachers developed go-to strategies for classroom management. Particularly, when teachers decided to praise appropriate classroom behaviors as opposed to ridicule inappropriate ones, teachers reduced their extraneous load and experienced less frustration during instruction. Similarly, as pre-service teachers learned and developed additional strategies over the course of teaching placements, they too effectively decreased their extraneous load – explicitly naming the

development of classroom management strategies as reasons for their decreased load (Moos & Pitton, 2014). These findings speak to the potential importance of automaticity among teachers, which is discussed next.

Instructional Automaticity among Teachers. Several studies spoke to the value of instructional *automaticity* (i.e., the unconscious processing of information; Feldon, 2007) for reducing teachers' cognitive load (Blackley et al., 2021; Hebert, 2018; Kondé et al., 2023; Moos & Pitton, 2014). Automaticity reduces instructional cognitive load because it allows processes to occur without conscious thought. As mentioned above, automatic go-to strategies (e.g., the decision to only praise appropriate student behavior) reduce the number of decisions a teacher must make during instruction (Blackley et al., 2021). While automaticity likely benefits teachers' cognitive load at all stages of teaching, it may be particularly important for early-career teachers. Automaticity is developed after repeated practice; therefore, given the inexperience of early career teachers, they likely experience heightened levels of cognitive load compared to their more experienced teacher counterparts (Feldon, 2007). The lack of automaticity among early-career teachers is also evident in another study as over the course of two teaching field placements, pre-service teachers reduced their cognitive load (Moos & Pitton; 2014). In other words, they effectively developed more automaticity for certain teaching tasks. Another study found that a lack of adequate levels of automatic teaching strategies was also prevalent among and noticed by in-service teachers – particularly those who had taught for two years or less (Hebert, 2018).

These findings suggest that even after teacher preparation, novice teachers have not yet developed adequate levels of cognitive load. In fact, novice teachers in one study expressed a desire for automatic strategies to have at their disposal to help lighten their teaching load

(Hebert, 2018). Overall, these findings speak to (a) the importance of automatic teaching strategies, (b) the need for additional research on how teachers' instructional automaticity develops over time, and (c) how to better foster the development of automatic strategies among early-career teachers.

Potential Outcomes of Cognitive Load. Several studies discuss the potential outcomes of increased cognitive load among teachers. For example, Blackley et al. (2021) aimed to understand the relationship between teachers' cognitive load and affect. In particular, the authors found that when teachers' cognitive load decreased, they also experienced a decrease in negative affect (e.g., decreased frustration; Blackley et al., 2021). Similarly, Hebert (2018) found that novice teachers reported experiences of frustration, stress, and anxiety in response to a high cognitive load. These findings suggest that teachers' cognitive load and negative affect may be closely and positively linked.

Another potential outcome of high teacher cognitive load commonly mentioned in the reviewed articles, is student outcomes. To demonstrate, teachers felt that when their cognitive load was heightened during instruction it led to less successful student learning (Hebert, 2018). Another study suggested that a high cognitive load among pre-service teachers resulted in an impaired ability to make modifications during instruction (Moos & Pitton, 2014). Given these findings, it is likely that a high cognitive load among teachers may negatively link to their instructional effectiveness and student learning outcomes. A high teacher cognitive load may also link to their motivation for teaching. For example, in one study, teachers reported that a high cognitive load lowered their self-esteem for teaching (Hebert, 2018). In other words, feeling cognitively overloaded may lead a teacher to feel less confident in their instructional abilities.

Taken together, extant literature suggests that teachers' cognitive load may result in (a) more experiences of negative affect, (b) less quality instruction, and (c) decreased motivation among teachers. These outcomes associated with cognitive overload are troublesome because they are often cited as reasons for teacher burnout and attrition (Madigan & Kim, 2021). In fact, both Blackley et al. (2021) and Hebert (2018) connected teacher attrition to cognitive load and its affective and motivational outcomes respectively. Therefore, more research is needed to (a) further uncover and confirm the outcomes of cognitive load among teachers and (b) understand how these relationships may influence teacher attrition.

Evidence of Teachers' Cognitive Load Throughout Related Literatures

Despite the limited amount of extant literature that explicitly explores teachers' cognitive load and/or is grounded in CLT, there is evidence that other research has done so indirectly. I review some of these literatures, specifically the workload, decision-making, and expertise literatures, that are highly related to cognitive load in the following section.

Workload. As aforementioned, the teacher workload literature lends itself to a comparison with the cognitive load literature. Through (a) long lists of tasks often reported by teachers and (b) reports of these tasks inducing feelings of being overwhelmed, it is not irrelevant to map on connection to teachers' cognitive load. Specifically, the list of tasks teachers must regularly accomplish (see Higton et al., 2017) are misaligned with cognitive load theory and the relatively small amount of information our working memory can process. In addition, feelings of being overwhelmed have often emerged as how humans generally describe being cognitively overloaded (Sewell et al., 2020), a feeling that also commonly appears within the teacher workload literature (Lagawid, 2024; Schaeffer, 2024). Despite the overlap between these

two literatures, the workload literature largely overlooks how the cognitive architecture of teachers plays a role in their instructional experiences.

Decision-Making. It is well-documented that teachers make a significant number of decisions on a daily basis (Eggleston, 2018). As a result, an extensive literature is dedicated to teacher-decision making in the classroom (e.g., see Borko et al., 2008). In fact, there are an array of teacher decision-making models and/or frameworks that ground the literature (e.g., see Bishop & Whitfield, 1972; Shavelson & Stern, 1981). At the heart of many of these models are constructs that directly or indirectly relate to the core tenets CLT. For example, Bishop and Whitfield (1972) proposed that two central influences that guide teachers' decisions are their (a) background and experience and (b) extant decision schema or frameworks. That is, prior knowledge (i.e., background and experience) plays a central role in how teachers come to make decisions while instructing (i.e., decision schema or frameworks). As previously mentioned, prior knowledge or an individual's existing schema structure plays a large role in the amount of space the information takes in their working memory (Sweller, 1988). Therefore, there is clear overlap in the teacher decision-making literature and the cognitive load literature; in fact, the decisions teachers must make are likely just one example of a cognitive load input. The relationship between these two literatures was directly observed in an article that found teachers reduced their amount of cognitive load during instruction by having go-to strategies for decision making (i.e., praising appropriate student behavior as opposed to deciding how to correct inappropriate behavior; Blackley et al., 2021). Despite the relevance of the decision-making literature, decision making is only one (though, important) type of cognitive processing that teachers may experience during instruction; thus, pointing to the need for a more comprehensive understanding of teachers' cognitive experiences through a CLT lens.

Teacher Expertise. The teacher expertise literature is especially related to the cognitive load literature. *Expertise* in general is broadly defined as "individuals whose performances show consistent patterns of advanced level achievement on objective measures over time" (Yates & Hattie, 2013, p. 40). However, teacher expertise has proven to be challenging to conceptually define given the complexity of the (a) teacher occupation, (b) classroom contexts, and (c) large quantity of tasks teachers take on – effectively pointing to the aforementioned workload literature (Anderson & Taner, 2023; Hattie, 2003).

In a recent metasummary of the teacher's expertise literature, cognition (in addition to knowledge base, beliefs, personal attributes, professionalism, and pedagogic practice) was found to be highly relevant among expert teachers (Anderson & Tanner, 2023). In particular, of the teacher expertise articles included in the review, many of them pointed to expert teachers having adequate pedagogical content knowledge, or in other words, sufficient subject-specific background knowledge and schema structures for the instructional content required of them to teach. These findings overlap with the cognitive load literature in that the more schemas an individual has, the less space certain information takes up in their working memory. Moreover, the teacher expertise literature often highlights the benefits of automaticity among expert teachers (Anderson & Tanner, 2023). Expert teachers typically have an extensive range of experience, and therefore, have had the opportunities to develop a wide range of automated processes related to instruction. Therefore, expert teachers are often able to unconsciously respond to classroom events which, aligned with CLT, frees up their working memory capacity – ultimately leaving space for other aspects of instruction that also need to be attended to and/or may be more important to attend to.

In this section, I have reviewed three literatures related to cognitive load, namely, the workload, decision-making, and teacher expertise literatures. Each of these literatures point to the extant cognitive load related research that has been conducted, though indirectly (i.e., without an explicit adoption of the construct of cognitive load or CLT). The workload, decision-making, and expertise literatures each point to the (a) ubiquitous nature of the teaching profession and (b) salience of developing schemas among teachers in addition to automaticity. While each of these literatures move the cognitive load literature forward, each considers the processing demands of teachers in silos. CLT on the other hand, effectively accounts for the numerous demands inflicted on teachers' processing experiences; and therefore, is better able to understand teachers' processing demands in a more holistic manner.

Mathematics Instruction and Teachers' Cognitive Load

Little research exists explicitly exploring teachers' cognitive load during mathematics instruction from a CLT perspective. In fact, much of the mathematics specific cognitive load literature focuses on students' cognitive load, experimentally manipulating the design of mathematics instruction to improve their achievement and/or retention (e.g., Gilmor et al., 2015; Kurban, 2024). Moreover, this research on students' cognitive load during mathematics instruction often concludes with several practical recommendations for teachers to implement in their mathematics classrooms. To demonstrate, Gupta and Zheng (2020) suggested that mathematics instruction should be scaffolded depending on the student's extant schema structures. Implementing practical recommendations (e.g., differentiation) in this manner, while necessary, would ultimately impose additional cognitive load among teachers. Given the large literature that suggests mathematics requires significant instructional differentiation depending on individualized student needs, mathematics instruction may especially impose a high cognitive

load among teachers in order to meet the needs of each of their students. Additional arguments for the importance of additional research on teachers' cognitive load in the mathematics domain, particularly, will be discussed in the following sections.

Elementary Teachers' Cognitive Load

Elementary grade level teachers' cognitive load may be particularly salient to explore for several reasons. First, elementary teachers typically report higher levels of stress and overwhelm in their careers and are the least likely to recommend teaching as a career to others when compared to their secondary level counterparts (Shaeffer, 2024). Clearly, elementary educators are especially dissatisfied with their occupation and thus additional attention to elementary teachers' professional experiences should be paid. Second, the existing cognitive load literature has only minimally considered and/or failed to center elementary teachers. However, the same literature suggests that the classroom management demands of teachers may be particularly additive to teachers' extraneous load. Given that elementary teachers are typically required to implement more classroom management strategies compared to their secondary teacher peers, cognitive load may be especially high for elementary teachers. Therefore, additional research on elementary educators' experiences of cognitive load is needed.

Motivation

In addition to the cognition, and CLT literatures, I also drew from the motivation literature throughout this study. Therefore, in the following sections, I briefly describe the two motivation theories I drew from to situate this study. Namely, *social cognitive theory (SCT)* and *situated expectancy-value theory (SEVT).*

Social Cognitive Theory

I ground this study in SCT. Initially developed by Albert Bandura in 1977, SCT emphasizes the interplay between an individual's personal, behavioral, and environmental processes (Bandura, 1986; Miele et al., 2024; Schunk & DiBenedetto, 2020). Importantly, SCT suggests that these personal, behavioral, and environmental processes impact one another in a reciprocal manner, a relationship Bandura titled *triadic reciprocality* (Bandura, 1977, 1986, 1997; Miele et al., 2024; Schunk & DiBenedetto, 2020). In other words, an individual's personal processes influence their environmental and behavioral processes and vice versa (Schunk & DiBenedetto, 2020). To demonstrate, an individual's personal processes (e.g., their confidence level for successfully completing a fraction exam) are mutually influenced by their behavioral processes (e.g., the choice to study for the exam) and their environmental processes (e.g., school context; Bandura, 1977; Miele et al., 2024; Schunk & DiBenedetto, 2020). Therefore, I adopted SCT throughout this study and explicitly drew from and adapted the model of triadic reciprocality. In addition, I drew from a central personal process proposed by SCT, self-efficacy. The construct of self-efficacy is discussed in detail below.

Self-Efficacy. *Self-efficacy*, or an individual's beliefs about their ability to complete a task successfully, is a key personal process that has emerged from SCT (Schunk & DiBenedetto, 2020). Self-efficacy has historically been and continues to be broadly researched throughout the educational psychology literature (Schunk & DiBenedetto, 2020; Zee & Koomen, 2016). Self-efficacy is well-documented as an important antecedent for an individual's level of effort, persistence, and overarching achievement (Bandura, 1997; Miele et al., 2024; Schunk & DiBenedetto, 2020). There are four sources of self-efficacy: *mastery experiences*, *vicarious experiences*, *social persuasion*, and *emotional and physiological states*. Often deemed as the

most salient of the four sources, mastery experiences occur when an individual experiences success on a given task (Miele et al., 2024; Usher & Pajares, 2008). When an individual sees another individual who are like them successfully accomplish a task, they are having a vicarious experience (Miele et al., 2024; Usher & Pajares, 2008). Social persuasion occurs when an individual receives encouragement on a given task, where emotional and psychological states are the affective triggers that inform the given task (e.g., frustration; Miele et al., 2024; Usher & Pajares, 2008). Taken together, a student's experience on a fraction exam may be dependent on their previous performance (i.e., mastery experiences), observations of peers' mastery of fractions (i.e., vicarious experiences), praise from their teacher (i.e., social persuasion), and/or their feelings about fractions or mathematics in general (i.e., emotional and physiological state). Lastly, self-efficacy is a domain-specific variable (Grether et al., 2018), therefore, in this study I was specifically interested in understanding teachers' self-efficacy for mathematics instruction.

Teachers' Self-Efficacy. *Teachers' self-efficacy*, or an educator's beliefs in their capabilities to provide students with effective instruction (Zee & Koomen, 2016), is salient for both teachers and students. Highly efficacious teachers experience a host of positive outcomes like increased abilities to (a) better differentiate instruction, (b) employ effective classroom management strategies, and (c) motivate their students (Lazarides & Warner, 2020; Skaalvik & Skaalvik, 2007; Zee & Koomen, 2016). In addition, teachers who are confident in their instructional abilities are often linked to classrooms with high levels of student achievement (Lazarides & Warner, 2020). Therefore, when teachers are efficacious it improves their overall instruction and students' achievement experiences; however, when teachers are inefficacious, it can result in damaging outcomes. For instance, inefficacious teachers are more likely to

experience job dissatisfaction and burnout (Lazarides & Warner, 2020; Skaalvik & Skaalvik, 2007, 2010; Zee & Koomen, 2016).

Research additionally suggests that teacher self-efficacy fluctuates over the course of a teacher's career and may be particularly low for early-career teachers (Zee & Koomen, 2016). Several studies indicate that pre-service teachers' self-efficacy increases over the course of their teaching preparation programs; however, it drops in a dramatic manner once they enter the profession (Lazarides & Warner, 2020; Woolfolk Hoy & Spero, 2005; Zee & Koomen, 2016). Then, these beliefs seem to increase and eventually stabilize as teachers gain experience – though some studies report an additional drop in teacher self-efficacy mid-career (Klassen & Chiu, 2010; Wolters & Daughtrey, 2007).

Teachers' Self-Efficacy Beliefs for Mathematics Instruction. Research also establishes that some teachers, particularly those who teach elementary grade levels (Drake et al., 2025), are generally less efficacious for mathematics instruction (Althauser, 2018; Bjerke & Xenofontos, 2024; Chang, 2015). Less mathematics instructional efficacy is concerning given evidence of a positive relationship between teacher self-efficacy for mathematics instruction and an array of teacher and student specific outcomes. For instance, when teachers are found to have a high teacher self-efficacy for mathematics, they are more likely to also have improved instructional quality and job satisfaction (Cross Francis, 2024; Holzberger et al., 2013, 2014; Perea & John, 2020). Furthermore, high levels of teacher self-efficacy among mathematics domains are also related to students' mathematics (a) self-efficacy beliefs and (b) achievement outcomes (Chang, 2015; Perea & John, 2020). Thus, lower teacher self-efficacy for mathematics instruction may result in less quality instruction and job dissatisfaction among teachers and ultimately lower student self-efficacy and achievement in the domain.

Extant research also suggests that mathematics teacher self-efficacy develops over time (Berg et al., 2025; Bjerke & Xenofotos, 2024). That is, the more experience a teacher gains in teaching mathematics, the more confident they are in their mathematics instruction. These findings speak to the importance of mastery experiences for teachers in mathematics. Along similar lines, one study suggested teachers who specialize in mathematics (e.g., in their teacher preparation training), and thus had higher qualification in the subject, were also more confident in their abilities to effectively teach mathematics. Mathematics specialization predicting mathematics teaching self-efficacy is likely to be problematic given the current state of the teaching profession: there are currently (a) considerably fewer pre-service teachers specializing in mathematics compared to other subject domains, (b) pre-service teachers often report not receiving enough mathematics-focused instruction in their preparation programs, and (c) many teachers are receiving emergency certifications and thus receiving little to no mathematics content level and practical level instruction (Drake et al., 2025; Partelow, 2019).

Despite the demonstrated importance of teacher self-efficacy in mathematics, little research has worked to understand how teachers' cognitive load may influence their efficacy beliefs. Nevertheless, understanding the extant literature on the relationship between the two constructs may provide novel information about the influences cognitive load may have on teachers' self-efficacy beliefs and vice versa. Therefore, a central goal of the present study was to better understand the interplay between teachers' cognitive load and their self-efficacy experiences.

Situated Expectancy-Value Theory

In addition to SCT, SEVT grounded this study. SEVT is a framework that suggests (a) individuals' *expectancies for success* and (b) *task values* are primary influencers of their

motivation (Eccles & Wigfield, 2002; 2020). Expectancies for success are similar to the construct of self-efficacy (discussed in more detail in the following sections), as they can be defined as an individual's performance expectations on a task (Eccles & Wigfield, 2020; Miele et al., 2024). For instance, an individual's confidence in their ability to do well on their upcoming fraction exam demonstrates an example of expectancies for success. On the other hand, task values include the level of desirability an individual has for a task (Miele et al., 2024). To demonstrate, a student engaging in a fraction assignment because they believe it will be helpful for their future fraction exam is just one task value example. Importantly, there are four dimensions of task values: *intrinsic value* (i.e., the level of task enjoyment), *attainment value* (i.e., the personal importance an individual places on a task), *utility value* (i.e., the usefulness of a task for the future), and *perceived cost* (i.e., an individual's awareness of the negative consequences that engaging in a task may produce; Beymer et al., 2022a; Eccles & Wigfield, 2002, 2020; Miele et al., 2024).

Importantly, recent advancements have been made to SEVT. For instance, in 2020, Eccles & Wigfield added the term "situated" to the theory, which had been formally referred to as EVT. Scholars now more explicitly acknowledge that an individual's motivational beliefs are shaped by social identity and context-specific factors. For instance, an individual's culture, gender, and personal beliefs influence their expectancies for success and overall task values (Eccles & Wigfield, 2020). Thus, one benefit to the adoption of an SEVT approach is that it allowed me to position teachers' experiences as highly dependent on an array of contextual factors and experiences.

Cost Perceptions. As aforementioned, cost perceptions are a sub dimension of task values. However, extant SEVT research has largely overlooked cost perceptions until recently.

As of late, research guided by SEVT has begun to more closely examine cost perceptions and realize the construct as highly influential to as an individual's motivational experiences (e.g., Flake et al., 2015). Cost perceptions are broken down into four types: (1) *effort cost* (i.e., the amount of effort required of an individual to complete a task), (2) *loss of valued alternatives cost* (i.e., when an individual gives up an alternative, more valued task in order to engage with the task at hand), (3) *emotional cost* (i.e., the adverse emotional states that engagement in a task elicits), and (4) *outside effort cost* (i.e., the other tasks required of an individual that make it difficult to put effort into the task at hand; Beymer et al., 2022a; Eccles & Wigfield, 2020; Flake et al., 2015). To demonstrate, studying for a fraction exam may be more or less costly for a student depending on the (a) amount of effort studying for the exam will require (i.e., effort cost), (b) other tasks a student could accomplish instead of studying (i.e., loss of valued alternatives cost), (c) level of frustration studying fractions elicits (i.e., emotional cost), and (d) number of other tasks also needing to be accomplished (i.e., outside effort cost).

Teachers' Cost Perceptions. *Teachers' cost perceptions* are defined as what a teacher feels they must abandon to engage in teaching-related tasks (Beymer et al., 2022a). There is an especially limited literature on teachers' cost perceptions. In fact, in a search of the literature (i.e., via ERIC and PsycInfo), I only located two articles that explicitly addressed cost perceptions among teachers (i.e., Bergey & Ranellucci, 2025; Beymer et al., 2022a).

In a mixed-methods study, Beymer et al. (2022a) found that all four domains of teachers' cost perceptions were associated with several self-reported teaching challenges. To demonstrate, high teacher workload was associated with the perception that teaching was too demanding and required too much effort (i.e., task effort cost). Workloads in addition to time challenges were mapped onto teachers' perceptions of what they sacrifice to teach (i.e., loss of valued alternatives

cost). Student discipline, grading, and paperwork challenges were associated with perceptions of high demands unrelated to instruction itself (i.e., high outside effort cost). Finally, teachers reported that they struggle to motivate students with unsupportive home lives which were associated with perceptions that teaching prompted negative emotional outcomes (i.e., emotional cost). Beymer et al. (2022a) additionally discovered that teachers' perceptions of cost were associated with lowered job satisfaction and attrition intentions.

Another study indicates that cost perceptions may operate differently among early-career teachers (Bergey & Ranellucci, 2025). Years spent pre-service teaching were associated with increased perceptions of the teaching profession as demanding. Further, pre-service teachers with lead student teaching experiences reported higher perceived teaching cost when compared with pre-service teachers without lead student-teaching experience (Bergey and Ranellucci, 2025). Like Beymer et al. (2022a), pre-service teachers with lead student-teaching experiences perceptions of high teaching cost were associated with lower career choice satisfaction and planned persistence.

Teachers' Cost Perceptions for Mathematics Instruction. Less research exists pertaining to teaching cost perceptions for teaching the subject of mathematics. Several studies, however, have investigated students' perceptions of cost related to the mathematics subject, which may prove to be relevant to the context of teachers. For example, one study found that students held high perceptions of cost for mathematics, yet perceived achievement in and utility of the subject as important (Gaspard et al., 2017). While empirical testing is needed, it is possible that like students, some teachers may find teaching mathematics costly regardless of the subject's salience. The idea that some teachers could perceive mathematics instruction as costly is supported by research that found mathematics anxiety and cost perceptions were positively

related (St. Omer & Chen, 2023). That is, when students were more anxious when it came to the subject of mathematics, they were more likely to view engagement with mathematics as costly. It is possible that teachers could also hold high cost perceptions for mathematics as research suggests a long-term relationship between mathematics anxiety and cost perceptions (St. Omer & Chen, 2023). Moreover, given the relation between anxiety and cost, it may be especially salient to explore teachers' perception of emotional cost in mathematics.

The limited literature on teachers' cost perceptions suggests that (a) teachers' perceptions of cost may be related to certain teaching-related classroom challenges, (b) pre- and in-service teachers have differing perceptions of cost, and (c) teaching cost perceptions are linked to job satisfaction and attrition intentions. However, little research has explicitly investigated how cognitive load may influence a teacher's cost perceptions. Given evidence that high levels of perceived teaching cost influence their attritional decisions, it is critical to better understand the relationship between cognitive load and cost perceptions among teachers. Taken together, then, an additional goal of this study was to unpack the relationship between teachers' cognitive load and cost perceptions.

Integrating SCT and SEVT

Given the (a) central overlap of and (b) recent and enduring calls in the motivation literature for theoretical integration (see Koenka & Wigfield, 2023), I integrated across SCT and SEVT in this study. The theories overlap in several ways. First, they both are situative and acknowledge the contextual underpinnings that impact how each theory functions. For instance, a teacher's social identity as well as the location of their school (i.e., rural, suburban, urban) each can centrally impact their motivational experiences across both theories (Eccles & Wigfield, 2020; Schunk & DiBenedetto, 2020). Second, there is overlap between SCT's self-efficacy and

SEVT's expectancies for success (see Anderman, 2020). Though, many scholars have argued that self-efficacy and expectancies for success are theoretically distinct (see Schunk & DiBenedetto, 2016; Wigfield & Eccles, 2000), empirical findings suggest there is "...almost complete overlap…" between the two (Eccles & Wigfield, 2020, p. 4). Thus, in my research program, I use the term self-efficacy to understand individuals' beliefs about their ability to succeed in a task and acknowledge its critical role throughout both the SCT and SEVT literatures.

Regardless of their overlap, SCT and SEVT each provide a unique lens to understand teachers' experiences and were thus necessary for me to draw from. SCT is critical for me to draw from in my work given the (a) emphasis on the interplay between personal, behavioral, and environmental factors an individual experiences and (b) significance of self-efficacy in the model. Teachers experience a host of reciprocal factors that are associated with their classroom experiences including their teaching self-efficacy, which influences and is influenced by their classroom context (e.g., school community, subject domain) and their classroom choices and teaching persistence (Schunk & DiBenedetto, 2020). SEVT, however, diverges from SCT when considering the task value component of the theory – and especially so for cost perceptions. Some research suggests that teachers experience each of the four dimensions of cost SEVT proposes (Beymer et al., 2022a); therefore, SEVT provides a framework to better understand how teachers experience cost throughout their profession. Therefore, to holistically understand teachers' motivational experiences in the classroom, I integrated SCT and SEVT throughout this study. In the following section, I describe how I further integrated across these motivation theories and CLT.

Integrating CLT, SCT, and SEVT

In addition to integrating across SCT and SEVT, I also integrated SCT and SEVT with CLT to comprehensively understand teachers' cognitive load and its motivational and attritional consequences. Some scholars have worked to understand the relationship between CLT and motivation theories (e.g., SEVT, self-determination theory; Evans et al., 2024; Feldon et al., 2019). In fact, recent studies have found explicit relationships between students' cognitive load and several motivation constructs (e.g., self-efficacy, cost, persistence; Evans et al., 2024; Feldon et al., 2019; Hawthorne et al., 2019). However, little research has conceptually or empirically worked to understand this overarching relationship and theoretical overlap among teachers. Therefore, guided by (a) CLT, SCT, and SEVT and (b) literature that has begun to investigate the interplay between the cognitive load and motivation literatures (see Evans et al., 2024; Feldon et al., 2018, 2019), I theorized that when teachers experience cognitive load, it would likely influence their (a) teaching self-efficacy beliefs and (b) teaching cost perceptions. In addition, the SCT model of triadic reciprocality, allowed me to theorize that a dynamic relationship between cognitive load and motivation could also influence teachers' behavioral decisions (e.g., attrition). In the following sections, I present a summary of the research gaps presented in this chapter.

Research Gaps

In this chapter, numerous literature gaps emerged that guided the objectives and research questions of this study. First, there is an overarching need to better understand cognitive load among teachers closer to their actual experiences. The minimal existing literature on teachers' cognitive load (see Table 1), paired with related literatures (i.e., see discussion about the workload, decision-making, and expertise literatures) suggest that teachers (a) do experience

high cognitive load and (b) are aware of it when it occurs (Hebert, 2018). Despite evidence from prior work indicating that teachers likely experience high cognitive load, much of the existing cognitive load literature among teachers (and in general) uses forms of measurement that require teachers to retroactively recall their experiences with cognitive load (e.g., retrospective survey instruments, qualitative interviews about their overarching or generalized cognitive load). Given that cognitive load can change moment-to-moment and considering issues of accuracy regarding retrospective forms of measurement when capturing higher-order processes (Dent & Koenka, 2016), there is a clear need to measure cognitive load in a manner that better captures its day-to-day fluctuations. Measuring cognitive load among teachers closer to their actual experiences of it, may be especially important for teachers given the unpredictable nature of the classroom environment. Therefore, in this study, I employed measurement techniques (i.e., daily diary surveys) to capture teachers' cognitive load experiences much closer to instruction.

Second, there is a need to investigate the cognitive load among *elementary grade level* teachers during *mathematics* instruction. Elementary grade level teachers often report feeling less satisfied with their occupations and likely have a higher amount of extraneous load due to classroom management disruptions (Schaeffer, 2024). However, the teacher cognitive load research has not yet directly centered the experiences of these teachers (see Table 1). Moreover, mathematics as a subject involves high element interactivity (i.e., intrinsic load; Chinnappan & Chandler, 2010); thus, making some teachers – particularly teachers who do not have expertise in the subject area – more susceptible to overload in the domain (Anderson & Tanner, 2023). In addition to the complexity of mathematics on its own, elementary teachers often hold a lower self-efficacy in the subject (Althauser, 2018; Bjerke & Xenofontos, 2024; Chang, 2015). Taken

together, despite the importance of cognitive load (a) among elementary grade level teachers and (b) in math, no research, to my knowledge, had yet addressed those experiences in tandem.

Third, there is a need to explore how years of teaching experience predict teachers' cognitive load. A central theme that emerged throughout this chapter was the importance of automaticity, prior knowledge, and schemata. In other words, the literature suggests that the longer teachers have been in the profession, the less they must consciously think through each instructional task and/or decision throughout their day – effectively making more space in their working memory and lowering cognitive load. Despite the likelihood that teachers earlier in their career may be experiencing exacerbated cognitive load, the current literature has yet to directly address the interactions between teachers' cognitive load and years of experience. Doing so is essential for developing tailored interventions and practices during and following teacher preparation programs to equip early-career educators with strategies for managing and minimizing their cognitive load.

Fourth, there is a need to better understand how teachers' cognitive load predicts their motivational beliefs. To my knowledge, no empirical literature exists that investigates teachers' cognitive load experiences, teachers' self-efficacy, and teaching cost perceptions. However, by integrating literatures, I argue there is ample evidence to hypothesize that this relationship may exist. Therefore, this study empirically investigated how these three constructs interact among the teacher population. Additionally, given the consistent connections to teacher burnout and attrition among each of these literatures, research should further investigate whether attrition intentions are related to teachers' cognitive load, teacher self-efficacy, and teaching cost perceptions.

Finally, the studies I reviewed did not consider how teachers with disabilities and/or who are racially and/or ethnically minoritized may experience teaching cognitive load, which is reflective of the educational psychology literature as a whole (see DeCuir-Gunby & Schutz, 2014; Kumar & DeCuir-Gunby, 2023). The findings from this chapter, paired with ample existing literature that underscores how context and identity-specific variables dynamically and inextricably shape individuals' motivational beliefs (Nolen, 2020). Therefore, my (a) hypothesized connection between cognitive load, motivational beliefs, and attrition intentions and (b) intentional inclusion of teachers who are minoritized, may be a crucial step in yielding insight on how to better support and retain teachers who are minorized. Moreover, given the current political climate, along with home-school dissonance (Kumar, 2006; Archer et al., 2022), it is possible that these extra, systematically inequitable barriers that many minorized teachers confront could add additional inputs they must cognitively navigate while teaching – thereby exacerbating their cognitive load. Taken together, it is necessary to further ascertain how teachers' cognitive load and its motivation and attritional outcomes operate specifically among teachers who are minoritized in the profession and during mathematics instruction. This study aimed to address this important gap. Taken together, the present study addressed the following research questions:

Research Questions

1. To what extent does teachers' daily cognitive load during mathematics instruction vary within and between teachers over a two-week period? (*Quantitative*)
    a. To what extent do years of teaching experience predict daily experiences with cognitive load? (*Quantitative*)

2. To what extent does the variation in teachers' daily cognitive load during mathematics instruction predict teachers' daily (a) self-efficacy, (b) cost perceptions, and (c) attrition intentions? (*Quantitative*)
3. How do teachers describe their daily experiences with cognitive load during mathematics instruction? (*Qualitative*)
    a. How do teachers with underrepresented identities within the teaching profession experience cognitive load? (*Qualitative*)
4. How do teachers' qualitative descriptions of their daily experiences with cognitive load during mathematics instruction, motivational beliefs, and attrition intentions map onto the experiences reported on the daily quantitative surveys? (*Mixed*)

Chapter 3: Research Methods

Overview of Chapter 2

In Chapter 2, I described the construct of cognitive load, followed by its historical account and associated theory: cognitive load theory (CLT). In this historical account, I described (a) each of the cognitive load subdimensions (i.e., extraneous, intrinsic, and germane loads), (b) the prominent ways of measuring cognitive load (i.e., task and performance based measures, physiological measures, and subjective rating scales) and the challenges associated with measuring cognitive load in these ways (e.g., accuracy of retrospective measurement), (c) how cognitive load has expanded across numerous domains and populations, and (d) the lack of cognitive load research existing among the teacher population. I then reviewed the extant literature that addresses teachers' cognitive load during instruction. Several themes emerged from the search of this literature: (a) teachers are conscious and aware when cognitive overload occurs, (b) extraneous load is especially prominent among teachers, (c) instructional automaticity may be key to reducing teachers' cognitive load, and (d) numerous outcomes emerge as a result of cognitive overload among teachers (e.g., negative affective states, lowered student achievement, suboptimal motivational beliefs). In addition to these themes, the literature review also revealed that teachers' cognitive load is prominently studied using qualitative techniques and is often not the central construct of study throughout the reviewed articles.

Following the review of teachers' cognitive load, I also highlighted two prominent theories of motivation: social cognitive theory (SCT) and situated expectancy-value theory (SEVT) as well as two relevant constructs central to each respective theory: self-efficacy and cost perceptions. I discussed the extant literature on the powerful associations between teachers' self-efficacy beliefs and student achievement and job satisfaction as well as teachers often

lowered self-efficacy beliefs for mathematics instruction compared to other subject domains. I also reviewed the teachers' cost perception literature, which revealed that little research has been explicitly conducted among teachers. Of the extant literature, findings suggest that teachers commonly perceive their workloads, student home lives, and classroom management challenges as costly. Lastly, I described how I integrated across (a) SCT, (b) SEVT, and (c) CLT to inform this study.

Finally, I presented a summary of research gaps that guided this study. These gaps include a need (a) to better understand teachers' cognitive load experiences during mathematics instruction broadly, (b) for more in-the-moment measurement of cognitive load, and (c) for a greater comprehension of how teachers' cognitive load interacts with their motivational beliefs, particularly their self-efficacy, cost perceptions, and attrition intentions.

In the following sections, I describe the research design I adopted for this study: an explanatory sequential mixed methods design. Then, I specify the guiding objectives of the study and the research questions. Next, I describe the participants of the study and the procedures I adopted to recruit them. I then detail the procedures I adopted to carry out the study as well as provide a description of the instruments and protocol I used to collect data. Finally, I describe the data analytic procedures I adopted to analyze the data.

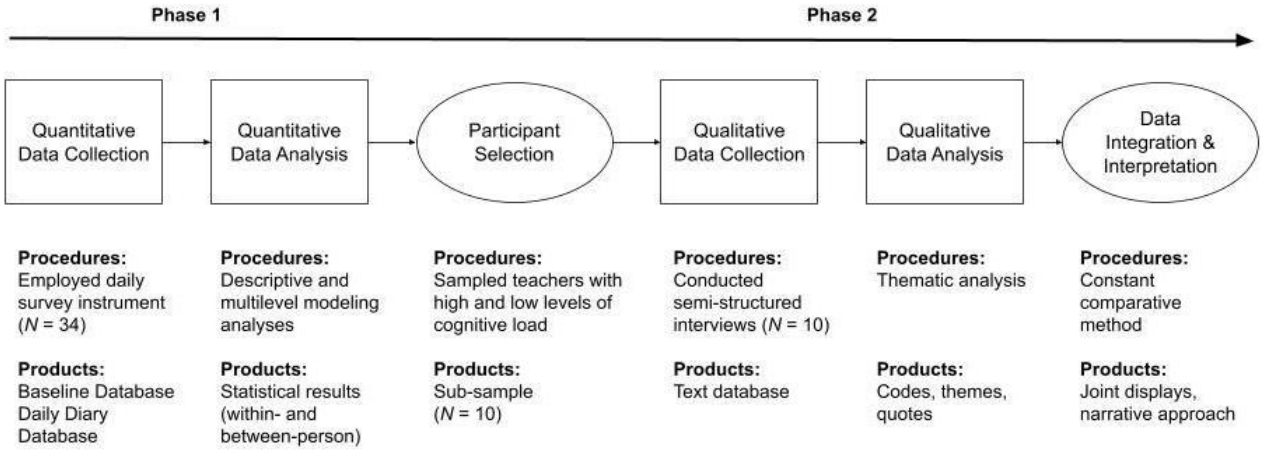
Mixed Methods Research Design and Rationale

To investigate the guiding research questions of this study, I employed a *mixed methods* design (i.e., the use of both quantitative and qualitative data because their combined strengths "...will accomplish more than would have been possible with one method alone"; Morgan, 2014, p. xiii). In particular, I adopted an *explanatory sequential mixed methods* research design (i.e., QUAN → qual; see Figure 1) which is a "two-phase research design where quantitative data are

collected initially and is used to identify the qualitative data to be collected" (DeCuir-Gunby & Schutz, 2017, p. 87; Plano Clark & Ivankova, 2016). Therefore, the study occurred in two phases: during Phase 1, quantitative data was collected and then analyzed; then, the quantitative results informed the participants chosen to be interviewed for the second, qualitative phase (i.e., Phase 2) of the study. Following data collection and analysis for both Phase 1 and Phase 2, I integrated the findings and relayed informed implications of them (DeCuir-Gunby & Schutz, 2017; Plano Clark & Ivankova, 2016).

Figure 1

Explanatory Sequential Mixed Methods Design



There are several reasons why a mixed methods research design was appropriate for this study. First, the quantitative data will provide insight into numeric fluctuations of teachers' cognitive load both within and between mathematics instructional experiences. My quantitative approach also provided insight into potential outcomes of these cognitive load experiences (i.e., teaching self-efficacy, teaching cost perceptions, and attrition intentions). Additionally, a quantitative approach allowed me to draw statistical inferences, and therefore, draw conclusions that could be generalized to other populations of teachers (Hahs-Vaughn & Lomax, 2020). The qualitative data, on the other hand, illuminated new information across a group of teachers by

providing more in-depth detail about teachers' context-specific and personalized accounts of these experiences. Further, educational research has historically ignored and/or failed to incorporate the voices of practicing teachers and particularly teachers with minoritized identities (DeCuir-Gunby & Schutz, 2014; Gillett-Swan & Baroutsis, 2024). Thus, including qualitative data provided necessary and detailed descriptions of teachers' cognitive load experiences, articulated in their own voices. Therefore, combining quantitative and qualitative methods allowed me to offset some of the limitations inherent to each method, and instead, leverage the strengths of each (Plano Clark & Ivankova, 2016).

Second, a mixed methods approaches allowed me to *triangulate* the data. That is, a mixed methods design allowed for the direct comparison of "...results obtained from quantitative methods to those obtained from qualitative methods for convergence and divergence;" Plano Clark and Ivankova, 2016, p. 84). This kind of integration was particularly needed among the quantitative measures and qualitative cognitive load responses given the difficulty associated with measuring cognitive load (see Chapter 2; Paas et al., 2003b). In other words, the qualitative responses from participants captured insights that contextualized the quantitative findings that would not have otherwise emerged and vice versa. Moreover, by comparing and integrating the quantitative and qualitative results, I was able to determine *convergence* (i.e., when quantitative and qualitative results are in agreement; Plano Clark & Ivankova, 2016) or *divergence* (i.e., when discrepancies emerge from quantitative and qualitative results; Plano Clark & Ivankova, 2016) and increase the overall trustworthiness of the findings. If convergence of quantitative and qualitative data was present, I could be more confident in the reliability and validity of the results (Plano Clark & Ivankova, 2016). If divergence of the data was present, I was able to more explicitly identify next steps for further research (Plano Clark & Ivankova, 2016). Relatedly, meaningful conceptual and methodological insight emerged from divergence.

Lastly, given the lack of research associated with the variables of focus in this study, collecting and analyzing quantitative data first better informed the (a) participants I chose to interview and (b) the interview protocol. Taken together, the use of an explanatory sequential mixed methods research design allowed me to (a) develop a holistic and contextualized understanding of teachers' cognitive load during mathematics instruction and its outcomes and (b) develop additional trustworthiness (discussed in detail below) of my findings.

Objectives, Research Questions, and Hypotheses

In consideration of the literature gaps described in Chapter 2, in this study I aimed to understand teachers' cognitive load experiences during mathematics instruction and its relationship to teachers' (a) self-efficacy beliefs, (b) cost perceptions, and (c) attrition intentions. I addressed the following research questions:

1. To what extent does teachers' daily cognitive load during mathematics instruction vary within and between teachers over a two-week period? (*Quantitative*)
    a. To what extent do years of teaching experience predict daily experiences with cognitive load? (*Quantitative*)
2. To what extent does the variation in teachers' daily cognitive load during mathematics instruction predict teachers' daily (a) self-efficacy, (b) cost perceptions, and (c) attrition intentions? (*Quantitative*)
3. How do teachers describe their daily experiences with cognitive load during mathematics instruction? (*Qualitative*)
    a. How do teachers with underrepresented identities within the teaching profession experience cognitive load? (*Qualitative*)

4. How do teachers' qualitative descriptions of their daily experiences with cognitive load during mathematics instruction, motivational beliefs, and attrition intentions map onto the experiences reported on the daily quantitative surveys? (*Mixed*)

Hypothesis 1

Based on the existing literature, I hypothesized that teachers would experience (a) moderate to high cognitive load across all three dimensions (i.e., intrinsic, extraneous, and germane load) and (b) especially high daily fluctuations in their cognitive load (i.e., greater cognitive load fluctuations at the within-person level compared to the between-person level). Moreover, I hypothesized that extraneous load would be especially heightened among teachers. There are several reasons for this hypothesis. First, the well-documented teacher workload literature suggests teachers juggle a great deal of tasks, especially from the classroom environment, during instruction (see Higton et al., 2017). From actively instructing, answering student questions, to managing technology, teachers are expected to constantly multitask (Brante, 2009). Along similar lines, the teacher decision-making literature points to the large number of decisions teachers must make during instruction which were found to result in a high teacher cognitive load on days when more decisions were required of teachers (Eggleston, 2018; Moos & Pitton, 2014). Together, teachers juggle many informational inputs which may be exacerbated for some during mathematics instruction. For example, research points to the high element interactivity of the math domain (Chinnappan & Chandler, 2010), increasing the complexity of that math instruction, potentially resulting in a heightened intrinsic load.

Hypothesis 1a

I also hypothesized that early-career teachers (i.e., teachers within their first five years of instruction; Rowe et al., 2025) may be especially vulnerable to experiences of cognitive load

(i.e., experience moderate to high cognitive load) given the lack of automatic teaching strategies at their disposal (i.e., minimal automaticity; Feldon, 2007; Moos & Pitton, 2014). That is, early-career teachers may have to more actively and intentionally think about certain teaching decisions while engaging in instruction (e.g., which classroom management strategies to employ during a given moment; how to use classroom technology; Hebert, 2018). My hypothesis is aligned with the teacher expertise literature. For example, Anderson & Tanner (2023) found in a meta summary that expert teachers, who had more schemas for teaching, were able to unconsciously respond to certain classroom events. In other words, these teachers were more automatic in their teaching practices and responses, freeing up space in their working memory. Therefore, given the automaticity and expertise literature, I hypothesized that early career teachers would experience moderate to high cognitive load compared to their later-career counterparts.

Hypothesis 2

I hypothesized that there would be a negative relation between all three dimensions of teachers' cognitive load (i.e., intrinsic, extraneous, and germane loads) and their teaching self-efficacy beliefs in math. That is, when teachers experienced a high cognitive load during math instruction, I hypothesized they would experience a decrease in their self-efficacy beliefs for math teaching. This hypothesis was aligned with research that suggests there is an existing predictive relationship between cognitive load and self-efficacy among students (see Feldon et al., 2018, 2024). In addition, I hypothesized that there would be a positive relation between all three dimensions of teachers' cognitive load during math instruction and their (a) teaching cost perceptions in math and (b) attrition intentions. In other words, when teachers experience a high cognitive load, they would likely experience higher perceptions of cost for math teaching and

heightened attrition intentions. While there was no empirical evidence to confirm the relationship between cognitive load and cost perceptions, extant conceptual research suggests that one dimension of cognitive load (i.e., extraneous load) should be conceptualized as its own dimension of cost (see Feldon et al., 2019).

Moreover, I expected that one dimension of cost in particular, emotional cost, would be more strongly related to teachers' cognitive load during math instruction The hypothesized strong relation between cognitive load during math instruction and emotional cost for math was aligned with extant cognitive load literature that points to affect as an outcome of cognitive load (e.g., frustration; Blackley et al., 2021) and salience of emotional cost among teachers (Beymer et al., 2022a). Therefore, I suspected that when teachers experience heightened levels of cognitive load during math instruction, they would also experience heightened levels of emotional cost for math teaching. Additionally, there is research suggesting teachers' cognitive load may be related to burnout experiences (i.e., Hebert, 2018). Therefore, given the close relation between burnout and teacher attrition (Madigan & Kim, 2021), I hypothesized cognitive load may increase the likelihood that teachers decide to leave the profession.

Finally, given the (a) qualitative and exploratory nature of Research Question 3 and (b) my goal to center teachers' voices and experiences in the classroom as opposed to my own, it was inappropriate for me to draw inferences. Refraining from drawing hypotheses for these questions are appropriate and recommended based on the foundations of qualitative research. That is, the goal of qualitative research is to allow findings to emerge rather than impose what I perceived to be relevant (Meinefeld, 2004). In a similar manner, it was inappropriate for me to draw inferences for Research Question 4 given the mixing of qualitative findings.

Positionality

My prior experiences as a pre-and in-service elementary teacher have inspired my line of research, including the present study. I often recall teaching my lessons as a novice teacher and being considerably overwhelmed by the seemingly never-ending happenings around me. As a result, I have become committed to fostering more supportive, realistic instructional experiences for educators. I identify as a white, cisgender woman with a learning disability. Therefore, I interpret this research through a lens in which different aspects of my identity are both (a) overrepresented as a white woman and (b) underrepresented due to my learning disability in the teaching workforce (NCES, 2023). Throughout this study, and my research program overall, I strongly believe in and acknowledge the importance of asset-based approaches to center and amplify the voices of teachers who have been historically underrepresented and understudied. Taken together, my (a) own identity, personal, and professional experiences, (b) commitment to conducting equitable and inclusive research, and (c) dedication to fostering actionable practical research implications each informed how I approached the present study.

Participants and Sampling

Phase 1: Participants and Sampling

Phase 1 Participants. Participants were $N = 34$ teachers recruited from three public elementary schools (i.e., grades pre-school to fifth grade) located in a suburban district in the south-central region of the United States via *convenience sampling* (i.e., a type of nonprobability sampling that "seeks access respondents with characteristics of interest from easily located groups among a population"; Kelly, 2010, p. 317). Of the teachers in the sample, 91.2% self-identified as cisgender women and 8.8% identified as cisgender men. Additionally, 82.4% of teachers identified as white, 8.8% identified as Multiracial, and 8.8% did not report their race

and/or ethnicity. All teachers who completed the demographics survey identified as heterosexual (85.3%), and 8.8% did not report their sexual orientation. Finally, 8.8% of the teachers identified as having a disability, 79.4% reported they did not have a disability, and 8.8% did not report their disability status. Table 2 presents a full breakdown of teachers' self-reported social-identity characteristics.

Table 2

Phase 1 Sample Demographics

Characteristic	Quantitative Phase 1		Qualitative Phase 2	
	n	%	*n*	%
Gender Identity				
Cisgender Woman	31	91.2	9	90
Cisgender Man	3	8.8	1	10
Sexual Orientation				
Heterosexual	29	85.3	10	100
Race/Ethnic Identity				
Multiracial: Black & white	3	8.8	1	10
white	28	82.4	9	10
Disability Status				
ADHD	2	5.9	1	10
Dyslexia	1	2.9	0	0
No disability	27	79.4	9	10

Note. Not all categories add up to 100% because some participants did not fully complete the demographics questionnaire or responded, "Prefer not to say."

In addition to social identity characteristics, teachers also self-reported relevant teaching characteristics. In particular, out of the three schools from which teachers were recruited, 29.4% taught at School A, 38.2% taught at School B, and 32.4% taught at School C. Additionally, 2.9% of the teachers taught pre-school, 11.8% taught kindergarten, 17.6% taught first grade, 8.8% taught second grade, 11.8% taught third grade, 14.7% taught fourth grade, 17.6% taught fifth

grade, 8.8% taught special education, and 5.9% taught gifted and talented programs. Finally, 32.4% of the teachers sampled were in their first five years of their teaching career, 17.6% had six to 10 years of teaching experience, and the remainder of teachers (i.e., 44.1%) had 16 or more years of teaching experience. Table 3 presents a more detailed breakdown of the participants' teaching characteristics.

Table 3

Sample Teaching Characteristics

Characteristic	Quantitative Phase 1		Qualitative Phase 2	
	n	%	*n*	%
School Site				
School A	10	29.4	5	50
School B	13	38.2	3	30
School C	11	32.4	2	20
Grade Level				
Pre-K	1	2.9	1	10
Kindergarten	4	11.8	2	20
First	6	17.6	1	10
Second	3	8.8	2	20
Third	4	11.8	1	10
Fourth	5	14.7	0	0
Fifth	6	17.6	1	10
Special Education	3	8.8	1	10
Gifted and Talented	2	5.9	1	10
Years of Experience				
Year 1-5	11	32.4	3	30
Year 6-10	6	17.6	2	20
Year 11-15	3	8.8	0	0
Year 16-20	3	8.8	1	10
Year 21-25	3	8.8	2	20
Year 26-30	3	8.8	1	10

Characteristic	Quantitative Phase 1		Qualitative Phase 2	
	n	%	*n*	%
Year 30-35	3	8.8	1	10
Years of Grade Level Experience				
Year 1-5	18	52.9	5	50
Year 6-10	5	14.7	4	40
Year 11-15	2	5.9	0	0
Year 16-20	2	5.9	0	0
Year 21-25	1	2.9	0	0
Year 26-30	3	8.8	1	10
Teacher Preparation				
Traditional preparation program	29	85.3	8	80
Accelerated preparation program	1	2.9	1	10
Emergency Certified	1	2.9	1	10

Note. Not all categories add up to 100% because some participants did not fully complete the demographics questionnaire or responded, "Prefer not to say."

Phase 1 Recruitment Procedures. First, in January 2025, my advisor and I began to establish relationships and eventually research-practice partnerships with each of the principals at the three school sites. Then, the following recruitment procedures took place at each school site, which were determined by the preferences of each principal. In total, I attempted to recruit 65 teachers, 34 of whom agreed to participate, resulting in a response rate of 52.3%. Each participating teacher received a $30 gift card as incentive.

School A. In August 2025, I attended a professional development meeting at School A to introduce the research study. Then, in October 2025, I sent a recruitment email (see Appendix B) and flyer (see Appendix C) that contained information about the study and directed them to an online consent form (see Appendix D) via Qualtrics. At School A, 10 out of 17 eligible teachers enrolled in the study, which resulted in a response rate of 58.8%.

School B. In November 2025, I attended a staff meeting at School B, which allowed me to engage in in-person recruitment. To do so, I presented the study to the teachers at the staff meeting. At the end of the presentation teachers were able to access the online consent form (see Appendix D) in three ways: (1) via a QR code or Qualtrics link posted on the final slide of the presentation; (2) via an infographic flyer that was passed out at the beginning of the recruitment presentation (see Appendix C); or (3) via a recruitment email (see Appendix B) that I sent to all eligible teachers the day after I attended the staff meeting. At School B, 13 out of 28 eligible teachers enrolled in the study, which resulted in a response rate of 46.4%.

School C. In December 2025, I attended a staff meeting at School C, which allowed me to engage in in-person recruitment. To do so, I presented the study to the teachers at the staff meeting. At the end of the presentation teachers were able to access the online consent form (see Appendix D) in three ways: (1) via a QR code or Qualtrics link posted on the final slide of the presentation; (2) via an infographic flyer that was distributed at the beginning of the recruitment presentation (see Appendix C); or (3) via a recruitment email (see Appendix B) that I sent to all eligible teachers the day after I attended the staff meeting. At School C, 13 out of 20 eligible teachers initially enrolled in the study; however, one teacher dropped out of the study due to personal reasons after completing the baseline survey. Therefore, 12 out of 20 eligible teachers enrolled to participate in the study, which resulted in a response rate of 60%.

Phase 2: Participants and Sampling

Identification of Phase 2 Participants. To identify participants for the second, qualitative phase of the study, I adopted several steps. First, I calculated means across the sample of teachers to determine those of whom had (a) high or low levels of cognitive load relative to the rest of the sample and/or (b) interesting combinations of average cognitive load and other

variables (i.e., self-efficacy, cost perceptions, attrition intentions). Second, after calculating means across participants, I then located the two highest and two lowest means at each school site for each variable and documented them in a table (see Appendices E, F, G). The table allowed me to better visualize which participants had high/low cognitive load as well as interesting combinations of high/low self-efficacy, cost perceptions, and attrition intentions. Third, given Research Question 3a, which aims to understand the cognitive load experiences of teachers who are underrepresented in the profession, I also considered the social-identity characteristics of teachers when making final decisions on participants to recruit. In particular, I considered social identities that are underrepresented throughout the teaching occupation (i.e., teachers of color, teachers with disabilities, teachers who identify as LGBTQ+, and male teachers; NCES, 2023). In total, I selected 21 teachers to recruit from the larger, Phase 1 sample. Out of the 21 teachers recruited, 10 opted to participate in an interview. Therefore, while teachers with the highest and lowest levels of cognitive load were recruited, not all teachers who participated in interviews represent the absolute extreme cases of high or low cognitive load (see "Limitations" section for a more detailed discussion).

Phase 2 Participants. Participants were $N = 10$ teachers recruited from the larger, Phase 1 sample (recruitment procedures discussed in detail below) via *purposeful sampling* (i.e., a type of non-probability sampling "...used to select respondents that are most likely to yield appropriate and useful information"; Kelly, 2010, p. 317). Of the teachers selected for interviews, nine self-identified as cisgender women and one identified as a cisgender man. Additionally, nine of the teachers identified as white, and one identified as Multiracial (i.e., Black and white). All 10 teachers interviewed identified as heterosexual. Finally, one teacher reported having ADHD while the remaining nine teachers reported that they did not have a

disability. Table 4 presents a full breakdown of Phase 2 teachers' self-reported social-identity characteristics.

Table 4

Phase 2 Sample Characteristics

Pseudonym	School Site	Grade Level	Teaching Exp	Grade Level Exp	Gender ID	Race/ Ethnic ID	Disability Status
Ms. Baker	B	Pre-K	30 years	10 years	Cisgender Woman	white	None
Ms. Collins	A	Kindergarten	22 years	9 years	Cisgender Woman	white	None
Ms. Klein	A	Kindergarten	2 years	2 years	Cisgender Woman	white	None
Ms. Myers	A	1st	7 years	2 years	Cisgender Woman	white	None
Ms. Hall	A	2nd	3 years	3 years	Cisgender Woman	white	ADHD
Ms. Lee	C	2nd	31 years	29 years	Cisgender Woman	white	None
Ms. Keller	B	3rd	3 years	3 years	Cisgender Woman	white	None
Ms. Scott	A	5th	22 years	9 years	Cisgender Woman	white	None
Mr. Clark	B	Upper Elementary	18 years	7 years	Cisgender Man	white	None
Ms. Thomas	C	Upper Elementary	10 years	5 years	Cisgender Woman	Multiracial: Black & white	None

In terms of teaching characteristics (see Table 3), five of the interviewed teachers taught at School A, three taught at School B, and two taught at School C. Additionally, one of the teachers taught pre-school, two taught kindergarten, one taught first grade, two taught second grade, one taught third grade, one taught fifth grade, and two taught upper elementary grades. Finally, three of the teachers interviewed were in their first five years of their teaching career,

two had six to 10 years of teaching experience, and the remaining five had 16 or more years of teaching experience. Table 4 presents each teachers' demographics and teaching characteristics broken down by individual teacher.

Phase 2 Recruitment Procedures. In January 2026, I sent an interview recruitment email (see Appendix H) to the first wave of teachers. I recruited 13 teachers of whom six teachers signed up to participate. However, one teacher cancelled their interview, and therefore, a total of five teachers completed an interview after the first wave of recruitment. Because I aimed to maximize the thoroughness and rigor of the qualitative phase of this study by increasing my sample size, I reached out to a second wave of teachers in February 2026. During the second wave, I recruited an additional eight teachers to maximize the likelihood of a larger sample size, of whom five teachers signed up to participate. Taken together, 10 out of 21 teachers recruited participated in an interview, for a response rate of 47.6%.

Recruitment procedures for Phase 2 of the study were the same across all three school sites. Teachers were contacted via an interview recruitment email (see Appendix H) and were sent to each teacher a maximum of three times. In the email, teachers were able to read about the interview phase of the study and access a Calendly link to schedule their interview. I then followed up with each teacher via email who signed up, (a) confirming their interview date and time, (b) confirming their interview location (i.e., in-person at their school site or online via Zoom, whichever they preferred), and (c) with a consent form (see Appendix I) that they completed via Qualtrics. Each teacher who participated in an interview received a second $30 gift card as incentive.

Research Procedures

As aforementioned, the present study adopted an explanatory sequential mixed methods research design (QUAN → qual). Prior to engaging in the study, I received approval from the Institutional Review Board (IRB) at my institution as well as the review board at the district level for the elementary schools I am partnered with. Appendices J and K present each of the respective IRB approval letters. After receiving IRB approval, I engaged in the following research procedures.

Phase 1: Procedures

After engaging in the Phase 1 recruitment procedures described above (see "Participants and Sampling" section), during Fall 2025, I obtained consent from all teachers who chose to participate in the study via Qualtrics (see Appendix D). If participants were not 18 years of age or older and/or did not consent to participate, they were immediately directed to the end of the Qualtrics survey and were not included in the study. If participants did consent to participate in the study and were 18 years of age or older, they were then directed to a baseline survey (see Appendix L), which was followed by a demographic's questionnaire (see Appendix M). The baseline survey allowed me to gather data on teachers' general experiences of cognitive load, self-efficacy, cost perceptions, and attrition intentions during math instruction. The demographics questionnaire not only allowed me to collect key information regarding teachers' social-identity and teaching characteristics, but it allowed me to collect each teachers' math instructional start and end times – which were key for sending the daily diary surveys out to teachers each day.

After the consent form, baseline survey, and demographics survey were each completed, I began collecting daily diary data. To do so, I engaged in the following procedures. Because I sent each participant their daily survey at different items depending on when they completed

their math instruction each day, I first created a spreadsheet to organize this information and to keep track of survey distribution and participant daily completion. Appendix N presents an example of this spreadsheet. I then proceeded with daily diary data collection.

Daily surveys that assessed teachers' cognitive load, self-efficacy, cost perceptions, and attrition intentions were sent to teachers once a day for 10 consecutive school days (i.e., Monday through Friday; see Appendix O). One data point each day over the course of 10 days was deemed appropriate based on (a) extant recommendations in the literature (see Bolger & Laurenceau, 2013), (b) recommendations and preferences from my school partners, and (c) the importance of balancing data collected as close as possible to the math event and the necessity of reducing as many instructional interruptions as possible. Specifically, excessive instructional interruptions risked burdening teachers further and could even exacerbate cognitive load – which was antithetical to the goals of the study.

To further reduce the number of interruptions and to ensure I did not interfere with classroom instruction, I emailed teachers their daily surveys at *fixed time points* (i.e., measurement that occurs at previously specified time points; Zirkel et al., 2015). That is, I emailed teachers their daily survey each day immediately following their math instruction. Appendix P presents the daily survey email. In the event that a teacher did not complete their daily survey by the end of the school day (i.e., approximately 3:00 pm), I sent them one additional reminder email. Appendix Q presents the daily reminder email. Measuring these processes immediately following math instruction or at the end of the school day did not capture teachers' experiences at the exact moment that they occur during math instruction. However, it is likely to be more accurate than the traditional self-report and retrospective forms of cognitive load measurement that is prominent (Jiang & Kalyuga, 2020) given the close proximity to the

instructional event. Finally, at the end of the 10 days of data collection, all participants were given a $30 gift card.

Data Cleaning. After collecting the quantitative data and in order to begin data analysis that would inform the participants selected for Phase 2, I cleaned my data. Both the baseline (which included the demographics data) and daily diary data sets were exported from Qualtrics to Microsoft Excel spreadsheets. The baseline data and daily diary data sets were cleaned separately in IBM SPSS Statistics (Version 31), then merged once they were finalized.

Baseline Data Cleaning. After de-identifying the baseline data and assigning identification numbers to each teacher, I uploaded it to SPSS. Next, I reverse scored three out of the seven self-efficacy items. Finally, I computed scale scores for each scale (i.e., baseline extraneous load, baseline intrinsic load, baseline germane load, baseline self-efficacy). Because each of the dimensions of cost perceptions (i.e., task effort cost, outside effort cost, emotional cost, and loss of valued alternatives cost) as well as attrition intentions were each only one item, I did not need to compute a scale score for them.

Daily Diary Data Cleaning. After de-identifying the data and assigning the same identification number to each teacher as was given to them during the cleaning of the baseline data, I uploaded the daily diary data set to SPSS. As is the case with most longitudinal data sets, it was necessary to ensure the data were in long format (i.e., data are organized at the response level rather than the more common person level; Bolger & Laurenceau, 2013; Hektner et al., 2007). Conveniently, the data were in long format when downloaded from Qualtrics and thus did not require any re-structuring.

After ensuring the data were structured properly, I then checked for multiple responses from a single teacher on the same day. In total, there were two instances where a teacher responded twice in one day. In this case, I retained the response that came in first and removed

the second response from the data set. Additionally, there was one participant who only responded to one out of the ten possible surveys. Aligned with recommendations from the literature that at least three responses in daily diary data sets are recommended for retention (Bolger & Laurenceau, 2013; Hektner et al., 2007), I removed this participant from the data set. The remaining participants ($N = 34$) had at least three out of ten survey responses.

I then reverse scored the same three self-efficacy items that were also reversed scored in the baseline dataset. Next, I centered my variables. To do so, I first computed scale scores for all variables measured. Then, and as previously mentioned, one of the benefits of short-term longitudinal designs like daily diary methods is that from the data emerges both between-person differences as well as within-person differences (Bolger & Laurenceau, 2013; Hektner et al., 2007). However, in order to account for these between and within person differences using multilevel modeling analyses in R, it is necessary to calculate the between and within person mean for each variable (Bolger & Laurenceau, 2013). I took the following steps to calculate the between and within person means. First, I calculated the between person means, which represented an individual's average across all days on a given item. Then, using the between person means I calculated the within person means. To do so, I subtracted each individuals' between person mean from their raw score on a given item. Therefore, within person means represented how an individual deviates from their own mean on a day-to-day basis. Finally, I merged the cleaned baseline data with the cleaned daily diary data. To do so, I used the "*merge*" and "*add cases*" function in SPSS to maintain data integrity. I then checked ten cases at random to ensure that the baseline data and daily diary data were properly linked. In the next section, I describe the procedures I adopted for the second, qualitative phase of this study – from recruitment to data cleaning and preparation.

Phase 2: Procedures

Following quantitative, Phase 1 data collection, I then began to analyze the quantitative data to select the participants to recruit for the second, qualitative phase of this study (see "Identification of Participants for Phase 2" above for more details). In particular, in order to understand teachers' varied experiences of cognitive load, I recruited participants based on if they had (a) a high cognitive load on average, (b) a low cognitive load on average, (c) interesting combinations of their average cognitive load with other variables (i.e., average self-efficacy, cost perceptions, attrition intentions), and/or (d) identified as having an underrepresented social identity characteristic within the teaching profession. After selecting participants to be recruited and engaging in the Phase 2 recruitment procedures as described above (see "Participants and Sampling" section), I obtained consent from all teachers who chose to participate in an interview via Qualtrics (see Appendix I) in Spring 2026.

I sent teachers one reminder email about their interview the day before or morning of the date that it was scheduled to take place (see Appendix R). Interviews took place either in-person at their school site or online via Zoom depending on their preference. In total, two interviews occurred in person and eight occurred online via Zoom. All interviews were audio recorded via Zoom or using the "Voice Memos" application on the Apple iPhone. Additionally, for each interview, I followed the same semi-structured interview protocol; however, each of my school partners added one to two related questions of their choice to be included in the protocol. Therefore, one to two questions on the interview protocol were different across the three schools. Appendix S presents the full interview protocol and the questions that were different across each school. Interviews lasted 44 minutes on average. After each participant completed their interview, they received a $30 gift card.

Data Cleaning. Before engaging in coding of the qualitative interviews, I took several steps to clean the data. First, I de-identified the data by assigning all 10 teachers a pseudonym (see Table 4). In addition, I ensured that all schools and their district information were also de-identified (i.e., by using School A, School B, and School C) and to ensure that no identifiable data was able to be traced back to participants. Second, I uploaded all audio files to Otter.ai, a secure platform approved by the IRB that aids in audio transcription (Otter.ai, 2026). After uploading these files to Otter.ai, I then carefully and closely listened to and read each transcript to ensure their accuracy. If there were any errors present in the transcript, I edited them as I went. Once all 10 of the interviews were accurately transcribed, I then uploaded the transcripts to NVivo (Lumivero, 2025), a qualitative storage and data analysis software, in preparation for coding. Finally, throughout interview recruitment, data collection, and analysis, I engaged in memoing (Ezzy, 2002). For example, immediately after every interview, I would handwrite how I felt the interview went and my biggest takeaways and/or impressions from the interview. Therefore, in preparation for data analysis and triangulation, I transferred each of the 21 memos I wrote to a Microsoft Word document which was ultimately uploaded to NVivo to aid in data coding. In the next section, I describe the data analytic approach I adopted to analyze the quantitative and qualitative data as well as integrate them.

Data Sources and Materials

In the following sections, I describe the data sources and materials I adopted during quantitative (Phase 1) and qualitative (Phase 2) data collection. First, I describe the demographic information I obtained. Then, I present the instruments I used to measure my central constructs of focus: cognitive load, self-efficacy, cost perceptions, and attrition intentions. Finally, I present the semi-structured interview protocol I developed for this study. Following this section, I describe the procedures in detail.

Phase 1: Daily Diary Method

Quantitative data were collected via a *daily diary* methodology. Daily diary methodology is a "set of assessment methods that allow researchers to study individuals' experiences, behavior, and circumstances in natural settings, in or close to real time, and on repeated measurement occasions…" (Lischetzke & Könen, 2024, p. 1413). The term "daily diary" is often used interchangeably with experience sampling methodology, ecological momentary assessment, and ambulatory assessment; however, daily diary methods specifically collect self-report data once per day over the course of a few days to several weeks (Bolger & Laurenceau, 2013; Lischetzke & Könen, 2012). In particular, a daily diary approach allowed me to collect data about teachers' cognitive load, motivation, and attrition intentions once per day over the course of 10 days. I conducted this study over the course of 10 days specifically, given that it was (a) feasible for my school partners to implement and (b) suitable to run statistical analyses of interest (Hoyle & Gottfredson, 2015)

Advantages of Approach. There are numerous advantages to collecting daily diary data in social science research (see Patall et al., 2018 for an example of capturing motivational processes via daily diary methods in a school-based setting). First, daily diary techniques are often more accurate at capturing complex, higher-order psychological processes than traditional, retrospective self-report measures (Bolger et al., 2003; Hektner et al., 2007; Zirkel et al., 2015). That is, self-report measures typically require participants to retrospectively recall their mental states, which may be misguided given research suggesting humans are not always able to do so with their higher-order processes (such as cognitive load and motivational beliefs) accurately (Bolger et al., 2003; Dent & Koenka, 2016; Nisbett & Wilson, 1977; Zirkel et al., 2015). These issues with retrospective measurement may be especially true for understanding phenomena like

cognitive load. For example, the construct of cognitive load itself is momentary and can change within seconds given (a) the allotted space of one's working memory at a certain point in time and (b) additional inputs that may arise at any given moment (Choi et al., 2014; Cowan, 2014). Further, cognitive load is challenging to measure – which is largely attributed to issues with retrospective recall (Jiang & Kalyuga, 2020; Sweller et al., 1998). However, the nature of the classroom environment considerably limits my ability to simply measure teachers' cognitive load using direct, in-the-moment data collection approaches (e.g., experience sampling methodology). For example, it would be infeasible and unfairly disruptive to interrupt classroom instruction as it is occurring to collect survey data. However, a daily diary approach allowed me to collect data (a) once per day and thus considerably closer to teachers' actual experiences with cognitive load and motivational fluctuations and (b) immediately following math instruction as to not interrupt classroom instruction (Frenzel et al., 2024).

Second, using a daily diary design allowed me to collect daily data over the course of several weeks (Hektner et al., 2017; Lischetzke, 2024). The recurring time points collected produced a greater understanding of not only *inter*personal (i.e., between-person) results but also *intra*personal (i.e., within-person) results (Bolger & Laurenceau, 2013; Hektner et al., 2007; Zirkel et al., 2015). For instance, daily diary data provides information not only on how participants' experiences fluctuate across the sample but also on how these experiences fluctuate within an individual. Collecting intrapersonal data is critical given that humans do not necessarily hold the same baseline levels of a given cognitive load or motivational experience (e.g., one individual's quota for feeling overwhelmed may not be consistent with others' quota for feeling overwhelmed; Hektner et al., 2007). Relatedly, all theories that guide this research conceptualize cognitive load and motivation constructs as highly context-specific, thereby

fluctuating widely in response to contextual variation (e.g., Bernacki et al., 2015). In addition, teachers vary based on their personal characteristics, prior teaching experiences, subject expertise, grade level, and personal working memory capacity (Cowan et al., 2005; 2010). Thus, a daily diary design allows these differing experiences to be captured, and therefore, modeled during data analysis (Hektner et al., 2007). Still, measuring cognitive load interpersonally remains important to understand the overall patterns and consequences related to teachers' cognitive load. A daily diary design is thus well-positioned to contribute needed insight into both intrapersonal and interpersonal cognitive load experiences.

Instruments. In this section, I describe the baseline survey, demographics questionnaire, and instruments that were included in a 22-item daily diary survey, which I administered to measure each construct (i.e., teachers' cognitive load, teaching self-efficacy, teaching cost perceptions, teachers' attrition intentions). In line with extant daily diary research techniques, the current survey was brief so that repeated surveying techniques did not become burdensome for the participants (Hektner et al., 2007). Below, I present shortened, established scales, which took participants only a few minutes to complete on average.

Baseline Questionnaire. After completing the consent form, teachers were directed to a baseline survey (see Appendix L). The baseline survey assessed all the same items included in the daily diary surveys (see "Daily Diary Questionnaire" below); however, they assessed them generally rather than in reference to a particular day. The purpose of the baseline survey was to provide a benchmark data point for teachers' general cognitive load, self-efficacy, cost perceptions, and attrition intentions. I then included these variables as covariates in the daily diary analyses (see "Multilevel Modeling Approach" below), which ultimately controlled for

teachers' individual differences on each variable and accounted for confounding variables (Xing et al., 2026).

Demographics Questionnaire. After completing the consent form and baseline survey, teachers were directed to a short demographics questionnaire (see Appendix M). In this questionnaire, I collected the following information: math instruction start time, math instruction end time, instructional grade level, years spent teaching overall, years spent teaching at their current grade level, education/training background, gender identity, sexual orientation, race and/or ethnicity, and disability status. The demographics questionnaire provided vital information that will provide necessary context to the study. That is, the math instruction information allowed me to identify when teachers typically finished their math instruction, which is when I scheduled their survey to be sent out each day. Additionally, the experience level information was crucial to test whether experience level predicted teachers' cognitive load (i.e., Research Question 1) and the social-identity information was important for (a) identifying participants to recruit for interviews and (b) examining Research Question 3a.

Daily Diary Questionnaire. Teachers' daily cognitive load during mathematics instruction was measured using 10 items from an adapted and previously established questionnaire that is frequently used in cognitive load research, seven adapted self-efficacy items, four adapted cost perceptions items, and one attrition intention item (Appendix O). To assess the reliability of the daily diary instruments, I computed McDonalds Omega (McNeish, 2018; Peters, 2014) using the *omegaSEM* function from the *multilevelTools* R package (Wiley, 2025). The *omegaSEM* function assesses internal consistency while accounting for the nested structure of the data (van Alphen et al., 2022). Using this function, I was able to compute both the within- and between-person omegas for each scale. The within values represent how an

individuals' responses fluctuate within themselves over the 10 days, where the between values represent the fluctuations in responses across individuals over the 10 days. It is critical to account for both within and between reliability of the scales due to the nested data structure (Bolger & Laurenceau, 2013; Huang, 2023).

Using adapted items from a previously established instrument to measure cognitive load (see Leppink et al., 2013), three items measured teachers' intrinsic load (ω^w = .84, ω^b = .99;[1] Leppink et al., 2013), For example, teachers responded to the item, "The math topics I covered today were very complex to teach." Three items measured teachers' extraneous load (ω^w = .82, ω^b = .98; Leppink et al., 2013). For example, teachers responded to the adapted item, "The occurrences happening around me today during my math instruction were very distracting". Four items measured teachers' germane load (ω^w = .82, ω^b = .99; Leppink et al., 2013). For example, teachers responded to the adapted item, "My math instruction today enhanced my understanding of how to effectively teach math." Responses were recorded via a 5-point scale ranging from "Not at all the case" (i.e., 1) to "Completely the case" (i.e., 5).

Teachers' daily self-efficacy beliefs for mathematics instruction were measured using an adapted seven-item questionnaire previously established in teacher self-efficacy research (ω^w = .83, ω^b = .95; see Midgley et al., 2000; Appendix O). For example, teachers responded to the following adapted item, "Today I was good at helping all my students make significant improvement during math instruction." Responses were recorded via a 5-point scale ranging from "Not at all the case" (i.e., 1) to "Completely the case" (i.e., 5).

[1] In daily diary designs it is common for between-person omegas to be higher than within-person omegas due to their increased stability once within-person variance is partitioned out (e.g., see Haney et al., 2023).

Teachers' daily cost perceptions during mathematics instruction were measured using an adapted four-item questionnaire that was shortened and established in a previous study (see Beymer et al., 2022b; Appendix O). One item measured teachers' effort cost (i.e., "Teaching math today required too much effort"), one item measured their outside effort cost (i.e., "Because of other things that I had to do today, I didn't have much time to put into math teaching"), one item measured their loss of valued alternatives cost (i.e., "Teaching math today required me to give up too many other activities I value"), and one item measured their emotional cost (i.e., "Teaching math today was emotionally draining"). Responses were recorded via a 5-point scale ranging from "Not at all the case" (i.e., 1) to "Completely the case" (i.e., 5).

Teachers' overall attrition intentions were measured (see Appendix O) using a single adapted item from Beymer et al. (2022a): "I plan to leave the field of education altogether." Responses were recorded via a 5-point scale ranging from "Not at all the case" (i.e., 1) to "Completely the case" (i.e., 5).

Email. I used a secure email address (as opposed to an app) to administer the daily diary surveys. Email was used for the following reasons. First, it allowed me to schedule emails with each daily survey link to teachers ahead of time and immediately after their math instruction (which were all at different times of the day) to ensure that the surveys do not interrupt instructional periods (see "Research Procedures" below for more information). Second, based on our school partner recommendations, email was easier for teachers to use as it did not require them to sign up for any platform or download an application to their personal devices. Finally, email was free to use.

Phase 2: Semi-Structured Interviews

Qualitative data were collected via semi-structured interviews. The purpose of semi-structured interviews is to collect "...in-depth information pertaining to the participants' experiences and viewpoints of a particular topic" (Turner, 2010, p. 754). Therefore, collecting interview data allowed me to expand on and complement the findings from Phase 1 with greater richness and depth and in teachers' own voices – which are often underrepresented in the literature (Gillett-Swan & Baroutsis, 2024).

Semi-structured Interview Protocol. I collected qualitative data via semi-structured interviews (Brown & Danaher, 2019; Turner, 2010) with teachers who reported high cognitive load or low cognitive load experiences during Phase 1. In the interviews, I asked open-ended, non-leading questions to teachers about their experiences with cognitive load and motivation during mathematics instruction as well as questions about their overarching attrition intentions. Appendix S presents the questions asked during the interviews. Given the semi-structured nature of each interview, some interview questions changed slightly depending on where the participant guided the conversation and the needs of the school site.

Data Analytic Approach

Phase 1: Quantitative Analyses

To analyze my quantitative research questions one through two, I conducted descriptive, correlational, and multilevel modeling analyses. However, before I engaged in those analyses, I addressed the missing data.

Missing Data Approach. One limitation of short-term longitudinal designs like daily diary designs is the increased likelihood of missing data (Hektner et al., 2007). Teachers responded to 6,818 data points out of a possible 7,700. In other words, the proportion of missing data across the daily diary surveys was 9.1% (i.e., a 90.9% response rate), which is less than or

similar to other daily diary studies across the educational psychology literature (e.g., see Beymer et al., 2020; Patall et al., 2018). Despite the high response compliance, it was necessary to address this missing data. Beyond issues of power that can emerge due to missing data, if missing data is not handled correctly, it can risk undermining interpretations (e.g., biased parameters estimates and standard errors) depending on the mechanism of missing data (Enders, 2010). Therefore, to handle missing data, I examined the mechanism of missingness: missing completely at random (MCAR; i.e., no systematicity to the missingness between missing and observed values), missing at random (MAR; i.e., systematicity to the missingness between missing and observed values can be explained by the data collected), or missing not at random (MNAR; there is systematicity to the missing data; Huang, 2023). I did so by running Little's MCAR test in R using the *naniar* package (Little, 1988). Little's test was non-significant $\chi^2(98) = 117.57$, $p = .09$, which suggests that the data is MCAR. Because there was sufficient evidence to conclude that the data was MCAR, the missing data did not have any systematicity to it. Thus, especially given the low proportion of missing data, no additional steps were necessary to handle the missing data (Enders, 2010).

Testing Assumptions. MLM assumes that residuals are normally distributed (Huang, 2023; Snijders & Berkhof, 2008). In other words, there should be no correlation between Level 2 (i.e., teacher-level) residuals once the data is clustered. Therefore, I graphed the standardized residual distributions using a histogram (i.e., using the *hist* function in R) to assess their normal distribution (Appendix T presents each histogram). In addition, I ran skewness and kurtosis values (i.e., using the *describe* function in the *psych* package in R; Huang, 2023). Skewness and kurtosis absolute values of two or less indicate no issues with normality (Hahs-Vaughn & Lomax, 2020; Snijders & Bosker, 2012). No violations to the normal distribution assumption

were violated after analyzing the histograms as well as skewness and kurtosis values. Appendix T presents histograms and Table 5 below presents the skewness and kurtosis results.

Table 5

Skewness and Kurtosis Values

Variable	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8	Day 9	Day 10
Intrinsic Load										
Skewness	.57	.51	.25	-.48	-.10	.17	.16	-.06	.07	.62
Kurtosis	-.32	-1.0	-1.01	-.74	-1.43	-1.00	-1.29	-1.19	-.78	-.38
Extraneous Load	-.34	-.84	-.51	-.28	-.49	-.44	-.53	-.28	-.26	-.83
Skewness	-.27	.03	-.42	-.29	-1.00	-.74	-.39	-.94	-1.21	.29
Kurtosis										
Germane Load										
Skewness	-.54	-.31	-.29	-.22	-.36	-.70	.27	-.48	-.38	-.13
Kurtosis	-.56	-.05	-.65	.62	-.24	.28	-.98	-.68	-.59	.15
Self-Efficacy										
Skewness	-.79	.15	-.39	-.09	-.22	-.13	.15	-.42	-.34	.00
Kurtosis	.64	-.76	-.42	-.50	-.16	-.90	-1.07	-.31	-.56	-.41
Task Eff. Cost										
Skewness	.94	.37	.50	-.20	.07	.52	.16	.14	.68	.41
Kurtosis	.40	-1.20	-1.21	-1.24	-1.26	-.88	-1.4	-1.03	-.47	-1.18
Outside Eff. Cost	.40	1.03	.60	.25	.38	.61	.50	.73	.00	.41
Skewness	-1.28	.23	-1.27	-1.24	-1.24	-1.20	-1.39	-.64	-1.61	-1.18
Kurtosis										
Emotional Cost										
Skewness	.08	-.18	-.15	.01	-.24	-.17	-.57	-.06	.23	-.38
Kurtosis	-1.66	-1.42	-1.46	-.84	-1.42	-1.38	-1.08	-1.26	-1.35	-1.56
LVA Cost										
Skewness	1.11	1.09	1.14	.49	.58	.64	.77	.99	.89	.78
Kurtosis	.20	-.06	.02	-1.09	-1.30	-1.04	-.76	-.14	-.33	-.48
Attrition Intent.										
Skewness	1.45	1.15	.88	.76	.84	1.15	1.15	1.45	1.39	1.12
Kurtosis	.86	-.11	-.78	-1.04	-.90	-.19	-.29	.57	.76	-.43

Note. Skewness and kurtosis values of +/- 2 indicate normality. Eff = effort, LVA = loss of valued alternatives, Intent. = intentions.

In addition, I also checked for evidence of multicollinearity by analyzing the correlations (see Table 6) between predictors. Two predictors had higher correlations at the between level (i.e., extraneous load and germane load, $r = -.72$, $p < .001$; intrinsic load and germane load, $r = -.50$, $p < .001$). To adjust for the potential evidence of multicollinearity, I ran a sensitivity analysis (Nahhas, 2024) for each, which ultimately did not meaningfully change the results. Finally, I tested the nested structure of the data. Given that three schools participated in this research, teachers are also nested within their schools, presenting a third level of nesting (Snijders & Bosker, 2012). However, I did not have a sufficient number of schools to implement a three-level nesting structure (Hoyle & Gottfredson, 2015). Therefore, I tested the degree of clustering at the third, school level by fitting three unconditional (i.e., null, intercept-only) models: (1) an extraneous load outcome model, (2) an intrinsic load outcome model, and (3) a germane load outcome model. Each of these models contained a random intercept at the school level and a random intercept for each teacher nested within schools. Then, I calculated the intraclass correlation coefficient (ICC) to determine (a) the percent variance between and within teachers' cognitive load levels and (b) whether there was sufficient variation attributable to the clustering structure (Huang, 2023). An ICC of greater than .05 speaks to the need for using of a three-level multilevel modeling approach (Huang, 2023) because it would indicate that level three (school) is responsible for at least 5% of the variance in cognitive load (Snijders & Bosker, 2012). Across all three models, the ICC at the third, school level was essentially zero, which suggests that there was almost no variance in teachers' cognitive load between schools (see Chapter 4 for results). Therefore, aligned with existing recommendations, I moved forward with a two-level nesting structure (Hoyle & Gottfredson, 2015; Snijders & Bosker, 2012).

Multilevel Modeling Approach. Phase 1 data were analyzed using a multilevel modeling (i.e., MLM) approach to account for and understand the nested structure of the data (Snijders & Bosker, 2012). More specifically, a two-level nesting structure was analyzed (see section above for a discussion on the third level of nesting present within the data). That is, teachers' daily observations (Level 1) were nested within each teacher (Level 2). All data were analyzed using the *R lme4* package (Bates et al., 2014; R Core Team, 2018). MLM is a valuable approach for analyzing daily diary data given that it accounts for the clustering of the data (Huang, 2023). For example, repeated measures of the same individual are much more likely to be like each other when compared to measurements between different individuals (Huang, 2023). Failing to account for the clustering within the dataset would result in a Type I error (Huang, 2023). Moreover, an MLM approach (a) accounts for response-level variability and (b) allows for estimates within and between individuals (Hektner et al., 2007), which aligns closely with the focus of my research questions. I explain in detail how analyses were run for each research question in the sections below.

Research Question 1: To what extent does teachers' daily cognitive load during mathematics instruction vary within and between teachers? To understand the variance in teacher's cognitive load at each daily timepoint (i.e., within-person variance) as well as at the teacher level (i.e., between-person variance), I began by running descriptive statistics. Specifically, I computed the means and standard deviations for each cognitive load subscale and teacher on each day of data collection (e.g., Day 1 Teacher 1 intrinsic cognitive load, Day 1 Teacher 1 extraneous cognitive load, Day 1 Teacher 1 germane cognitive load, etc.). I also computed an average 10-day mean and standard deviation for each teacher. Doing so provided valuable information about how each individual teacher's cognitive load during mathematics

instruction fluctuates over the course of the 10 days. To visualize the individualized cognitive load patterns within teachers, I developed panel plots and spaghetti charts (Bolger & Laurenceau, 2013) for each of the 34 teachers (see Appendix U).

Then, accounting for a two-level nesting structure, I re-ran three unconditional models: (1) an extraneous load outcome model, (2) an intrinsic load outcome model, and (3) a germane load outcome model. Each of these models contained only a random intercept at the teacher level (i.e., Level 2). A central goal for running these null models was to calculate the ICC. Computing the ICC provided me with valuable inferential information that spoke to how much daily cognitive load during math instruction varied within and between teachers, which is discussed in detail in Chapter 4.

Research Question 1a: To what extent do years of teaching experience predict daily experiences with cognitive load? I used a two-level MLM approach to model how years of teaching experience predicted teachers' daily experiences with cognitive load (see "Research Question 1" above for unconditional model). Daily cognitive load timepoints (Level 1) were nested within teachers (Level 2). I ran three models: (1) an extraneous load outcome model, (2) an intrinsic load outcome model, and (3) a germane load outcome model. Each of these models contained the fixed-effect predictors of Time (in days), Years of Experience, and one of the three baseline cognitive load dimensions depending on the outcome (i.e., Baseline Extraneous Load, Baseline Intrinsic Load, or Baseline Germane Load). For example, for the model that included Extraneous Cognitive Load, I included the Baseline Extraneous Load variable as a covariate. Doing so allowed me to control for teachers' pre-existing differences on the outcome variable.

Research Question 2: To what extent does the variation in teachers' daily cognitive load during mathematics instruction predict teachers' daily (a) self-efficacy, (b) cost

perceptions, and (c) attrition intentions? To address Research Question 2, I ran three, two-level models for each of the six outcome variables (i.e., self-efficacy, task effort cost, outside effort cost, emotional cost, loss of valued alternatives cost, and attrition intentions). First, I ran an unconditional model for each outcome, which only contained a random intercept at the teacher level (i.e., Level 2). Second, I ran an intermediate model for each outcome, which contained (a) the fixed effect predictors of Time (in days), Within-Person Extraneous Load, Between-Person Extraneous Load, Within-Person Intrinsic Load, Between-Person Intrinsic Load, Within-Person Germane Load, Between-Person Germane Load, and the baseline of the outcome variable (i.e., Baseline Self-Efficacy, Baseline Task Effort Cost, Baseline Outside Effort Cost, Baseline Emotional Cost, Baseline Loss of Valued Alternatives Cost, or Baseline Attrition Intentions). In addition, a random intercept at the teacher level was included. Third, I ran a full model which included everything in the intermediate model plus (a) three interaction terms (i.e., Time x Within-Person Extraneous Load, Within-Person Intrinsic Load, and Within-Person Germane Load) and (b) random slopes for Time. Including the interaction term allowed me to statistically test how the relations between time and each of the six outcome variables varied based on each dimension of teachers' cognitive load during their math instructional experiences. Including the random slope of time allowed for each teacher to vary in the outcome variable over Time.

Finally, I evaluated model fit using Likelihood Ratio Tests (LRT) as well as Akaike and Bayesian Information Criterion estimates (i.e., AIC, BIC). The LRT allows for a comparison of models (e.g., comparing the intermediate and full models) and produces a significance test of model improvement. If the LRT test is significant, the more complex model should be retained (Huang, 2023). Additionally, lower AIC and BIC values suggest a better model fit (Huang,

2023). All models were estimated using Restricted Maximum Likelihood (REML)[2] as it generally handles (a) data with smaller cluster and sample sizes more appropriately and (b) is less prone to underestimating or biasing standard errors (Huang, 2023; Snijders & Bosker, 2012).

Phase 2: Qualitative Analyses

Research Question 3, 3a: How do teachers describe their daily experiences with cognitive load during mathematics instruction? How do teachers with underrepresented identities within the teaching profession experience cognitive load? To analyze the qualitative interview data, I engaged in a thematic analysis. A thematic analysis is "a method for identifying, analyzing and reporting patterns (themes) within data" (Braun & Clarke, 2006, p. 79). Importantly, it is an inductive method of qualitative data analysis given that themes and/or codes are emergent rather than decided on ap riori (Ezzy, 2002). A thematic analytic approach was appropriate for this study given the limited extant research on teachers' cognitive load – and particularly research that centers their voices (Gillett-Swan & Baroutsis, 2024); therefore, a thematic analysis introduced an exploratory lens. To engage in a thematic analysis of the interview data, I followed the six-step process recommended by Braun and Clarke (2006). I describe each of the steps taken to conduct the thematic analysis in detail in the following sections.

Step 1: Familiarizing Myself with the Data. Early on during the second phase of this study, I began to familiarize myself with the data. Becoming familiar with the data included transcribing the interviews, a thorough re-read of the entire data set, and the recording of any

[2] When comparing models in R, Maximum Likelihood (ML) must be used. R automatically refits models using ML when these comparisons are run. All model findings in Chapter 4 representing output from model fits using REML and ML were only used for model comparison as suggested by statisticians (e.g., see Huang, 2023).

idea or ideas that emerged. Therefore, as previously mentioned, to accomplish this first step of the thematic analysis, I adopted the following procedures. First, I engaged in *memoing* (i.e., the "systematic attempt to facilitate the interpretive process") following the completion of each interview and throughout the data analysis process (Ezzy, 2002, p. 71). Memoing allowed me to immediately reflect upon my own emotions, thoughts, reactions, and overarching takeaways that emerged from the interviews. Additionally, as recommended by Ezzy (2002), continued memoing allowed me to record how my interpretations of data fluctuated throughout the coding process. Ultimately, writing these memos aided in the development of my overarching understanding of the data as well as in later phases of my analysis (see "Step 5: Defining and Naming Themes"). Appendix W presents each of the 21 memos I wrote. I also transcribed each interview followed by an in-depth re-read of each transcript. Each of these methods gave me a comprehensive, overarching understanding of the data.

Step 2: Generating Initial Codes. After all interview data were uploaded to NVivo, I began generating initial codes (Braun & Clarke, 2006). To do so, I went through each transcript and organized all data into initial codes. At the end of Step Two, I had developed 68 codes.

Step 3: Searching for Themes. I then began organizing codes similar or relevant to one another into categories. Each category served as a potential theme within the data. To aid in the sorting process and given existing recommendations (e.g., see Braun & Clarke, 2006), I developed a thematic map to visualize the data (see Appendix X). At the end of Step Three, 12 initial themes emerged and total codes were reduced to 52.

Step 4: Reviewing Themes. I began reviewing each of the initial themes I generated in step three. The purpose of this fourth step was to continue organizing codes and themes, but also to make sense of them in relation to the data set as a whole. To do so, I copied and then re-

worked the thematic map of the themes first generated during step three Appendix Y presents how the thematic maps evolved during step four. During this step, I was able to further parse apart themes and codes related to each other as well as develop sub-themes. At the end of Step Four, I had generated five themes, eight sub-themes, and the total codes were reduced to 44.

Step 5: Defining and Naming Themes. After further parsing down codes and themes in Step Four, I was satisfied and confident with the story that was emerging from the data as a result of the thematic analysis thus far. However, to (a) further refine the extant themes developed and (b) further establish trustworthiness of the data, I began linking the memos I'd written to the codes, sub-themes, and themes developed. I found that each memo linked to at least one code, sub-theme, or theme, which increased the trustworthiness of my findings (see "Trustworthiness" section below for a more detailed discussion). Finally, I developed a codebook which facilitated the process of defining and naming each theme (see Appendix Z).

Step 6: Producing the Report. The final step to thematic analysis is to produce the report (Braun & Clarke, 2006). In other words, I selected key quotes that define each theme as well as wrote up how the themes relate to the research questions and existing literature.

Trustworthiness. It was imperative that I established *trustworthiness* (i.e., a criterion for assessing quality among qualitative research; Plano Clark & Ivankova, 2016) among my findings. There are four criteria for establishing trustworthiness in qualitative research (Nowell et al., 2017). First, *credibility* involves the perception that findings accurately describe what the participant actually experienced and/or reported (Nowell et al., 2017; Plano Clark & Ivankova, 2016). I ensured credibility through data *triangulation*. To triangulate the data, I directly compared the qualitative results to the quantitative results to investigate whether the findings agree (i.e., converge); thus, establishing confidence in the derived findings. Triangulation of the

data also resulted in data disagreement (i.e., divergence) at times, which highlighted areas for future research as well as the unique affordances of quantitative versus qualitative methodologies (Plano Clark & Ivankova, 2016). Moreover, I also engaged in *theoretical triangulation* (i.e., the use of "…different theories to analyze and interpret data" to "…assist the researcher in supporting or refuting findings," Carter et al., 2014, p. 545). In particular, I interpreted my findings through the lens of three theories (i.e., CLT, SCT, SEVT). Drawing from each of these theories reduced my own interpretation bias and resulted in a more comprehensive, theoretically sound understanding of the data. In addition to triangulation, I engaged in memoing before, during, and after data collection and analysis (Ezzy, 2002). I wrote 21 memos (see Appendix W) throughout data collection and analysis. Memoing allowed me to reflect upon my initial thoughts, ideas, and reactions to each of the interviews. Additionally, as recommended by Ezzy (2002), continued memoing allowed me to record how my interpretations of data fluctuated throughout the coding process. Finally, memoing also enabled me to further triangulate the data. That is, towards the end of the coding process, I returned to and coded each memo using the same codebook I developed to code the interview data. Importantly, I was able to map memos onto codes and themes which ultimately reinforced the consistency of the findings.

Second, to achieve *transferability* (i.e., relative generalizability of qualitative findings), I included thick descriptions when discussing findings (Nowell et al., 2017). Through my Results and Discussion sections, I provide quotes paired with important contextual information about participants' experiences (e.g., gender, race, grade level, years spent teaching) so that readers can draw conclusions and apply them in a more accurate manner (Nowell et al., 2017; Plano Clark & Ivankova, 2016).

Third, *dependability* (i.e., when the steps of the research project from start to finish are easy to ascertain) was established by documenting detailed notes (e.g., memoing) throughout the data collection and analysis processes (Nowell et al., 2017). For example, as aforementioned, after engaging in memoing, I then coded those memos to see how they aligned with the existing codes and themes that emerged.

Fourth, *confirmability* (i.e., clear reasoning for how the research derived findings) is reached once credibility, transferability, and dependability are each established (Nowell et al., 2017). Taken together, trustworthiness of the qualitative data was established via data triangulation, memoing, thick descriptions, and detailed documented notes.

Finally, throughout the coding process I continually assessed for *data saturation*, or the "…degree to which new data repeat what was expressed in previous data…" (Saunders et al., 2018, p. 1897). As noted in Memo #14 (see Appendix W), I noticed redundancy among interviews following the eighth interview; however, small deviances among the interviews were still present after probing. Therefore, I engaged in two additional interviews until I reached full data saturation (see Appendix W, Memo #16).

Research Question 4: How do teachers' qualitative descriptions of their daily experiences with cognitive load during mathematics instruction, motivational beliefs, and attrition intentions map onto the experiences reported on the daily quantitative surveys?

To integrate the data at the interpretation level, I used a combination of data transformation, narrative weaving, and joint displays as suggested by mixed methodologists (e.g., see DeCuir-Gunby & Schutz, 2017; Fetters et al., 2013; Plano Clark & Ivankova, 2016). *Transformation* occurs when one form of the data (i.e., either quantitative or qualitative) is converted into the opposite form and then merged with data that has not been converted (Fetters et al., 2013). For

the purposes of the present study, I transformed the qualitative data into numeric frequencies. That is, I calculated how often each code was referenced within each theme. Then, I combined the code frequencies with the non-transformed, quantitative data to compare and develop higher-level findings across both datasets. Transforming the qualitative data in this way allowed me to develop a greater sense of the prominence of each theme and compare the qualitative dataset to the quantitative dataset using descriptive statistics.

Additionally, I adopted a *narrative* approach to analyze and integrate the datasets. A narrative approach allowed me to describe and discuss themes across quantitative and qualitative findings (DeCuir-Gunby & Schutz, 2017). More specifically, I used a narrative *weaving* approach, or the process of "writing both qualitative and quantitative findings together on a theme-by-theme or concept-by-concept basis" (Fetters et al., 2013, p. 2142). Using a weaving approach allowed me to systematically compare the quantitative findings to the qualitative findings and determine whether (a) *confirmation* (i.e., when the quantitative and qualitative findings are in support of each other; Fetters et al., 2013), (b) *expansion* (i.e., when quantitative and qualitative findings complement each other but diverge enough to reveal different or new insights; Fetters et al., 2013), or (c) *discordance* (i.e., when the quantitative and qualitative findings contradict one another; Fetters et al., 2013) emerged. Finally, I also used *joint displays*, or visuals that help to explain how the data intersects or produces a new idea (DeCuir-Gunby & Schutz, 2017). Joint displays allowed me to demonstrate (e.g., through a table and/or figure) the quantitative and qualitative findings together. Joint displays are a useful tool for integration and aid in reader interpretation of the integrated findings.

Chapter Summary

In Chapter 3, I described the research methods I adopted to carry out the present study. I presented an explanatory sequential mixed methods design that aimed to understand teachers'

cognitive load experiences during math instruction and its motivational and attritional outcomes. I described my adoption of a daily diary design to capture teachers' cognitive load, motivation, and attritional experiences once a day for 10 days. In addition, I described the second, qualitative phase in which I conducted 10 semi-structured interviews with teachers from the larger sample. Finally, I described my analysis approach for each of the phases of this research.

Chapter 4: Results

Overview of Chapter 3

In Chapter 3, I described the research methods I adopted to carry out the present study. In particular, I defined and rationalized the explanatory sequential mixed methods (QUAN → qual) research design adopted in which I collected: (a) quantitative survey data from $N = 34$ teachers once a day for 10 days and (b) qualitative interview data from $N = 10$ teachers. Then, I described my overarching objectives of the study, the research questions guiding the study, and my hypotheses.

Next, I presented the characteristics of the participants across both phases and my sampling procedures, including participant recruitment across the three elementary schools. I then described the data sources I adopted across both phases of the research. After describing my data sources, I delineated the procedures I followed to effectively carry out this study. These procedures included in-person and online recruitment, informed consent, distribution of baseline surveys, demographics surveys, daily diary surveys, audio recordings and transcriptions, and data cleaning.

Finally, I described my approach to data analysis for each phase, including the integration phase of the study. In particular, I relayed how I (a) handled missing data, (b) conducted and analyzed descriptive statistics, and (c) adopted a multilevel modeling approach to delineate findings for Research Questions 1, 1a, and 2. I then described how I adopted Braun and Clarke's (2006) six step process to perform a thematic analysis among the qualitative interviews – thus producing results for Research Questions 3 and 3a. Lastly, I presented my methods for integrating the data, particularly through joint displays and a narrative approach.

In the following sections, I present the findings for Phase 1, Phase 2, and the integration phase of the present study. For Phase 1, I begin by presenting the results from the descriptive analyses I conducted. Then, I present and break down the results for the quantitative Research Questions 1, 1a, and 2. For Phase 2, I present and break down the results for the qualitative Research Questions 3 and 3a, which is followed by a discussion of the trustworthiness of my findings. Finally, I present the data integration results for Research Question 4.

Phase 1: Quantitative, Daily Diary Results

In the following sections, I describe the results that emerged from the quantitative, daily diary surveys. I first present the results for the preliminary analyses, specifically the descriptive and correlational findings. Then, I present the MLM results for research questions 1, 1a, and 2.

Descriptive Analyses

Prior to running the MLM analyses, I first calculated descriptive statistics across variables (i.e., between and within means; standard deviations) as well as correlations between those variables. Means, standard deviations, and correlations are each presented in Table 6.

Table 6

Within- and Between-Person correlations, Means, and Standard Deviations

	1	2	3	4	5	6	7	8	9
Within-person									
1. Intrinsic Load									
2. Extraneous Load	.02								
3. Germane Load	.31***	-.25***							
4. Self-Efficacy	.01	-.55***	.45***						
5. Task Effort Cost	.22***	.35***	-.11	-.41***					
6. Outside Effort Cost	-.07	.15**	-.27***	-.31***	.20***				
7. LVA Cost	-.04	.23***	-.14*	-.30***	.21***	.31***			
8. Emotional Cost	.19***	.49***	-.12*	-.44***	.53***	.08	.17**		

	1	2	3	4	5	6	7	8	9
9. Attrition Intentions	.06	.03	-.15**	-.18**	.09	.06	.19**	.02	
Between-person									
1. Intrinsic Load									
2. Extraneous Load	-.26***								
3. Germane Load	.72***	-.50***							
4. Self-Efficacy	.42***	-.81***	.70***						
5. Task Effort Cost	.05	.39***	-.28***	-.43***					
6. Outside Effort Cost	-.16**	.59***	-.42***	-.60***	.75***				
7. LVA Cost	.08	.32***	-.16**	-.32***	.84***	.84***			
8. Emotional Cost	.02	.59***	-32***	-.59***	.78***	.71***	.68***		
9. Attrition Intentions	-.14*	.10	-.07	-.18***	.29***	.29***	.19***	.39***	
Mean	2.59	3.20	3.16	3.27	2.31	2.47	1.84	2.92	1.72
SD	1.04	1.10	0.87	0.89	1.15	1.41	1.02	1.32	1.07

Note. LVA = Loss of valued alternatives. *$p < .05$. **$p < .01$. ***$p < .001$.

Second, with short-term longitudinal designs like daily diary designs, panel and spaghetti plots are recommended to visualize the data and help gain a relative understanding of it prior to turning to more intensive methods (e.g., MLM; Bolger & Laurenceau, 2013). Therefore, I developed panel plots for each variable among each teacher (see Appendix U) as well as spaghetti plots for each variable (see Appendix V). In the following sections, and to effectively test each of my hypotheses presented in Chapter 3, I present the results of the MLM analyses by research question.

Research Question 1: To what extent does teachers' daily cognitive load during mathematics instruction vary within and between teachers over a two-week period?

In the following sections, I present the three unconditional (i.e., null; intercept-only) models for each dimension of cognitive load: intrinsic load, extraneous load, and germane load (see Tables 8-10). I adopted a two-level nesting structure (i.e., days within teachers) for each

model as ICCs at the third level (i.e., schools) introduced very little variability (i.e., $\rho < .05$; Snijders & Bosker, 2012; see Table 7).

Table 7

Intraclass Correlation Coefficients for Each Dimension of Cognitive Load

Outcome	2-level nesting structure	3-level nesting structure
Intrinsic Load		
Level 1: Day	.67	.69
Level 2: Teacher	.33	.31
Level 3: School	–	<.01
Extraneous Load		
Level 1: Day	.65	.66
Level 2: Teacher	.35	.34
Level 3: School	–	<.01
Germane Load		
Level 1: Day	.57	.60
Level 2: Teacher	.43	.40
Level 3: School	–	<.01

Note. Some of the level three ICC values are greater than one due to rounding.

Unconditional model for intrinsic load. The unconditional model revealed an ICC of $\rho = .33$ at the teacher level (Level 2) and $\rho = .67$ at the day level (Level 1). The teacher-level ICC suggests that 33% of the variation in intrinsic load is explained by differences between teachers. The day-level ICC suggests that 67% of the variation in intrinsic load is explained within teachers via their daily fluctuations. The teacher and day-level ICCs for the intrinsic load model illustrate the need for an MLM approach due to the clustering of the data. Overall, this intercept-only model (see Table 8) was significant, $b = 2.59$, t (29.68) = 21.56, $p < .001$, 95% CI [2.35, 2.83]. In other words, the average intrinsic load across teachers was 2.59 on a 5-point scale.

Table 8

Intrinsic Load Unconditional Model Results

	b	β	SE	95% CI	*t*	*df*	*p*
Intercept	2.59	.02	0.12	(2.35, 2.83)	21.56	29.68	<.001

Note. SE = standard error, CI = confidence interval, df = degrees of freedom.

Unconditional model for extraneous load. The unconditional model for the second cognitive load outcome, extraneous load, revealed an ICC of ρ = .35 at the teacher level (Level 2) and ρ = .65 at the day level (Level 1). The teacher-level ICC suggests that 35% of the variation in extraneous load is explained by differences between teachers. The day-level ICC suggests that 65% of the variation in extraneous load is explained within teachers via their daily fluctuations. The teacher and day-level ICCs for the extraneous load model illustrate the need for an MLM approach due to the clustering of the data. Overall, this intercept-only model (see Table 9) was significant, b = 3.20, t (30.20) = 24.53, p < .001, 95% CI [2.94, 3.46]. In other words, the average extraneous load across teachers was 3.20 on a 5-point scale.

Table 9

Extraneous Load Unconditional Model Results

	b	β	SE	95% CI	*t*	*df*	*p*
Intercept	3.20	.02	0.13	(2.94, 3.46)	24.53	30.20	<.001

Note. SE = standard error, CI = confidence interval, df = degrees of freedom.

Unconditional model for germane load. The unconditional model revealed an ICC of ρ = .43 at the teacher level (Level 2) and ρ = .57 at the day level (Level 1). The teacher-level ICC suggests that 43% of the variation in germane load is explained by differences between teachers. The day-level ICC suggests that 57% of the variation in germane load is explained within teachers via their daily fluctuations. The teacher and day-level ICCs for the germane load model

illustrate the need for an MLM approach due to the clustering of the data. Overall, this intercept-only model (see Table 10) was significant, $b = 3.16$, t (30.18) = 28.37, $p < .001$, 95% CI [2.94, 3.39]. In other words, the average germane load across teachers was 3.16 on a 5-point scale.

Table 10

Germane Load Unconditional Model Results

	b	β	SE	95% CI	*t*	*df*	*p*
Intercept	3.16	.02	.11	(2.94, 3.39)	28.37	30.18	<.001

Note. SE = standard error, CI = confidence interval, df = degrees of freedom.

Research Question 1a: To what extent do years of teaching experience predict daily experiences with cognitive load?

In the following sections and building off the three unconditional models presented in Research Question 1, I present the three additional models with teaching experience as a predictor of each cognitive load dimension: intrinsic load, extraneous load, and germane load (see Tables 11-16). Given the above-mentioned ICCs, a two-level nesting structure (i.e., days nested within teachers) was adopted for each model (see Table 7).

Years of Teaching Experience on Intrinsic Load Model. The Level 1 predictor of Day and Level 2 predictors of experience level and baseline intrinsic load were added to the Intrinsic Load outcome model. Baseline intrinsic load was a significant predictor of intrinsic load ($b = .39$, t(30.17) = 3.47, $p < .001$, CI [.21, .56]). However, neither day ($b = .02$, $p = .33$) nor experience level ($b = .01$, $p = .40$) were significant predictors of intrinsic load. Table 11 presents model specifications. The likelihood ratio test (LRT) suggests that, compared to the unconditional model, model fit significantly improved with the addition of the three predictors ($\chi^2(3) = 15.81$, $p < .01$). Table 12 presents LRT results.

Table 11

Results for Experience Level and Intrinsic Load Model

	b	β	SE	95% CI	*t*	*df*	*p*
Intercept	1.23	.01	.35	(55, 1.91)	3.47	30.17	<.01
Day (L1)	.02	.05	.02	(-.02, .05)	.98	256.30	.33
Experience Level (L2)	.01	.08	.01	(-.01, .03)	.85	27.44	.40
Baseline IL (L2)	.39	.40	.09	(.21, .56)	4.14	27.40	<.001

Note. SE = standard error, CI = confidence interval, df = degrees of freedom, IL = intrinsic load.

Table 12

LRT results for experience and intrinsic load model

Model	AIC	BIC	χ^2	*df*	*p*
Unconditional	782.66	793.63	–	–	–
Experience Level	772.85	794.81	15.81	3	<.01

Note. SE = standard error, CI = confidence interval, df = degrees of freedom.

Years of Teaching Experience on Extraneous Load Model. The Level 1 predictor of Day and Level 2 predictors of experience level and baseline extraneous load were added to the extraneous load outcome model. Baseline extraneous load was a marginally significant[3] predictor of extraneous load (b = .32, t (28.59) = 1.62, p = .10, CI [-.06, .70]). However, neither day (b = -.01, p = .55) nor experience level (b = -.002, p = .86) were significant predictors of extraneous load. Table 13 presents model specifications. The LRT suggests that, compared to the unconditional model, model fit did not significantly improve with the addition of the three

[3] Given the arbitrary nature of the widely-accepted .05 cutoff of significance, methodologists have argued that it is also important to report marginal significance, or *p*-values between .05 to .10 (Olsson-Collentine et al., 2019).

predictors ($\chi^2(3) = 3.24$, $p = .36$) and the more parsimonious model should be retained. Table 14 presents LRT results.

Table 13

Results for Experience Level on Extraneous Load Model

	b	β	SE	95% CI	*t*	*df*	*p*
Intercept	2.04	.01	.82	(.47, 3.61)	2.50	29.08	<.05
Day (L1)	-.01	-.03	.02	(-.05, .03)	-.60	254.64	.55
Experience Level (L2)	-.002	-.02	.01	(-.03, .02)	-.18	27.47	.86
Baseline EL (L2)	.32	.18	.19	(-.06, .70)	1.62	28.59	.10

Note. SE = standard error, CI = confidence interval, df = degrees of freedom, EL = extraneous load.

Table 14

LRT results for experience and extraneous load model

Model	AIC	BIC	χ^2	*df*	*p*
Unconditional	809.07	820.04	–	–	–
Experience Level	811.83	833.76	3.24	3	.36

Note. SE = standard error, CI = confidence interval, df = degrees of freedom.

Years of Teaching Experience on Germane Load Model. The Level 1 predictor of Day and Level 2 predictors of germane load and baseline intrinsic load were added to the germane load outcome model. Baseline germane load was a significant predictor of germane load ($b = .37$, $t(29.62) = 2.32$, $p < .05$, CI [.06, .68]). However, neither day ($b = -.02$, $p = .17$) nor experience level ($b = -.003$, $p = .78$) were significant predictors of germane load. Table 15 presents model specifications. The LRT suggests that, compared to the unconditional model, model fit improved (at a marginally significant level; Olsson-Collentine et al., 2019) with the addition of the three predictors ($\chi^2(3) = 15.81$, $p < .01$). Table 16 presents LRT results.

Table 15

Results for Experience Level and Germane Load Model

	b	β	SE	95% CI	*t*	*df*	*p*
Intercept	1.80	.02	.66	(.53, 3.08)	2.71	30.32	<.05
Day (L1)	-.02	-.06	.01	(-.05, .01)	-1.36	254.41	.17
Experience Level (L2)	-.003	-.03	.01	(-.02, .02)	-.29	27.50	.78
Baseline GL (L2)	.37	.27	.16	(.06, .68)	2.32	29.32	<.05

Note. SE = standard error, CI = confidence interval, df = degrees of freedom, GL = germane load.

Table 16

LRT results for experience and germane load model

Model	AIC	BIC	χ^2	*df*	*p*
Unconditional	643.42	654.39	–	–	–
Experience Level	642.10	664.03	7.33	3	.06

Note. SE = standard error, CI = confidence interval, df = degrees of freedom.

Research Question 2: To what extent does the variation in teachers' daily cognitive load during mathematics instruction predict teachers' daily (a) self-efficacy, (b) cost perceptions, and (c) attrition intentions?

In the following sections, I present unconditional, intermediate, and full models for each of the six outcome variables of focus (i.e., self-efficacy, task effort cost, outside effort cost, emotional cost, loss of valued alternatives cost, and attrition intentions) to address Research Question 2 (see Tables 17-41). The unconditional, or intercept-only models, do not include any predictors, but provide critical information regarding the amount of variance at each level. To each intermediate model day, within-person intrinsic load, within-person extraneous load, within-person germane load was added as level 1 predictors and between-person intrinsic load,

between-person extraneous load, between-person germane load, and the baseline of the outcome variable were each added as level 2 predictors. Then building off the intermediate model, I included a random slope of day as well as three interactions: Day x within-intrinsic load, Day x within-extraneous load, and Day x within-germane load. A two-level nesting structure (i.e., days within teachers) was adopted for each model as ICCs at the third level (i.e., schools) introduced very little variability (i.e., < .05; Snijders & Bosker, 2012; see Table 17).

Table 17

Intraclass Correlation Coefficients for RQ2 Outcome Variables

Outcome	2-level nesting structure	3-level nesting structure
Self-Efficacy		
Level 1: Day	.52	.51
Level 2: Teacher	.48	.49
Level 3: School	–	<.01
Task Effort Cost		
Level 1: Day	.71	.73
Level 2: Teacher	.29	.27
Level 3: School		0
Outside Effort Cost		
Level 1: Day	.53	.59
Level 2: Teacher	.47	.41
Level 3: School	–	<.01
Emotional Cost		
Level 1: Day	.67	.68
Level 2: Teacher	.33	.31
Level 3: School	–	.01
LVA Cost		
Level 1: Day	.63	.62
Level 2: Teacher	.37	.38
Level 3: School	–	<.01

Outcome	2-level nesting structure	3-level nesting structure
Attrition Intentions		
Level 1: Day	.08	.10
Level 2: Teacher	.92	.90
Level 3: School	–	<.01

Note. Some of the level three ICC values add up to greater than one due to rounding. LVA = loss of valued alternatives.

Self-Efficacy Outcome Model. In this section, I present the results of three models (i.e., unconditional, intermediate, and full) with self-efficacy as the outcome (see Tables 18-21). Ultimately, the intermediate model fit best and was therefore retained and interpreted. Table 18 presents the full Likelihood Ratio Test Statistics, including the Akaike and Bayesian Information Criterion (i.e., AIC; BIC) estimates.

Table 18

Self-Efficacy Intermediate Model Fit

Model	AIC	BIC	χ^2	*df*	*p*
Unconditional	626.96	637.92	–	–	–
Intermediate	464.34	504.52	178.62	8	<.001
Full	469.70	528.14	4.64	5	.46

Note. AIC = Akaike Information Criterion, BIC = Bayesian Information Criterion, SE = standard error, CI = confidence interval, df = degrees of freedom.

Unconditional Self-Efficacy Model. The unconditional model for self-efficacy revealed an ICC of $\rho = .48$ at the teacher level (Level 2) and $\rho = .52$ at the day level (Level 1). The teacher-level ICC suggests that 48% of the variation in self-efficacy is explained by differences between teachers. The day-level ICC suggests that 52% of the variation in self-efficacy is explained within teachers via their daily fluctuations. The teacher and day-level ICCs for the intrinsic load model give reason to why a MLM approach was needed due to the clustering of the

data. Overall, this intercept-only model (see Table 19) was significant, $b = 3.28$, t(30.28) = 27.97, $p < .001$, 95% CI [3.05, 3.52]. In other words, the average self-efficacy across teachers was 3.28 on a 5-point scale.

Table 19

Unconditional Self-Efficacy Model Results

	b	β	SE	95% CI	*t*	*df*	*p*
Intercept	3.28	-.01	.12	(3.05, 3.52)	27.97	30.28	<.001

Note. SE = standard error, CI = confidence interval, df = degrees of freedom.

Intermediate Self-Efficacy Model. The Level 1 predictors of Day, within-person intrinsic load, within-person extraneous load, and within-person germane load and Level 2 predictors of between-person intrinsic load, between-person extraneous load, between-person germane load, and baseline self-efficacy were each added to the self-efficacy outcome model at this stage. Moreover, this intermediate model represented a significant improvement in model fit when compared to the null model ($\chi^2(8) = 178.62$, $p < .001$). Table 18 presents LRT results, including AIC and BIC estimates.

At Level 1, all three within-cognitive load dimensions were significant or marginally significant. That is, within-person intrinsic load was a marginal, significant predictor of self-efficacy ($b = -.07$, t(250.74) = -1.88, $p = .06$, CI [-.15, .00]: on days when teachers reported an intrinsic load 1 unit higher than their own average, their self-efficacy was, on average, .07 units lower. Within-person extraneous load was also a significant predictor of self-efficacy ($b = -.33$, t(251.35) = -9.08, $p < .001$, CI [-.40, -.26]: on days when teachers reported an extraneous load 1 unit higher than their own average, their self-efficacy was, on average, roughly a third of a unit (i.e., .33 units) lower. Within-person germane load was a significant predictor of self-efficacy ($b = .34$, t(252.99) = 6.47, $p < .001$, CI [.24, .44]: on days when teachers reported a germane load 1

unit higher than their own average, their self-efficacy was, on average, roughly a third of a unit (.34 units) higher. Day was not a significant predictor of teachers' self-efficacy (b = -.01, p = .22).

At Level 2, between-person extraneous and germane loads were significant predictors of self-efficacy in addition to baseline self-efficacy being a marginally significant predictor. That is, between-person extraneous load significantly predicted teachers' self-efficacy beliefs (b = -.44, t(27.38) = -4.27, p < .001, CI [-.63, -.25]: for each 1 unit increase in average teachers' extraneous load, their average self-efficacy was .44 units lower. Additionally, between-person germane load significantly predicted teachers' self-efficacy beliefs (b = .51, t(26.44) = 3.06, p < .01, CI [.20, .82]: for each one unit increase in average teachers' germane load, their average self-efficacy was over half-unit (.51 units) lower. Baseline self-efficacy was a marginally significant predictor of teachers' self-efficacy beliefs (b = .20, t(32.84) = 1.74, p = .09, CI [-.01, .42]), indicating that higher self-efficacy beliefs on the baseline survey also indicated higher self-efficacy beliefs on the daily surveys. Between-person intrinsic load was not a significant predictor of teachers' self-efficacy beliefs.

Table 20

Intermediate Self-Efficacy Model Results

	b	β	SE	95% CI	*t*	*df*	*p*
Intercept	2.57	<.01	.80	(1.07, 4.06)	3.21	28.95	<.01
Level 1 Predictors							
Day	-.01	-.04	.01	(-.03, .01)	-1.24	251.78	.22
Within IL	-.07	-.04	.04	(-.15, .00)	-1.88	250.74	.06
Within EL	-.33	-.31	.04	(-.40, -.26)	-9.08	251.35	<.001
Within GL	.34	.24	.05	(.24, .44)	6.47	252.99	<.001

	b	β	SE	95% CI	*t*	*df*	*p*
Level 2 Predictors							
Between IL	-.05	-.04	.14	(-.32, .21)	-.38	27.77	.71
Between EL	-.44	-.36	.10	(-.63, -.25)	-4.27	27.38	<.001
Between GL	.51	.35	.17	(.20, 82)	3.06	26.44	<.01
Baseline Self-Efficacy	.20	.13	.12	(-.01, .42)	1.74	32.84	.09

Note. *b* = unstandardized estimate, β = standardized estimate, SE = standard error, CI = confidence interval, df = degrees of freedom, EL = extraneous load, IL = intrinsic load, GL = germane load.

Full Self-Efficacy Model. In the full model, I added the random slope of day, three interaction terms (i.e., day x within-intrinsic load, day x within-extraneous load, day x within-germane load), and all Level 1 and Level 2 predictors included in the intermediate model (see Table 21). However, there was no improvement in model fit ($\chi^2(5) = 4.64$, $p = .46$). Therefore, the intermediate model was retained and interpreted.

Table 21

Results for Full Self-Efficacy Model

	Fixed Effects						
	b	β	SE	95% CI	*t*	*df*	*p*
Intercept	2.51	.01	.79	(1.03, 3.98)	3.20	28.68	<.01
Level 1 Predictors							
Day	-.01	-.04	.01	(-.04, .01)	-1.00	26.74	.32
Within IL	-.02	-.07	.08	(-.17, .13)	-.22	253.94	.82
Within EL	-.24	-.30	.07	(-.38, -.10)	-3.27	256.16	<.01
Within GL	.25	.25	.10	(.05, .44)	2.48	252.76	<.05
Level 2 Predictors							
Between IL	-.07	-.05	.14	(-.33, .20)	-.48	27.57	.63

	Fixed Effects						
	b	β	SE	95% CI	*t*	*df*	*p*
Between EL	-.44	-.35	.10	(-.63, -.24)	-4.30	27.25	<.001
Between GL	.52	.36	.16	(.21, .83)	3.20	26.19	<.01
Baseline Self-Efficacy	.22	.13	.12	(.00, .43)	1.87	32.52	.07
Interactions							
Day x Within IL	-.01	-.03	.01	(-.04, .02)	-.85	257.26	.40
Day x Within EL	-.02	-.04	.01	(-.04, .01)	-1.21	263.34	.23
Day x Within GL	.02	.05	.02	(-.01, .06)	1.21	258.12	.23
	Random Effects						
	σ^2	SD					
Random Intercept (Day)	.09	.30					
Random Slope (Day)	<.01	.10					

Note. A random slope for Day was included in this model. SE = standard error, CI = confidence interval, df = degrees of freedom, EL = extraneous load, IL = intrinsic load, GL = germane load, SD = standard deviation.

Task Effort Cost Outcome Model. In this section, I present the results of three models (i.e., unconditional, intermediate, and full) with task effort cost as the outcome variable (see Tables 22-25). Ultimately, the intermediate model fit best and was therefore retained and interpreted. Table 22 presents the full Likelihood Ratio Test Statistics, including the Akaike and Bayesian Information Criterion (i.e., AIC; BIC) estimates.

Table 22

Task Effort Cost Model Fit

Model	AIC	BIC	χ^2	*df*	*p*
Unconditional	808.07	818.91	–	–	–
Intermediate	758.75	798.49	65.33	8	<.001

Full	765.36	823.17	3.39	5	.64

Note. AIC = Akaike Information Criterion, BIC = Bayesian Information Criterion, SE = standard error, CI = confidence interval, df = degrees of freedom.

Unconditional Task Effort Cost Model. The unconditional model for task effort cost revealed an ICC of $\rho = .29$ at the teacher level (Level 2) and $\rho = .71$ at the day level (Level 1). The teacher-level ICC suggests that 29% of the variation in task effort cost is explained by differences between teachers. The day-level ICC suggests that 71% of the variation in task effort cost is explained within teachers via their daily fluctuations. The ICCs are evidentiary as to the importance of using a MLM to analyze this data given clustering present. The teacher and day-level ICCs for the task effort cost model give reason to why a MLM approach was needed due to the clustering of the data. Overall, this intercept-only model (see Table 23) was significant, $b = 2.33$, $t(26.31) = 18.31$, $p < .001$, 95% CI [2.08, 2.58]. In other words, the average task effort cost across teachers was 2.33 on a 5-point scale.

Table 23

Task Effort Cost Unconditional Model

	b	β	SE	95% CI	*t*	*df*	*p*
Intercept	2.33	.04	.13	(2.08, 2.58)	18.31	26.31	<.001

Note. SE = standard error, CI = confidence interval, df = degrees of freedom.

Intermediate Task Effort Cost Model. The Level 1 predictors of Day, within-person intrinsic load, within-person extraneous load, and within-person germane load and Level 2 predictors of between-person intrinsic load, between-person extraneous load, between-person germane load, and baseline task effort cost were each added to the task effort cost intermediate outcome model. Moreover, this intermediate model represented a significant improvement in

model fit when compared to the null model ($\chi^2(8) = 65.33$, $p < .001$). Table 22 presents LRT results, including AIC and BIC estimates.

At Level 1, all three within-cognitive load dimensions were significant or marginally significant. That is, within-person intrinsic load was a significant predictor of task effort cost ($b = .27$, $t(239.12) = 3.86$, $p < .001$, 95% CI [.13, .40]: on days when teachers reported an intrinsic load that was one unit higher than their own average, their task-effort cost was, on average, .27 units higher. Within-person extraneous load was also a significant predictor of task effort cost ($b = .32$, $t(239.73) = 4.94$, $p < .001$, 95% CI [.19, .45]: on days when teachers reported an extraneous load one unit higher than their own average, their task effort cost was, on average, roughly a third of a unit (i.e., .32 units) higher. Within-person germane load was a marginally significant predictor of task effort cost ($b = -.16$, $t(241.45) = -1.74$, $p = .08$, 95% CI [-.35, .02]: on days when teachers reported a germane load one unit higher than their own average, their task effort cost was, on average, .16 units lower. Day was not a significant predictor of teachers' task effort cost ($b = -.01$, $p = .45$).

At Level 2, between-person germane load and baseline task effort cost were significant predictors of task effort cost. That is, between-person germane load significantly predicted teachers' perceptions of task effort cost ($b = -.57$, $t(22.87) = -2.15$, $p < .05$, 95% CI [-1.06, -.08]: for each one unit increase in average teachers' germane load, their average task effort was over a half unit (i.e., .57) lower. Additionally, baseline task effort cost significantly predicted teachers' task effort cost perceptions ($b = .27$, $t(22.65) = 3.27$, $p < .01$, 95% CI [.12, .43]: indicating that higher task effort cost perceptions on the baseline survey also indicated higher task effort cost perceptions on the daily surveys. Between-person intrinsic and extraneous loads was not a significant predictor of teachers' perceptions of task effort cost.

Table 24

Task Effort Cost Intermediate Model Results

	b	β	SE	95% CI	*t*	*df*	*p*
Intercept	1.76	.02	.92	(.06, 3.45)	1.91	24.69	.07
Level 1 Predictors							
Day	-.01	-.04	.02	(-.05, .02)	-.76	240.31	.45
Within IL	.27	.19	.07	(.13, .40)	3.86	239.12	<.001
Within EL	.32	.24	.06	(.19, .45)	4.94	239.73	<.001
Within GL	-.16	-.09	.09	(-.35, .02)	-1.74	241.45	.08
Level 2 Predictors							
Between IL	.39	.21	.24	(-.06, .83)	1.61	22.89	.12
Between EL	.25	.16	.16	(-.03, .54)	1.62	23.88	.12
Between GL	-.57	-.31	.27	(-1.06, -.08)	-2.15	22.87	<.05
Baseline Task Effort Cost	.27	.28	.08	(.12, .43)	3.27	22.65	<.01

Note. SE = standard error, CI = confidence interval, df = degrees of freedom, EL = extraneous load, IL = intrinsic load, GL = germane load.

Full Task Effort Cost Model. In the full model, I added the random slope of day, three interaction terms (i.e., day x within-intrinsic load, day x within-extraneous load, day x within-germane load), and all Level 1 and Level 2 predictors included in the intermediate model (see Table 25). However, there was no improvement in model fit ($\chi^2(5) = 3.39$, $p = .64$). Therefore, the intermediate model was retained and interpreted.

Table 25

Results for Full Task Effort Cost Model

	Fixed Effects						
	b	β	SE	95% CI	*t*	*df*	*p*

Intercept	1.86	.02	.91	(.17, 3.55)	2.04	25.15	.05
Level 1 Predictors							
Day	-.02	-.05	.02	(-.07, .03)	-.78	26.51	.44
Within IL	.29	.19	.14	(.01, .56)	2.04	241.64	<.05
Within EL	.23	.24	.13	(-.03, .49)	1.80	243.89	.07
Within GL	-.24	-.10	.18	(-.59, .11)	-1.33	243.60	.18
Level 2 Predictors							
Between IL	.38	.21	.24	(-.06, .82)	1.59	22.74	.12
Between EL	.24	.15	.15	(-.05, .52)	1.55	23.93	.13
Between GL	-.58	-.32	.26	(-1.06, -.10)	-2.22	22.79	<.05
Baseline Task Eff. Cost	.28	.29	.08	(.13, .43)	3.35	23.48	<.01
Interactions							
Day x Within IL	-.01	-.01	.03	(-.06, .05)	-.26	244.30	.79
Day x Within EL	.02	.04	.02	(-.03, .06)	.69	248.35	.49
Day x Within GL	.01	.02	.04	(-.05, .08)	.40	248.56	.69

	Random Effects	
	σ^2	SD
Random Intercept (Day)	.32	.56
Random Slope (Day)	.01	.07

Note. A random slope for Day was included in this model. SE = standard error, CI = confidence interval, df = degrees of freedom, EL = extraneous load, IL = intrinsic load, GL = germane load.

Outside Effort Cost Outcome Model. In this section, I present the results of three models (i.e., unconditional, intermediate, and full) with outside effort cost as the outcome variable (see Tables 26-29). Ultimately, the intermediate model fit best and was therefore retained and interpreted. Table 26 presents the full Likelihood Ratio Test Statistics, including the Akaike and Bayesian Information Criterion (i.e., AIC; BIC) estimates.

Table 26

Outside Effort Cost Model Fit

Model	AIC	BIC	χ^2	*df*	*p*
Unconditional	860.95	871.79	–	–	–
Intermediate	814.74	854.48	62.21	8	<.001
Full	819.64	873.84	3.10	4	.54

Note. AIC = Akaike Information Criterion, BIC = Bayesian Information Criterion, SE = standard error, CI = confidence interval, df = degrees of freedom.

Unconditional Outside Effort Cost Model. The unconditional model for outside effort cost revealed an ICC of $\rho = .47$ at the teacher level (Level 2) and $\rho = .53$ at the day level (Level 1). The teacher-level ICC suggests that 47% of the variation in outside effort cost is explained by differences between teachers. The day-level ICC suggests that 53% of the variation in outside effort cost is explained within teachers via their daily fluctuations. The teacher and day-level ICCs for the outside effort cost model give reason to why a MLM approach was needed due to the clustering of the data. Overall, this intercept-only model (see Table 27) was significant, $b = 2.50$, $t(27.73) = 13.23$, $p < .001$, 95% CI [2.13, 2.88]. In other words, the average outside effort cost across teachers was 2.50 on a 5-point scale.

Table 27

Outside Effort Cost Unconditional Model Results

	b	β	SE	95% CI	*t*	*df*	*p*
Intercept	2.50	.05	.19	(2.13, 2.88)	13.23	27.73	<.001

Note. SE = standard error, CI = confidence interval, df = degrees of freedom.

Intermediate Outside Effort Cost Model. The Level 1 predictors of Day, within-person intrinsic load, within-person extraneous load, and within-person germane load and Level 2 predictors of between-person intrinsic load, between-person extraneous load, between-person

germane load, and baseline outside effort cost were each added to the outside effort cost intermediate outcome model. Moreover, this intermediate model represented a significant improvement in model fit when compared to the null model ($\chi^2(8) = 62.21$, $p < .001$). Table 26 presents LRT results, including AIC and BIC estimates.

At Level 1, within-extraneous and germane load dimensions were significant or marginally significant. That is, within-person extraneous load was a marginally significant predictor of outside effort cost ($b = .13$, t(240.25) = 1.93, $p = .05$, 95% CI [.00, .27]: on days when teachers reported an extraneous load that was one unit higher than their own average, their outside effort cost was, on average, .13 units higher. Within-person germane load was a significant predictor of outside effort cost ($b = -.54$, t(241.96) = -5.37, $p < .001$, 95% CI [-.74, -.35]: on days when teachers reported a germane load one unit higher than their own average, their outside effort cost was, on average, over a half unit (i.e., .54 units) lower. Neither day nor within-person intrinsic load were significant predictors of teachers outside effort cost ($b = .02$, $p = .40$; $b = .08$, $p = .30$).

At Level 2, between-person extraneous load was the only significant predictor of outside effort cost. That is, between-person extraneous load significantly predicted teachers' perceptions of outside effort cost ($b = .68$, t(24.19) = 3.00, $p < .01$, 95% CI [.26, 1.11]: for each one unit increase in average teachers' extraneous load, their average outside effort cost was nearly two thirds of a unit (i.e., .68) higher. Between-person intrinsic and germane loads as well as baseline outside effort cost each were not significant predictors of teachers' perceptions of outside effort cost ($b = .17$, $p = .63$; $b = -.39$, $p = .32$; $b = .18$, $p = .14$).

Table 28

Outside Effort Cost Intermediate Model

	b	β	SE	95% CI	*t*	*df*	*p*
Intercept	.51	.02	1.35	(-1.98, 3.00)	.38	25.20	.71
Level 1 Predictors							
Day	.02	.04	.02	(-.02, .06)	.84	240.48	.40
Within IL	.08	.05	.07	(-.07, .22)	1.04	239.66	.30
Within EL	.13	.08	.07	(.00, .27)	1.93	240.25	.05
Within GL	-.54	-.24	.10	(-.74, -.35)	-5.37	241.96	<.001
Level 2 Predictors							
Between IL	.17	.16	.35	(-.48, .82)	.50	24.42	.63
Between EL	.68	.36	.23	(.26, 1.11)	3.00	24.19	<.01
Between GL	-.39	-.17	.38	(-1.09, .32)	-1.01	23.75	.32
Baseline Outside Effort Cost	.18	.17	.12	(-.04, .40)	1.51	24.42	.14

Note. SE = standard error, CI = confidence interval, df = degrees of freedom, EL = extraneous load, IL = intrinsic load, GL = germane load.

Full Outside Effort Cost Model. In the full model, I added the random slope of day, three interaction terms (i.e., day x within-intrinsic load, day x within-extraneous load, day x within-germane load), and all Level 1 and Level 2 predictors included in the intermediate model (see Table 29). However, there was no improvement in model fit ($\chi^2(4) = 3.10$, $p = .54$). Therefore, the intermediate model was retained and interpreted.

Table 29

Results for Full Outside Effort Cost Model

	Fixed Effects						
	b	β	SE	95% CI	*t*	*df*	*p*
Intercept	.21	.02	1.32	(-2.24, 2.69)	.16	24.81	.88
Level 1 Predictors							
Day	.02	.03	.02	(-.03, .06)	.74	38.58	.47
Within IL	-.09	.04	.15	(-.38, .21)	-.56	244.20	.57

	Fixed Effects						
	b	β	SE	95% CI	*t*	*df*	*p*
Within EL	.02	.07	.14	(-.26, .29)	.14	246.64	.89
Within GL	-.44	-.25	.19	(-.83, -.07)	-2.27	245.08	<.05
Level 2 Predictors							
Between IL	.19	.08	.34	(-.44, .81)	.56	23.41	.58
Between EL	.69	.36	.22	(.28, 1.10)	3.11	23.43	<.01
Between GL	-.34	-.17	.37	(-1.03, .35)	-.91	22.85	.38
Baseline Out. Eff. Cost	.21	.17	.12	(-.01, .42)	1.80	23.45	.08
Interactions							
Day x Within IL	.03	.05	.03	(-.02, .09)	1.22	246.28	.22
Day x Within EL	.02	.04	.03	(-.03, .07)	.87	250.62	.38
Day x Within GL	-.03	-.03	.04	(-.10, .05)	-.67	249.30	.50
	Random Effects						
	σ^2	SD					
Random Intercept (Day)	.38	.61					
Random Slope (Day)	<.01	.05					

Note. A random slope of Day was included in this model. SE = standard error, CI = confidence interval, df = degrees of freedom, EL = extraneous load, IL = intrinsic load, GL = germane load.

Emotional Cost Outcome Model. In this section, I present the results of three models (i.e., unconditional, intermediate, and full) with emotional cost as the outcome variable (see Tables 30-33). Ultimately, the intermediate model fit best and was therefore retained and interpreted. Table 30 presents the full Likelihood Ratio Test Statistics, including the Akaike and Bayesian Information Criterion (i.e., AIC; BIC) estimates.

Table 30

Emotional Cost Model Fit

Model	AIC	BIC	χ^2	*df*	*p*
Unconditional	887.46	898.31	–	–	–
Intermediate	802.19	841.97	101.27	8	<.001

Model	AIC	BIC	χ^2	*df*	*p*
Full	805.52	859.77	4.67	4	.32

Note. AIC = Akaike Information Criterion, BIC = Bayesian Information Criterion, SE = standard error, CI = confidence interval, df = degrees of freedom.

Unconditional Emotional Cost Model. The unconditional model for emotional cost revealed an ICC of $\rho = .33$ at the teacher level (Level 2) and $\rho = .67$ at the day level (Level 1). The teacher-level ICC suggests that 33% of the variation in emotional cost is explained by differences between teachers. The day-level ICC suggests that 67% of the variation in emotional cost is explained within teachers via their daily fluctuations. The teacher and day-level ICCs for the emotional cost model give reason to why a MLM approach was needed due to the clustering of the data. Overall, this intercept-only model (see Table 31) was significant, $b = 2.89$, $t(27.37) = 18.49$, $p < .001$, 95% CI [2.58, 3.21]. In other words, the average emotional cost across teachers was 2.89 on a 5-point scale.

Table 31

Results for Unconditional Emotional Cost Model

	b	β	SE	95% CI	*t*	*df*	*p*
Intercept	2.89	.04	.16	(2.58, 3.21)	18.49	27.37	<.001

Note. SE = standard error, CI = confidence interval, df = degrees of freedom.

Intermediate Emotional Cost Model. The Level 1 predictors of Day, within-person intrinsic load, within-person extraneous load, and within-person germane load and Level 2 predictors of between-person intrinsic load, between-person extraneous load, between-person germane load, and baseline emotional cost were each added to the emotional cost intermediate outcome model. Moreover, this intermediate model represented a significant improvement in

model fit when compared to the null model ($\chi^2(8) = 101.27$, $p < .001$). Table 30 presents LRT results, including AIC and BIC estimates.

At Level 1, within-extraneous and intrinsic loads were significant. That is, within-person intrinsic load was a significant predictor of emotional cost ($b = .28$, t(240.19) = 3.74, $p < .01$, 95% CI [.13, .42]: on days when teachers reported an intrinsic load that was one unit higher than their own average, their emotional cost was, on average, .28 units higher. Within-person extraneous load was also a significant predictor of emotional cost ($b = .56$, t(240.77) = 8.12, $p < .001$, 95% CI [.43, .70]: on days when teachers reported an extraneous load one unit higher than their own average, their emotional cost was, on average, roughly over a half unit (i.e., .56 units) higher. Neither Day nor within-person germane load were significant predictors of teachers' emotional cost ($b = .00$, $p = .76$; $b = -.06$, $p = .54$).

At Level 2, between-person extraneous load and baseline emotional cost were significant predictors of emotional cost. That is, between-person extraneous load significantly predicted teachers' perceptions of emotional cost ($b = .56$, t(23.82) = 3.12, $p < .01$, 95% CI [.23, .90]: for each one unit increase in average teachers' extraneous load, their average emotional cost was over a half unit (i.e., .56) higher. Additionally, baseline emotional cost significantly predicted teachers' emotional cost perceptions ($b = .25$, t(22.84) = 2.95, $p < .01$, 95% CI [.09, .40]: indicating that higher emotional cost perceptions on the baseline survey also indicated higher emotional cost perceptions on the daily surveys. Between-person intrinsic and germane loads were not a significant predictor of teachers' perceptions of emotional cost ($b = .37$, $p = .21$; $b = -.45$, $p = .16$).

Table 32

Results for Intermediate Emotional Cost Model

	b	β	SE	95% CI	*t*	*df*	*p*
Intercept	.76	.02	1.09	(-1.23, 2.76)	.70	24.59	.49
Level 1 Predictors							
Day	.001	.01	.02	(-.03, .05)	.30	241.23	.76
Within IL	.28	.17	.07	(.13, .42)	3.74	240.19	<.01
Within EL	.56	.36	.07	(.43, .70)	8.12	240.77	<.001
Within GL	-.06	-.03	.10	(-.26, .13)	-.61	242.36	.54
Level 2 Predictors							
Between IL	.37	.17	.28	(-.16, .89)	1.29	23.2	.21
Between EL	.56	.31	.18	(.23, .90)	3.12	23.82	<.01
Between GL	-.45	-.21	.31	(-1.02, .12)	-1.45	22.93	.16
Baseline Emotional Cost	.25	.25	.08	(.09, .40)	2.95	22.84	<.01

Note. SE = standard error, CI = confidence interval, df = degrees of freedom, EL = extraneous load, IL = intrinsic load, GL = germane load.

Full Emotional Cost Model. In the full model, I added the random slope of day, three interaction terms (i.e., day x within-intrinsic load, day x within-extraneous load, day x within-germane load), and all Level 1 and Level 2 predictors included in the intermediate model (see Table 33). However, there was no improvement in model fit ($\chi^2(4) = 4.67$, $p = .32$). Therefore, the intermediate model was retained and interpreted.

Table 33

Results for Full Emotional Cost Model

	Fixed Effects						
	b	β	SE	95% CI	*t*	*df*	*p*
Intercept	.60	.01	1.08	(-1.39, 2.62)	.55	24.65	.59
Level 1 Predictors							
Day	.01	.02	.02	(-.03, .05)	.47	50.06	.64

Within IL	.24	.17	.15	(-.05, .54)	1.59	246.26	.11
Within EL	.77	.38	.14	(.49, 1.03)	5.48	247.07	<.001
Within GL	-.17	-.03	.19	(-.54, .19)	-.88	247.54	.38
Level 2 Predictors							
Between IL	.37	.17	.28	(-.15, .89)	1.32	22.84	.20
Between EL	.59	.32	.18	(.26, .93)	3.29	23.81	<.01
Between GL	-.44	-.20	.31	(-1.00, .13)	-1.41	22.66	.17
Baseline Emotional Cost	.24	.24	.08	(.09, .40)	2.89	22.82	<.01
Interactions							
Day x Within IL	.01	.01	.03	(-.05, .06)	.27	249.99	.79
Day x Within EL	-.04	-.08	.03	(-.09, .01)	-1.71	253.31	.09
Day x Within GL	.02	.03	.04	(-.05, .10)	.58	253.58	.56

	Random Effects	
	σ^2	SD
Random Intercept (Day)	.23	.48
Random Slope (Day)	<.01	.04

Note. A random slope for Day was included in this model. SE = standard error, CI = confidence interval, df = degrees of freedom, EL = extraneous load, IL = intrinsic load, GL = germane load.

Loss of Valued Alternatives Cost Outcome Model. In this section, I present the results of three models (i.e., unconditional, intermediate, and full) with loss of valued alternatives cost as the outcome variable (see Tables 34-37). Ultimately, the intermediate model fit best and was therefore retained and interpreted. Table 34 presents the full Likelihood Ratio Test Statistics, including the Akaike and Bayesian Information Criterion (i.e., AIC; BIC) estimates.

Table 34

Loss of Valued Alternatives Cost Model Fit

Model	AIC	BIC	χ^2	*df*	*p*
Unconditional	737.35	748.20	–	–	–
Intermediate	723.50	763.28	29.85	8	<.001
Full	730.18	784.43	1.32	4	.86

Note. AIC = Akaike Information Criterion, BIC = Bayesian Information Criterion, SE = standard error, CI = confidence interval, df = degrees of freedom.

Unconditional Loss of Valued Alternatives Cost Model. The unconditional model for loss of valued alternatives cost revealed an ICC of ρ = .37 at the teacher level (Level 2) and ρ = .63 at the day level (Level 1). The teacher-level ICC suggests that 37% of the variation in loss of valued alternatives cost is explained by differences between teachers. The day-level ICC suggests that 63% of the variation in loss of valued alternatives cost is explained within teachers via their daily fluctuations. The teacher and day-level ICCs for the loss of valued alternatives cost model give reason to why a MLM approach was needed due to the clustering of the data. Overall, this intercept-only model (see Table 35) was significant, b = 1.91, t(24.38) = 15.03, p < .001, 95% CI [1.66, 2.17]. In other words, the average loss of valued alternatives cost across teachers was 1.91 on a 5-point scale.

Table 35

Loss of Valued Alternatives Cost Unconditional Model Results

	b	β	SE	95% CI	*t*	*df*	*p*
Intercept	1.91	.06	.13	(1.66, 2.17)	15.03	24.38	<.001

Note. SE = standard error, CI = confidence interval, df = degrees of freedom, LVA = loss of valued alternatives.

Intermediate Loss of Valued Alternatives Cost Model. The Level 1 predictors of Day, within-person intrinsic load, within-person extraneous load, and within-person germane load and Level 2 predictors of between-person intrinsic load, between-person extraneous load, between-

person germane load, and baseline loss of valued alternatives cost were each added to the loss of valued alternatives cost intermediate outcome model. Moreover, this intermediate model represented a significant improvement in model fit when compared to the null model ($\chi^2(8) = 29.85$, $p < .001$). Table 34 presents LRT results, including AIC and BIC estimates.

At Level 1, within-person extraneous load was significant. That is, within-person extraneous load was a significant predictor of loss of valued alternatives cost ($b = .22$, t(236.67) = 3.74, $p < .001$, 95% CI [.10, .33]: on days when teachers reported an extraneous load that was one unit higher than their own average, their loss of valued alternatives cost was, on average, .22 units higher. Neither Day, within-person intrinsic load, nor within-person germane load were significant predictors of teachers' loss of valued alternatives cost ($b = .01$, $p = .51$; $b = .03$, $p = .69$; $b = -.12$, $p = .15$).

At Level 2, between-person extraneous load was a marginally significant predictor of loss of valued alternatives cost. That is, between-person extraneous load marginally significantly predicted teachers' perceptions of loss of valued alternatives cost ($b = .35$, t(20.04) = 1.78, $p = .09$, 95% CI [-.01, .71]: for each one unit increase in average teachers' extraneous load, their average loss of valued alternatives cost was .35 units higher. Neither between-person intrinsic load, between-person germane load, nor baseline loss of valued alternatives cost were significant predictors of teachers' perceptions of loss of valued alternatives cost ($b = .50$, $p = .12$; $b = -.44$, $p = .21$; $b = .09$, $p = .47$).

Table 36

Results for Intermediate Loss of Valued Alternatives Cost Model

	b	β	SE	95% CI	*t*	*df*	*p*
Intercept	.69	.04	1.12	(-1.35, 2.73)	.62	20.84	.54

	b	β	SE	95% CI	*t*	*df*	*p*
Level 1 Predictors							
Day	.01	.03	.02	(-.02, .04)	.66	236.92	.51
Within IL	.03	.02	.06	(-.10, .15)	.41	235.96	.69
Within EL	.22	.18	.06	(.10, .33)	3.74	236.67	<.001
Within GL	-.12	-.07	.08	(-.29, .04)	-1.43	238.62	.15
Level 2 Predictors							
Between IL	.50	.30	.31	(-.07, 1.05)	1.63	20.17	.12
Between EL	.35	.25	.20	(-.01, .71)	1.78	20.04	.09
Between GL	-.44	-.27	.34	(-1.05, .18)	-1.31	19.65	.21
Baseline LVA Cost	.09	.09	.12	(-.13, .30)	.73	19.33	.47

Note. SE = standard error, CI = confidence interval, df = degrees of freedom, EL = extraneous load, IL = intrinsic load, GL = germane load.

Full Loss of Valued Alternatives Cost Model. In the full model, I added the random slope of day, three interaction terms (i.e., day x within-intrinsic load, day x within-extraneous load, day x within-germane load), and all Level 1 and Level 2 predictors included in the intermediate model (see Table 37). However, there was no improvement in model fit ($\chi^2(4) = 1.32$, $p = .86$). Therefore, the intermediate model was retained and interpreted.

Table 37

Loss of Valued Alternatives Cost Full Model

	Fixed Effects						
	b	β	SE	95% CI	*t*	*df*	*p*
Intercept	.80	.04	1.09	(-1.20, 2.79)	.74	20.79	.47
Level 1 Predictors							
Day	.01	.03	.02	(-.01, .05)	.67	39.47	.51
Within IL	.04	.02	.13	(-.21, .29)	.29	240.00	.78

Within EL	.22	.19	.12	(-.02, .45)	1.77	240.50	.08
Within GL	-.18	-.07	.16	(-.51, .13)	-1.07	242.40	.28
Level 2 Predictors							
Between IL	.53	.30	.30	(-.02, 1.07)	1.80	19.83	.09
Between EL	.31	.25	.19	(-.04, .67)	1.63	19.89	.12
Between GL	-.47	-.27	.33	(-1.06, .14)	-1.43	19.44	.17
Baseline LVA Cost	.10	.09	.12	(-.12, .31)	.83	19.50	.42
Interactions							
Day x Within IL	<.01	<.01	.02	(-.05, .04)	-.11	242.80	.91
Day x Within EL	<.01	<.01	.02	(-.04, .04)	.02	242.00	.99
Day x Within GL	.01	.02	.03	(-.05, .08)	.35	246.90	.73

	Random Effects	
	σ^2	SD
Random Intercept (Day)	.27	.52
Random Slope (Day)	<.01	.05

Note. A random slope of Day was included in this model. SE = standard error, CI = confidence interval, df = degrees of freedom, EL = extraneous load, IL = intrinsic load, GL = germane load.

Attrition Intentions Outcome Model. In this section, I present the results of three models (i.e., unconditional, intermediate, and full) with attrition intentions as the outcome variable (see Tables 38-41). Ultimately, the intermediate model fit best and was therefore retained and interpreted. Table 38 presents the full Likelihood Ratio Test Statistics, including the Akaike and Bayesian Information Criterion (i.e., AIC; BIC) estimates.

Table 38

Comparison of Attrition Intentions Model Fit

Model	AIC	BIC	χ^2	*df*	*p*
Unconditional	315.41	326.26	–	–	–

Intermediate	306.79	346.57	24.63	8	<.01
Full	303.55	357.80	11.24	4	.05

Note. AIC = Akaike Information Criterion, BIC = Bayesian Information Criterion, SE = standard error, CI = confidence interval, df = degrees of freedom.

Unconditional Attrition Intentions Model. The unconditional model for attrition intentions revealed an ICC of $\rho = .92$ at the teacher level (Level 2) and $\rho = .08$ at the day level (Level 1). The teacher-level ICC suggests that 92% of the variation in attrition intentions is explained by differences between teachers. The day-level ICC suggests that 8% of the variation in attrition intentions is explained within teachers via their daily fluctuations. While the variation at the Day level (Level 1) is smaller than the other variables included in this study, the ICC is greater than .05, which indicates that an MLM approach was most appropriate to analyze the data due to clustering (Snijders & Bosker, 2012). Overall, this intercept-only model (see Table 39) was significant, $b = 1.78$, $t(28.85) = 8.82$, $p < .001$, 95% CI [1.36, 2.18]. In other words, the average attrition intentions across teachers were 1.78 on a 5-point scale.

Table 39

Attrition Intentions Unconditional Model Results

	b	β	SE	95% CI	*t*	*df*	*p*
Intercept	1.78	.08	.20	(1.36, 2.18)	8.82	28.85	<.001

Note. SE = standard error, CI = confidence interval, df = degrees of freedom.

Intermediate Attrition Intentions Model. The Level 1 predictors of Day, within-person intrinsic load, within-person extraneous load, and within-person germane load and Level 2 predictors of between-person intrinsic load, between-person extraneous load, between-person germane load, and baseline attrition intentions were each added to the attrition intentions intermediate outcome model. Moreover, this intermediate model represented a significant

improvement in model fit when compared to the null model ($\chi^2(8) = 24.63$, $p < .01$). Table 38 presents LRT results, including AIC and BIC estimates.

At Level 1, within-person germane load was significant. That is, within-person germane load was a significant predictor of attrition intentions ($b = -.10$, t(241.70) = -2.93, $p < .01$, 95% CI [-.17, -.03]: on days when teachers reported an germane load that was one unit higher than their own average, their attrition intentions was, on average, .10 units lower. Neither Day, within-person intrinsic load, nor within-person extraneous load were significant predictors of teachers' attrition intentions ($b = .01$, $p = .39$; $b = .03$, $p = .24$; $b = -.02$, $p = .37$).

At Level 2, only baseline attrition intentions significantly predicted teachers' attrition intentions ($b = .37$, t(26.14) = 3.49, $p < .01$, 95% CI [.27, .88]: indicating that higher attrition intentions on the baseline survey also indicated higher attrition intentions on the daily surveys. Neither between-person intrinsic load, between-person extraneous load, nor between-person germane load were significant predictors of teachers' attrition intentions ($b = .00$, $p = .99$; $b = .02$, $p = .94$; $b = -.28$, $p = .59$).

Table 40

Results for Intermediate Attrition Intentions Model

	b	β	SE	95% CI	*t*	*df*	*p*
Intercept	1.44	.02	1.62	(-1.56, 4.44)	.97	25.18	.38
Level 1 Predictors							
Day	.01	.02	.01	(-.01, .02)	.85	241.30	.39
Within IL	.03	.02	.03	(-.02, .08)	1.17	241.10	.24
Within EL	-.02	-.02	.02	(-.07, .03)	-.89	241.30	.37
Within GL	-.10	-.06	.03	(-.17, -.03)	-2.93	241.70	<.01
Level 2 Predictors							

	b	β	SE	95% CI	*t*	*df*	*p*
Between IL	.00	<.01	.47	(-.87, .86)	.00	25.91	.99
Between EL	.02	.01	.27	(-.49, .53)	.07	25.22	.94
Between GL	-.28	-.16	.52	(-1.24, .68)	-.54	25.58	.59
Baseline Attrition Intentions	.57	.57	.16	(.27, .88)	3.49	26.14	<.01

Note. SE = standard error, CI = confidence interval, df = degrees of freedom, ECL = extraneous load, ICL = intrinsic load, GCL = germane load.

Full Attrition Intentions Model. In the full model, I added the random slope of day, three interaction terms (i.e., day x within-intrinsic load, day x within-extraneous load, day x within-germane load), and all Level 1 and Level 2 predictors included in the intermediate model (see Table 41). However, there was no improvement in model fit above and beyond the more parsimonious intermediate model ($\chi^2(4) = 11.24$, $p < 05$). Therefore, the intermediate model was retained and interpreted.

Table 41

Results for Full Attrition Intentions Model

	Fixed Effects						
	b	β	SE	95% CI	*t*	*df*	*p*
Intercept	1.23	.03	1.56	(-1.64, 4.12)	.79	25.10	.44
Level 1 Predictors							
Day	.01	.02	.01	(-.01, .03)	.77	28.34	.45
Within IL	.04	.02	.05	(-.06, .14)	.72	230.11	.47
Within EL	-.02	-.02	.05	(-12, .07)	-.48	232.71	.63
Within GL	-.20	-.05	.07	(-.32, -.07)	-2.99	229.01	<.01
Level 2 Predictors							
Between IL	.02	<.01	.45	(-.81, .84)	.04	25.63	.97
Between EL	.03	.02	.26	(-.45, .52)	.13	25.06	.90
Between GL	-.23	-.15	.50	(-1.15, .69)	-.46	25.24	.65

	Fixed Effects						
	b	β	SE	95% CI	*t*	*df*	*p*
Baseline Attrition Intent.	.55	.56	.16	(.25, .84)	3.45	25.95	<.01
Interactions							
Day x Within IL	.00	<.01	.01	(-.02, .02)	-.30	231.39	.77
Day x Within EL	.00	<.01	.01	(-.02, .02)	-.01	232.69	.99
Day x Within GL	.02	.04	.01	(.00, .05)	1.80	231.47	.07
	Random Effects						
	σ^2	SD					
Random Intercept (Day)	.78	.88					
Random Slope (Day)	<.01	.04					

Note. A random slope of Day was included in this model. SE = standard error, CI = confidence interval, df = degrees of freedom, EL = extraneous load, IL = intrinsic load, GL = germane load.

Phase 2: Qualitative, Interview Findings

In the following sections, I describe the results that emerged from the qualitative, semi-structured interviews. I first present the findings from Research Question 3, in which five themes emerged from the thematic analysis. Then, I present the results for Research Question 3a, in which several trends also emerged.

Research Question 3: How do teachers describe their daily experiences with cognitive load and motivation during mathematics instruction?

Five themes emerged from the thematic analyses and in response to Research Question 3: (1) The compounding challenges of math instruction; (2) The unpredictable nature of the classroom environment; (3) The cognitive and emotional endurance required of teachers; (4) Experience enables instructional adaptation; and (5) Students as a buffer to teacher attrition (see Appendix Z for theme definitions, example quotes, and frequencies).

Theme 1: The Compounding Challenges of Math Instruction. The first theme refers to teachers' perceptions of the level of difficultly of their math instruction, including personal,

student, and district level factors that exacerbate its level of challenge. Across the 10 interviews I conducted, it was clear that teachers held differing views regarding the level of challenge associated with teaching math to their elementary grade level students. Three of these teachers felt that math was generally an easy subject, content-wise, for them to teach. For example, Ms. Klein, a kindergarten teacher, stated, "I don't think it's [math] very challenging, just because it's understanding what 10 is." Another two teachers explained that in general, they found math to be relatively simple to teach; however, there were exceptions to this ease. For instance, Mr. Clark, an upper-level elementary teacher, explained, "The content itself, besides being tricky, I don't think it's challenging. There's some tricky things, you know, when you have the double negative or turning a fraction into a decimal…" Four teachers described their math instruction as quite difficult. For example, Ms. Thomas, an upper-level elementary teacher, stated, "...it's [math] pretty challenging because now math is taught where they want the kids to know multiple ways to show math. And so with one skill, we're showing like four different methods. And to me, that is very difficult…." Despite the differing perceptions of math instruction difficulty, each of the teachers pointed to at least one of three compounding challenges associated with math instruction that make teaching the subject all the more difficult. Therefore, three sub-themes emerged from the analysis: (1) Differentiation in a shifting educational landscape; (2) Frequent changes to math curriculum; and (3) Teachers' own personal ability beliefs in math. Each of the three sub-themes are described in detail below.

Sub-Theme 1a: Differentiation in a Shifting Educational Landscape. Sub-Theme 1a refers to the need to tailor instruction to meet the different academic levels of students, who have needs that are perceived by teachers as heightened in today's classroom contexts. For example, above and beyond the math content itself, it was common (31 references across 7 teachers) for

teachers to point to differentiation as an aspect of math instruction that makes teaching the subject especially challenging. For example, Ms. Collins, an experienced kindergarten teacher, expressed her anxiety about differentiating math in her classroom:

> "...it's so difficult to differentiate in my group with some of these math activities. You know, I have one student who is figuring out what arrays are, and then I have one student who can't tell me how many fingers I'm holding up, one through five. So having those huge gaps between some of the students makes my tier one instruction really difficult."

Other teachers across grade levels were in agreement with Ms. Collins' sentiments about differentiation. Ms. Scott, a 5th grade teacher, explained that she avoids whole-group math instruction due the differing needs of her students. Ms. Collins stated: "What I find extremely challenging, and I mean extremely – and I've taught a really long time – is teaching math whole group because they're all at different places." Further, the need to supplement materials as a result of students' differentiation needs was described as frustrating and overwhelming by Ms. Thomas, an upper-level elementary teacher:

> "I think it [math] becomes overwhelming when I'm having to supplement so much to meet where the kids are at. So maybe we're not ready to look at the textbook yet, so I'm having to go and find other materials, in such a short amount of time…"

While differentiation is not new within the field of education, several seasoned teachers (n = 5) expressed that differentiation needs are dissimilar in today's contemporary classrooms than they ever have been in the past. To explain, four teachers – all of whom have been in the field for a minimum of 18 years or more (i.e., Mr. Clark, Ms. Baker, Ms. Scott, and Ms. Collins) – explained that the current generation of students in their classrooms over the past few years are more dissimilar to their previous students than ever before. More specifically, they feel that

students today have greater needs than the students of generations past or even just a few years before. To demonstrate, Ms. Baker, an early childhood teacher of 30 years and a current pre-K teacher, said:

> "In the last 30 year period… you might have a challenging student or a student with really high needs once every three to four years. And now you have four [students with high needs] every year. So the level of support needed… I mean, you've got to work a lot of areas to be able to keep this [math instruction] running at a high level."

Drawing from Ms. Baker's quote above, as more students arrive at the classroom with different needs, the more Ms. Baker needs to differentiate her material to effectively teach every learner in her math classroom. Interestingly, even Ms. Myers, who has fewer years of teaching experience (i.e., seven years) than her above-mentioned peers, explained that she has noticed a change in students since she began her career. Ms. Myers stated:

> "...my first and second year I could probably teach whole group math. Everybody would get it for the most part and I'd have one or two kids that would need a little bit more intervention. But compared to this year, it's like night and day…"

Ms. Myers went on to explain that she noticed this shift in students following the COVID-19 pandemic, while Ms. Collins and Mr. Clark both attributed the shift in students to their increase in technology usage at home. Regardless of the reasoning behind the perceived shift in the contemporary population of students today, many teachers in the sample believe the increasing needs of students have resulted in a need for more differentiation during math instruction – thereby increasing the instructional complexity of the subject.

Sub-Theme 1b: Frequent Changes to Math Curriculum. Sub-Theme 1b refers to the challenges associated with recurring changes to the curriculum used to teach math. In particular,

on top of the heightened differentiation needs of students during math instruction, many teachers (23 references across 8 teachers) expressed frustration and overwhelm due to frequent changes to their math curriculum that is required of them to teach math. Teachers went on to explain that adopting a new math curriculum requires a considerable adjustment period to re-learn the material and the curriculum's suggested practices to teach it. To demonstrate, Ms. Collins stated:

> "But it seems like every time I get used to a curriculum and I start to learn how to do my own thing with it, and pace it based on the standards and the concepts… it's very frustrating that once I do get it figured out, they change the curriculum on us."

Similarly, Ms. Keller, a third-grade teacher in her third year, expressed that the adjustment period associated with the new curriculum, which came during her second year of teaching, was particularly frustrating. Ms. Keller stated, "I think that I was hoping that my adjustment period [for math curriculum] wouldn't come during my second year of teaching." Moreover, Ms. Baker also expressed her frustration with changing math curricula, describing that she often reverts back to a prior curriculum she is more familiar with in-the-moment. She stated:

> "...it's [former math curriculum] already in my mind, it's in my back pocket. I've taught it many times, and I can do it basically standing on my head. I can navigate everything. But if I get a new curriculum all the time, and it changes the way to do it [teach math], I'm more likely to use my old method of teaching the same thing the new curriculum wants me to teach, because it's the same standard. Because then I can do everything else. So I think constant curriculum change can really add to the load."

Taken together, teachers were quick to emphasize the importance of strong background knowledge and familiarity with their math curriculum. However, frustration arises among

teachers when they need to re-start the curriculum familiarization process every few years; thus, compounding the difficulty level of their math instruction.

Sub-Theme 1c: Teachers' Personal Ability Beliefs in Math. Sub-Theme 1c refers to teachers' own beliefs about their math ability level and its implications for how challenging they perceive their math instruction to be. To demonstrate, throughout interviews, I asked teachers to describe the difficulty level of their math instruction; in response to this question, an interesting finding emerged: teachers (12 references across 6 teachers) were quick to associate their own perceptions of math instruction difficulty with their own personal ability beliefs in math. In particular, teachers who felt math instruction was one of their most challenging subjects to teach often qualified these challenges with statements like: "...math has always been harder for me…" (Ms. Lee) and "...math was not my strongest skill in school…" (Ms. Thomas). Further, when teachers held more fixed beliefs (i.e., belief that ability is innate and an uncontrollable trait; Dweck & Leggett, 1988) about their math abilities, they often connected those beliefs to their confidence for teaching the subject. To demonstrate, Ms. Collins stated:

> "I feel a lot more confident doing the younger grades than the older grades. I have a daughter in seventh grade right now. She is doing algebra… and she's in advanced math. She has to get that from her daddy – numbers guy."

In the quote above, Ms. Collins discusses her confidence for teaching math diminishing depending on the grade level and attributed the decreasing confidence to her perceived lack of ability in math. A similar pattern emerged for teachers who (a) perceived teaching math to be relatively an easy task for them and (b) were confident in teaching math. That is, this group of teachers had positive perceptions of their math abilities overall. For example, Ms. Keller, who

expressed that she was confident in her math instructional abilities, said: “I’ve, like, always been a math person, and so math has always been like my favorite thing to teach.”

Taken together, when teachers described perceptions of lower or fixed ability beliefs in math, they were more likely to report that math was challenging for them to teach. Thus, a central finding that emerged from Sub-Theme 1c is that teachers' ability beliefs in math are inextricably tied to their perceptions of math instruction difficulty. However, the opposite was true for teachers who held higher, or more positive ability beliefs in math.

Theme 2: The Unpredictable Nature of the Classroom Environment. The second theme refers to the unexpected and everchanging occurrences that happen in and around the classroom during math instruction, particularly those that are not related to the instructional materials themselves. Specifically, throughout each interview, teachers were by far most likely to comment on the spontaneous demands of the classroom environment. To demonstrate, Ms. Klein, a Kindergarten teacher in her second year said,

> “...well, it's me in a room with 15, five and six year olds, and so what they're distracted by, I'm pretty distracted by because my goal is to get them focused up on the… board and so I myself can lose track pretty easily.”

Further, teachers were quick to comment on miscellaneous distractions that occurred during their math instruction. In fact, there were 135 references (across all 10 teachers) to distraction-related codes – the highest of all coding references across themes (i.e., next closest reference frequency being 83). Therefore, it became clear that disruptions during math instruction – student and non-student-related – played a large role in teachers’ instructional experiences during math. In addition, teachers also commonly described that the number of distractions that occurred depended not only on the day, but the month and the year as well.

Therefore, there sub-themes emerged: (a) An unlimited number of student distractions; (b) Non-student related distractions; and (c) Every day, month, and year are different. I begin by discussing examples of student-related distractions.

Sub-Theme 2a: An Unlimited Number of Student Distractions. Sub-Theme 2a refers to the high frequency of disruptions that occur during math instruction due to student needs, behaviors, or other miscellaneous happenings that could occur within the context of an elementary classroom. That is, teachers commonly (62 references across all 10 teachers) commented on the impact of students' behaviors during math lessons, the impact of those behaviors on their feelings of overwhelm, and therefore the necessity of strong classroom management. To demonstrate, when I asked Ms. Collins about how well she is typically able to concentrate during her math lessons she stated:

> "Not very well. I don't have ADHD, but I sure feel like it when I teach math instruction… I can't even get one sentence out about the lesson without being like, I need you to be quiet. I need you to focus. Are you looking this way? Cross-cross, mountain, or mermaid? Are you looking this way? And I have super strong classroom management. I've been doing this a long time."

It is clear that the distractions Ms. Collins described in the quote above do not stem from the math content itself, but the student-related disruptions within the classroom environment. Further, many of the teachers interviewed shared a similar sentiment about the classroom environment. Ms. Keller explained:

> "I honestly feel like feeling overwhelmed and overstimulated comes from external factors more than like internal of myself feeling that way towards the [math] content. To give a little bit of background context, I've got one kiddo that just needs a whole lot of extra

support and so constantly crawling around the room, taking things out of people's desks, throwing things, banging against the window, throwing things against the ceiling. Those kind of external factors, I feel like is what makes me feel so overstimulated."

Another interesting trend that emerged when discussing student behavior during math was teachers' specific call outs to noise or sounds students make as being particularly distracting. Ms. Hall stated, "I would say, like, the noise factor [is distracting]. Sometimes it's conversations. Most of the time it's just like little noises here and there. Well, they're not little, they're usually big." Along similar lines, Ms. Keller mentioned that classroom conversations during math can cause her to feel overstimulated. Ms. Keller stated, "...if I feel like a lot of side conversations are happening, sometimes I feel like the extra noise can feel overstimulating." Overall, the quotes above are only a small number of the many examples that teachers reported; however, they demonstrate the salience and range of environmental, student-related stimuli teachers may experience at any given moment during math instruction.

Sub-Theme 2b: Non-Student Related Distractions. Sub-Theme 2b refers to the high frequency of disruptions that occurred in and around the classroom during math instruction that did not stem from the students themselves. That is, outside of student-related distractions, teachers also discussed (37 references across 8 teachers) many non-student related distractions (i.e., layout of the classroom, timing of math instruction, assessments and benchmarks, pace of curriculum, technology, fire drills, demands from administration and district leaders, teaching observations or evaluations) that commonly occur during their math instruction. One of the most common distractions teachers brought up was the constant reminder of required state and district level assessments and benchmarks that teachers put a lot of pressure on themselves to meet. To demonstrate, Ms. Collins explained,

> "...it kind of feels like I'm letting kids down, or that I'm letting almost like our team down, because for me, when the benchmark data hits, if I don't see growth – I'm not looking for perfect scores – but if I don't see what I deem aggressive growth in their scores, that overwhelms me quite a bit. And then I feel like I'm not giving them what they deserve."

It became clear that Ms. Collins put a lot of pressure on herself to reach benchmarks, even acknowledging them as a source of her overwhelm in math. Moreover, Mr. Clark shared his frustration with benchmarks and testing in his higher-level math classes, stating that his biggest source of overwhelm during his math instruction is:

> "... that I don't feel like we can have as much fun with it because just all the pressure around it… That's my problem with math… we're just checking boxes and taking tests and saying we're done, when I'd rather have fun with it."

Ms. Keller shared similar sentiments with benchmarks and state testing pressures, specifically pointing to the rush to cover all the necessary material before state testing occurs. Ms. Keller shared: "...another piece of feeling overwhelmed would be that we really try to get through like, if not all, most of the curriculum before state testing because all of it will be on the state test…" Moreover, Ms. Keller's statement reflects an additional source of distraction for teachers: the pace of the curriculum. Ms. Myers similarly stated,

> "...with all the demands and all the pressures from parents and administration and higher up people in education, and just how fast everything moves to get kids ready for the next grade, but also like college ready and job ready. We all have that in the back of our minds, so its like, ahhh!"

An interesting aspect of Ms. Myers' quote above is the idea that teachers actively processing many different thoughts (e.g., student readiness) all while instructing. The conscious processing of each of these different thoughts, likely splits the attention of teachers, when it would be ideal for them to remain focused on their central task at hand: math instruction.

Teachers also pointed to a wide variation of other non-student related distractions throughout the interviews. For example, Ms. Myers discussed how administration and district level demands were always on her mind and thus a sub-conscious distraction during instruction (see Ms. Myers quote above). Moreover, Ms. Scott relayed how distracting it is for her when people (e.g., administrators, other teachers, student teachers) come and observe her math instruction, mentioning: "...when random people come in and watch me – that can be a little overwhelming. Like I feel like, come watch me teach anything… but math, I'm like… why is somebody here? Please go away." Finally, teachers also commented on how classroom technology has impacted their classroom environment, Ms. Myers stated: "I will say the biggest distraction or issue is technology… sometimes the iPads are not working, or the internet's down at school, or the app is glitching." Taken together, teachers are receiving, interpreting, and managing many distractions, often student related, but non-student related as well.

Sub-Theme 2c: Math Instruction Depends on the Day, Month, and Year. Sub-Theme 2c refers to the everchanging and evolving nature of the classroom environment; the reality that no one day is the same as the next. That is, teachers often (i.e., 36 references across all 10 teachers) responded to interview questions with "it depends" on the day, month, and year – emphasizing that no single math lesson is the same. Ms. Hall even described differences down to the time of day, explaining that "certain times of day are more difficult than others." Moreover, Ms. Keller stated that student behaviors changed daily, stating:

> "Honestly, I feel like it does depend on the day. I would say there are certain days where, like, I've got one kiddo in particular… who like, when they are needing extra support, those days are definitely harder to juggle everything because I've found that they have a way of… riling everybody up to the point where we just didn't recover for the rest of the day… So I would say those days, I feel like it is harder to juggle…"

Mr. Clark even mentioned how the daily diary surveys were a great check in tool for him each day, stating:

> "It [success of math instruction] depends on the day. And that's what I loved seeing about the little surveys. Like, some days I was like, yeah, I made a change in the world today. Other days, I was like I did nothing. And it wasn't really the content. It was more like just how the kids come in some days."

As teachers continued to do throughout interviews, Mr. Clark explained that the uncertainty around his math instruction was typically due to how students arrive to the classroom rather than the math content itself.

Not only did math instruction and the classroom environment change daily, but teachers also shared that it changes depending on the month and year. For example, Ms. Lee stated, "there's ebb and flow on behavior during the year. There's points that are harder with the kiddos. October seems to be hard. February seems to be hard." Ms. Lee was not the only teacher to discuss how instruction and student behaviors change depending on the time of the year, as Ms. Thomas mentioned, "I would say almost every year, there's only certain times… I would say around October and about right now [February]... there's a lot of burnout going on." Interestingly, both Ms. Lee and Ms. Thomas pointed to the same two months in which the classroom environment was especially unpredictable: October and February.

Finally, teachers described how math instruction and the classroom environment change on a yearly basis, particularly emphasizing that every group of students is very different from the past group. Ms. Baker explained that the changing classroom environment on a yearly basis is something that she particularly enjoys, stating "And every year it's a whole new year… It's great. It's always fresh. There's always new children and new families and family partnerships." However, Ms. Hall described how both her feelings towards math instruction and student behaviors differ from year to year, stating:

> "Just in general, I would say it [feelings towards math] depends a lot year to year. I really like math, and I enjoy math instruction, just because it is so straightforward. And so I would say, [it] usually depends on what kinds of like behaviors happen in the room year to year. So some years, math feels weightier than others, which I would say is common for a lot of my days, but for me, it's the behavior aspect."

Ms. Myers shared similar beliefs about student behaviors during math instruction, saying that she's "had those years where I've had tougher classes, and had to stop and deal with behaviors. Behaviors are a big thing." Finally, Ms. Lee described how the success of and own feelings of overwhelm during math instruction has depended on the class and group of students within it over her last 30 years of teaching. She particularly described the differences between her current group of students to past years, stating:

> "Last year or the year before, we might have a grand explosion in the middle of math and have to shut it all down. And this year I don't have the grand explosions, so I know I can be a lot more, you know, present and relaxed… I don't have a chair thrown across the room this year. That makes a huge difference."

Overall, teachers emphasized the evolving nature of the classroom and particularly the environment that changes depending on the day, the month, and each year.

Theme 3: The Cognitive and Emotional Endurance Required of Teachers. Theme 3 refers to the unrelenting cognitive and emotional demands that teachers endure throughout instruction. In other words, interviews revealed (83 references across all 10 teachers) that day in and day out there was a level of cognitive and emotional stamina, resilience, and self-regulation required of teachers to keep their math instruction "running at a high level" as Ms. Baker put it. For example, Ms. Lee explained that there is a level of "with-itness" needed as a teacher, continuing to say, "…you got to make sure that you're always scanning and know and thinking about all those things." Teachers across the sample described the feeling of being "always on" during math instruction, or constantly giving 100% of their attention to their math lesson, as well as the things going on around them. Moreover, teachers also commonly reported actively thinking about, interpreting, and regulating the range of emotions they experience during instruction. Therefore, two sub-themes emerged: (a) Teachers are "always on" and (b) The range of emotions during math instruction.

Sub-Theme 3a: Teachers are "Always On." Sub-Theme 3a refers to the consistent cognitive engagement required of teachers to remain aware, alert, and responsive during instruction. In other words, teachers commonly reported (i.e., 39 references across 9 teachers) that they need to be "always on" when teaching math and throughout the school day. For example, Ms. Myers stated:

> "You definitely have to be on it and paying attention. And like I said before, problem solving in the moment. So it's not like you can just be like 'okay, two plus two' and then passively listen. You have to be paying attention, or [asking yourself] are they getting

this, looking at you kids, noticing their body cues, their body language… so you have to be on it and paying attention."

Similarly, Ms. Lee described an example of her thought process during math instruction, stating that she is constantly thinking about

> "... what to do next, or you know, Student A is doing this – what do I need to do for them? Is Student B getting the concept? Student C might be drawing on their board. Someone comes to get a child for this, that, or the other, and they're going to miss out – how can I make that up?"

It was obvious throughout the interviews, and is demonstrated in Ms. Lee's quote above, that teachers have much more on their mind than math instruction alone and are consistently thinking one step ahead. "Ms. Hall even stated that she feels she must give 100% effort to her math instruction, "Because a lot of times teaching feels like you're putting on a show."

Moreover, many teachers described the many in-the-moment decisions they make during any given math lesson. Ms. Lee described the high level of concentration she needs in order to mitigate the "constant decisions happening." Ms. Myers provided an example of her thought process around decisions she makes during instruction; specifically, when instruction is not going as planned:

> "I have to stop and re-think this [math lesson] on the spot, in-the-moment, so that can overwhelm me sometimes because I'm like, okay, do I stop the lesson and send them to their independent work and re-teach something tomorrow? Or do I try to problem solve now? So it's a lot of in-the-moment decisions that you have to make."

Importantly, many teachers connected the feeling of being "always on" during instruction to "severe exhaustion" as Ms. Thomas put it. Ms. Thomas continued by explaining how math is

not only tiring for her to teach, but for her students to learn as well. She stated, "most of my effort [throughout the school day] is given during math. Like after math, we all need a nap." Many teachers also shared how their exhaustion influences their personal lives. Ms. Lee stated, "My husband and I are both teachers. We come home and plop on the couch for a little bit… And I think most teachers do, do that. Friday night date night? What is that? We're too tired by then." Finally, Ms. Myers also shared how teaching influences cognitive engagement with those around her once she arrives home from school, stating: "I come home and I tell my dog, don't even talk to me… I'll play with you a little bit, but don't overwhelm me. I need a minute. I think the mental load is definitely a thing." Overall, teachers described their experiences of feeling like they are consistently cognitively engaged during math instruction, specifically pointing to in-the-moment problem solving and decision-making as well as how that cognitive engagement eventually manifests into experiences of exhaustion post-instruction.

Sub-Theme 3b: The Range of Emotions During Instruction. Sub-Theme 3b refers to the wide variation in affective states that teachers experience throughout math instruction. It was clear that teachers' own emotions during math instruction played a large role in their instructional experiences (44 references across all 10 teachers). In fact, it became clear that negatively valanced emotions often serve as a distraction to teachers and are something they often need to regulate. Moreover, teachers expressed a range of negative emotions throughout interviews including frustration, overwhelm, anxiety or stress, annoyance, and hopelessness. Frustration was the most common emotion teachers described, which most often stemmed from student disruptions or district-level policies that prohibit students from learning the material. Ms. Lee referred to her frustration with student-related disruptions by stating: "I get real frustrated if

we get a lot of distractions, if I am not able to teach what I'm supposed to be." Ms. Hall shared a similar sentiment, explaining,

> "...sometimes frustrated. Out of like, I know that you can do this, but it's like, if you would just listen for a little bit, then I can show you how. And some, they just don't want to engage at all. And even in a small group setting, I'm like, that's okay. I can't control that. But it does build."

Ms. Scott similarly described her frustration when students do not engage in math instruction, specifically connecting it to fixed mindset beliefs:

> "And so I think with math, that's where I find that frustration, you know. Where some kids will just kind of shut down, or some kids kind of come with, like, 'I'm not good at math', like they kind of started developing that mindset."

Frustration among teachers also stemmed from the district level. For example, Mr. Clark stated: "That's my problem with math – and frustration – is that we don't get to have fun. We're just checking boxes, and taking tests and saying we're done, when I'd rather have fun with it."

Teachers also commonly described their experiences of feeling overwhelmed during math instruction. Ms. Keller described feeling overwhelmed on certain days, explaining:

> "...there are definitely days that feel overwhelming or overstimulating, or like even emotional, like I've had days where… there's just been a lot that's happened, or I hear stories, or I find out things about my kids that just makes me emotional… like some days, I just feel tired or burnt out, or just like overwhelmed to a point where I can't really recover."

Ms. Collins also attributed feeling overwhelmed to those in her environment around her as opposed to the math content itself. She stated: "...I have some heightened emotions when I'm

feeling overwhelmed or overstimulated, but… I don't think that correlates directly to math as much as it does the students I'm supporting."

Moreover, an interesting finding that emerged from the teachers' discussions about emotions experienced during instruction was the salience of self-regulation strategies. For example, some teachers described how they engage in breathing exercises when feeling frustrated or overwhelmed – which not only helps them to self-regulate but helps their students to learn those strategies as well. Ms. Lee stated, "We do lots of breathing. We train the kids to breathe. We breathe. We've got to be regulated, so we can regulate them." In other words, teachers described the use of Conscious Discipline to regulate all individuals in the classroom. Ms. Collins stated, "but a big thing that we use in our classroom for self-regulation is conscious discipline, and so we have, like, breathing techniques that's built into that [math instruction]..." Taken together, teachers commonly reported a range of negative emotions during instruction, though most commonly frustration and overwhelm, which often stemmed from student disruptions or district-level policies that required them to engage in emotional regulation strategies during instruction.

Theme 4: Experience Enables Instructional Adaptation. Theme four refers to the perception that math instruction, including the handling of various environmental inputs, gets easier with time and experience. Moreover, there was an overwhelming sense across all teachers, regardless of their current state of teaching experience, that teaching math eventually becomes easier. Ms. Baker and Ms. Lee, both of whom have been in the field for over 30 years, described how their math instruction has become second nature to them. For example, Ms. Baker talked about the "teacher toolbox" she has built over the years. She explained her knowledge of many different curriculums over the years and an array of go-to strategies that had helped her build this

toolbox. Ms. Baker stated, “The toolbox I have is really big and I’m pulling out tool after tool and doing it inside the context of teaching the math objective or target.” Ms. Lee similarly commented on her teacher toolbox that she has built over the years, stating, “you build that teacher toolbox, and you have all the tricks. And some days you go through the whole toolbox, and some days that first one works.” Ms. Lee went on to continue how her level of overwhelm and “with-itness” had changed since she began in the profession over 30 years ago, explaining:

> “...the with-itness as a teacher, you got to make sure that you’re always scanning you know, and thinking about all those things… But as a younger teacher, I didn’t have all that. So there would have been more, you know, overwhelm.”

Similar ideas were shared across the mid-career teachers interviewed. Ms. Collins, who has been teaching for 22 years, stated,

> “...as I’ve taught over the years, and I’ve kind of honed in on my craft, I’ve figured out how to adjust in the moment… or how to let things go. That’s been, I think, a big shift in it for me.”

Moreover, regardless of their career stage, teachers were quick to compare their current expertise to the beginning of their career. For example, Ms. Myers, a teacher in her seventh year, described how she has developed over the years, explaining, “you definitely learn tricks of the trade the longer that you teach. So the teacher I was my first year is not the same teacher I am now, just because I’ve learned a lot…” Even very early-career teachers were prone to commenting on their progression since their first year in the profession. Ms. Klein, who is in her second year, stated, “...because I’m still so new at this, I can even see the progression from last year to this year. But I mean, I can quickly recall my first few math lessons and how garbage they were.”

However, despite teachers across the sample underscoring the importance of time and experience in teaching math, they still often mentioned that there are some aspects of teaching that will always be challenging and out of their control. To demonstrate, Ms. Collins said, "...because I've been doing it a long time, I'm pretty good at multitasking, but it's a struggle still, even just for me, because there's so many things happening." Moreover, when Ms. Baker was asked how well she is able to juggle everything happening in her classroom during math, she explained, "As a novice? Impossible. As a master teacher? Doable. Day after day, tricky…" In addition, Ms. Lee described how even with 30 years of experience, there are some things that are out of her control that experience does not necessarily help with. In particular, she explained that changing curriculum makes her math teaching more difficult, stating that she could teach the previous math curriculum "in my sleep," which is no longer the case for her after their district's recent curriculum shift. In all, teachers of all stages had an overwhelming sense that the challenges associated with math instruction get easier with time; however, some environmental distractions cannot be controlled and are thus unavoidable.

Theme 5: Students as a Buffer to Teacher Attrition. Theme 5 refers to teachers' beliefs that students keep them in the field of teaching despite the demands of the profession. In particular, all 10 teachers were candid about their experiences with burnout and attrition intentions. In fact, each teacher discussed their past and future expectations for burnout – each claiming that they have all either experienced burnout or expect to experience burnout in the future. Moreover, teachers commented on how burnout can lead them to question their longevity in the field. Ms. Keller, a 3rd year teacher, stated: "there are definitely days where I kind of sit and reflect and I'm like, am I going to be able to last in this profession as long as I'd hoped to?"

She went on to say that it is especially discouraging for her to see her mentor teachers also struggling in the profession, stating,

> "...it's hard whenever I watch like mentor teachers and people that I really look up to who feel like they're experiencing that [burnout] now and they're not sure how much longer they feel like they can take on the role of being a classroom teacher."

Ms. Keller continued by explaining that for those reasons, she is pursuing a master's degree to give her other options to move around within the field of education.

Interestingly, Ms. Keller was not the only teacher who mentioned that their burnout experiences have led them to pursue or consider pursuing additional degrees as a back-up plan. In fact, Ms. Baker, Ms. Thomas, Ms. Collins, and Ms. Hall each have already pursued, are pursuing, or are planning on pursuing future degrees to become administrators or college-level instructors. Importantly, each of these teachers emphasized that if they leave teaching itself, it would be necessary for their next position to at least "touch education in some way" as Ms. Hall put it. Further, Ms. Klein and Ms. Myers each shared that they plan to leave the field once they have a family. They expanded that they do not think they would have the capacity to both teach and parent simultaneously well. Ms. Myers stated:

> "For people [teachers] who have families, I don't know how they do it because having to be a mom at home or a dad at home, and then separating that from school would be really hard… because you have to be on it while you're at school, and then you have to be on it while you're at home. And that's something I think would be very hard to juggle."

Regardless of teachers' past and future expectations for burnout and their back-up career plans, every teacher (11 references across all 10 teachers) had one response as to what keeps

them in the field, either for now or long-term: their students. Moreover, teachers overwhelmingly expressed joy and fulfillment when it came to their students, and each pointed to their students as the top reason for why they remain in teaching. For instance, Ms. Thomas stated:

> "I love working with kids and I love being able to, like, make a change in kids' lives. And it's usually not just academic-related. For me, personally, it's great to be able to teach them to read and to add up things like that. But to me, it's just kind of instilling like hope of what they could be or do in the future."

Table 42 provides quotes from all 10 teachers, who each responded that students are the central reason why they remain in teaching. Overall, it is possible that students are a buffer to teacher attrition, or at the very least, retain them in the field for a few years longer.

Table 42

Teachers Identifying Students as Their Reason for Remaining in the Teaching Field

Teacher	Quote
Ms. Baker	"...I enjoy working with children, inspiring children, helping them realize their own capabilities and competencies and all of that kind of stuff… So I enjoy empowering children to take the role as the leader… and to get to help people become the best version of themselves."
Ms. Collins	"For me, it's the kids… I love the children… It's like my heart and soul, like I am the weirdo that misses them over break or misses being with kids over the summer. They're just they're my people. They make more sense to me. You know, where you stand with kids. You know? They find joy in the most mundane, tiny things. And I think that's how I've stayed in the classroom so long. I find joy every day in what I do, maybe not all day, maybe not more than once a day. But there's at least one moment a day that's really joyful and meaningful to me…"
Ms. Klein	"I love kids, and they love especially the littles in kindergarten. I feel like it's such a sweet spot… if I can be the teacher that gets them wanting to come to school and having really fun experiences, I want to do that and give that to them. Because I know, especially, what keeps me in public school is I know that there's so many kids going home to crazy things, and kids need safe places.
Ms. Myers	"I will say the kids. And like, their joy, and how much fun they have at school. Like, we celebrated the 100th day of school, and we just did… little simple

Teacher	Quote
	things. And the kids were like, this is the best day ever seeing like their joy at school and their engagement with each other, with me, in their growth, is definitely like a thing that I'm like, 'Yes!,' I did that. Like, this is why I do this."
Ms. Hall	"...I really care about kids… a lot of it, it's just kids. I care about them. My goal was always making a safe space to be able to learn, and flourish, and be able to discover a little bit to who you are along the way for the kids…"
Ms. Lee	"The kiddos. And the sense of purpose. I'm doing something that I can look back on and say I made a difference on this planet."
Ms. Keller	"Definitely, the kids… My kids just make every day so fun… And honestly, like, just getting to see them, like, progress throughout the year. I feel like I see so much growth in third grade, of like, where they start versus where they end, that I just like, I love reflecting on like, how far they've come and how much they grow. And I think that whenever I can really stop and like, think about those things, and even just like the smallest of things that are making impacts… I think those are the things that I really try to stop and reflect on that keeps me going.
Ms. Scott	"The kids."
Mr. Clark	"...it's the students. It's just, they're just fun, you know? It's just to get to joke around with them and have fun with them and learn, like, learn with them,. And see all their different personalities… there's no better line of work… So that's, that's definitely what keeps me coming back."
Ms. Thomas	"I love working with kids and I love being able to, like, make a change in kids' lives. And it's usually not just academic-related. For me, personally, its great to be able to teach them to read and to add up things like that. But to me, it's just kind of instilling like hope of what they could be or do in the future."

Research Question 3a: How do teachers with underrepresented identities within the teaching profession experience cognitive load?

Three teachers with underrepresented identities in the teaching profession participated in an interview: Ms. Thomas, Ms. Hall, and Mr. Clark. In particular, teachers of color, teachers with disabilities, and male teachers are underrepresented in the field of education (NCES, 2023). However, while certain identities are underrepresented in the field of education (e.g., white male teachers), they are overrepresented in much of the remaining workforce (Tomaskovic-Devey & Hoyt, 2019). However, in the context of the (a) overarching sample (i.e., n = 3; 8.8%) male teachers), (b) sub-sample of teachers interviewed (i.e., n = 1; 10%) male teacher), and (c)

overarching population of elementary teachers in the United States as a whole (i.e., roughly 11% of U.S. elementary teachers are male; NCES, 2023), male teachers are largely underrepresented – especially at the elementary level. Therefore, I included Mr. Clark, a white heterosexual, neurotypical male, teacher in my focus on understanding teachers who are underrepresented cognitive load and motivational experiences during math instruction. In addition, I included Ms. Thomas, a biracial (i.e., Black and white), heterosexual, neurotypical, female, teacher as well as Ms. Hall, a neurodivergent (i.e., ADHD), white, heterosexual, female teacher. I describe each of their experiences in detail below.

Ms. Hall's Experiences During Math Instruction. Ms. Hall is a second-grade teacher, in her third year as a teacher. Ms. Hall was the only teacher throughout all the interviews who explicitly discussed how a social identity characteristic salient to their identity (i.e., her learning disability) influences their teaching experiences. In the following section, I describe the overarching cognitive load, motivational, and attritional experiences Ms. Hall shared with me throughout her interview, including how these experiences are shaped by her experiences with ADHD.

Ms. Hall's Cognitive Load Experiences. Ms. Hall discussed that she was keenly aware of how her learning disability (i.e., ADHD) influences her cognitive processing during instruction. Ms. Hall described (a) often feeling flustered, stressed, and stretched-thin and (b) how her attention is commonly split between teaching and managing the classroom environment during math instruction – both of which she perceives as exacerbated by her ADHD. She stated, "I have ADHD and so I have a really hard time… being able to multitask and doing two things at the same time." Moreover, Ms. Hall expanded, explaining that she feels as though the demands of being an elementary teacher does not align with the structure of her brain; she stated:

> "I always tell people I'm like, in this movie, it's crazy. This is how I kind of define it. It feels like sometimes the actual task of being a teacher doesn't always match up with the way I feel like my brain works."

However, Ms. Hall does not necessarily view her learning disability as a disadvantage. Instead, she described the ways in which her ADHD can be an asset in the classroom. For example, she discussed how hyper-awareness of her overwhelm signals to her that her students also need a break. She stated, "...I know I need a break. And I know y'all need a break…" She went on to say, "That's when the ADHD is helpful… I know when I'm tapped out, they're tapped out."

Ms. Hall's Motivational Experiences. Ms. Hall described her confidence level as something that wavers day-to-day, yet math is her most confident subject that she teaches overall. Moreover, she described the central reason as to why it might fluctuate as being "…a person that is heavily impacted on like the products and the results." She explains that low standardized test scores can be discouraging and greatly impact her self-efficacy. However, she relayed that when these inefficacious thoughts arise, she works on reminding herself that "…students do take several touches of the same instruction…" and that some students will retain information at different rates than others "…depending on how their brain is wired…" – again returning to her heightened awareness and knowledge of the human cognitive architecture.

Ms. Hall's Attritional Experiences and Intentions. Ms. Hall explained that in her three years of teaching she has gone through phases where she feels burnout "bubbling up." She clarified, however, that her feelings of burnout do not last for long periods of time and that she is intentional with pausing and interrogating where her burnout stems from so she can change certain habits. Despite having developed strategies and support systems to combat burnout, Ms.

Hall still expects to experience more severe episodes of burnout in the future. She explained: "there's some point where it's like, I can't always control my nervous system… we can try to manage all of the factors, food, sleep, stress... Because teaching can be crazy and sometimes you just can't control what's going on." Finally, Ms. Hall explained that she does not plan to remain a teacher long-term and that teaching "feels like a springboard for something else." Ms. Hall continued, "Do I see myself making it to retirement? No." Regardless, she explained that she hopes her future career path continues to "touch education in some way."

Ms. Thomas' Experiences During Math Instruction. Ms. Thomas is an upper-level elementary teacher of 10 years and self-identified as a biracial (i.e., Black and white), cisgender woman. In the following sections, I describe Ms. Thomas' overarching experiences with cognitive load, motivation, and attrition in detail.

Ms. Thomas' Cognitive Load Experiences. Ms. Thomas described math as one of the more challenging and overwhelming subjects that she teaches. She described that the difficulty level of teaching math as well as her feelings of overwhelm often stem from (a) "having to supplement so much to meet where the kids are at", (b) re-teach basic math skills, and (c) her lack of time to accomplish all that needs to be completed in any given lesson. Additionally, Ms. Thomas explained that she felt math was more of a mental demand than an emotional one – underscoring the cognitive load she experienced teaching the subject. Despite the feelings of overwhelm and heightened mental demands during math, Ms. Thomas described she does feel that "it's gotten better over the years" and that she is able to juggle teaching and the surrounding environment more efficiently than when she started teaching. However, she qualified this by explaining, "I think I've sort of normalized things that are not normal, but to me, it's just like my everyday thing." Ms. Thomas' statement begs the question of whether teachers develop

automaticity over time, which makes juggling the classroom somewhat more manageable, or if teachers simply become more accustomed to the chaotic environment – or both.

Ms. Thomas' Motivational Experiences. Like Ms. Hall and an overarching theme described above (see Sub-Theme 2c), Ms. Thomas explained that her confidence level for math instruction depends on the day. On days in which Ms. Thomas feels less confident, it is often due to challenging math content that is difficult to teach. Ms. Thomas stated: "Some days I feel like, oh, this is great. I'm rocking it. And then some days there's a part where maybe I don't understand the math in-depth to where I can… really break it down." Moreover, Ms. Thomas explained that math instruction requires the most effort to teach out of her day – even stating that both her and her students are typically exhausted after math. In line with her exhaustion after math, Ms. Thomas explained that her exhaustion extends beyond school and into her personal life. She stated:

> "I'm really exhausted when I get home, especially later on in the year. Like I'm definitely gonna go lay down for 30 minutes. And then I have a 13 year old daughter, so it just impacts my ability to have energy for her when I get home."

Ms. Thomas' Attritional Experiences and Intentions. Ms. Thomas continued to speak on the exhausting nature of teaching by also describing in the context of burnout. She stated, "I think burnout comes from you not resting" and continued by adding that she does experience waves of burnout each year. Moreover, while Ms. Thomas plans to stay in the education field, she believes that at some point she will move into a different type of position, stating: "I know I'm gonna move into admin, probably soon next year… I might leave like the public education work and maybe into like collegiate or private."

Mr. Clark's Experiences During Math Instruction. Mr. Clark is an upper-level elementary teacher of 18 years. Mr. Clark self-identified as a white, cisgender man. In the following sections, I describe Mr. Clark's experiences with cognitive load, motivation, and attrition in detail.

Mr. Clark's Cognitive Load Experiences. Mr. Clark shared that he is typically able to process and concentrate during math instruction; however, he struggles most with getting his students to concentrate. Moreover, he described feeling overwhelmed during those moments where he must change his plans to get his students interested in the material. He stated, "you feel that moment of like, I'm not getting through to them. So… how else can we do it?" Further, Mr. Clark described how specific student distractions overwhelm him "all the time"; he stated: "sometimes they come [into the classroom] and they're just very loud… that's what frustrating, is I'm trying to teach something, and I can't get them to focus up." Mr. Clark continued, explaining that those student-related distractions are the biggest additive to his cognitive load and that he feels the content itself is not challenging for him to teach. Finally, Mr. Clark also described the pressures surrounding his upper elementary math courses, explaining that parents have the "most eyes on it," and therefore, those pressures become something that is always in the back of his mind.

Mr. Clark's Motivational Experiences. Mr. Clark described his confidence level for teaching as "100%" on days in which his students are trying and come in ready to focus; however, he shared that his level of confidence for teaching math falls to "75%" on days that are more challenging (e.g., struggles to gain and keep student attention). When Mr. Clark discussed his effort levels required of him to successfully teach math, he explained "I give the most effort." He feels a lot of his effort stems from the external pressures from parents for math specifically.

Mr. Clark stated: “I’ve been teaching long enough that as long as you keep the parents happy, you don’t have to worry.”

Mr. Clark’s Attritional Experiences and Intentions. Mr. Clark shared that he most likely will never leave the field of education, even stating that he has no plans to ever even retire from the field. Further, while Mr. Clark explained that he has experienced burnout, he explained that he believes burnout really depends on “how hot your flame is when you start” and that his flame is still “...very hot. It’s not gonna burn out anytime soon.” Despite Mr. Clark’s clear dedication to the field, he did offer the caveat that he would consider another position if it was perfect for him; he said, “But I’m also not naive that if something came along that fit my interests and job security…” he would consider it.

Data Integration Results

Research Question 4: How do teachers' qualitative descriptions of their daily experiences with cognitive load during mathematics instruction, motivational beliefs, and attrition intentions map onto the experiences reported on the daily quantitative surveys?

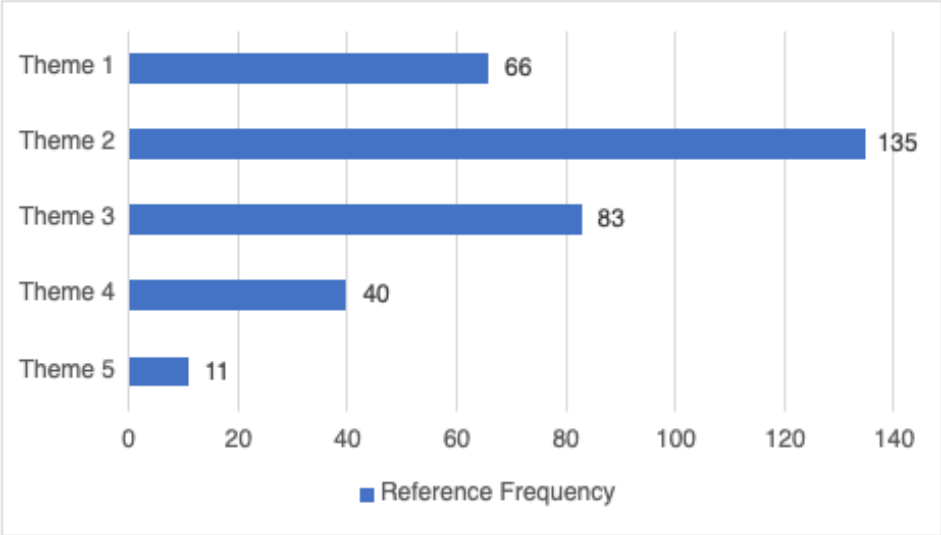
In the following sections, I describe the results that emerged after integrating the quantitative data with the qualitative data to address Research Question 4. I used transformation, a narrative, weaving (i.e., theme-by-theme) approach, and joint displays to present the integration results in the sections below.

Transformation. I first transformed the qualitative data into quantitative frequencies to gain a sense of theme relevance across the dataset (see Fetters et al., 2013). I calculated how often each overarching theme (a) occurred across the 10 teachers in the qualitative sub-sample and (b) was referenced in general across interviews. Themes 2, 3, and 5 were each present across all 10 teachers in the sample, where Themes 1 and 4 were present among nine of the 10 teachers.

Additionally, I calculated how often the codes associated with each theme were referenced across the 10 interviews. Codes for Theme 2 were most frequently referenced, with 135 (or 40.3%) references, followed by Theme 3 with 83 (or 24.8%) references, Theme 4 with 40 (or 11.9%) references, and Theme 5 with 11 (or 3.3%) references. Figure 2 visually depicts the frequency of references by each theme.

Figure 2

Reference Frequencies by Theme



Next, I merged the findings from the transformed qualitative data with the quantitative data. The high frequency of references across Theme 2 and Theme 3 (together accounting for more than 65% of the codes), is aligned with findings from the quantitative data. In particular, across each of the six intermediate models retained in Research Question 2, extraneous load (either within-person, between-person, or both) predicted five out of the six outcomes tested – which was more than both intrinsic and germane loads. Further, Theme 2 and Theme 3 are highly related to the environmental factors of teaching, or in other words, the extraneous load associated with math teaching. Taken together, drawing from the (a) high frequency of references across Themes 2 and 3, (b) alignment of Themes 2 and 3 with extraneous load, and (c)

salience of extraneous load as a predictor across the (intermediate) multilevel models presented in Research Question 2, it is clear that extraneous load may be particularly impactful among teachers during math instruction.

Narrative Weaving. To further integrate the data, I used a narrative, weaving approach, which is presented in the section below. For ease of presentation and interpretation of the integrated findings, I break them down by integration fit (Fetters et al., 2013). That is, I organize the present section by confirmation, expansion, and discordance. In addition, I summarize the central quantitative, qualitative, and mixed findings in a joint display (see Table 43).

Confirmation. There were two instances of confirmation after integrating the quantitative and qualitative findings. First, both sets of data pointed to the daily differences in teachers' cognitive load experiences during math instruction. For example, in the quantitative data, the ICCs across the three dimensions of cognitive load represented a large proportion of variation in cognitive load explained within teachers via their *daily* fluctuations. Similarly, Sub-Theme 2c emerged from the qualitative data, which suggested that *everyday* teaching math differs and even extends these findings to suggest math changes depending on the time of the year and that year's group of students. Therefore, the qualitative data confirmed what was discovered in Research Question 1: the cognitive load experienced during math instruction fluctuates daily.

Second, the quantitative and qualitative data each spoke to the impact of extraneous load and its connection to the amount of effort required of teachers for math instruction. When teachers' extraneous load for a certain day was high, these perceptions predicted higher perceptions of effort required to engage in math instruction (i.e., task effort cost; $b = .32$, $p < .001$). The predictive relation between within-person extraneous load and task effort cost was confirmed by Sub-Theme 3a: Teachers are "always on." Sub-Theme 3a similarly suggested that

teachers felt a lot of effort and consistent attention is needed to be given to their math instruction, particularly when there are a lot of environmental distractions present. For example, Ms. Collins explained how it is hard for her to maintain her focus when there are so many environmental distractions present, stating: "...it's hard to keep myself on track and them on track and keep focused when there's so many of them just interrupting and shouting out and doing it often." Therefore, there was a clear convergence between the quantitative and qualitative data regarding the overlap between extraneous load and the effort and maintained focus required of teachers during math instruction.

Expansion. There were seven points of expansion after integrating the quantitative and qualitative findings. First, and as aforementioned, teachers' daily fluctuations of cognitive load varied considerably. Moreover, Theme 3: The unpredictable nature of the classroom environment, confirmed and extended the quantitative findings regarding the daily fluctuations during math instruction. In interviews, teachers largely categorized these daily fluctuations into two categories: the (1) unlimited student-related disruptions and (2) non-student related disruptions that arise without warning daily. Teachers specified some of the most distracting things to them that make every day in the classroom unique. Noise disruptions (student-related) and constant reminders of assessments and benchmarks (non-student-related) were some of the most prominent examples.

Second, the quantitative findings revealed that germane load (within $b = .34$, $p < .002$; between $b = .51$, $p < .01$) positively predicted teachers' self-efficacy during math instruction. In other words, when teachers allocated more of their mental effort to building schemas during math instruction, they were more likely to experience higher self-efficacy beliefs for that instruction. The qualitative findings help to explain the unexpected positive relation between

germane load and self-efficacy. Within Sub-Theme 1b: Frequent changes to math curriculum, teachers shared that while frequent changes to math curriculum made teaching the subject more challenging, it was their second year on a new curriculum, which was often described as easier than the year prior. Drawing from these qualitative findings, teachers are likely expanding their existing schemas they began building the year prior, potentially feeling as though they are developing a greater understanding of and proficiency for teaching that curriculum, thereby building their confidence for teaching it. For example, Ms. Collins stated:

> "...last year was our first year with this curriculum and so I feel like it was a little bit more challenging because I had to use more prep time for it. I think once you've had a curriculum for a year, and you kind of see what the end goal is, it's easier."

Similarly, Ms. Keller stated, "...but this year, I feel like it's [the new curriculum] been so much better, because now I have a year of working through the curriculum." I return to this interpretation in Chapter 5.

Third, the qualitative data both confirmed and expanded upon the quantitative finding that within-person intrinsic load ($b = .27$, $p < .001$) predicted teachers' task effort cost. That is, the more inherently difficult a teacher perceived their math instruction to be on a given day, the more costly they perceived the effort they needed to put forth for math instruction. Not only did the qualitative findings provide confirmation of the quantitative findings via Theme 1: The compounding challenges of math instruction, but they also provided additional context to the quantitative findings. Notably, throughout Theme 1 (and its sub-themes) teachers explained that two contemporary issues related to math instruction have exacerbated its difficulty: differentiation challenges and frequent changes in the math curriculum required of them to utilize. Teachers consistently described the differentiation and curriculum challenges as

frustrating and difficult to balance among other things occurring in and around the classroom, each leading to increased effort required to be given to effectively teach math.

The fourth point of expansion that emerged was the influence of environmental distractions that are unrelated to the (a) math instruction itself and (b) the students. In particular, the quantitative results revealed that when teachers' average cognitive load associated with environmental distractions (i.e., extraneous load) was high compared to each other, they perceived the tasks they had to complete unrelated to math instruction as more costly (i.e., higher outside effort cost). This quantitative finding is consistent with the Sub-Theme 2b: Non-student related distractions that emerged. Throughout this theme, teachers reported an array of situations, unrelated or indirectly related to math, where their attention was drawn away from their task at hand (i.e., math instruction). For example, teachers described technology, fire drills, administration and district level demands, assessments and benchmarks, teaching observations and evaluations, to name a few.

The fifth point of expansion upon the quantitative results is via Sub-Theme 3b: The range of emotions during math instruction. In particular, the quantitative results suggested that a higher extraneous load (within $b = .56$, $p < .001$; between $b = .56$, $p < .01$) predicted more adverse affective states due to engagement in math instruction (i.e., increased emotional cost). Sub-Theme 3b confirms and extends the quantitative findings. For example, teachers reported via interviews that more environmental distractions caused them to experience a range of negative emotions, including frustration, overwhelm, anxiety, stress, annoyance, and hopelessness. To demonstrate, and as reported above, Ms. Lee stated: "I get real frustrated if we get a lot of distractions, if I am not able to teach what I'm supposed to be."

Sixth, the quantitative findings suggest that higher levels of extraneous load (within b = .22, $p < .001$; between b = .35, p = .09) during math instruction predict increased perceptions of having to give up other tasks important to teachers (i.e., loss of valued alternatives cost). These findings were confirmed and expanded upon given the findings that emerged from Theme 3: The cognitive and emotional endurance required of teachers. Throughout Theme 3 and its sub-themes, teachers described the feeling of being "always on" and consistently giving 100% of their attention to their math instruction. Further, they described how they must constantly regulate an array of negative emotions they experience throughout the day – especially feelings of frustration and overwhelm. Importantly, given the constant attention and emotional regulation required of teachers throughout their math instruction, teachers described feeling exhausted by the end of the day. Ms. Thomas said, "after math, we all need a nap." In fact, teachers reported that this exhaustion extends into their personal lives, many suggesting the lack of energy to engage in personal activities after school.

The seventh and final point of expansion stemmed from the quantitative findings that cognitive load plays a very minimal role in predicting teachers' attrition intentions. That is, besides the small predictive effect of germane load on attrition intentions, cognitive load did not play a significant role in teachers' decisions to remain in the field. These quantitative findings are qualified by Theme 5: Students as a buffer to teacher attrition. To explain, many teachers in the qualitative sub-sample confirmed that they plan to remain in the field – at least in the short-term – which confirm the quantitative results. However, the interviews helped to expand upon the lack of impact of cognitive load on attrition intentions as each teacher explained their students are the reason they remain in the field and thus act as a buffer to teacher attrition despite their experiences with cognitive load. Moreover, despite Ms. Hall and Ms. Thomas also sharing

that, for now, students keep them in the profession, they each specifically shared their intentions to leave teaching in the short-term during interviews. In fact, Ms. Thomas shared she will likely move into an administrative role as soon as the following school year. Further, given that Ms. Hall and Ms. Thomas each hold identities that are minoritized in society in general and especially within the teaching profession, it may be the case that the systemic barriers they likely face in the education system (Milner & Howard, 2013), accelerate their attrition intentions.

Discordance. There were two instances of discordance after integrating the quantitative and qualitative findings. First, the quantitative findings revealed that years of teaching experience did not predict cognitive load. Despite these findings, Theme 4: Experience enables instructional adaptation emerged from the qualitative findings. Throughout Theme 4 teachers, particularly mid-to-late career teachers, described how their experience level allows them to adapt to many of the different and often spontaneous obstacles that evolve during math instruction. For example, Ms. Baker described the large "teacher toolbox" she has built over the years and how she is able to pull out "tool after tool" during math instruction. These divergent findings are discussed in detail in Chapter 5.

Second, the quantitative findings revealed that (a) higher extraneous load (within b = -.33, $p < .001$; between b = -.44, $p < .001$) significantly predicted lower self-efficacy beliefs in math among teachers and (b) intrinsic load (within b = -.07, p = .06; between not significant) only significantly predicted teachers' self-efficacy beliefs at a marginal level or not at all. Despite these quantitative findings, the qualitative data suggested the opposite via Sub-Theme 1c: Teachers' own personal ability beliefs in math. That is, throughout Sub-Theme 1c teachers discussed their confidence level for teaching math and in doing so they were much more prone to reference the difficulty of the math itself and their own personal ability beliefs in math – which

directly speaks to their intrinsic load. The discordance between the salience of extraneous and intrinsic loads in relation to teachers' self-efficacy beliefs are discussed in detail in Chapter 5.

Table 43

Joint Display: Summary of Quantitative, Qualitative, and Mixed Findings

Quantitative Findings	Qualitative Findings	Mixed Findings
A large portion of variation in each dimension of cognitive load (IL: $\rho = .67$; EL: $\rho = .65$; GL: $\rho = .67$) is explained within teachers via their daily fluctuations	Sub-Theme 2c: Every day, month, and year are different Theme 2: The unpredictable nature of the classroom environment	*Confirmation*: Both sets of data point to the idea that teaching math can vary from day to day. *Expansion*: The qualitative data help to explain *why* there is a large portion of variation within teachers via their daily fluctuations – there is many distractions (student and non-student related) that are (a) unpredictable and (b) differ day-to-day.
Years of teaching experience did not predict any of the cognitive load dimensions (IL: $b = .01$, $p = .40$; EL: $b = -.002$, $p = .86$; GL: $b = -.003$, $p = .78$)	Theme 4: Experience enables instructional adaptation	*Discordance*: The quantitative and qualitative data are misaligned on the teachers' years of experience in the field and its relation to their cognitive load during math instruction. The quantitative data suggest that years of teaching experience do not play a role in teachers' cognitive load experiences during math. The qualitative data suggest that years of teaching experience are useful to adapt and respond effectively in real-time during math instruction – pointing to their reduced cognitive load.
Within IL ($b = -.07$, $p = .06$), within EL ($b = -.33$, $p < .001$), and between EL ($b = -.44$, $p < .001$) predicted teachers' self-efficacy; Between IL ($b = -.05$, $p = .71$) did not predict teachers' self-efficacy beliefs	Subtheme 1c: Teachers' own personal ability beliefs in math	*Discordance*: The quantitative and qualitative data are misaligned on the factors that predict teacher's self-efficacy beliefs. The quantitative data suggests that extraneous load was much more important than intrinsic load in the self-efficacy outcome model; however, when teachers discussed their confidence level for teaching math during qualitative

Quantitative Findings	Qualitative Findings	Mixed Findings
		interviews, they were more likely to reference (a) the difficulty of the math content itself (i.e., intrinsic load) and/or (b) their own ability beliefs in math.
Within GL (b = .34, p < .001) and between GL (b = .51, p < .01) predicted teachers' self-efficacy	Theme 1b: Frequent changes to curriculum	*Expansion*: The qualitative data helps explain the positive relation between germane load and self-efficacy. In interviews, teachers explained this is their second year using a new math curriculum and that this year is easier than the first year. Thus, teachers are likely expanding existing schemas they have built for the new math curriculum and while that may result in a lot of mental effort, the feeling of "getting it" may result in increased confidence.
Within IL (b = .27, p < .001) predicted teachers task effort cost	Theme 1: The compounding challenges of math instruction; Sub-Theme 1a; Sub-Theme 1b	*Expansion*: The qualitative data provided additional context to why increased intrinsic load for math instruction might make the act of teaching math more "costly": differentiation challenges and changing math curriculum potentially exacerbate the difficulty level of math instruction.
Within EL (b = .32, p < .001) predicted teachers' task effort cost	Theme 3a: Teachers are "Always on"	*Confirmation:* Both the quantitative and qualitative data confirmed that the more load imposed by the environment during math instruction, the higher the perceived costliness of that math instruction.
Between EL (b = .68, p < .01) predicted teachers' outside effort cost	Sub-Theme 2b: Non-student related distractions	*Expansion*: Both the quantitative and qualitative data confirmed that distractions and/or tasks unrelated to the actual act of math instruction are challenging to juggle.
Within EL (b = .56, p <	Sub-Theme 3b: The	*Expansion*: The more environmental

Quantitative Findings	Qualitative Findings	Mixed Findings
.001) and between EL (b = .56, p < .01) predicted teachers' emotional cost	range of emotions during math instruction	distractions unrelated to math, the more frustration and overwhelm (i.e., increased negative emotions) during math instruction.
Within EL (b = .22, p < .001) and between EL (b = .35, p = .09) predicted teachers' loss of valued alternatives cost	Theme 3: The cognitive and emotional endurance required of teachers	*Expansion*: The more teachers must juggle from their environment during math, the more they experience exhaustion at the end of the day, forcing them to give up things after school they otherwise might enjoy.
Besides within GL (b = -.10, p < .01) no other dimensions of cognitive load predicted teachers' attrition intentions	Theme 5: Students as a buffer to teacher attrition; Minoritized teachers' intentions to leave	*Expansion*: Students keep teachers in the field – at least in the short term – even if they experience cognitive load challenges. However, drawing from interviews with teachers who are minoritized (i.e., Ms. Hall, Ms. Thomas) this may not be the case given their intentions to leave teaching soon.

Note. IL = Intrinsic Load, EL = Extraneous Load, GL = Germane Load.

Chapter Summary

In Chapter 4, I presented the results of the present study. I first relayed the quantitative results that emerged from the multilevel modeling analyses of the daily diary data. Then, I presented the qualitative results that emerged from them thematic analysis of the semi-structured interviews. Finally, I integrated the quantitative and qualitative results using transformation, a narrative weaving approach, and a joint display. In Chapter 5, I will discuss the quantitative, qualitative, and mixed results in detail.

Chapter 5: Discussion

Overview of Chapter 4

In Chapter 4, I presented the results of the current study. First, I described the findings that emerged from the quantitative Phase 1, daily diary surveys. Central findings from Phase 1 include, (a) a high variation in teachers' cognitive load at the day level, (b) a non-significant relationship between years of experience and teachers' cognitive load experiences, and (c) predictive relations across cognitive load dimensions and motivational outcomes (i.e., self-efficacy, all four dimensions of cost, and attrition intentions).

Second, I described the findings that emerged from the qualitative, Phase 2, semi-structured interviews. I relayed the five central themes that emerged as well as the eight related sub-themes. The five themes include: (1) The compounding challenges of math instruction, (2) The unpredictable nature of the classroom environment, (3) The cognitive and emotional endurance required of teachers, (4) Experience enables instructional adaptation, and (5) Students as a buffer to teacher attrition.

Finally, I presented the findings that emerged from combining the quantitative Phase 1 and qualitative Phase 2 data: The integration phase. To do so, I first transformed the qualitative data, which revealed the salience of teachers' extraneous load experiences across both the quantitative and transformed qualitative data. Then, through a narrative, weaving approach and joint display, I discussed the ways in which confirmation, expansion, and discordance appeared across both datasets. Central findings include (a) the confirmation of the daily variation in teachers' cognitive load, (b) continued evidence and expansion regarding the salience of extraneous load throughout teachers' everyday realities, and (c) the discordance between teaching experience and cognitive load experiences during math instruction.

In the following sections, I interpret each of the findings presented throughout Chapter 4 in detail. Then, I discuss the key theoretical, methodological, and practical implications that emerged from the present study. Lastly, I summarize the limitations of the study, future directions for research, and key conclusions.

Interpretation of Findings

Intrinsic Load

On average, and as I hypothesized (see Chapter 3, "Hypothesis 1"), teachers reported moderate levels of intrinsic load (M = 2.59 on a 5-point scale) across 10 days of math instruction – the lowest across the three cognitive load dimensions. However, on a daily basis, teachers' intrinsic load varied greatly (Appendices U and V present a visual representation of the daily variation in intrinsic load across teachers). In other words, teachers perceived that the inherent difficulty of their math instruction fluctuated depending on each specific day. Interestingly, while teachers occasionally pointed to the complexity associated with their math content itself when describing the challenges associated with their math instruction during interviews, they were more likely to discuss two key unexpected, but related math instructional challenges: (1) differentiation in a shifting educational landscape and (2) frequent changes to their math curriculum.

Differentiation. The finding that differentiation and curriculum changes exacerbate teachers' intrinsic load are aligned with and extend the existing literature. For example, as discussed in Chapter 2, differentiation in math is commonly perceived as challenging by teachers in general (Cody et al., 2023; Hayden et al., 2024); however, the present study revealed a unique extension to those perceptions: teachers in the sample appeared to perceive that contemporary classrooms, and the students within them, are more dissimilar from classrooms and students in

years past than ever before. Teachers specified that students today (a) have much greater needs (both academic and behavioral) and (b) are widely varied in math skill level compared to students they have taught in the past. Moreover, teachers often attributed the shift in the student population to lasting impacts of the COVID-19 pandemic, increased use of technologies at school and at home, and a shifting generation of parenting styles; these perceptions are at least partially supported in the literature (e.g., Fong, 2022). These overarching shifts among the student population and broader context has led to not only more frequent differentiation needed throughout every math lesson, but also a larger variation in math content based on students' range of skill levels. Therefore, drawing from CLT (Sweller, 1988), the wide variation in differentiation needs of contemporary students requires teachers to use more of their working memory capacity to teach any given math lesson in numerous different ways, effectively exacerbating their intrinsic load.

Curriculum. In addition to challenges associated with differentiating math content, teachers also identified changing math curricula as a strain on the difficulty level of their math instruction. More specifically, teachers explained that a new math curriculum seems to be implemented every few years in their district and that these changes are not only frustrating but create additional instructional burdens. For instance, teachers explained – regardless of their experience level – that having to implement new curriculum instills a lengthy adjustment period for them to re-learn new content and/or content that is taught in new, often unfamiliar ways. While adjustment periods for newly implemented curricula are (a) to be expected and (b) often needed to push new ways of math instruction and student learning forward (Irvine, 2025), this study uncovered an important question: How often is too often for districts to implement a new math curriculum? And potentially more importantly, despite the learning benefits that students

might experience because of new curricula, how do these frequent changes impact teachers' overarching cognitive load during math instruction from year to year?

Findings from the present study, coupled with the tenets of CLT (Sweller, 1988; Sweller et al., 1998) suggest that adopting a new math curriculum every few years can be problematic. That is, when teachers receive a new math curriculum, they receive an influx of new information about the content and how to effectively teach it (Flores, 2005; Xhemajli et al., 2025). In fact, many of the schema structures and the automaticity teachers had developed for their prior curriculum are no longer as useful, forcing them to actively process the new curriculum content and pedagogical techniques in their working memory (Sweller, 2010). Overall, according to CLT, an increased amount of new, unpracticed information in teachers' working memory increases the challenge of their math instruction on specific days and in general (Kalyuga, 2010; Kirschner et al., 2009; Sweller, 2010).

Taken together, both differentiation and curriculum challenges are problematic because they can act as barriers or slow down teachers' development of math instruction automaticity (i.e., non-conscious processing). As discussed in Chapter 2, automaticity is beneficial for teachers to develop as it helps to reduce the number of inputs teachers need to consciously process during instruction (Blackley et al., 2021; Feldon, 2007; Moos & Pitton, 2014). However, when teachers must re-accumulate automaticity for new curriculum or the differentiation needs of students, they use more of their working memory resources to accommodate the greater intrinsic load. In the next section, I discuss how intrinsic load and key motivational constructs are related.

Intrinsic Load and Motivation.

Intrinsic Load and Self-Efficacy. An interesting finding that emerged from the present study was the weak negative relation between intrinsic load and self-efficacy. That is, on days teachers reported a higher intrinsic load than their own average, they were slightly less confident in their math instruction. While the direction of this relation was as hypothesized, the effect size was not, even when interpreted in the context of effect sizes to be expected in field-based education research (Hattie, 2023; Kraft, 2020). There may be several reasons for the weak predictive relationship between teachers within intrinsic load and self-efficacy. First, interviews revealed that teachers were in the second year of teaching a new math curriculum. While teachers reported continued difficulty with learning and adjusting to the new curriculum, many shared that this year felt much easier than last year. Therefore, teachers may have developed schema structures from teaching the curriculum the year prior (Kalyuga, 2010) and thus, feel more confident especially when compared to their previous year. These findings align with existing research that found a negative predictive relation between intrinsic load and self-efficacy among students (see Feldon et al., 2024).

Second, it is possible that teachers' own personal ability beliefs in math play a role in the relation between intrinsic load and self-efficacy. Although personal ability beliefs were not measured in the daily survey, interviews revealed that many of the teachers held differing ability beliefs in math, which they directly connected to their efficacy beliefs. Teachers who shared they are "good at math" also explained they were efficacious for teaching the subject. However, teachers who shared more negatively valanced ability beliefs in math (e.g., "I've never been good at math"), also shared their lack of confidence for teaching the subject. The link between teachers' ability beliefs and self-efficacy beliefs is consistent with the existing SEVT literature (see Wigfield & Eccles, 2000; Eccles & Wigfield, 2020). Moreover, and relatedly, perhaps

teachers' ability beliefs reflect an unexplored moderator of the relation between intrinsic load and self-efficacy beliefs during math instruction. That is, it is possible that intrinsic load only negatively predicts self-efficacy during instruction if they have low ability beliefs (i.e., teachers who view themselves to be 'bad at math" might find a more challenging math lesson to be more intimidating and thus lower their confidence). On the other hand, teachers who view themselves as "good at math" might encounter a more inherently challenging math lesson but remain confident in their ability to teach it (i.e., their ability beliefs may act as a buffer). More research is needed to directly investigate this possibility.

Intrinsic Load and Task Effort Cost. As hypothesized, intrinsic load positively predicted teachers' task effort cost during math instruction. However, this relation was only significant at the within person level (i.e., not between teachers). That is, on a day in which math instruction was more inherently challenging for a teacher than usual, that teacher experienced increased perceptions of the excessive effort necessary for math instruction. Teachers' firsthand descriptions of the compounding challenges associated with math instruction extended these findings, like the aforementioned differentiation needs of students and district-level curriculum changes. For example, according to teachers in the interview sample, on a day in which more differentiation of math content is needed, it would increase the difficulty of that instruction. The link between intrinsic load and teachers' perceptions of task effort cost reflect a unique contribution of the present study given prior research that found teachers' task effort cost perceptions were more closely associated with teachers' workload and administrative tasks (Beymer et al., 2022a), both of which are more closely aligned with extraneous load. Despite the recent publication date of previous work on teachers' cost perceptions these data were still collected prior to the global pandemic and many other significant national events (Beymer et al.,

2022a). Therefore, perhaps the relation between intrinsic load and task effort cost detected in the previous study may again speak to the dramatic shift in the education landscape over the past several years.

Furthermore, the tenets of both CLT and SEVT support the idea that when instruction is perceived to be more difficult – requiring teachers to allocate more of their working memory resources to intrinsic load (Sweller, 2010) – that their instruction would be perceived as more effortful. For example, prior SEVT research has found that perceived task difficulty and effort required of that task to be closely (and positively) related, though still distinct (see Eccles & Wigfield, 1995; 2020; Flake et al., 2015). Therefore, this study corroborates and extends this research: potentially, it is not only higher perceptions of task difficulty that influences increased perceptions of task effort cost, but how that task difficulty influences one's actual cognitive architecture. That is, the more load due to task difficulty, the more working memory space occupied by intrinsic load, ultimately making the task more effortful to cognitively process and enact. This contribution also speaks to the value of integrating CLT and SEVT (see Koenka & Wigfield, 2023), which I return to when reflecting on the current study's theoretical implications.

Intrinsic Load and Emotional Cost. On days in which teachers felt that their math lesson was more challenging and/or complex to teach, they experienced an increase in their perceptions of emotional cost. In other words, a more challenging lesson predicted more negatively valanced emotions during that instruction. Teachers partially explained these findings through their descriptions of heightened frustration and overwhelm commonly experienced during their math instruction. Further, teachers often associated feeling frustrated and overwhelmed with (a) changing curriculum, (b) an extensive amount of differentiation needs, and (c) environmental distractions. While I discuss environmental distractions in more detail in the following sections

(see "Extraneous Load and Emotional Cost"), both changing curriculum and differentiation challenges were found in this study to be key contributors to teachers' intrinsic load. Thus, drawing from both the quantitative and qualitative data, it is conceivable that curriculum changes and differentiation challenges may help to explain the predictive relation between intrinsic load and emotional cost for teachers within the context of this study.

Other research has made the link between differentiation challenges during instruction and emotional cost among teachers (Beymer et al., 2022a); however, in this earlier work, differentiation needs were less emotionally costly compared to other, more extraneous-related distractions (e.g., classroom management and administration challenges). Thus, the present study uniquely underscores the importance of heightened intrinsic load due to curriculum changes and differentiation and its consequences for teachers' negatively valanced resulting emotions (i.e., particularly frustration and overwhelm), especially given the theoretical and empirical connections between heightened cost perceptions and decisions to withdraw from those domains (Beymer et al., 2022a; Eccles & Wigfield, 2020; Rosenzweig et al., 2022)

Extraneous Load

On average, and aligned with my hypothesis (see Chapter 3, "Hypothesis 1"), teachers reported moderate to high (M = 3.22 on a five-point scale) extraneous load – the highest across the three dimensions of cognitive load. Similar to intrinsic load, however, teachers' cognitive load varied greatly over the course of 10 school days (Appendix U and V presents a visual representation of daily variation in extraneous load). That is, the cognitive load that teachers experienced unrelated to their math instruction itself fluctuated greatly depending on the day. There were several central aspects of the classroom environment during math instruction that teachers described which represented extraneous load: (1) student-related distractions, (2) non-

student-related distractions, and (3) emotional fluctuations, which I discuss in the following sections.

Environmental Distractions. Aligned with the extant teachers' cognitive load literature (e.g., see Blackley et al., 2021; Hebert, 2018; Moos & Pitton, 2014) as well as the broader cognitive load literature (e.g., see Choi et al., 2014), the present study revealed that the most common additive to teachers' extraneous load was environmental distractions. Teachers pointed to two different types of distractions: (1) student-related and (2) non-student related. When teachers pointed to student distractions, they often described miscellaneous noises and movements, spontaneous outbursts, and lack of student engagement. When teachers pointed to distractions unrelated to students that occurred in the classroom environment, they commonly described distractions like technology, constant reminders of math assessments and benchmarks, teaching observations, and people coming in and out of the classroom as phenomena that add to their extraneous load. Overall, it seems that even small environmental distractions (e.g., simple noises) that are abundantly common throughout elementary classrooms (Godwin et al., 2016; Marshall et al., 2024) act as a working memory input, which according to CLT, increases the chances of experiencing cognitive overload (Feldon, 2007; Sweller, 1988, 2010).

Emotional Fluctuations. Previous research has found a link between cognitive load and outcomes of negative emotions (e.g., frustration; Blackley et al., 2021; Brockbank & Feldon, 2024). However, the present study uncovered not only an explicit link between cognitive load and negative emotions, but how those emotional experiences can in turn act as an additional cognitive load input. In other words, interviews revealed that the varied emotions that teachers reported experiencing in the present study (e.g., frustration, overwhelm, anxiety, stress, hopelessness) were found to also serve as a source of extraneous load. For example, teachers in

this study described that experiencing negative emotions like frustration requires them to utilize emotion regulation strategies in order to mitigate those emotions. Thus, aligned with existing research that has begun to investigate the interplay between emotion and cognitive load (e.g., see Feldon et al., 2019; Park et al., 2014), the negative emotions teachers experience during math not only serve as a distraction to that instruction but also appear to occupy additional space in the working memory given the decisions and strategies teachers have to draw from in order to regulate those emotions.

Extraneous Load and Motivation.

Extraneous Load and Self-Efficacy. The present study's quantitative results revealed that extraneous load negatively predicted self-efficacy beliefs both within and across teachers. In other words, teachers who (a) consistently reported high extraneous load during math across all 10 days and (b) experienced a higher extraneous load than their average on certain days, were more likely to hold lower self-efficacy beliefs for math instruction. Simply put, the more environmental distractions (e.g., student disruptions) that occurred during math, the lower levels of confidence teachers reported for math instruction. These results are consistent with other research that has found a similar, predictive and negative relation between extraneous load and self-efficacy among higher education students (Feldon et al., 2018, 2024). This is the first known study that extends this relation beyond students to teachers, speaking to the need to minimize environmental distractions to maintain teacher efficacy – a powerful antecedent to teacher retention (Lazarides & Warner, 2020; Skaalvik & Skaalvik, 2007, 2010; Zee & Koomen, 2016).

Moreover, the negative and predictive relationship between extraneous load and self-efficacy is in alignment with key tenets of CLT. When there are a lot of extraneous distractions on a particular day, those each act as cognitive inputs. Too many inputs, especially those that do

not push math instruction forward in any way, overwhelm a teachers' working memory and likely result in cognitive overload and/or ineffective processing (Cowan, 2014; Moos & Pitton, 2014; Paas et al., 2003a). Therefore, drawing from this literature and the current study's findings, when teachers are extraneously overloaded and are therefore not able to properly process all that is occurring during math instruction, their beliefs in their own abilities to provide their students with effective math instruction falters. Taken together, the present study (a) extends the findings of the existing literature, by confirming that the negative, predictive relation between extraneous load and self-efficacy operates in the same manner among the teacher population and (b) further underscores the importance of minimizing extraneous load in order for teachers to maintain more optimal levels of self-efficacy beliefs for math instruction.

Extraneous Load and Task Effort Cost. Aligned with my second hypothesis, extraneous load positively predicted teachers' perceptions of task effort cost during math instruction. However, like intrinsic load, this relation was only detected at the within-person level. In other words, on days when teachers experienced more distractions unrelated to math instruction, they were more likely to perceive math instruction as more effortful. The connection between environmental distractions and task effort cost are consistent with the existing literature on teachers' cost perceptions. In particular, Beymer et al. (2022a) found an array of classroom factors that have been categorized as extraneous load in this study impacted teachers' task effort cost: student behaviors (i.e., see "Environmental Distractions" section above), administration challenges (i.e., see "Environmental Distractions" section above), and emotional stress (see "Emotional Fluctuations" section above).

Additionally, the predictive negative relation between extraneous load and perceptions of task effort cost can be further explained by the qualitative finding that teachers feel they are

"always on" during math instruction. Feeling "always on," which was often attributed to classroom management demands, suggests that teachers need to maintain consistent attention throughout math. Consistent attention is likely something that is therefore perceived by teachers as excessively effortful. Taken together, the present study (a) corroborates extant findings on key attributes to teachers' task effort cost perceptions and (b) is the first to confirm the positive, predictive relation between extraneous load and task effort cost among teachers.

Extraneous Load and Outside Effort Cost. Quantitative findings revealed that extraneous load positively predicted outside effort cost perceptions during math instruction. That is, both overall and on days when a large number of extraneous distractions occur, teachers perceive the other tasks beyond mathematics instruction required of them it even more costly. These findings may be explained by the conceptual overlap between extraneous load and outside effort cost perceptions. For example, extraneous load captures the load imposed due to happenings unrelated to math instruction while outside effort captures perceptions of tasks unrelated to math instruction that make it more challenging to put effort into math instruction. Each of these constructs deal with phenomena around the classroom that are (a) unrelated to and (b) distract from the task at hand: math instruction. Moreover, it is possible that the events teachers refer to when perceiving unrelated phenomena happening around the classroom, are the same for both extraneous load and outside effort cost. To demonstrate, student disruptions are a factor that add to teachers' extraneous load; however, these disruptions also likely add to a teachers outside effort cost perceptions due to the need to then engage classroom management strategies – and thus more effort unrelated to math instruction – in order to mitigate those disruptions. In fact, prior research confirms that teachers often perceive student discipline to be

associated with increased perceptions of outside effort cost during instruction, in addition to grading and other unrelated to instruction tasks (Beymer et al., 2022a).

Taken together, the present study is one of the first to (a) confirm a positive, predictive relation between teachers' extraneous load and perceptions of outside effort cost during instruction and (b) discuss the conceptual overlap between the two constructs. More research is needed to disentangle extraneous load and perceptions of outside effort cost.

Extraneous Load and Emotional Cost. Both on certain days and on average, when teachers experienced heightened levels of extraneous load, they were more likely to associate math instruction with more negative emotions. These findings were further expanded upon during interviews as teachers pointed to student and non-student disruptions during math and how those disruptions were often attributed to a range of emotions experienced throughout any given math lesson. Teachers often attributed environmental disruptions to feelings of frustration, overwhelm, stress, and anxiety. Therefore, it may be the case that environmental disruptions are a mechanism through which teachers experience emotional cost.

These findings agree with extant research that has uncovered (a) a relation between cognitive overload and sub-optimal emotional experiences (Brockbank & Feldon, 2024) and (b) that the feeling of being overwhelmed is how humans are generally able to describe the feeling of being cognitively overloaded (Sewell et al., 2020). Further, these findings continue to align with Beymer et al. (2022a) given the study's connection between emotional labor and stress, classroom/behavior management needs, and administrative challenges – all of which are extraneous in nature – and teachers' perceptions of emotional cost. Overall, the present study is one of the first to (a) discover a predictive relation between extraneous load and emotional cost

among teachers and (b) specifically point to the emotions of frustration, overwhelm, stress, and anxiety to be of key emotions that emerge from heightened cognitive load among teachers.

Extraneous Load and Loss of Valued Alternatives Cost. Extraneous load was the only dimension of cognitive load that predicted loss of valued alternatives cost. That is, on days and on average when teachers experienced more external distractions during math instruction, they were more likely to perceive math instruction as costly due to other tasks they had to forgo because of it. From a CLT perspective, this predictive relationship makes sense given that excess extraneous load during math instruction likely feels unproductive to teachers (Seufert, 2018; Sweller et al., 2011). Therefore, if teachers devote a significant portion of their mental effort to managing classroom occurrences unrelated to their math instruction, it would be logical for them to perceive that instruction as more costly due to other tasks that could have been accomplished otherwise. For example, teachers may even have to forgo planned math instruction when extraneous load is too high as teachers shared during interviews that on some days when the classroom environment is too much, they end their math lesson early and return to it the following day, thereby delaying math instruction and missing out on so-called "valued alternatives" (Flake et al., 2015, p. 235).

Alternatively, perhaps teachers perceive loss of valued alternatives when their extraneous load is high due to the level of exhaustion that coincides with having to manage extraneous distractions during math. For instance, throughout math instruction, teachers reported feeling "always on" which many explained led to "severe exhaustion" (Ms. Thomas) post math instruction. Moreover, teachers explained that this exhaustion extended throughout the remainder of their day and into their personal lives – many describing their lack of motivation to do anything after school due to their level of exhaustion. Beymer et al. (2022a) uncovered similar

findings: teachers reported feeling challenged by the amount of energy required of them to teach, which was positively related to their perceptions of loss of valued alternatives cost. Thus, it is possible that the extraneous demands during math are so mentally exhausting that teachers also forgo other activities in their personal lives. Future work should directly test the two above-mentioned possible mechanisms in the relation between extraneous load and loss of valued alternatives cost.

Germane Load

On average, and as I hypothesized (see Chapter 3, "Hypothesis 1"), teachers reported experiencing above moderate (M = 3.16) levels of germane load across the 10 days of math instruction – a mean value that is descriptively higher than intrinsic load, but lower than extraneous load. Similar to intrinsic and extraneous loads, there was a significant level of variation at the day level (Appendix U and V presents a visual representation of the daily variation in germane load across teachers). In the present study, germane load was operationalized by teachers' ability to effectively adapt and modify lessons. For instance, when teachers were able to try new pedagogical strategies or push their instruction forward in a way that broadened their own schemas for math instruction, they experienced higher levels of germane load. In other words, by allocating more of their mental effort to adapting their instruction to try new pedagogical tools and techniques, they are building upon their existing schema structures (Paas et al., 2003b; Sweller et al., 1998; Sweller, 2010). In time, teachers' mental effort devoted to schema building results increased pedagogical knowledge in their long-term memory and automaticity for using the instructional strategies. Therefore, as discussed throughout the cognitive load literature (e.g., see Sweller et al., 1998), and unlike excessive levels of intrinsic load and especially extraneous load, it is beneficial for a teacher to experience

a higher level of germane load rather than a lower level. In fact, existing literature suggests that it is ideal to maximize an individual's germane load as it results in more knowledge expansion and retention (Sweller et al., 1998).

Although the findings from the present study are inconsistent with the direction of my initial hypothesis relating to germane load (see Chapter 3, Hypothesis 2), they align with the literature suggesting that germane load is a more productive type of cognitive load (Paas et al., 2003a). In particular, germane load was negatively associated with intrinsic and extraneous load. Considering the broader literature in hindsight, these negative associations are unsurprising given how the human cognitive architecture is structured. For example, consider a third-grade teacher teaching a fraction lesson, which is high in information complexity (i.e., intrinsic load). Moreover, assume that during this teacher's math lesson, there are a lot of environmental distractions occurring in and around the classroom that they must process (i.e., extraneous load). Together, both the heighted intrinsic and extraneous loads leave little to no room left in the teacher's working memory. With such limited space left in that teachers' working memory, they are unable to direct any of their working memory towards germane load, and thus, their germane load would be low or essentially nonexistent. Therefore, the present study suggests that it is ideal for teachers' (a) intrinsic load to be managed and (b) extraneous load to be minimized as much as possible so that there remains space in the working memory to allocate to germane load (i.e., schema construction).

Germane Load and Motivation.

Germane Load and Self-Efficacy. The current study's results revealed that germane load was a positive predictor of self-efficacy across teachers and on specific days when germane load was higher than a teacher's average. That is, when teachers have enough working memory

resources to devote mental effort towards their own schema development for math instruction, they become more confident in that math teaching. Minimal existing research has directly investigated the predictive relation between germane load and self-efficacy. However, it is possible that increased mental effort delegated towards schema construction feels like a productive use of that mental effort given prior research that suggests germane load is associated with information retention (Debue & van de Leemput, 2014). More specifically, when teachers dedicate additional mental effort (i.e., germane load) to math instruction and then experience information retention or another form of instructional success, they may encounter a form of mastery experience (i.e., experiences of success; Miele et al., 2024; Usher & Pajares, 2008). If this interpretation is accurate, the positive relation between germane load and self-efficacy aligns nicely with the social cognitive theory literature given that mastery experiences are one of the most powerful sources of self-efficacy (Usher & Pajares, 2008). More research is needed to further investigate the relation between germane load and self-efficacy – particularly mastery experiences serving as a possible mechanism.

Germane Load and Task Effort Cost. While germane load also predicted teachers' task effort cost, unlike intrinsic and extraneous loads, germane load predicted task effort cost (a) negatively and (b) at the between-person level. Simply put, teachers who had a higher germane load on average were less likely to view math instruction as overly effort-inducing. These findings are aligned with existing literature that suggests germane load is a useful kind of load (Sweller et al., 1998). In particular, it may be the case that when teachers are able to utilize some of their working memory capacity for schema construction, they may feel as though the effort they devote to their math instruction is reduced because they are developing knowledge and strategies they will be able to use again the future – which ultimately would reduce the effort

required of them in the future. Moreover, existing operationalizations of task effort cost emphasizes increased perceptions stemming from *too much* effort (Beymer et al., 2022a, 2022b; Flake et al., 2015); therefore, perhaps germane load represents a productive, not overly challenging type of cognitive effort. In addition, as reported during interviews, the teachers were in their second year of teaching math from a new curriculum. Potentially, because they have some existing schemas for the curriculum from the year prior, they were able to make some room in their working memory the second time teaching it for germane load. The additional germane load, again, may feel productive and less effortful if they are building teaching strategies (and schemas) that will be useful for them again in the future. More research is needed to further test and understand the mechanisms behind the negative relationship between germane load and task effort cost.

Germane Load and Outside Effort Cost. Germane load at the within-person level negatively predicted teachers outside effort cost. That is, on days in which teachers were able to devote more of their working memory resources to building and expanding upon existing schemas, they were more likely to experience lower perceptions of outside effort cost. While the relation between germane load and outside effort cost had remained unexplored until the present study, CLT and the cognitive architecture as a whole helps to explain the direction of this relation. Germane load is only able to come into the picture if there are enough working memory resources available to the individual (Sweller et al., 1998; Sweller, 2010). That is, both intrinsic and extraneous loads must be managed and/or minimized to be able to devote working memory resources to building schemas. Therefore, when an individual has a high germane load, it means their intrinsic load has been effectively managed and their extraneous load has been minimized (Sweller et al., 1998). Moreover, given the formerly discussed conceptual overlap between

extraneous load and outside effort cost, when teachers in the present study experience heightened germane load, their external disruptions and tasks unrelated to math instruction were likely minimized, reducing their outside effort cost perceptions (and extraneous load, for that matter) associated with those tasks. Taken together, the present study (a) was the first to explore the predictive relation between germane load and outside effort cost and (b) suggests that the negative relation between the variables is aligned with CLT and the broader literature on the human cognitive architecture.

The Interplay Between Teachers' Intrinsic, Extraneous, and Germane Loads

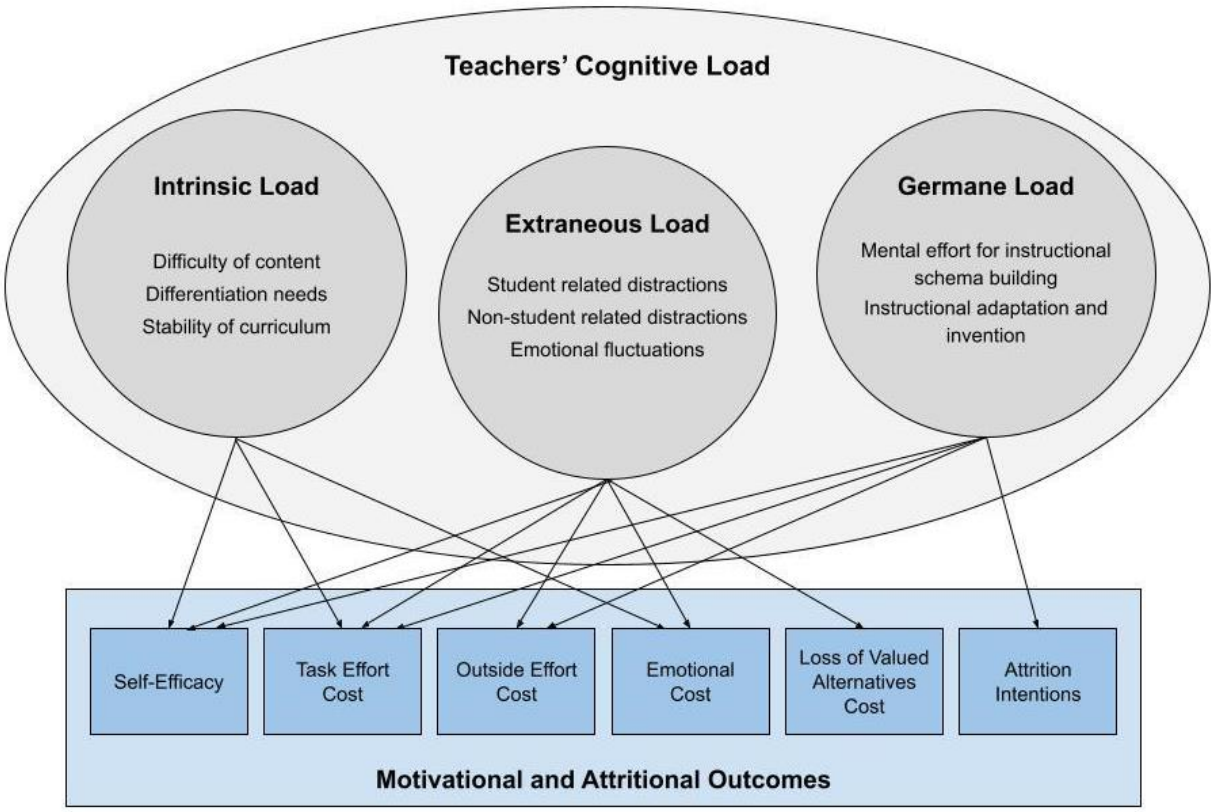
While each dimension of cognitive load was discussed above independently, it is crucial to note that intrinsic, extraneous, and germane loads each work together to account for an individual's total cognitive load. In particular, the existing literature details the additive nature of the cognitive load dimensions: intrinsic load + extraneous load + germane load = the sum of cognitive load imposed on that individual (Paas et al., 2003a). However, an important caveat is that these loads cannot sum to exceed an individual's working memory capacity (Sweller et al., 1998; Paas et al., 2003a).

Considering the results from the present study and the additive nature of cognitive load, an important finding emerged: the prominence of extraneous load. Throughout the quantitative, qualitative, and mixed findings, extraneous load emerged as overwhelmingly and uniquely impactful to teachers' cognitive load experiences, and consequently, their motivational experiences as well (see Figure 3). Therefore, day-in and day-out extraneous load occupies a large portion of teachers working memory capacity during instruction, leaving less space in the working memory capacity. An important implication emerges from this finding: teachers' cognitive load, resulting motivational beliefs, and, drawing from the broader literature (e.g.,

Sweller, 2010; Usher & Pajares, 2008), teaching effectiveness would all benefit if teachers, administrators, and stakeholders worked together to reduce teachers' extraneous load during math instruction.

Figure 3

Joint Display: Teachers' Cognitive Load and Its Outcomes



Although extraneous load emerged as the most prominent type of load during math instruction, intrinsic load remained an important additive to teachers' cognitive load as well. For example, despite the experience level of the teachers, many reported intrinsic load in the form of considerable and increasing differentiation needs throughout contemporary classrooms and challenges with changing curriculum. Thus, on days or for classes that need more differentiation

and/or when adjustment to new curriculum comes into the picture for teachers, their intrinsic load also takes up more space than normal in their working memory.

Taken together and drawing from the findings of the present study, it is likely that teachers' working memory often (a) reaches maximum capacity or (b) exceeds capacity after only accounting for their consistently higher extraneous load plus their fluctuating intrinsic load (i.e., based on differentiation needs and familiarity with the current curriculum). That is, teachers are likely reaching or even exceeding their working memory capacity, and therefore, unable to engage the beneficial and productive type of load: germane load. Failure to utilize their working memory for schema building, and thus, long-term retention is problematic for two reasons. First, teachers are not expanding their schemas for math instruction regularly, leading to less development of automated, go-to strategies that have been found to be beneficial for reducing teachers load during instruction (e.g., see Blackley et al., 2021; Moos & Pitton, 2014). Second, out of the three cognitive load dimensions, germane load was the only dimension to predict teachers' attrition intentions. That is, when teachers experienced greater germane load, they had fewer intentions to leave the field. This finding moves beyond statistical significance to practical significance: despite this relation being correlational rather than causal in nature (Shadish et al., 2002), it still points to a possible means for retaining more teachers in the field. Therefore, in the following section, I discuss cognitive load and attrition intentions in greater detail.

Attrition Intentions and Cognitive Load. Neither intrinsic nor extraneous loads significantly predicted teachers' attrition intentions. Aligned with CLT (Sweller, 1988; Sweller et al., 1998), the lack of relation may be due to differences in the nature of the two dimensions. For instance, at any given moment, a teacher's extraneous load may change depending on the environment. Furthermore, attrition intentions are conceptualized as a long-term behavioral

decision (Beymer et al., 2022a). Therefore, teachers may attribute the fluctuations in intrinsic and extraneous loads as temporary and in the end, may not drive teachers' attrition intentions. Moreover, teachers in the study were only followed for 10 days. Potentially, sustained experiences of heightened intrinsic and extraneous loads may have a different effect on teachers' attrition intentions over time. Another possible reason for the lack of relation could be attributed to a limitation of the present study: attrition intentions were only measured with a single item (see Appendix O). Therefore, perhaps intrinsic and extraneous loads are in fact predictive of attrition intentions, but the attrition measure was not sensitive enough to detect the relation. Finally, during interviews, teachers explained that despite the overwhelming demands of the classroom environment, they remain in the field because of their students and the joy they experience from working with them. Therefore, potentially students serve as a preventative buffer to attrition intentions, above and beyond the influences of intrinsic and extraneous loads.

Unlike intrinsic and extraneous loads, germane load did significantly predict teachers' attrition intentions at the within-person level; though, this predictive relation was small in effect size (Hattie, 2023; Kraft, 2020). Regardless, CLT helps to explain why heightened working memory allocation to building schemas may positively link to a teachers' willingness to remain in the field (Kalyuga, 2010). That is, compared to intrinsic and extraneous load, effort exerted due to germane load is more permanent in its long-term influences on math instruction due to the resulting schema expansion and greater development of background knowledge for teaching the subject. Therefore, on days when teachers are able to engage in schema expansion during math, those skills may ease the burden of their cognitive load, leading to teachers being more willing to teach day-in and day-out. More research is needed to further explore the relation between teacher' germane load and attrition intentions.

Experience Level and Cognitive Load. In contention with the hypothesized relation between experience level and teachers' cognitive load during math instruction (see Chapter 3, "Hypothesis 1a"), the quantitative results revealed that years of teaching experience did not significantly predict teachers' cognitive load during math instruction across any of its three dimensions. The lack of relation between experience and cognitive load was surprising given existing literature that suggests teachers develop (a) go-to strategies for instruction and (b) automaticity overtime (Blackley et al., 2021; Feldon, 2007; Moos & Pitton, 2014) – which in theory, would leave more space in teachers' working memory and effectively reduce their cognitive load.

Interestingly however, thematic analyses of qualitative interviews did not align with the unexpected quantitative findings. That is, teachers throughout the qualitative interviews underscored the importance of the years of teaching experience they have gained over time and emphasized that that experience allows them to more effectively adapt to the multitude of instructional and environmental demands that arise during math instruction. For example, mid-to-late career teachers interviewed explained that while math teaching often remains a challenge for them day in and day out, it has become easier and second nature to them over the years. One teacher described their experience in the form of a "toolbox," mentioning after 30 years of math instruction, they are able to try an array of different tools they have gained over the years when instruction is not going as planned.

There are several possible explanations for the discordance between the quantitative and qualitative data. First, from a measurement perspective, the quantitative, daily diary surveys and qualitative semi-structured interviews measured cognitive load in two different ways. That is, teachers *daily* cognitive load experiences during math instruction versus teachers *generalized*,

retrospective experiences of cognitive load during math instruction. Therefore, it is possible that in retrospect, teachers perceive a reduction in their cognitive load over the years; however, that on a day-to-day basis experience is not as impactful to teachers' cognitive load fluctuations.

Second, during interviews, teachers reported their district implemented a new curriculum the school year prior; and therefore, were only in their second year of teaching the new curriculum. As discussed in the section above (see Chapter 5, "Intrinsic Load"), a new curriculum may increase teachers' cognitive load – regardless of their experience level – as they need to re-build math instruction schemas to align with that curriculum. Thus, in the present study, it is possible that the new curriculum increased all teachers' cognitive load despite their experience level. Moreover, if this is the case, it would align with the *expertise-reversal effect*, or the idea that information beneficial to more novice learners is redundant for more experienced ones, ultimately unnecessarily increasing experienced teachers' cognitive load (Kalyuga et al., 2012). In this case, when experienced teachers receive a new curriculum, it requires them to re-process information they already know (i.e., how to effectively teach the math content using techniques from the prior curriculum) and thus re-organize existing schemas they had already developed – unnecessarily increasing their load. Since novice teachers have not yet built expansive schema structures for math teaching in the same way, they do not have to rewrite their schema structure to learn the new curriculum. Finally, there is a possibility that the relation between teachers' years of experience and cognitive load are not linear in nature (e.g., potentially the relation is quadratic) and future work should investigate this possibility.

Taken together, despite the divergent results surrounding the interaction between teachers' experience level and cognitive load, measurement differences and the adoption of new curriculum may help to explain why that divergence was present. More research is needed to

further investigate the relation between teachers' experience level and cognitive load to (a) best support teachers at different career stages and (b) conceptually unpack the nature of cognitive load in a teaching context.

Teachers' Social Identity and Cognitive Load. Given the dearth of strengths-based literature centering underrepresented teachers in the cognitive load and broader educational psychology literature (Archer et al., 2022; DeCuir-Gunby & Schutz, 2014), the present study aimed to address this gap by exploring the cognitive load experiences of minoritized teachers (see Chapter 4, Research Question 3a). Ultimately, I was partially successful in achieving this aim through qualitative interviews. That is, I conducted three interviews with teachers who are underrepresented and/or minoritized in the teaching workforce (NCES, 2023); however, the demographics of the present study's sample limited my ability to interview more teachers with underrepresented and/or minoritized identities. Despite this caveat, several findings emerged, particularly related to teachers with disabilities, that begin to address these crucial gaps and underscore the importance of future research in this area.

For example, Ms. Hall, a second-grade teacher with ADHD, described how she was actively aware of how her learning disability impacted her ability to manage all that occurs around her during math instruction – and importantly distinguished between the unique affordances of her disability in the classroom and the challenges that arise as well. In fact, Ms. Halls' statement, "...it feels like sometimes the actual task of being a teacher doesn't always match up with the way I feel like my brain works," is true of the teaching profession. That is, a central finding that emerged from the present study is the lack of alignment between the vast number of demands teachers are expected to manage during instruction and what the human cognitive architecture can actually (and effectively) manage. Therefore, when instructional

demands exceed capabilities of neurotypical teachers, those same demands are likely to be exacerbated among teachers with learning disabilities (e.g., ADHD) due to differences in the working memory capacities of neurodivergent individuals (Al-Saad et al., 2021; Tolonen et al., 2024). In other words, the structure of classroom instruction has not been built for neurotypical adults' cognition and thus especially not for neurodivergent adults. However, Ms. Hall also reflected on the assets of her learning disability in the classroom: that it allowed her to be hyper-aware to signals that her students may need a break. This finding is worth amplifying because it speaks to the value of adopting a strengths-based approach to centering minoritized teachers' experiences and centering their voices in the process (Milner & Howard, 2013; Silverman et al., 2023).

In contrast to Ms. Hall, Ms. Thomas, the only teacher in the interview sample with a minoritized racial identity (biracial; Black and white) did not explicitly reflect on her social identity when discussing her cognitive load experiences in mathematics. There are many possible reasons for this, but failing to draw from her social identity in her reflections should not be interpreted as a lack of relevance. In fact, holding a minoritized social identity likely equips teachers with unique assets (Silverman et al., 2023) and barriers due to the systemic inequities they confront within and beyond the teaching workforce (Milner & Howard, 2013). For example, given their own experiences navigating white, Eurocentric learning contexts, the process of teaching math in a more culturally responsive manner may be more automatic and thus less cognitively taxing (Feldon, 2007; Kumar et al., 2015).Teachers of color may also experience exacerbated cognitive load due to the need to assimilate to a dominant culture different from their own (i.e., experiences of home-school dissonance, cultural cost; Archer et al., 2022; Kumar, 2006) or other negotiations with systemically inequitable barriers (e.g., potentially a lack of

belonging-opportunities structures for diverse teachers; Gray et al., 2018) within the education system.

Thus far, I have been unable to locate literature that properly considers how social identity characteristics and CLT are related. While there has been some consideration of the individual differences across the literature (e.g., see Sweller, 2024), to my knowledge salient social identities like race and ethnicity are underexplored. The lack of consideration of individuals' social identities is both a limitation and area for future research, given the (a) existing cognitive psychology literature that emphasizes the role that an individual's social experiences and beliefs play into one's working memory capacity and (b) findings of the current study. For example, Meyer & Lieberman (2012) presented *social working memory* (or SWM) as the consideration and attributions of "…mental states to the self and others, people must access, maintain, and manipulate information about the person (self or other) and draw some sort of conclusion about their related mental state…" (p. 1). Therefore, and when considering teachers in the present study, they are not only holding and processing information about their math instruction, the classroom environment, and their own emotions in their working memories; they are also holding and processing information about their own (and their students') social identities – adding yet another input(s) during instruction that may exacerbate their cognitive load.

Taken together, while the current study began to address the gaps that exist between CLT and the social identities of minoritized teachers in particular, more explicit, focused research on minoritized populations and their cognitive load experiences are needed – especially in light of this study's findings that both minoritized teachers who participated in interviews shared their short-term intentions for exiting the teaching profession altogether.

Implications

Theoretical Implications

Several theoretical implications emerged from the present study. First, consistent with recent calls in the literature (e.g., Koenka & Wigfield, 2023), the power of integrating across theories of cognition and motivation became apparent. This study uncovered relations across CLT, SCT, and SEVT constructs. Results revealed that intrinsic load predicted self-efficacy, task effort cost, and emotional cost; extraneous load predicted self-efficacy and all four dimensions of cost perceptions; and germane load predicted self-efficacy, task effort cost, and outside effort cost. These findings are especially important given that, to my knowledge, this is the first study to uncover these relations among an immensely understudied population across the CLT literature: teachers (Feldon, 2007). Moreover, the relations between intrinsic and extraneous loads and (a) self-efficacy and (b) cost perceptions may be especially noteworthy expansions to the literature given the existing research that links decreases in self-efficacy and increases in cost perceptions to burnout and attrition intentions (Beymer et al., 2022a; Skaalvik & Skaalvik, 2007; Zee et al., 2018). Further, given this study's novel findings that intrinsic load and extraneous load do not predict attrition intentions, it may be the case that self-efficacy and cost perceptions act as mediators between intrinsic load, extraneous load, and attrition, which aligns with the tenets of SEVT (Eccles & Wigfield, 2020). More research is needed to further investigate this possible mediating relation.

Second, the present study uncovered potential theoretical overlap among two CLT and SEVT constructs: extraneous load and outside effort cost. Both constructs capture the load or costs associated with phenomena unrelated to the central task at hand. Further, it could be that teachers even perceive the extraneous load they experience as an outside effort cost, especially

considering prior research that suggests extraneous load should be conceptualized as its own dimension of cost within an expectancy-value-cost framework (which is highly consistent with SEVT; Feldon et al., 2019). Future research would benefit from using structural equation modeling techniques to directly investigate the possible overlap between extraneous load and outside effort cost perceptions (see Bollen & Hoyle, 2012).

Third, the present study advances the ongoing debate surrounding germane load (see Kalyuga, 2011) as a standalone dimension of cognitive load by investigating its relevance among an underrepresented population in the cognitive load literature: teachers. This study discovered that germane load was negatively related to intrinsic and extraneous load, which is the expected direction of the relation based on theory (Sweller, 2010). Despite the theoretically aligned direction of the relation, teachers explicitly discussed limited examples of germane load during interviews. Moreover, while the ability to adapt instruction and engage in new pedagogical techniques to build upon new schemas was attributed to germane load in this study, it remains unclear if adaptation and utilizing new pedagogical techniques are truly distinct from simply the inherent challenge of that instruction (i.e., intrinsic load). Taken together, the current study's findings suggest that additional research is needed to explicitly address the enduring lack of clarity surrounding intrinsic load and germane load, including how these dimensions operate among the teacher population.

Methodological Implications

To my knowledge, this study was the first to use a short-term longitudinal design (i.e., daily diary) to measure teachers' experiences of cognitive load. The repeated measurement of cognitive load as close as possible to the teachers' actual experience of it materialized as essential for measuring the ever-fluctuating nature of the construct (Boehm et al., 2021). Because

teachers took surveys immediately following their daily math instruction over the course of 10 days, it allowed them to respond to surveys as close as possible to their actual cognitive load experiences. Measuring cognitive load in this manner likely reduced retrospection bias that is often a limitation of self-report surveys across social science research (Bolger et al., 2003; Dent & Koenka, 2016; Hektner et al., 2007; Zirkel et al., 2015). Moreover, repeated measures allowed me to model how cognitive load varied both across teachers as well as within each teacher. Interestingly, across several models, there were instances where a dimension of cognitive load predicted teachers' motivational beliefs at the within-person level but not at the between-person level (e.g., extraneous load predicted task effort cost at the within-person level but not at the between-person level). Therefore, if cognitive load had not been measured repeatedly over the course of 10 days, key information regarding how the construct operates within each individual teacher may have been lost. Therefore, future cognitive load research should consider using short-term longitudinal designs to more closely align with the fluctuating nature of the construct.

Additionally, using a mixed methods approach (a) to more holistically understand how constructs operate among populations for whom those constructs have been underexplored (e.g., cognitive load among teachers) and (b) when integrating across theories was also an important methodological implication that emerged from the current study. In particular, the explanatory-sequential mixed methods design, was necessary in order to gain (a) insight into how cognitive load and motivational variables are related among the teacher population given the lack of research investigating these relations and (b) context as to teachers' own conceptualizations of cognitive load and motivation in the classroom as well as explain why certain relations existed and in the direction that they did. To demonstrate the significance and value of the mixed methods approach, without the qualitative interviews, I would not have apprehended the key

attributes to teachers' cognitive load (e.g., differentiation and curriculum challenges contribute to teachers' intrinsic load). On the other hand, without the quantitative data, I would not have been able to confirm the novel relations between cognitive load and motivation (e.g., cost perceptions) that emerged. Thus, future research on teachers' cognitive load should continue to consider using mixed methodologies to comprehensively understand teachers' experiences, especially in the near future given the continued lack of research in the area despite the present study.

Practical Implications

Several practical implications emerged from the present study that should be taken into consideration by policy makers, district leaders, administrators, and teachers.

Minimizing Teachers' Extraneous Load. First, a central finding of this research was the pervasiveness of extraneous load throughout teachers' math instruction. In fact, not only did teachers consistently report high extraneous load throughout both surveys and interviews, but extraneous load was also the only cognitive load dimension that predicted teachers' self-efficacy beliefs and all four dimensions of cost perceptions. In all, the demands teachers face unrelated to math instruction (e.g., environmental distractions) was the biggest additive to teachers' cognitive load. The prevalence of extraneous load during math instruction is problematic from a practical perspective given the strong recommendations throughout the CLT literature that extraneous load should be minimized (Sweller, 2010). Therefore, there is a need for adjustments to be made at the policy, district, and teacher level to reduce teachers' extraneous load during instruction.

For example, policy makers and district leaders should consider the benefits of allocating more adults into each elementary classroom or making efforts to reduce the class sizes of elementary classrooms. As classrooms currently stand, the number of cognitive inputs teachers receive during instruction are simply misaligned with the amount of information the human

cognitive architecture can take in. Moreover, given the misalignment between the cognitive capacity of humans and the immensely high cognitive load teachers receive, it results in less confidence for teaching math, more costly perceptions of that instruction, and severe levels of exhaustion. Altogether, the cognitive load placed on a single teacher during their math instruction is poorly calibrated with the general human cognitive capabilities, particularly due to the extraneous distractions and needs from a classroom of 20 students or more. Therefore, more resources should be allocated to (a) introducing more adults into the classroom (e.g., paraprofessionals) and/or (b) a reduction in class sizes to ease the cognitive burden placed on teachers during instruction. If financial or other resource limitations prevent stakeholders from implementing these recommendations, insights from the teacher interviews suggest that even smaller tweaks such as (a) implementing "call out" systems when some students' needs require more attention and are disrupting the learning environment and (b) minimizing external disruptions to the classroom environment (e.g., by minimizing entries into the classroom environment during math instruction) would be fruitful.

Additionally, the present study found that teachers' emotional fluctuations (e.g., feelings of frustration, overwhelm, stress, and anxiety) throughout instruction also played a role in exacerbating their levels of extraneous load. However, interviews revealed that when teachers adopted emotion regulation strategies (e.g., deep breathing), they were able to improve and reduce those negatively valanced feelings. Further, teachers often engaged in these regulation strategies alongside their students, effectively re-centering their class and reducing their extraneous load. Therefore, district leaders and administration might consider implementing and/or continuing to prioritize professional development seminars related to how teachers can

effectively implement emotion regulation strategies in the classroom (e.g., Conscious Discipline; Bailey, 2015).

Finally, there are several strategies teachers may consider adopting in order to reduce their extraneous load during instruction. Similar to findings from other existing research (e.g., see Blackley et al., 2021), it is useful for teachers to develop go-to strategies for instruction and particularly for classroom management. Finding a few key go-to classroom management strategies that work for teachers and their students will develop more automated teacher responses, helping to mitigate spontaneous distractions quickly and efficiently before the extraneous load caused by those distractions results in cognitive overload. Along similar lines, classroom routines have long been regarded as beneficial for students in classrooms, especially those at elementary levels (Harper & O'Brien, 2015). However, the benefits of building routines, particularly during math instruction, are useful to help teachers themselves reduce the amount of conscious processing that occurs indirectly related to math (e.g., if from routine practice, students know that when math starts they need to pull out their white boards and sit on the carpet, teachers no longer have to consciously process and repeat those instructions to students). Thus, teachers should continue to build routines in their classroom as much as possible and acknowledge that those routines are beneficial both for themselves and their students. Lastly, on days when math instruction is perceived to be more complex and challenging by teachers (i.e., high in intrinsic load), teachers should consider making that lesson as simple to enact as possible. For example, when introducing fractions the first time to students, it may be more beneficial to reduce the number of unnecessary activities or manipulatives used during that math instruction. Simplifying the lesson allows teachers to retain space in their working memory for the cognitive

processing of the complex content instead of taking up working memory space due to giving students instructions for activities, manipulatives, etc.

Managing Teachers' Intrinsic Load. In addition to minimizing teachers' extraneous load during math instruction, it is also important to appropriately manage teachers' intrinsic load.

First, policy makers, district leaders, and administrators should take teachers' cognitive load and the overarching human cognitive architecture into account when weighing the advantages and disadvantages to implementing a new math curriculum. The present study found that introducing a new math curriculum re-instilled a high intrinsic load among teachers – regardless of their experience level – for several years following its implementation given the need for them to re-learn and adjust to the curriculum. That is, many of the existing knowledge and schema structures teachers had for teaching math using the prior curriculum were no longer as useful, causing teachers to use more of their working memory capacity to think through and teach the new curriculum (Sweller, 2010). Therefore, when curriculum changes are being contemplated in math, practitioners should consider (a) whether the novelty of the curriculum is worth the increased intrinsic load demands it will place on teachers, (b) refraining from changing curriculum too often, and/or (c) providing extra support to teachers in advance and during the first year using a curriculum.

Second, the present study uncovered that the level of differentiation required in math classrooms today is greater than ever before given the shifting generation of students with greater needs (due to the COVID-19 pandemic, increase in technologies at school and at home, etc.). These differentiation needs exacerbate the challenge associated with teachers' math instruction daily and therefore take up more space in their working memory on top of the significant space already occupied by extraneous load. In all, it is impossible for one teacher to so widely

differentiate instruction for all 20 plus different students' needs in classrooms today. Therefore, aligned with recommendations made above, more supports (e.g., more paraprofessionals, smaller class sizes) are needed in the classroom to (a) reduce teachers' intrinsic load related to differentiation demands and (b) more effectively meet each student where they are at in math.

Finally, it is important to consider how new technologies may aid in reducing teachers' intrinsic load during math instruction by helping to differentiate material. For example, teachers, especially those who teach upper-level elementary students, may consider adopting tools like artificial intelligence (i.e., AI) to aid in math differentiation (Rutherford et al., 2025). Current AI platforms allow teachers to set up problems for their students to work through and the AI platform will adjust the problem based on students' responses as it learns their ability level. One teacher in the present study even shared that AI has been extremely helpful for their math differentiation, saying "...computers and AI have this ability to differentiate without you having to do anything. Like you just plug in a few things and go." Thus, teachers should consider how they can utilize AI and other technological tools thoughtfully and with intention to effectively differentiate in math without inflicting additional intrinsic load (Rutherford et al., 2025).

Maximizing Teachers' Germane Load. The present study, in addition to prior research (e.g., see Blackley et al., 2021; Moos & Pitton, 2014), also underscores the importance of developing schemas for instruction in order for automaticity to develop and free up working memory space. Therefore, when teachers find that a lesson worked particularly well, it may be beneficial for them to reflect on that lesson and potentially even record the aspects of that math instruction that were successful. Then, when that lesson needs to be taught the following year, they can (a) remember exactly what they did and why it was successful and (b) repeat it. Eventually, repeating successful lessons year after year will become more automatic to teachers,

allowing for more working memory space to be allocated to other demands in and around the classroom (Sweller, 2010). Moreover, the additional working memory space that emerges from more automated lessons will allow teachers to tweak and improve those lessons year after year (i.e., higher germane load). To demonstrate, when lessons feel like second nature to teachers, then they can begin to implement other highly important pedagogical tools (e.g., integrating culturally responsive pedagogies); however, without sufficient working memory space, those important pedagogical tools often will fall away (Feldon, 2007; Kumar et al., 2015).

Therefore, drawing from the present study, teachers should consider repeating aspects of instruction that worked especially well for them year after year and slowly build in other essential pedagogical tools, as opposed to attempting to implement several strategies all at once. Allocating time during professional development and/or faculty meetings to intentionally reflect on these successful aspects of math instruction could result in two major benefits. First, drawing from SCT and as discussed earlier, mastery experiences reflect one of the most powerful sources of self-efficacy (Usher & Pajares, 2008). Therefore, actively reflecting on these successes should boost teacher efficacy. Second, drawing from the results of the present study along with the broader cognitive load literature (e.g., Moos & Pitton, 2014), doing so should promote germane load. Finally, and pending additional work that explores the causal and directional nature of germane load and attrition intentions, findings from this study suggest that promoting more germane load among teachers could be a tangible, actionable strategy for helping to minimize teacher attrition – further emphasizing the need to maximize teachers' germane load.

Limitations

Despite the novel findings that emerged as a result of the present study, results should be interpreted in the context of seven limitations. First, the daily diary surveys may have acted as an

additional cognitive load input for teachers; however, I implemented several strategies to reduce this possibility (Bolger & Laurenceau, 2013). While trying to measure teachers' cognitive load experiences during math instruction as close as possible to the event, teachers received surveys immediately after instruction as to (a) not interfere with math instruction in general and (b) refrain from inflicting a cognitive load input. Therefore, assuming math instruction did not go over in time, the surveys should not have directly interfered with teachers' cognitive load.

Second, and related to the first limitation above, teachers were not always able to take the survey immediately following their math instruction. Therefore, though less common, some teachers on some days took the survey at the end of the school day as opposed to immediately following math instruction. The delay in survey response increases the possibility for additional retrospective bias (Dent & Koenka, 2016; Nisbett & Wilson, 1977). However, despite the introduction of retrospection, the present study measured cognitive load much closer to and more often that most existing studies that measure cognitive load via self-report surveys (Sweller et al., 1990; Jiang & Kalyuga, 2020) representing a unique contribution to the CLT literature. Moreover, the design and timing of the surveys were aligned with existing recommendations emphasizing the importance of ensuring that intensive longitudinal designs are not burdensome or intrusive in a way that negatively impacts the participant or those around them (Bolger & Laurenceau, 2013). That is, surveying teachers during math instruction would have been inappropriate given the impact that doing so would potentially have on teachers' instruction and students' learning.

Third, surveys were distributed to teachers at different school sites on different weeks and at slightly different times of the academic year. It was a priority of the present study to ensure that the study was conducted on a timeline that was most convenient and appropriate for my

school partners. Therefore, I adhered to the timeline preferred by each individual school. Regardless of the difference in timing of the surveys at each school site, timing did not seem to greatly influence teachers' responses as quantitative analyses revealed little variation in teachers' reported levels of cognitive load across the three schools.

Fourth, the instruments for which the cognitive load items were adapted (Leppink et al., 2013) were initially developed and established based on students' experiences of cognitive load. As a result, the items may not have captured teachers' cognitive load as accurately as a measure intentionally developed for the population of teachers may have (Clark & Watson, 1995). An additional, related limitation is that cost perceptions and attrition intentions were only measured with one item each (i.e., one item for each of the four dimensions of cost and one item for attrition intentions; see Appendix O). While these shortened scales were empirically tested and established in prior studies (see Beymer et al., 2022a, 2022b), single-item measures can be less reliable and lack the depth needed to capture complex psychological constructs (i.e., content validity; Allen et al., 2022; Fuchs & Diamantopoulos, 2009). Despite the drawbacks of using single-item measures, they are deemed appropriate in the context of an intensive-longitudinal design such as the one adopted in this study to reduce burden on the participant and the chances of participant attrition (Bolger & Laurenceau, 2013). Therefore, future research endeavors should include developing and empirically testing a novel cognitive load survey for the teacher population.

Fifth, all quantitative models had strong conceptual underpinnings and thus were grounded in the CLT, SCT, and SEVT literatures (Sweller, 1988; Schunk & DiBenedetto, 2020; Eccles & Wigfield, 2020). However, all predictive associations between constructs were measured simultaneously rather than sequentially. Therefore, establishing temporal precedence

in future research would be ideal to better assess the causality of each of the cognitive load, motivational, and attrition intentions variables.

Sixth, while I attempted to recruit teachers for interviews who (a) had the highest and lowest cognitive load levels across the entire sample and (b) had underrepresented identities in the teaching profession, not all these teachers signed up to participate in interviews. Therefore, not all teachers interviewed represented the extremes of cognitive load. In addition, less underrepresented teachers agreed to participate despite being recruited.

Seventh, I was unable to engage in *member checking*, or the process of confirming researcher findings and interpretations with study participants (Nowell et al., 2017), following qualitative interviews due to the wishes of my school partners. In addition, I did not have a second coder engage in coding of the interview transcripts in order to further establish reliability of the qualitative findings (Campbell et al., 2013). While I did not engage (a) in member checking or (b) a second coder, I still accounted for credibility and reliability of the interview findings in my assessment of trustworthiness (e.g., via data triangulation; Plano Clark & Ivankova, 2016) and recursive memoing throughout the data collection and analysis processes (Ezzy, 2002; see Chapter 3, "Trustworthiness" section). Taken together, each of these limitations described above should be considered in the context of interpreting the findings of the present study. In the following section, I describe the future research directions that emerged from the current study (Kendall et al., 2017).

Future Directions

The findings from the current study present important next steps for research at the intersection of teachers' cognition and motivation during math instruction. For example, findings from this study emphasize the daily fluctuations in teachers' cognitive load. Therefore, future

research should continue to explore cognitive load among teachers using designs (e.g., short-term longitudinal) that capture the momentary and everchanging nature of cognitive load. Future studies may also measure teachers' cognitive load over a longer span of time (e.g., four weeks; once a week over the course of a school year) to understand how cognitive load among teachers fluctuates over time as well as outcomes that speak to behavioral change (e.g., whether teachers actually stayed or left the field). In addition, given that the present study focused on preschool through fifth grade teachers' experiences during math instruction, future research should also consider the cognitive load experiences (a) among educators across grade levels (i.e., across sixth grade through higher education) and (b) during instruction for other subject domains (e.g., literacy, science). Along similar lines, given the (a) pervasiveness of extraneous load during math instruction and (b) existing literature that suggest extraneous load is malleable and can be intentionally modified (Sweller, 2010, 2011), future intervention studies aimed at reducing teachers' extraneous load may provide valuable insight into more actionable ways teachers' extraneous load can be effectively reduced during instruction.

Furthermore, the present study also found that cognitive load during instruction may be especially exacerbated for teachers with ADHD. Aligned with existing literature discussing how ADHD can introduce limitations to an individuals' working memory capacity (Al-Saad et al., 2021; Tolonen et al., 2024), more research should investigate and focus solely on teachers with ADHD, and teachers with disabilities more broadly (especially considering the underrepresentation of teachers with disabilities in the field; Neca et al., 2022). Further, future research should aim to explicitly understand how teachers with underrepresented identities in the profession (e.g., teachers of color) may uniquely experience cognitive load. For example, this research should explicitly work to understand how these teachers may experience differences in

their cognitive load and motivation during instruction given the systemic inequities they often face – and thus must process and reconcile – in the education system (Milner & Howard, 2013).

In addition, consistent with the ongoing debates across the CLT literature (see Jiang & Kalyuga, 2020; Kalyuga, 2011; Paas & van Merriënboer, 2020; Sweller et al., 2011) the overlap of germane load and intrinsic load remained unclear in general and among the teacher population. Future studies should more explicitly focus on disentangling intrinsic and germane load empirically. If it is found they cannot be disentangled as is often argued today (Sweller et al., 2011), then CLT research should move forward in a more concise and unified way in order to minimize confusion and theoretical misalignment across studies.

The present study also unexpectedly found that extraneous and intrinsic loads did not predict teachers' attrition intentions. However, surmounting evidence suggests that self-efficacy and cost perceptions do predict teachers' attrition intentions (Lazarides & Warner, 2020; Madigan & Kim, 2021; Skaalvik & Skaalvik, 2007, 2010; Zee & Koomen, 2016). Given that extraneous load and intrinsic load predicted these motivational beliefs in the present study, future research should test the mediating effect of teachers' motivation during math instruction on the relationship between teachers' cognitive load and attrition. In addition, throughout interviews teachers were more likely to discuss burnout rather than attrition. Because burnout is a critical precursor to teacher attrition (Beymer et al., 2022a; Madigan & Kim, 2021), future studies should also test the relations between cognitive load, motivation, and burnout.

Finally, and as aforementioned, the present study adapted a survey measure initially developed and established to measure students' experiences of cognitive load (see Leppink et al., 2013). To measure teachers' cognitive load experiences as accurately as possible, future research should develop and test a questionnaire with the goal of measuring cognitive load specifically

among teachers. The present study and its identification of attributes to each dimension of cognitive load among teachers is an actionable step towards developing a more accurate teachers' cognitive load instrument.

Conclusion

The present research was the first known study to investigate elementary teachers' cognitive load and its motivational and attritional consequences during math instruction. Results revealed that teachers' extraneous load is pervasive throughout their math instruction and is particularly associated with the environmental distractions in and around the classroom as well as teachers' own emotional fluctuations during instruction. In addition, intrinsic load emerged as important for teachers to manage during math and is especially heightened when there are a broad range of differentiation needs among students within the classroom and due to frequent math curriculum changes. Findings also revealed that cognitive load significantly predicted both teachers' self-efficacy beliefs and cost perceptions, underscoring the dynamic relation between cognition and motivation among teachers. Taken together, the present study presented important findings and implications for theory, methods, and practice.

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Appendix A

Key Construct Definitions

Construct	Definition	Reference(s)
Attainment Value	The personal importance an individual places on a task.	Eccles & Wigfield (2020); Miele et al. (2024)
Cognitive Load	The magnitude of demands inflicted on an individual's working memory, plays an important role in effective human processing.	Paas & van Merriënboer (1994); Sweller (1988)
Cost Perceptions	What one believes they must abandon to engage in a certain task.	Eccles & Wigfield (2020)
Task Effort Cost	The amount of effort required of an individual to complete a task.	Eccles & Wigfield (2020); Flake et al. (2015)
Emotional Cost	The adverse affective states that engagement in a task elicits.	Eccles & Wigfield (2020); Flake et al. (2015)
Intrinsic Value	The level of task enjoyment.	Eccles & Wigfield (2020); Miele et al. (2024)
Long-Term Memory	An unconscious component of human cognition where an extensive amount of knowledge is retained.	Sweller et al. (2011); Van Merriënboer & Sweller (2005)
Loss of Valued Alternatives Cost	When an individual gives up an alternative, more valued task to engage with the task at hand.	Eccles & Wigfield (2020); Flake et al. (2015)
Motivation	The beliefs about one's ability to successfully complete a task and their reasons for task engagement.	Eccles & Wigfield (2020)
Outside Effort Cost	The other tasks required of an individual that make it difficult to put effort into the task at hand.	Eccles & Wigfield (2020); Flake et al. (2015)
Self-Efficacy	An individual's beliefs about their ability to successfully complete a task.	Bandura (1977); Schunk & DiBenedetto (2020)

Construct	Definition	Reference(s)
Teachers' Self-Efficacy	An educator's beliefs in their capabilities to provide students with effective instruction.	Zee & Koomen (2016)
Teaching Cost Perceptions	What a teacher feels they must abandon to engage in teaching-related tasks.	Beymer et al. (2022a)
Utility Value	The usefulness of a task for the future.	Eccles & Wigfield (2020); Miele et al. (2024)
Working Memory	A conscious component of human cognition that can process roughly two to four pieces of information within a 30-second timespan.	Choi et al. (2014); Cowan (2014)

Appendix B

Phase 1: Daily Diary Recruitment Email

SUBJECT: Opportunity to Participate in the Teachers' Cognitive Load Project

Hello!

My name is Danielle Berry and I am a doctoral candidate in educational psychology at the University of Oklahoma. I am working with Dr. Alison Koenka to understand teachers' cognitive load (i.e., mental exhaustion) during math instruction. In other words, we are working to understand teachers' experiences with feeling overwhelmed or burnt-out during math teaching.

This research opportunity is voluntary. It is your choice if you want to participate. If you choose not to participate it will in no way negatively affect you.

If you choose to participate in this study, you will receive a short 3–5-minute survey once a day for 10 school days. Additionally, you will receive a $30 gift card in the form of compensation for your time. To learn more about the study and how you may benefit from it, please see the attached infographic.

If you choose to participate, please follow the link below to be navigated to a survey in which you will (a) consent to participate in this research and (b) be asked a few baseline questions about your math teaching experiences.

Access the survey by clicking this link: <Qualtrics link to consent form>

Please contact Danielle Berry (email), one of the lead researchers, with any questions about this study.

Thank you!
Danielle Berry



IRB NUMBER: 19062
IRB APPROVAL DATE: 10/22/2025

Appendix C

Phase 1: Recruitment Flyer

TEACHERS' COGNITIVE LOAD PROJECT

You're invited to participate in a research study investigating teachers' cognitive load (i.e., mental exhaustion) during mathematics instruction.

Key Goals:

- Learn more about all teachers must process and manage during instruction.
- Understand how consistent mental exhaustion impacts teacher motivation.
- Center teachers' voices to understand and explain findings.
- Use findings to support teachers and to inform needed policy changes in the teaching profession.

What will you do?

Engage in Short Daily Surveys

- For a total of 10 school days in a row, you will take a short 2-3 minute survey via email.



You will recieve:

Compensation

- All participants will receive a $30 gift card as a small token of appreciation for your time.



A Summary of your Results

- All participants will receive a visual depiction of their cognitive load fluctuations over the 10-day data collection period.



If interested, please **click here** or scan the QR code to complete the consent form & initial survey

<QR Code>

Please contact Danielle Berry with any questions

Appendix D

Phase 1 Consent Form

Would you like to be involved in research at the University of Oklahoma?

I am Danielle Berry from the Jeannine Rainbolt College of Education, Educational Psychology Department, and I invite you to participate in my research entitled the Teachers' Cognitive Load Project. This research is being conducted at the University of Oklahoma. You were selected as a possible participant because you are a teacher at a school we have developed a research practice partnership with. You must be at least 18 years of age to participate in this research.

Please read this document and contact me to ask any questions you may have BEFORE agreeing to participate in my research.

What is the purpose of this research?
This research aims to explore elementary teachers' cognitive load teachers' cognitive load during their teaching placements. In other words, we are working to understand particular experiences with feeling overwhelmed or burnt-out during instruction.

How many participants will be in this research?
A maximum of 50 people will take part in this research.

What will I be asked to do?
If you agree to be in this research, you will complete a 2-3-minute online survey following your math instruction once a day over the course of 10 school days total. In addition, you may be asked to download and install the Remind App on your mobile device.

What are the risks and benefits if I participate?
Collection of demographic or geographic location data that could lead to deductive re-identification: You will be asked to provide demographic information that describes you. We may also gather information about your geographic location in this research. Different combinations of personal and geographic information may make it possible for your identity to be guessed by someone who was given, or gained access, to our research records. To minimize the risk of deductive re-identification, we will not combine identifying variables nor analyze, and report results for small groups of people with specific demographic characteristics.

Data collected online: The organization hosting the data collection platform has its own privacy and security policies for keeping your information confidential. There is a risk that the external organization, which is not part of the research team, may gain access to or retain your data or your IP address which could be used to re-identify you. No assurance can be made as to their use of the data you provide for purposes other than this research.

Please note that the survey data files contain identifiers which will be retained indefinitely in case of a longitudinal follow-up study.

Will I be compensated for participating?

You will be reimbursed for your time and participation in this research in the form of a $30 gift card. You will receive this gift card within a month of completing the final survey.

Who will see my information?
There will be no information in research reports that will make it possible to identify you. Research records will be stored securely, and only approved researchers and the OU Institutional Review Board will have access to the records.

Do I have to participate?
No. If you do not participate, you will not be penalized or lose benefits or services unrelated to the research. If you decide to participate, you don't have to answer any questions and can stop participating at any time.

What will happen to my data in the future?
We might share your de-identified data with other researchers, school administrators, or use it in future research without obtaining additional consent from you.

Who do I contact with questions, concerns, or complaints?
If you have questions, concerns, or complaints about the research or have experienced a research-related injury, contact me at <phone number> or <email>. You can also contact my advisor at <phone number> or <email>.
You can also contact the University of Oklahoma – Norman Campus Institutional Review Board (OU-NC IRB) at <phone number> or <email> if you have questions about your rights as a research participant, concerns, or complaints about the research and wish to talk to someone other than the researcher(s) or if you cannot reach the researcher(s). Please print this document for your records. By providing information to the researcher(s), I am agreeing to participate in this research.

I consent to participating in this research.
- o Agree
- o Disagree

Skip To: End of Survey If I consent to participating in this research. = Disagree

Are you 18 years of age or older?
- o Yes
- o No

Skip To: End of Survey If Are you 18 years of age or older? = No


IRB NUMBER: 19062
IRB APPROVAL DATE: 10/22/2025

Appendix E

School A: Interview Selection Table

Teacher ID	1	2	3	4	5	6	7	8	9	10
High Intrinsic Load			X					X		
Low Intrinsic Load				X					X	
High Extraneous Load		X		X						
Low Extraneous Load						X				X
High Germane Load			X					X		
Low Germane Load		X		X						
High Self-Efficacy						X		X		
Low Self-Efficacy		X		X						
High Overall Cost		X								X
Low Overall Cost						X		X		
High Attrition Intentions		X								X
Low Attrition Intentions					X	X				
Recruited to Participate?	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	No
Participated in Interview?	**Yes**	No	**Yes**	**Yes**	No	**Yes**	No	**Yes**	No	No

Appendix F

School B: Interview Selection Table

Teacher ID	11	12	13	14	15	16	17	18	19	20	21	22	23
High Intrinsic Load	X								X				
Low Intrinsic Load								X		X			
High Extraneous Load			X					X					
Low Extraneous Load		X									X		
High Germane Load	X			X									
Low Germane Load			X					X					
High Self-Efficacy		X		X							X		
Low Self-Efficacy			X					X					
High Overall Cost			X		X								
Low Overall Cost		X											X
High Attrition Intentions						X		X					
Low Attrition Intentions	X			X	X					X	X		X
Recruited to Participate?	Yes	Yes	Yes	Yes	No	No	No	Yes	Yes	No	Yes	No	No
Participated in Interview?	**Yes**	No	No	**Yes**	No	No	No	No	**Yes**	No	No	No	No

Appendix G

School C: Interview Selection Table

Teacher ID	24	25	26	27	28	30	31	32	33	34	35	36
High Intrinsic Load		X									X	
Low Intrinsic Load								X				X
High Extraneous Load								X		X		
Low Extraneous Load						X	X					X
High Germane Load							X				X	
Low Germane Load			X									X
High Self-Efficacy						X					X	
Low Self-Efficacy										X		X
High Overall Cost										X		X
Low Overall Cost						X					X	
High Attrition Intentions		X					X					
Low Attrition Intentions	X		X		X	X			X	X		X
Recruited to Participate?	No	No	Yes	No	No	Yes	Yes	Yes	No	Yes	No	Yes
Participated in Interview?	No	No	No	No	No	**Yes**	No	No	No	No	No	**Yes**

Appendix H

Phase 2: Interview Recruitment Email

SUBJECT: Opportunity to Participate in Follow-Up Interviews for the Teachers' Cognitive Load Project

Hello!

Thank you for your participation in the Teachers' Cognitive Load Project thus far. My name is Danielle Berry and I am working with Dr. Alison Koenka. I am reaching out to see if you would be interested in participating in a follow-up interview for the Teachers' Cognitive Load Project. That is, we are looking to hear directly from you to learn about your experiences with feeling overwhelmed, mentally exhausted, or burnt-out during math teaching.

This research opportunity is voluntary. It is your choice if you want to participate. If you choose not to participate it will in no way negatively affect you.

If you choose to participate in this study, you will engage in a 30-60 minute in-person or Zoom interview (depending on your preference) with the lead researcher (Danielle Berry). You will receive a $30 gift card in the form of compensation for your time.

If you choose to participate in this study, please follow the link below to schedule your interview: <Calendly link>

Please contact Danielle Berry (email), one of the lead researchers, with any questions about this study.

Thank you!
Danielle Berry



IRB NUMBER: 19062
IRB APPROVAL DATE: 10/22/2025

Appendix I

Phase 2: Interview Consent Form

Phase 2 Consent Form

Would you like to be involved in research at the University of Oklahoma?
I am Danielle Berry from the Jeannine Rainbolt College of Education, Educational Psychology Department, and I invite you to participate in my research entitled the Teachers' Cognitive Load Project. This research is being conducted at the University of Oklahoma. You were selected as a possible participant because you are a teacher at a school, we have developed a research practice partnership with and have previously participated in the survey portion of this project. You must be at least 18 years of age to participate in this research.
Please read this document and contact me to ask any questions you may have BEFORE agreeing to participate in my research.

What is the purpose of this research?
This research aims to explore elementary teachers' cognitive load teachers' cognitive load during their teaching placements. In other words, we are working to understand particular experiences with feeling overwhelmed or burnt-out during instruction.

How many participants will be in this research?
A maximum of 30 people will take part in this research.

What will I be asked to do?
If you agree to be in this research, you will participate in a 30–60-minute interview via Zoom or in-person, depending on your preference. During this interview you will be audio recorded. You will be asked a list of questions, but you will not be required to answer any if you do not wish to do so.

How long will this take?
Your participation in the interview will take about 30-60 minutes. At any point in time you may choose to no longer participate in the research/interview.

What are the risks and benefits if I participate?
Audio recorded data collection: There is a risk of accidental data release if we collect your data using audio recordings. If this occurred, your identity and statements you made would become known to people who are not on the research team. To minimize this risk, the researchers will transfer data to, and store your data on, a secure platform approved by the University's Information Technology Office.
Collection of demographic or geographic location data that could lead to deductive re-identification: You will be asked to provide demographic information that describes you. We may also gather information about your geographic location in this research. Different

combinations of personal and geographic information may make it possible for your identity to be guessed by someone who was given, or gained access, to our research records. To minimize the risk of deductive re-identification, we will not combine identifying variables nor analyze, and report results for small groups of people with specific demographic characteristics.

Will I be compensated for participating?
You will receive a $30 Amazon gift card for your time and participation in this research. The gift card will be sent to you within 4 weeks of your interview completion date.

Who will see my information?
There will be no information in research reports that will make it possible to identify you. Research records will be stored securely, and only approved researchers and the OU Institutional Review Board will have access to the records. In addition, this research is supported by a National Science Foundation Graduate Research Fellowship.
You have the right to access the research data that has been collected about you as a part of this research. However, you may not access this information until the entire research has finished and you consent to this temporary restriction.

Do I have to participate?
No. If you do not participate, you will not be penalized or lose benefits or services unrelated to the research. If you decide to participate, you don't have to answer any questions and can stop participating at any time.

Will my identity be anonymous or confidential?
Your name will not be retained. Please check all of the options that you agree to:

I agree for data records to include my identifiable information.
- Yes
- No

I agree to be quoted directly, without the use of my name.
- Yes
- No

I agree for my research to be archived for scholarly and public access.
- Yes
- No

What will happen to my data in the future?
We might share your de-identified data with other researchers or use it in future research without obtaining additional consent from you. Please note that recordings will be retained indefinitely.

Audio Recording of Research Activities

To assist with accurate recording of your responses, interviews may be recorded on an audio recording device. You have the right to refuse to allow such recording without penalty.

I consent to audio recording.

- Yes
- No

Who do I contact with questions, concerns, or complaints?
If you have questions, concerns, or complaints about the research or have experienced a research-related injury, contact Danielle Berry at: <phone number> or <email>. You can also contact the University of Oklahoma – Norman Campus Institutional Review Board (OU-NC IRB) at <phone number> or <email> if you have questions about your rights as a research participant, concerns, or complaints about the research and wish to talk to someone other than the researcher(s) or if you cannot reach the researcher(s).

Print First Name

_____

Print Last Name

_____

Please print this document for your records. By providing information to the researcher(s), I am agreeing to participate in this research.
<Signature>



IRB NUMBER: 19062
IRB APPROVAL DATE: 10/22/2025

Appendix J

University of Oklahoma IRB Approval

The UNIVERSITY of OKLAHOMA

Institutional Review Board for the Protection of Human Subjects

Approval of Initial Submission – Exempt from IRB Review – AP01

Date: October 22, 2025 **IRB#:** 19062

Principal Investigator: Danielle N Berry

Approval Date: 10/22/2025

Exempt Category: Category 2

Study Title: Investigating Teachers' Cognitive Load During Mathematics Instruction and Its Motivational and Attritional Consequences

On behalf of the Institutional Review Board (IRB), I have reviewed the above-referenced research study and determined that it meets the criteria for exemption from IRB review. To view the documents approved for this submission, open this study from the *My Studies* option, go to *Submission History*, go to *Completed Submissions* tab and then click the *Details* icon.

As principal investigator of this research study, you are responsible to:

- Conduct the research study in a manner consistent with the requirements of the IRB and federal regulations 45 CFR 46.
- Request approval from the IRB prior to implementing any/all modifications as changes could affect the exempt status determination.
- Maintain accurate and complete study records for evaluation by the HRPP Quality Improvement Program and, if applicable, inspection by regulatory agencies and/or the study sponsor.
- Notify the IRB at the completion of the project.

If you have questions about this notification or using iRIS, contact the IRB @ 405-325-8110 or irb@ou.edu.

Cordially,

Lara Mayeux, Ph.D.
Chair, Institutional Review Board

Marshall Cheney, Ph.D.
Vice Chair, Institutional Review Board

Eric Pennello, Ph.D.
Vice Chair, Institutional Review Board

Appendix K

School District Approval (Redacted)

Dear Ms. Danielle Berry,

I am pleased to inform you that your research request titled "Teachers' cognitive load and its motivational and attritional consequences" has been reviewed and approved by our Teaching and Learning Committee. Your study, which aims to explore elementary grade level teachers' cognitive load during mathematics instruction and its association with their motivational beliefs and attritional intentions, has been assessed and aligns with our district's mission by contributing valuable knowledge in important educational areas that may have an impact.

Please adhere to the following conditions for your research:

1. **Voluntary Participation:** Clearly communicate to all participants that their involvement is voluntary and that they can withdraw at any time without consequence
2. **Informed Consent:** Obtain and document informed consent from all participants, ensuring they are aware of the research objectives, procedures, and their right
3. **Letter:** When contacting [redacted] employees, you should include this approval letter with your request.
4. **Compliance:** Conduct the research in accordance with the approved request. The Teaching and Learning Committee must approve any deviation from procedu
5. **Reporting:** Copies of all research reports (dissertations, journal articles, etc.), collected within the [redacted] and a one-page summary of re

Congratulations on the approval of your research request. We look forward to the valuable contributions your study will bring to the field of education and school district.

If you have any questions or need further clarification on the approval conditions, please do not hesitate to contact me at [redacted] or

[redacted]

Sincerely,

--

[redacted]

Appendix L

Baseline Survey Items

Measure	Items	Response
Cognitive Load (IL: ω = .88, EL: ω = .68, GL: ω = .85; adapted from Leppink et al., 2013)	Daily Intrinsic Load 1. The math topics I cover are typically very complex to teach. 2. I perceive the math activities I often teach as very complex to enact. 3. The math content I cover often includes concepts that I perceive to be very complex to teach. Daily Extraneous Load 4. The math I often teach is unclear to me because of all that goes on around me. 5. The occurrences happening around me during my math instruction are often very distracting. 6. All that goes on around me in the classroom impacts the effectiveness of my math instruction. Daily Germane Load 7. The math I typically teach enhances my comprehension of math teaching as a whole. 8. The math I often teach enhances my overall knowledge and understanding of math instructional techniques. 9. My math instruction frequently enhances my understanding of how to effectively teach math. 10. The math content I teach enhances my overall understanding of effective teaching strategies.	5-point scale: 1 = not at all the case; 5 = completely the case.
Teaching Self-Efficacy (ω = .69; Midgley et al., 2000)	Daily Teaching Self-Efficacy 11. If I try really hard during my math instruction, I can get through to even the most difficult student. 12. Factors beyond my control during math instruction have a greater influence on my students' math learning than I do. (R) 13. I am good at helping all my students make significant improvements in math.	5-point scale: 1 = not at all the case; 5 = completely the case.

Measure	Items	Response
	14. Some students are not going to make a lot of progress in math, no matter what I do. (R) 15. I am certain that I am making a difference in the math abilities of my students. 16. There is little I can do to ensure that all my students make significant progress in math. (R) 17. I can deal with almost any math-related learning problem.	
Teaching Cost Perceptions (ω = .90; Beymer et al., 2022b)	Daily Task Effort Cost: 18. Teaching math requires too much effort. Daily Outside Effort Cost: 19. Because of other things that I do, I don't have time to put into math teaching. Daily Loss of Valued Alternatives Cost: 20. Teaching math requires me to give up too many other activities I value. Emotional Cost 21. Teaching math is emotionally draining.	5-point scale: 1 = not at all the case; 5 = completely the case.
Attrition Intentions (Beymer et al., 2022a)	22. I plan to leave the field of education altogether	5-point scale: 1 = not at all the case; 5 = completely the case.

Appendix M

Demographics Questionnaire

1. What time of the day do you typically start teaching math? (open-ended)
2. What time of the day do you typically finish teaching math? (open-ended)
3. What grade do you teach?
    a. Pre-K
    b. Kindergarten
    c. 1st grade
    d. 2nd grade
    e. 3rd grade
    f. 4th grade
    g. 5th grade
    h. All grade levels
    i. Other, please explain (open-ended)
4. How many years have you spent teaching in total? (open-ended)
5. How many years have you spent teaching at your current grade level? (open-ended)
3. What is your education background/teacher preparation background?
    a. I completed a traditional teacher preparation program at a university or college
    b. I completed an accelerated teacher preparation program at a university or college
    c. I was emergency certified
    d. Other, please explain (open-ended)
4. What is your gender identity?
    1. Cisgender woman
    2. Cisgender man
    3. Transgender woman
    4. Transgender man
    5. Non-binary/genderqueer/gender fluid
    6. Prefer to self-describe (open-ended)
    7. Prefer not to say
5. What is your sexual orientation?
    1. Straight/Heterosexual
    2. Gay or Lesbian
    3. Bisexual
    4. Queer
    5. Asexual
    6. Prefer to self-describe (open-ended)
    7. Prefer not to say
6. What is your ethnicity and/or race?
    1. American Indian or Alaska Native

2. Asian
3. Black or African American
4. Latiné or Hispanic
5. West Asian, or commonly referred to as Middle Eastern
6. Native Hawaiian or Other Pacific Islander
7. White
8. Multi-racial; please specify (open-ended)
9. Some other race, ethnicity, or origin; please specify (open-ended)
10. Prefer not to say

7. Do you have a disability?
    1. Yes, please specify (open-ended)
    2. No
    3. Prefer to self-describe (open-ended)
    4. Prefer to say

Appendix N

Example Daily Diary Tracking Spreadsheet

Note. This is not real data and solely for demonstration purposes.

			Day 1 (mm/dd/yy)								
			Initial Daily Email			Reminder Email			Day 1 Summary		
Teacher Name	Email	Time math is finished	Initial email sent?	Time sent	Completed survey after 1st email?	Reminder email sent?	Time sent	Completed survey after 2nd email?	Completed Day 1 Survey	Time Completed	Notes
Ms. Hall	email	9:50 am	●	9:50 am	●	●	n/a	●	●	10:00 am	
Ms. Thomas	email	10:45 am	●	10:45 am	●	●	n/a	●	●	11:00 am	
Mr. Clark	email	11:30 am	●	11:30 am	●	●	3:00 pm	●	●	3:05 pm	
Ms. Klein	email	1:05 pm	●	1:05 pm	●	●	n/a	●	●	1:08 pm	
Ms. Keller	email	2:00 pm	●	2:00 pm	●	●	3:00 pm	●	●	Did not complete	Home sick today

Appendix O

Daily Diary Survey Items

Measure	Items	Response
Cognitive Load (IL: ω^w = .84, ω^b = .99; EL: ω^w = .82, ω^b = .98; GL: ω^w = .82, ω^b = .99; adapted from Leppink et al., 2013)	Daily Intrinsic Load 1. The math topics I covered today were very complex to teach. 2. I perceived the math activities I most recently taught as very complex to enact. 3. The math content I covered today included concepts that I perceive to be very complex to teach. Daily Extraneous Load 4. The math I had to teach today was unclear to me because of all that was going on around me. 5. The occurrences happening around me today during my math instruction were very distracting. 6. All that was going on around me in the classroom impacted the effectiveness of my most recent math instruction. Daily Germane Load 7. The math I taught today really enhanced my comprehension of math teaching as a whole. 8. The math I taught today enhanced my overall knowledge and understanding of math instructional techniques. 9. My math instruction today enhanced my understanding of how to effectively teach math. 10. The math content I taught today enhanced my overall understanding of effective teaching strategies.	5-point scale: 1 = not at all the case; 5 = completely the case.
Teaching Self-Efficacy (ω^w = .83, ω^b = .95; adapted from Midgley et al., 2000)	Daily Teaching Self-Efficacy 11. Today I felt that if I tried really hard during my math instruction, I could get through to even the most difficult student. 12. Factors beyond my control during math instruction today had a greater influence on my students' math learning than I did. (R) 13. Today I was good at helping all my students make significant improvement during math instruction.	5-point scale: 1 = not at all the case; 5 = completely the case.

Measure	Items	Response
	14. Some students were not going to make a lot of progress in math today, no matter what I did. (R) 15. I am certain that I made a difference in the math abilities of my students today. 16. There is little I could do to ensure that all my students made significant progress in math today. (R) 17. I felt I could deal with almost any math-related learning problem today during math instruction.	
Teaching Cost Perceptions (adapted from Beymer et al., 2022b)	Daily Task Effort Cost: 18. Teaching math today required too much effort. Daily Outside Effort Cost: 19. Because of other things that I had to do today, I didn't have much time to put into math teaching. Daily Loss of Valued Alternatives Cost: 20. Teaching math today required me to give up too many other activities I value. Emotional Cost 21. Teaching math today was emotionally draining.	5-point scale: 1 = not at all the case; 5 = completely the case.
Attrition Intentions (adapted from Beymer et al., 2022a)	22. I plan to leave the field of education altogether	5-point scale: 1 = not at all the case; 5 = completely the case.

Appendix P

Initial Daily Survey Email

SUBJECT:

Please complete your Day 1 Survey for the Teachers' Cognitive Load Project

MESSAGE:

Hello!

Thank you for participating in the Teachers' Cognitive Load Project. Please follow this link to complete your Day 1 survey here: <survey link>.

Please contact Danielle Berry (email) with any questions.

Thank you!
Danielle Berry

Appendix Q

Reminder Daily Survey Email

SUBJECT:

Reminder: Please complete your Day 1 Survey for the Teachers' Cognitive Load Project

MESSAGE:

Hello!

Thank you for participating in the Teachers' Cognitive Load Project. Please follow this link to complete the Day 1 survey here: <survey link>.

Please contact Danielle Berry (email) with any questions.

Thank you!
Danielle Berry

Appendix R

Day Prior/Day of Interview Reminder

SUBJECT: Reminder of upcoming interview for the Teachers' Cognitive Load Project

Hello!

Thank you for scheduling an interview for the Teachers' Cognitive Load Project. This is a reminder that you are scheduled to participate in this interview on <Date> at <Time> via <Zoom/in person at Location>.

[Here is the Zoom link where our meeting will take place: <insert Zoom link>]

If you have not already done so, you will need to complete the consent form with details about the project, what you can expect, and your rights prior to your participation. Please feel free to complete the consent form before we meet or we can discuss the consent form when we meet for the interview. Please see the link to the consent form below:

<consent form link>

Please contact Danielle Berry (email), one of the lead researchers, with any questions about this study.

Thank you!
Danielle Berry

Appendix S

Semi-Structured Interview Protocol

Introduction:

- Thank you for agreeing to speak with me today, I appreciate you taking the time to meet. I am interested in knowing about your experiences teaching math.

- I would like this to be a conversation and not just a question-and-answer session. There are no wrong answers to the questions. I just want to hear what you honestly think.

- You do not have to answer every question, but I hope to hear your thoughts if you're comfortable sharing them.

- We will use the information only for research purposes and your name will not be used when sharing quotes or data. Do you have any questions about this interview?

- I will be recording our conversation on my phone. No one other than the researchers will have access to these conversations. Is it okay for me to start recording?

**********START RECORDING**********

General Teaching Context and Information

1. How many years have you spent teaching?
2. What grade level or levels do you teach?
3. Please describe a typical math instructional period. For example, how do you typically begin math instruction, what does the structure look like, etc.?

Teachers' Cognitive Load During Math Instruction

4. How does teaching math typically make you feel?
5. What types of emotions do you experience during math instruction?
    a. Probe: Why do you think you have these experiences?
6. During math instruction, how often do you find yourself needing to regulate your own thoughts and emotions?
    a. Probe: What strategies work best for you to regulate yourself in these moments?
7. When you are able to regulate yourself, in what ways does your math instruction change?
    a. Probe: How do your students respond?
8. Please describe how well you are typically able to concentrate during math instruction.
    a. Probe (if needed): can you further explain?
9. Feeling overwhelmed is something many teachers report experiencing.
    a. What does feeling overwhelmed mean to you?
        i. Probe: What does it mean in relation to math teaching?
10. **Do you ever feel overwhelmed or overstimulated during math instruction? Please

explain.

a. When/if you do feel overwhelmed or overstimulated during math instruction, what contributes to this overwhelm?
b. When/if you do feel overwhelmed or overstimulated during math instruction, what strategies do you adopt to help alleviate your overwhelm?

11. How challenging is it to juggle everything going on around you in your classroom while teaching math?
    a. What is typically the most distracting thing to you during math instruction?
12. How challenging are your math instructional tasks on a daily basis?
13. Do you only teach math, or do you teach other subjects as well?
    a. If no: move on
    b. If yes: How do your experiences during math instruction compare to your instructional experiences in other subjects?
        i. Probe: Do you ever feel overwhelmed during your ELA instruction? (only asked at one school site)
        ii. Probe: How does your mental capacity during ELA instruction differ from your mental capacity during mathematics instruction? (only asked at one school site)
14. During instruction, how often do you find yourself needing to regulate your own thoughts and emotions? (only asked at one school site)
    a. Probe: What strategies work best for you to regulate yourself in these moments? (only asked at one school site)

Teachers' Motivation During Math Instruction

15. How confident do you typically feel regarding your ability to successfully teach your students math?
    a. How does your confidence level during math instruction compare to your confidence level for other subjects you teach?
16. How do students lived experiences, including past experiences of trauma, impact your instruction? (only asked at one school site)
    a. How confident do you feel in supporting students who have experienced trauma in your classroom? (only asked at one school site)
17. How much effort do you typically feel you need to give to math teaching?
18. How emotionally demanding do you find teaching math to be?
19. How does other teaching-related tasks or competing responsibilities impact your ability to deliver effective math instruction?
20. How does teaching impact your ability to engage in activities unrelated to teaching, particularly in your personal life?

Teachers' Attrition Intentions

21. A common word that often gets thrown around in teaching is burnout.
    a. How do you define burnout?
    b. Have you ever experienced burnout related to teaching?

c. Do you expect to experience burnout in the future?

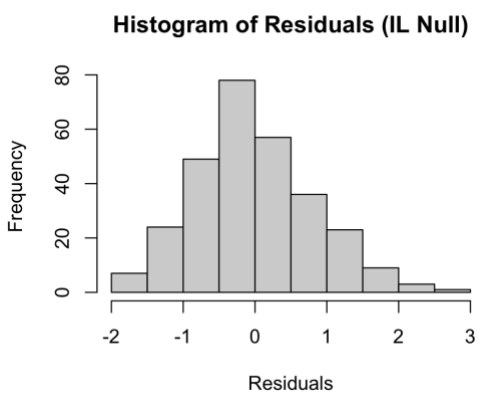
22. Do you have any plans to leave the field of teaching to pursue another career path?
    a. If yes: what do you plan on doing and what is your timeline for leaving?
    b. If no: what keeps you in this field?

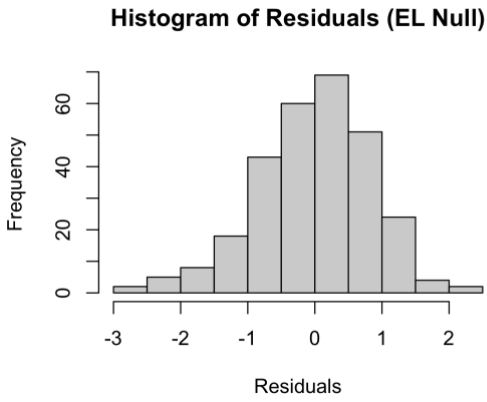
Closing

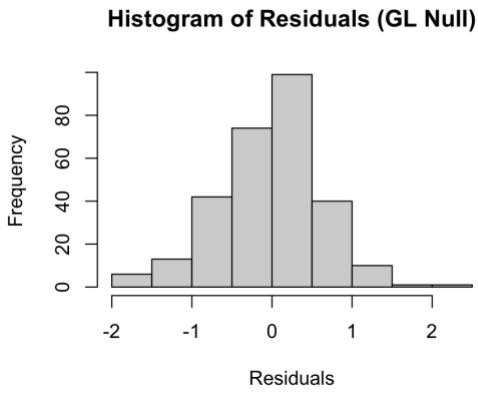
23. Is there anything else you'd like to share with me today?

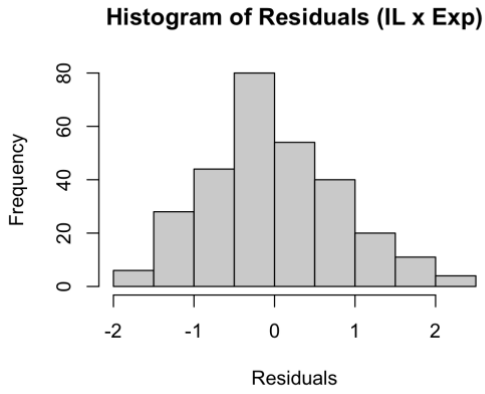
Appendix T

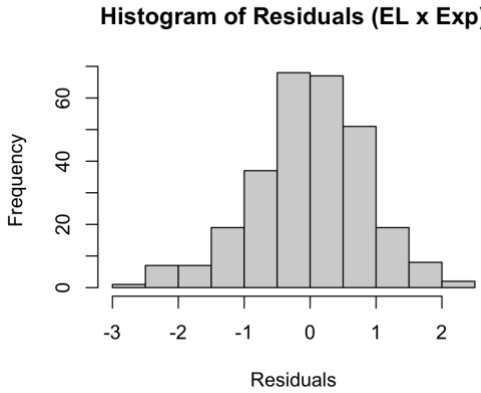
Standardized Residual Distribution Histograms

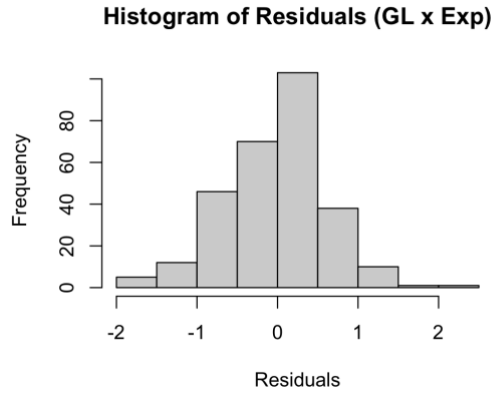


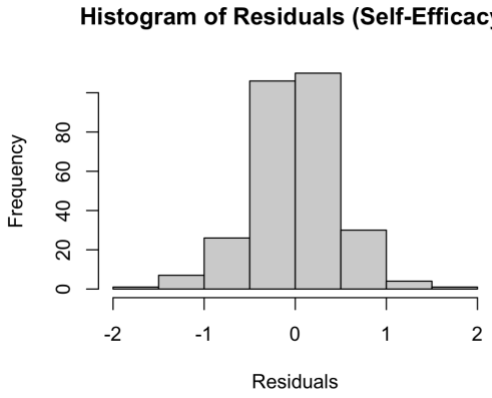


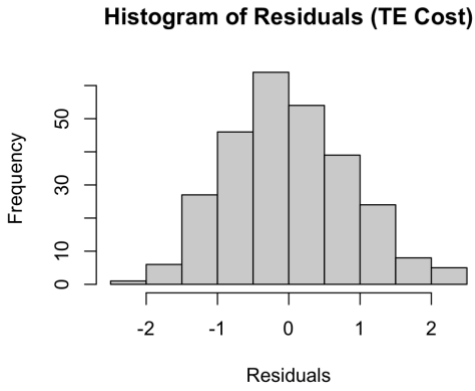




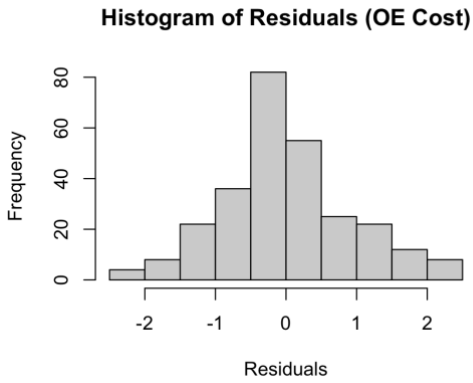


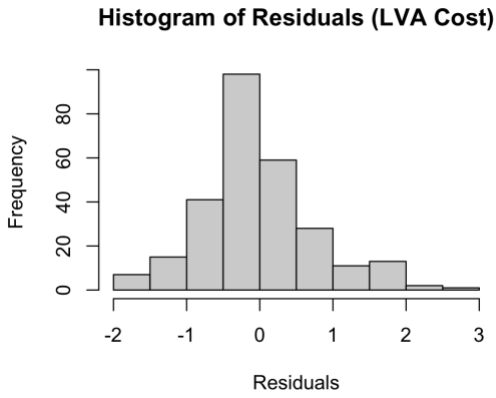


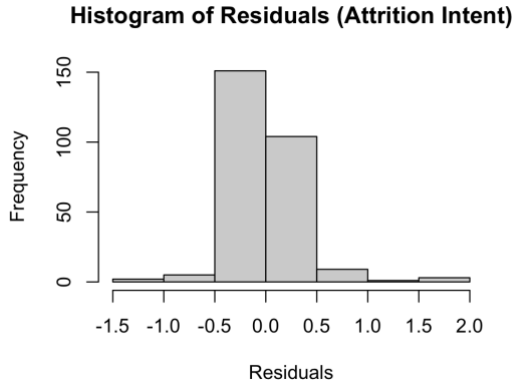

Histogram of Residuals (Self-Efficacy)
Frequency
0
20
40
60
80
-2
-1
0
1
2
Residuals


Histogram of Residuals (TE Cost)
Frequency
0
10
30
50
-2
-1
0
1
2
Residuals


Histogram of Residuals (Emotional Cost)
Frequency
0
10
30
50
-3
-2
-1
0
1
2
Residuals


Histogram of Residuals (OE Cost)
Frequency
0
20
40
60
80
-2
-1
0
1
2
Residuals

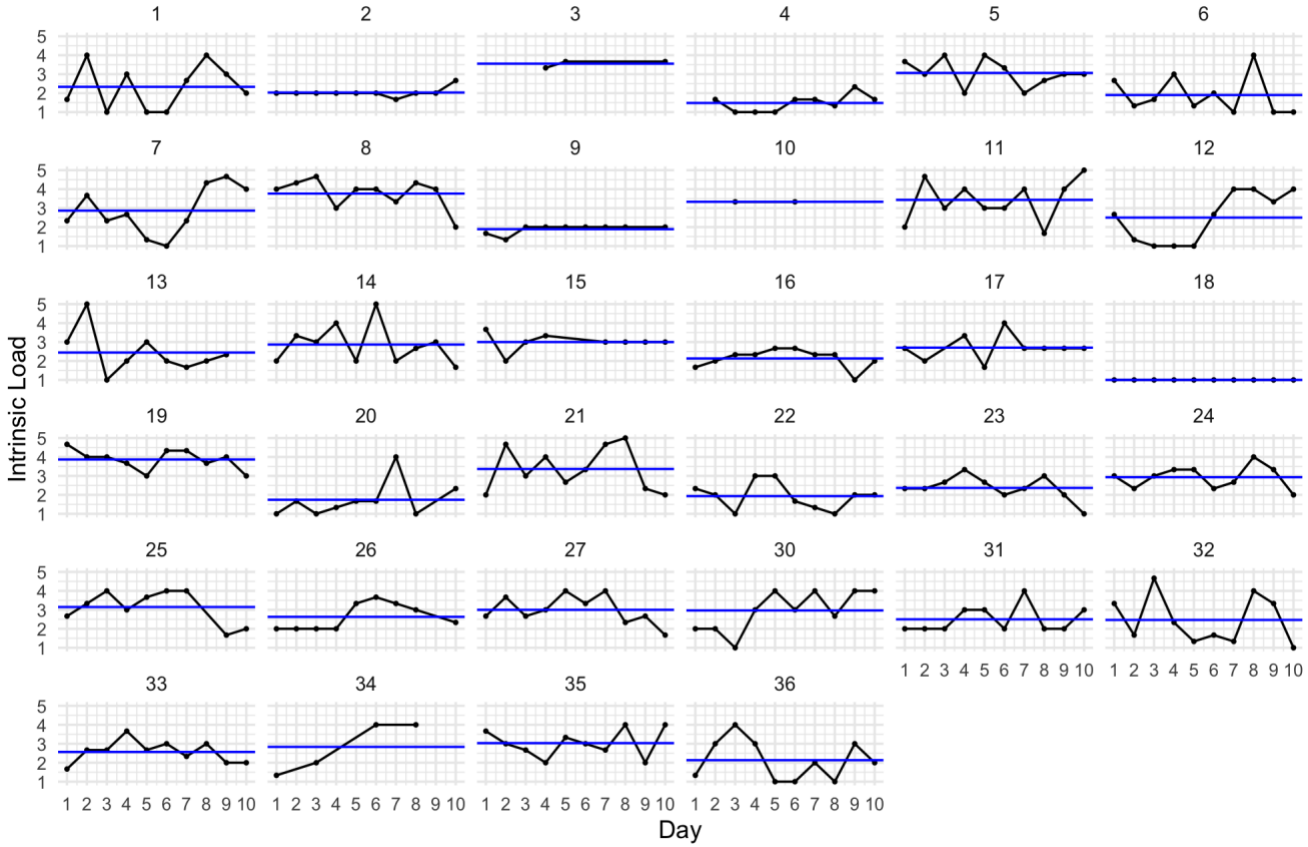

Histogram of Residuals (LVA Cost)
Frequency
0
20
40
60
80
-2
-1
0
1
2
3
Residuals


Histogram of Residuals (Attrition Intent)
Frequency
0
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100
150
-1.5
-1.0
-0.5
0.0
0.5
1.0
1.5
2.0
Residuals

Appendix U

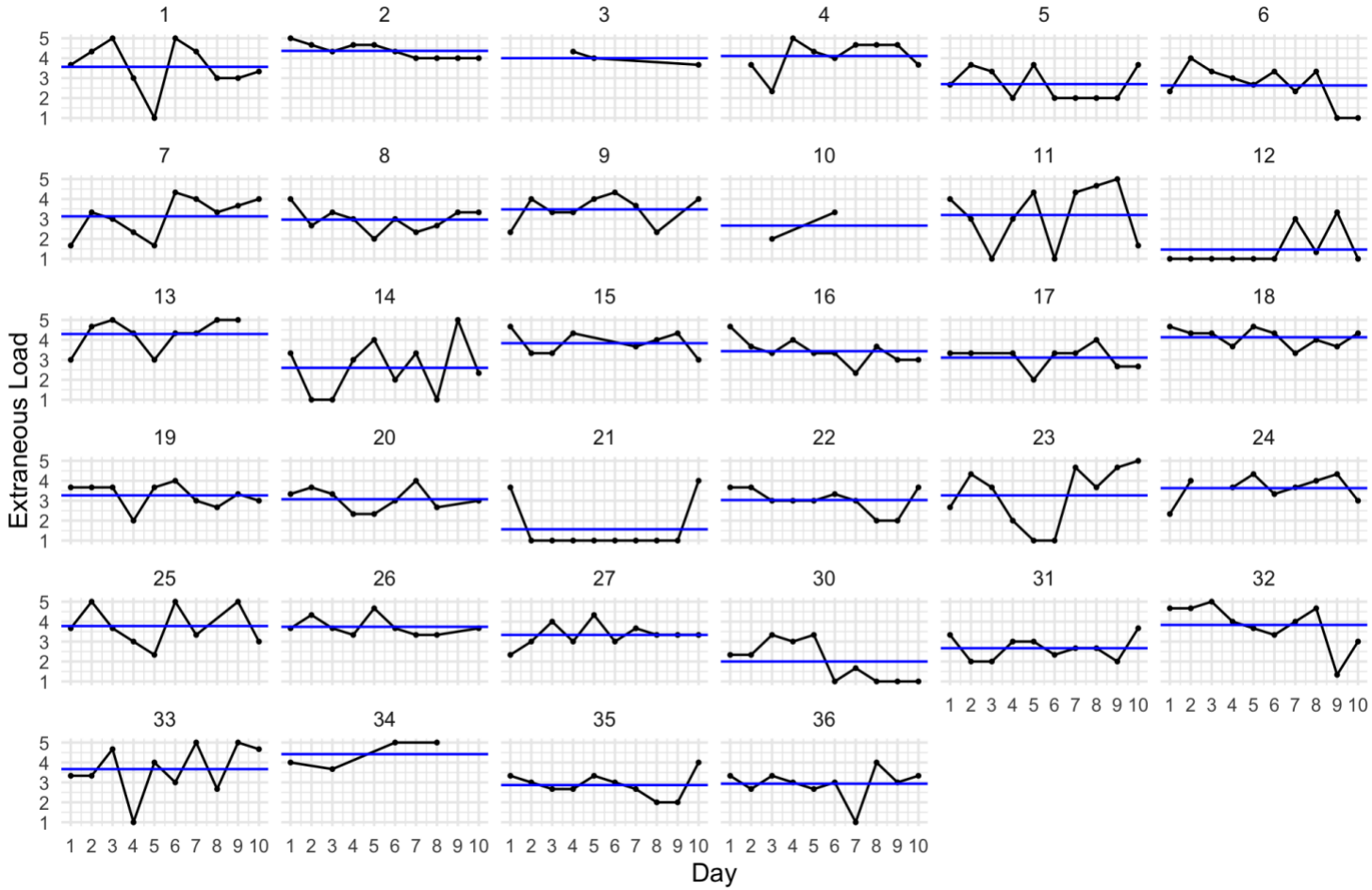
Panel Plots by Teacher

Daily intrinsic load panel plot



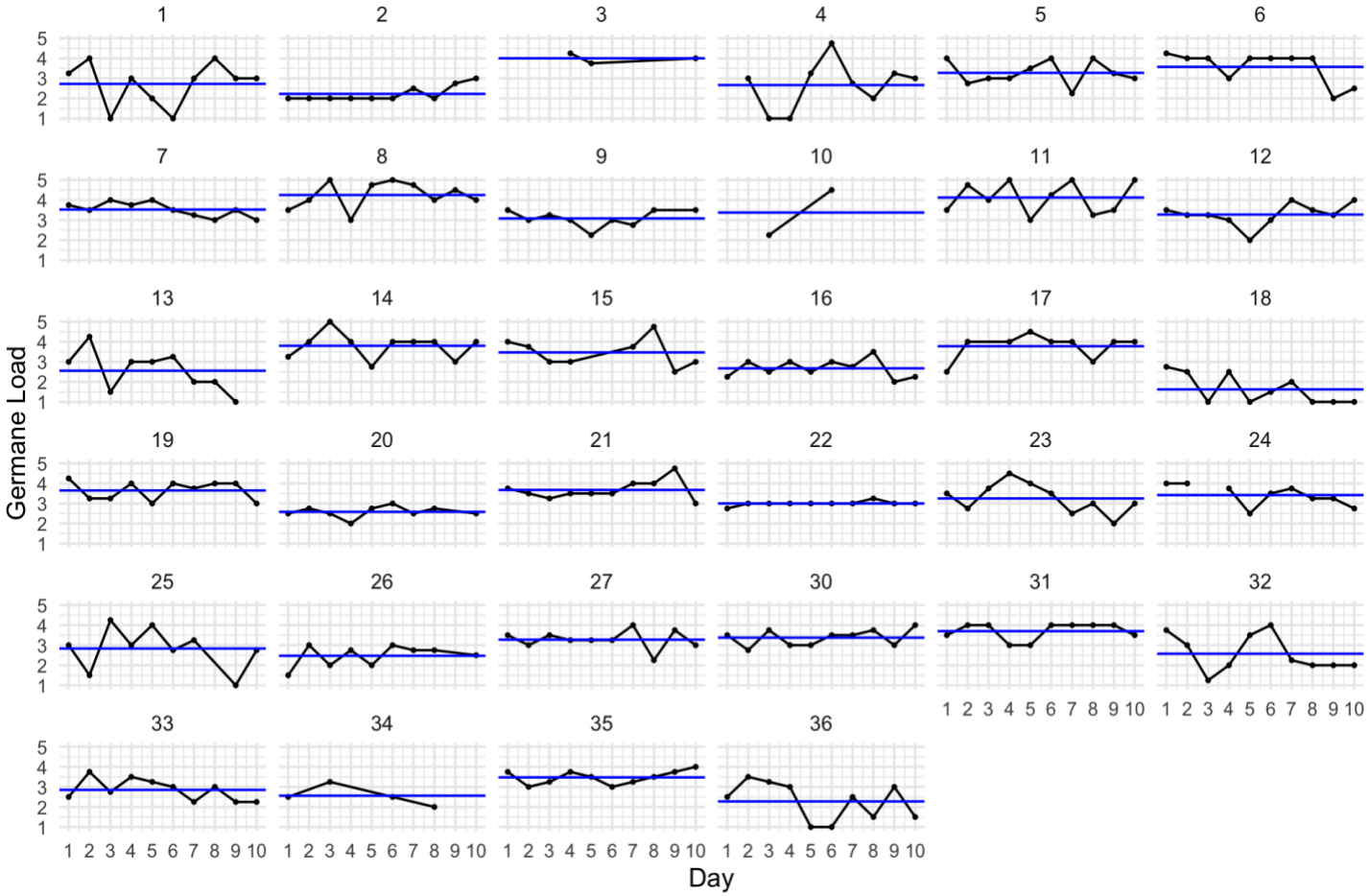
Note. The black lines and associated data points represent each teacher's average intrinsic load for that day. The blue line represents each teacher's average intrinsic load across all day

Daily extraneous load panel plot



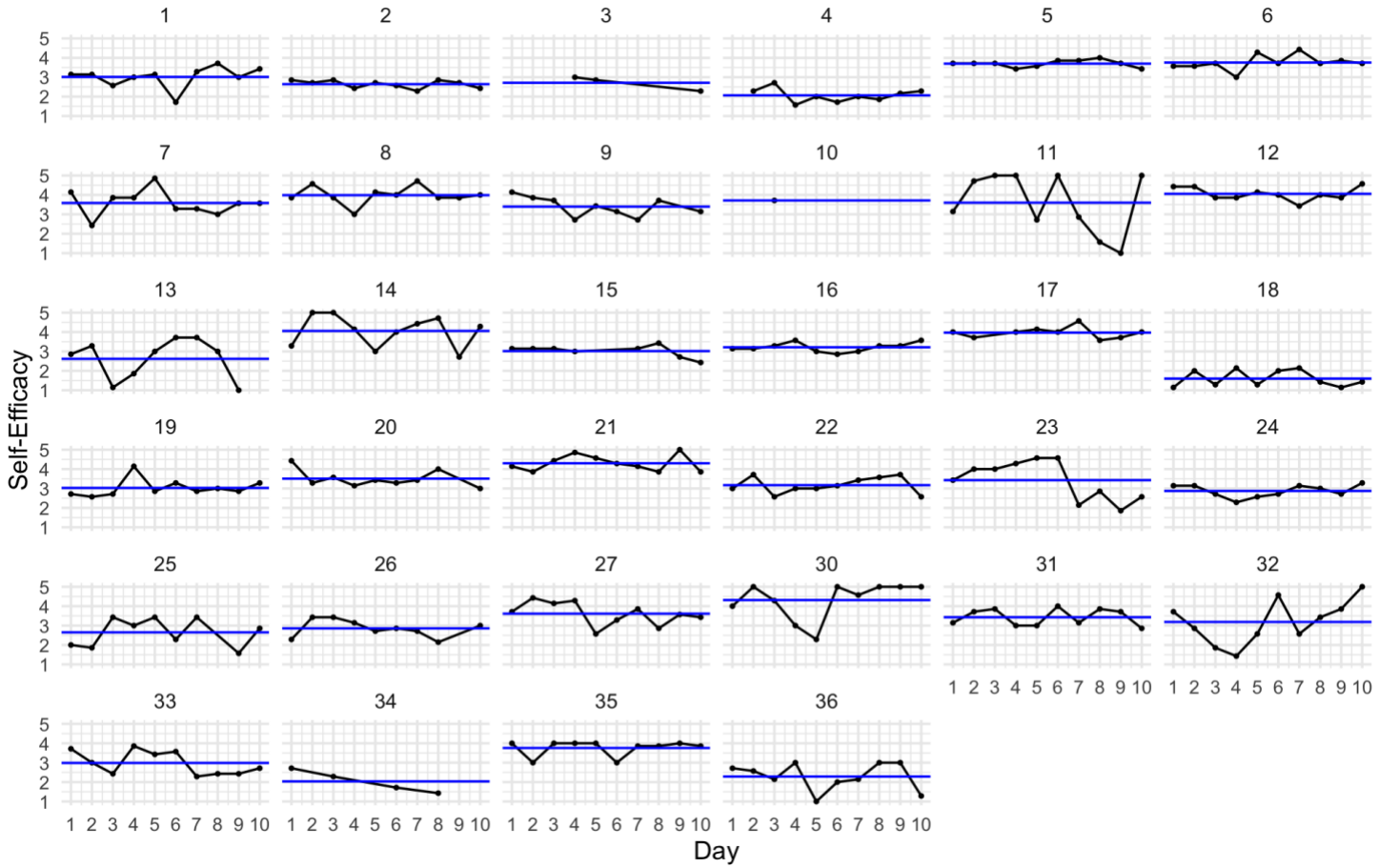
Note. The black lines and associated data points represent each teacher's average extraneous load for that day. The blue line represents each teacher's average extraneous load across all days.

Daily germane load panel plot



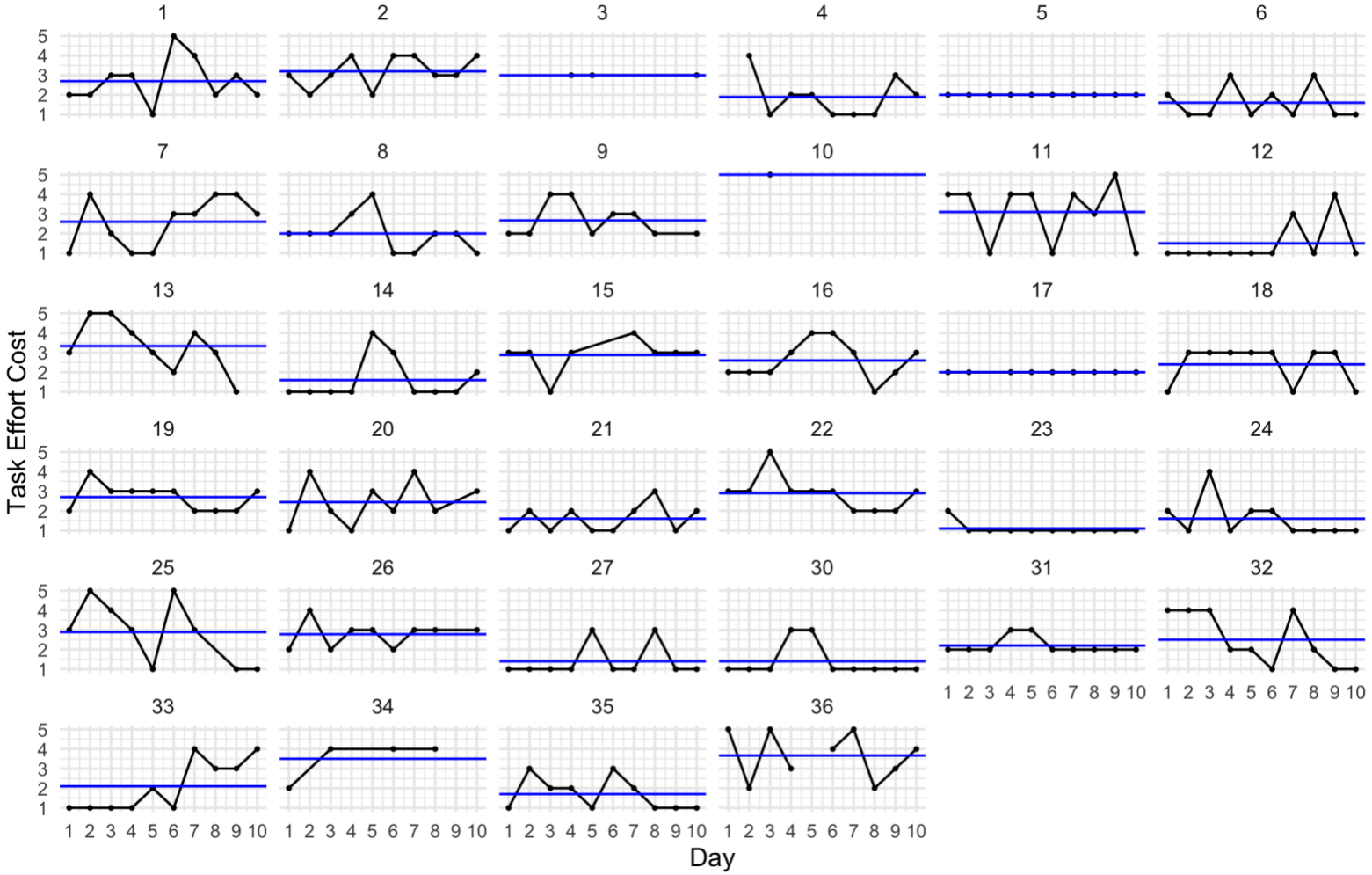
Note. The black lines and associated data points represent each teacher's average extraneous load for that day. The blue line represents each teacher's average extraneous load across all days.

Daily self-efficacy panel plot



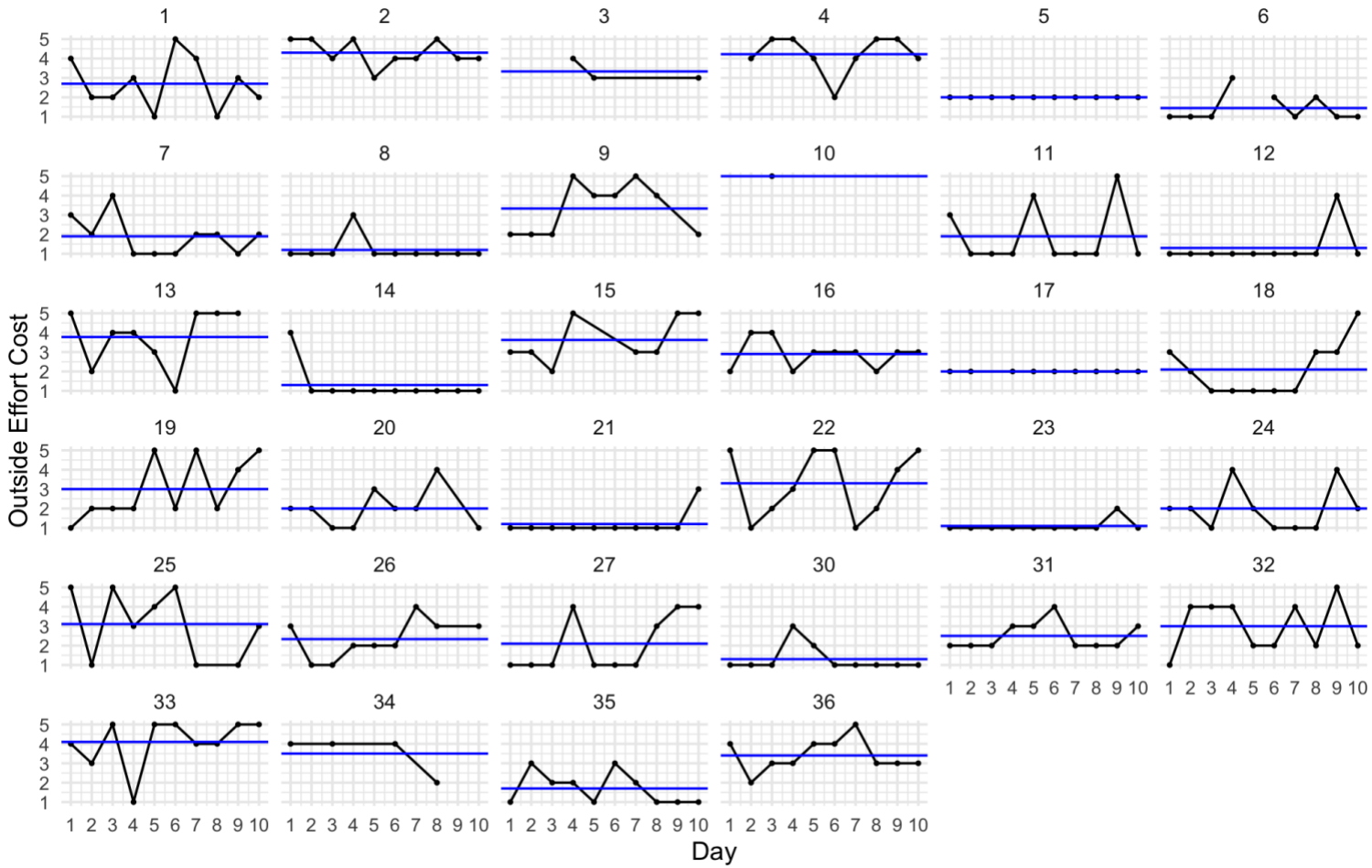
Note. The black lines and associated data points represent each teacher's average self-efficacy for that day. The blue line represents each teacher's average self-efficacy across all days.

Daily task effort cost panel plot



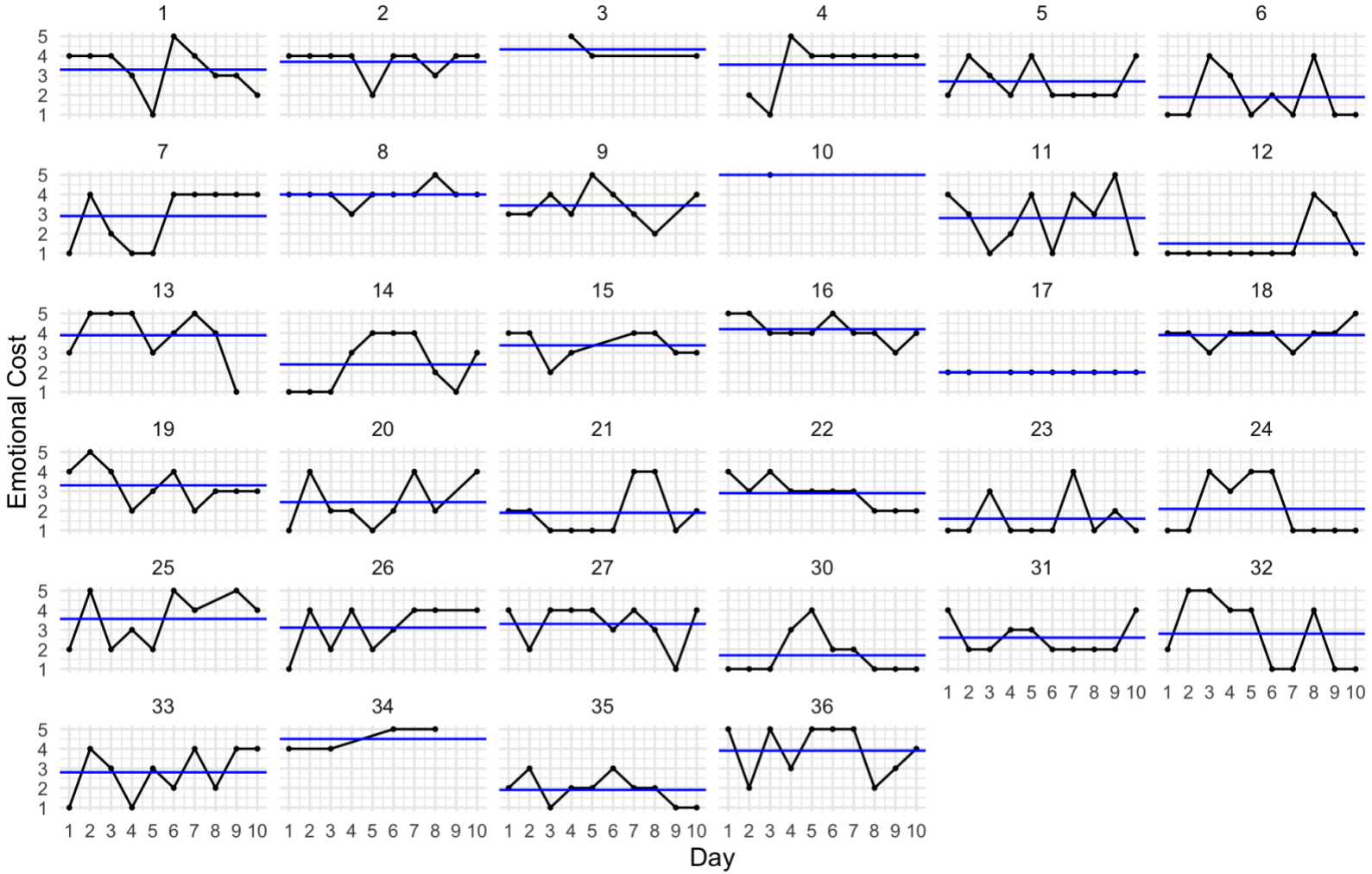
Note. The black lines and associated data points represent each teacher's average task effort cost for that day. The blue line represents each teacher's average task effort cost across all days.

Daily outside effort cost panel plot



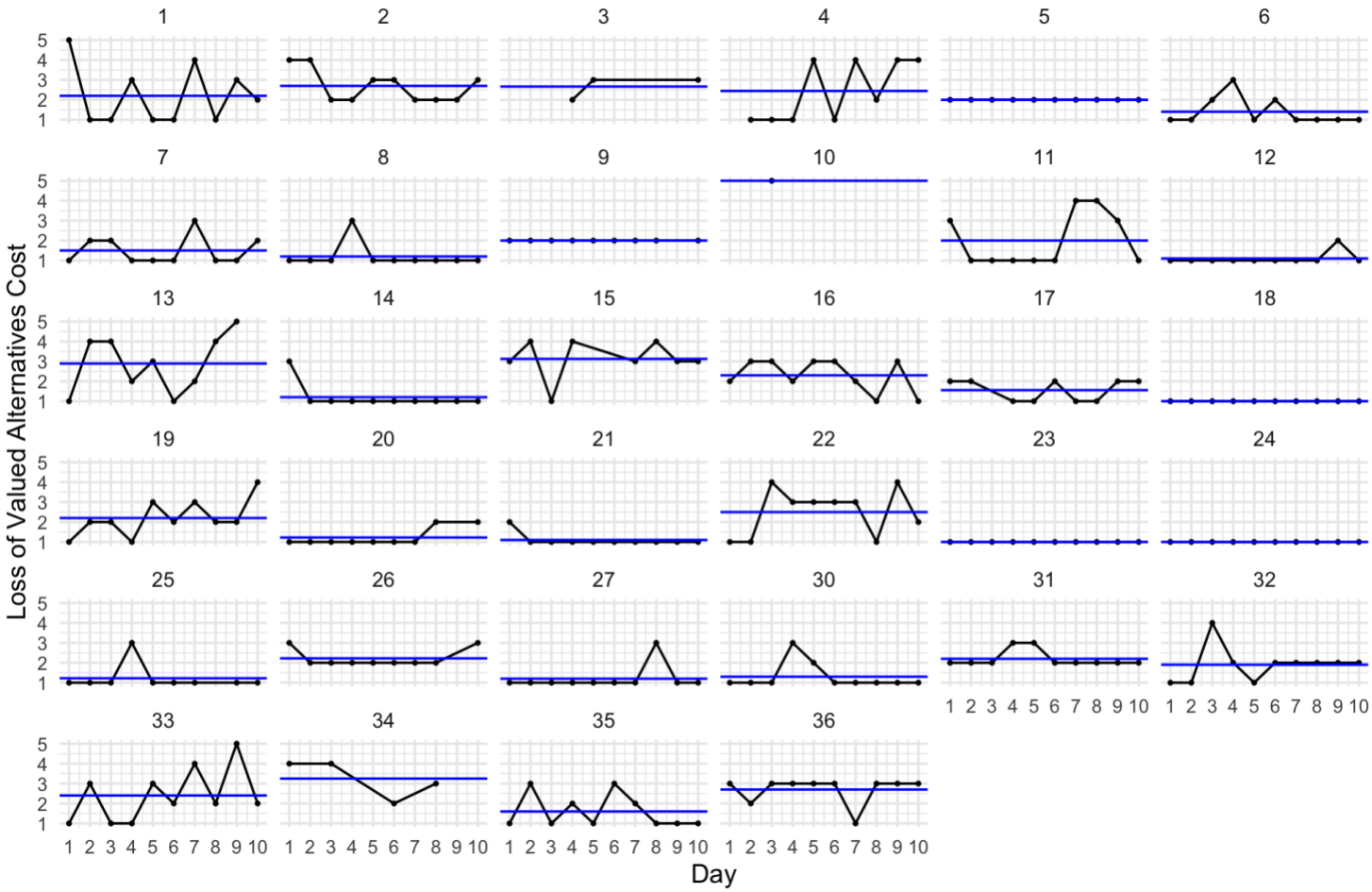
Note. The black lines and associated data points represent each teacher's average outside effort cost for that day. The blue line represents each teacher's average outside effort cost across all days.

Daily emotional cost panel plot



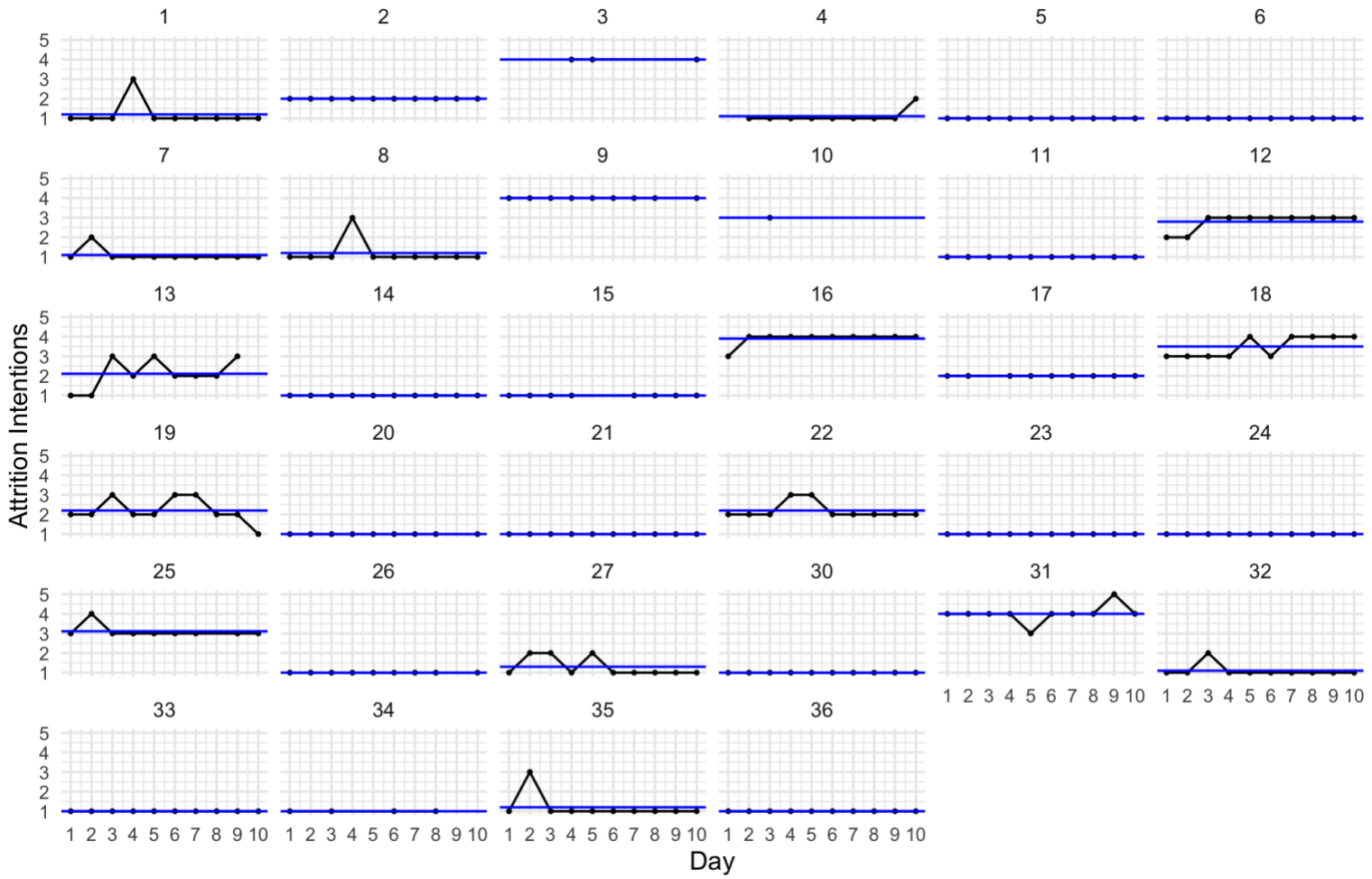
Note. The black lines and associated data points represent each teacher's average emotional cost for that day. The blue line represents each teacher's average emotional cost across all days.

Daily loss of valued alternatives cost panel plot



Note. The black lines and associated data points represent each teacher's average loss of valued alternatives cost for that day. The blue line represents each teacher's average loss of valued alternatives cost across all days.

Daily attrition intentions panel plot

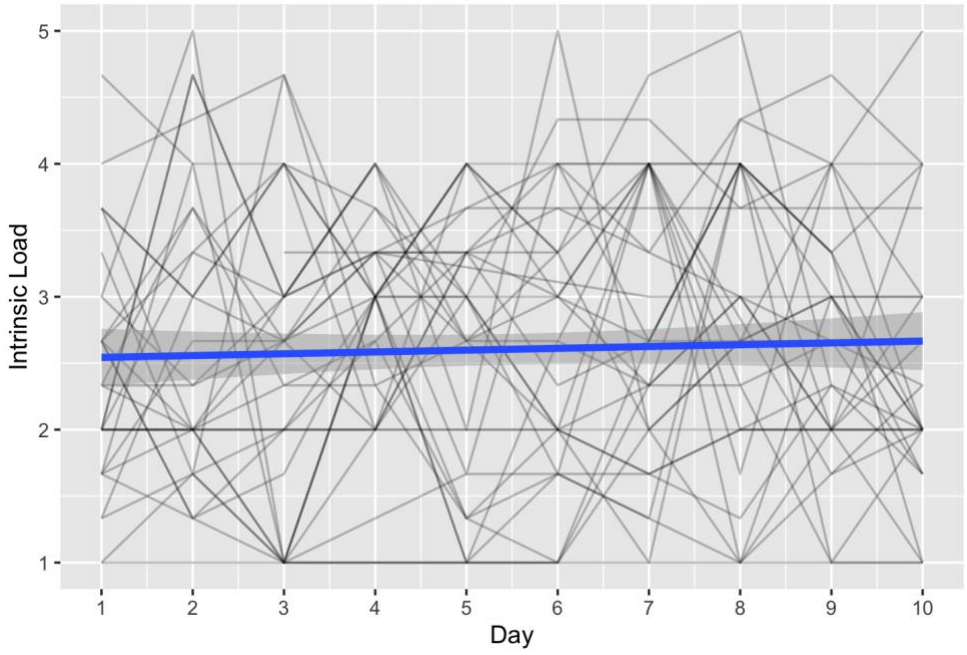


Note. The black lines and associated data points represent each teacher's average attrition intentions for that day. The blue line represents each teacher's average attrition intentions across all days.

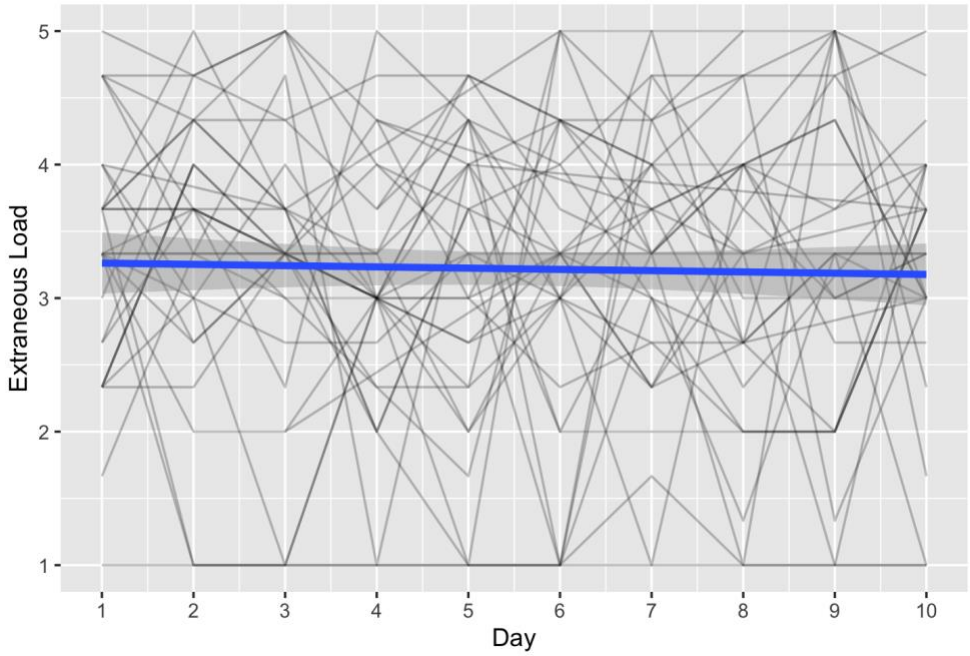
Appendix V

Spaghetti Plots

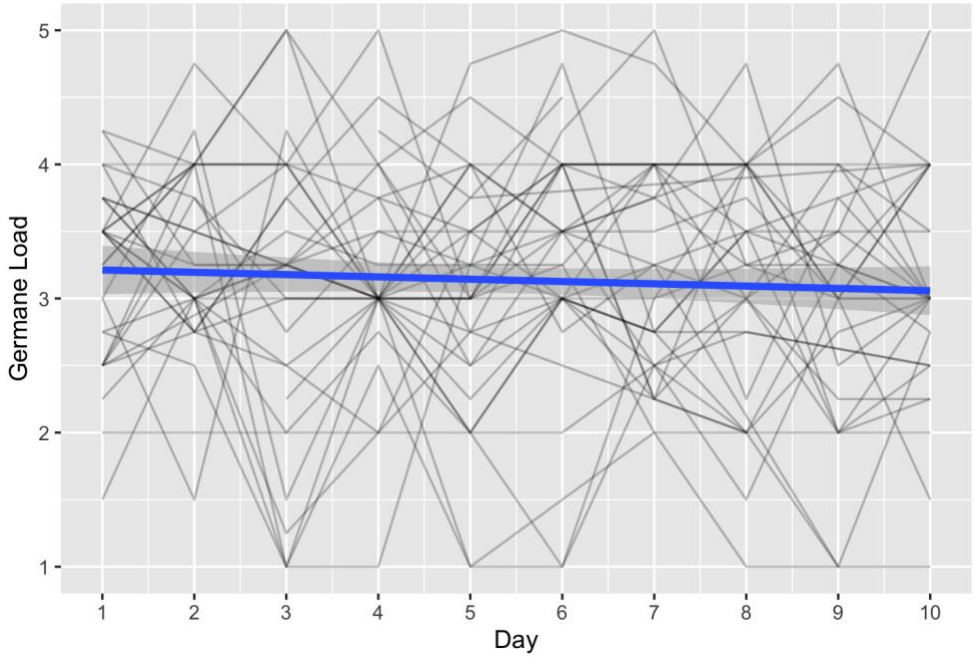
Daily intrinsic load spaghetti chart



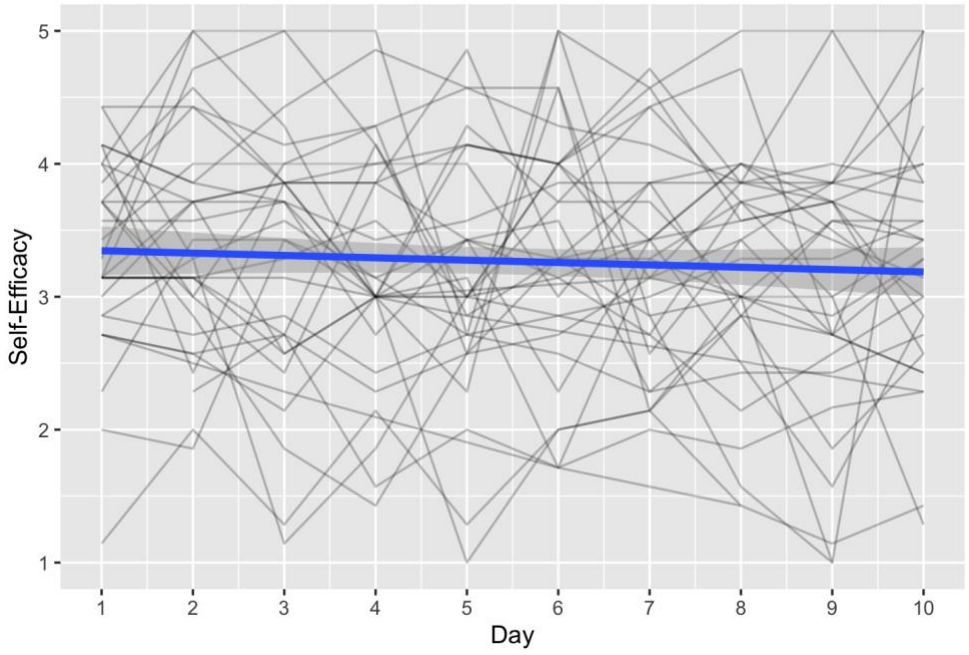
Daily extraneous load spaghetti chart



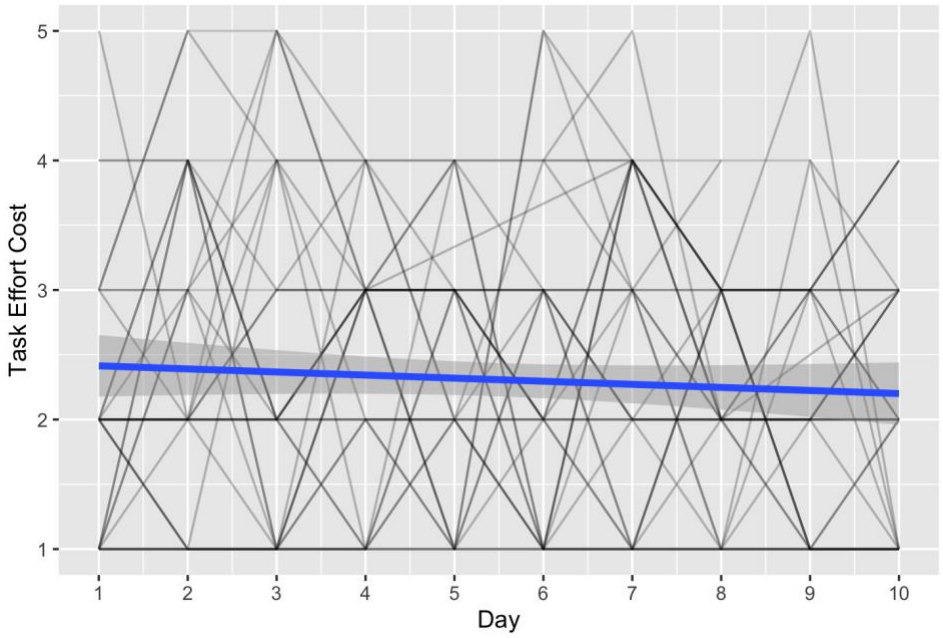
Daily germane load spaghetti chart



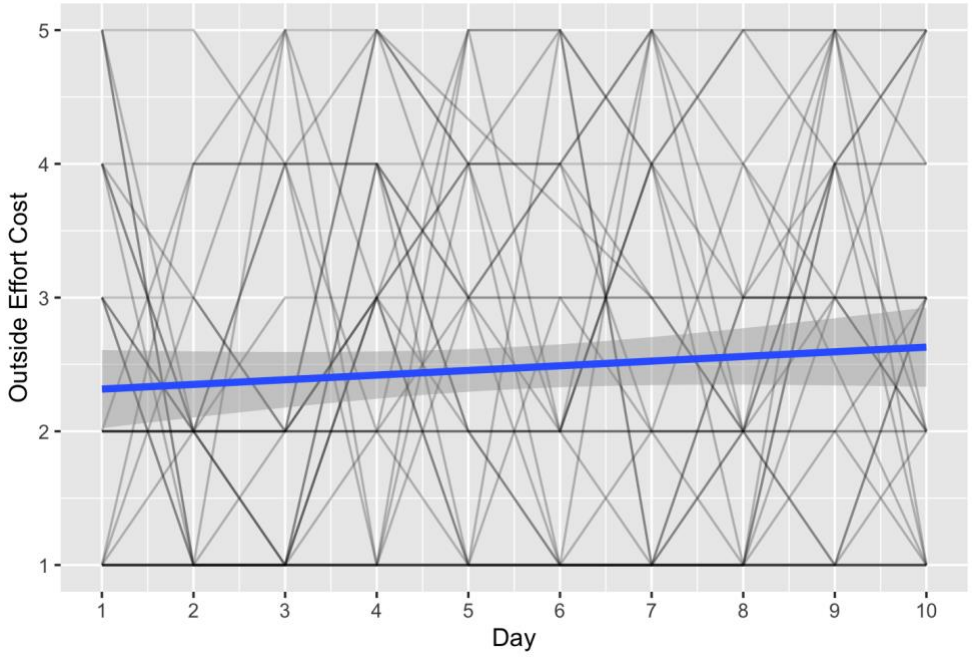
Daily self-efficacy spaghetti chart



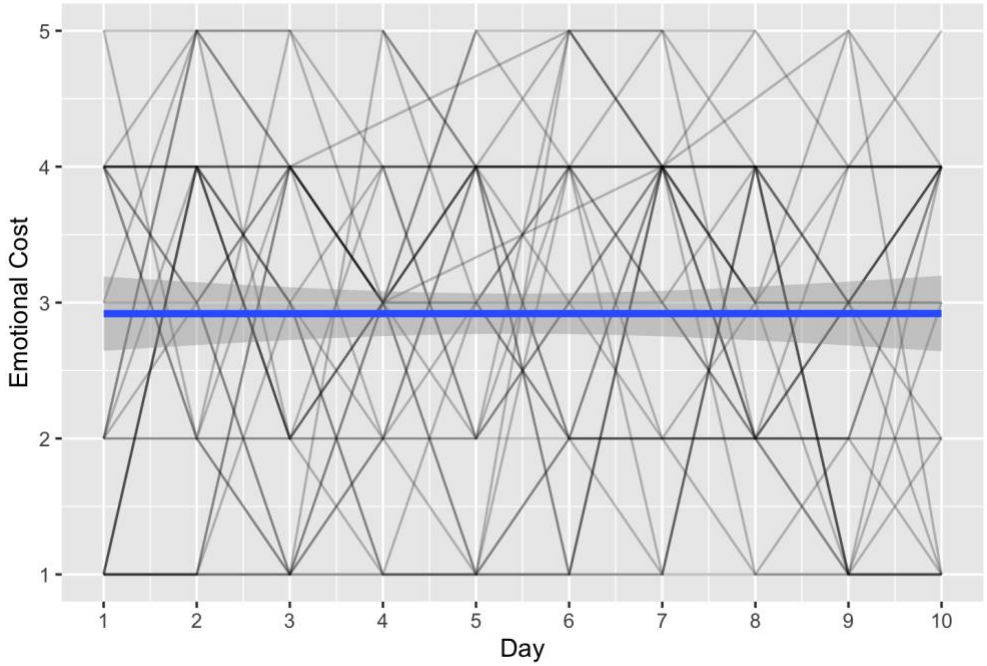
Daily task effort cost spaghetti chart



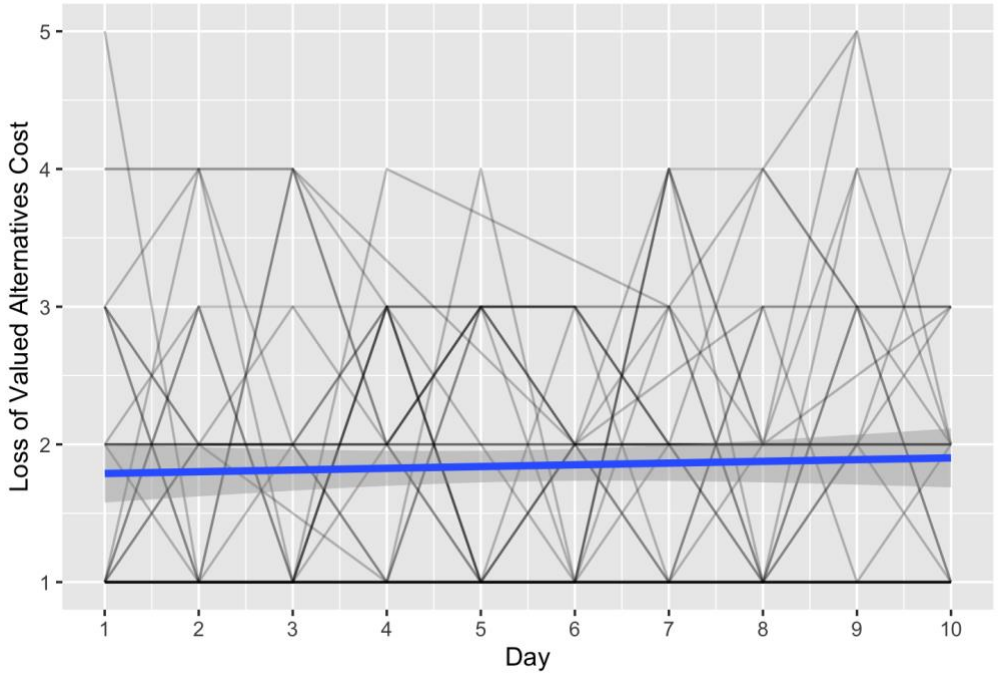
Daily outside effort cost spaghetti chart



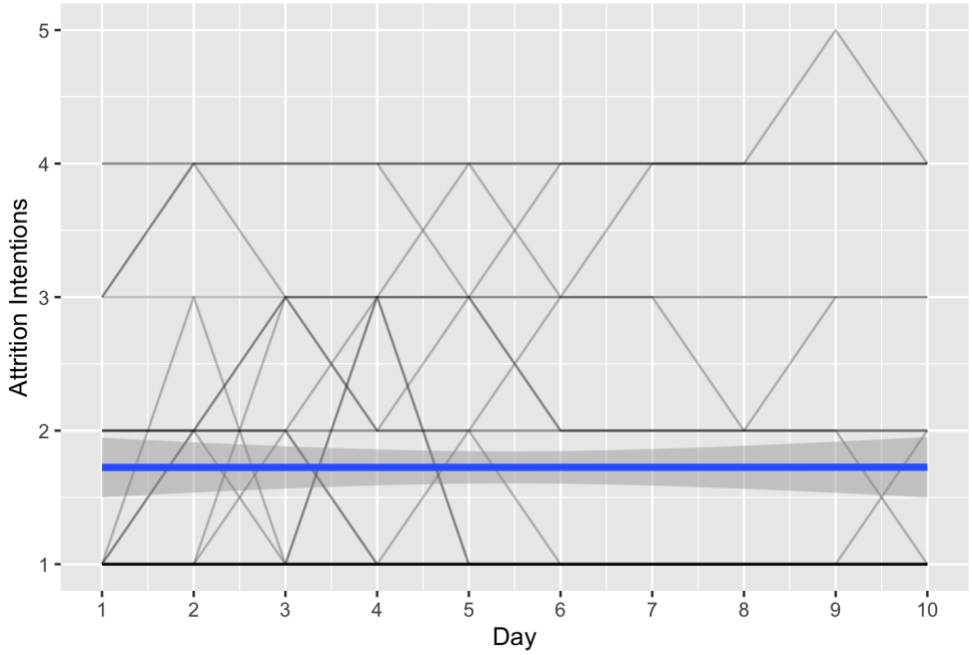
Daily emotional cost spaghetti chart



Daily loss of valued alternatives cost spaghetti chart



Daily attrition intentions spaghetti chart



Appendix W

Memos Throughout Qualitative Data Collection and Analyses

Memo #1: *Operational Memo*
I sent out recruitment. Note that I've selected participants mainly through/if they have high or low germane, extraneous, or intrinsic cognitive load. Though, I did decide it was important to select a few participants with interesting efficacy, cost, or attrition when paired with their cognitive load. I also found it necessary to sample at least a few teachers outside the predominant identity of US teachers (i.e., white women) and so I did that as well.

Memo #2: *Operational Memo*
I've now recruited 8/18 teachers whom I've reached out to. Will reach out to 2 more on Monday.

Memo #3: *Operational Memo*
I got one more teacher signed up, now for a total of 9 teachers.

Memo #4: *Analytical Memo – Ms. Scott*
Referring to my first interview. My first interview was very interesting with this teacher. Something that immediately stood out to me was her lack of confidence for math instruction. This teacher is mid-career and a 5th grade teacher. Another thing that stood out to me was that she mentioned her cognitive load during math instruction is always much higher than it is during small group instruction. A very interesting interview. I was unable to ask cost questions because her students came in!

Memo #5: *Analytical Memo – Mr. Clark*
I absolutely loved/found this interview fascinating. This was an upper elementary teacher. A few things that stood out in this one: this teacher felt very confident in math and his ability to teach students. However, it was clear extraneous load is a frequent demand. Another interesting thing was the anxiety he expressed when recommending his students for certain math classes – particularly when recommending them for higher levels than their current grade level. Feels that it influences the course of their math school career. Overall great interview.

Memo #6: *Analytical Memo – Ms. Lee*
The interview with this teacher was interesting. This teacher has been teaching for 34 years. It was hard to get her to say too much, but I feel this was because many of her answers were that she didn't really experience what I was asking that often. My overarching takeaway from this one is: teaching gets easier/less cognitively demanding with time and experience. It was the case that she had a lower cognitive load despite being the least confident in math compared to other subjects (though still confident). She's seemed to figure out strategies that work well for her. She

also mentioned quite a bit that it really depends on the class year to year and this year is a less challenging class.

Memo #7: *Analytical Memo – Ms. Keller*
This interview was also interesting and such a contrast from yesterday's interview, the 34th year veteran teacher. Specifically, because she was a 3rd year teacher. A few things that stuck out to me: this teacher identified herself as a "math person" and felt confident in her math, though this was slightly lowered last year because a new math curriculum was introduced at her school. Though, she does feel more confident teaching that math curriculum this year. As far as cognitive load, she, like her peers I've already interviewed thus far, specifically mentioned that the external factors (e.g., certain students, behavior) is the hardest to manage during math instruction. Much more than internal factors. Speaking to the prevalence of extraneous load during math instruction. She did mention if she had to pick internal factors that are distracting it would be that she sometimes tries to think too many steps ahead during instruction. Speaking to her intrinsic cognitive load. Also, this teacher will likely transition to a reading specialist position in the next five years as she's getting a master's degree in the area. Eventually might transition to another education-adjacent occupation.
Note: so far, every teacher has answered "the students, the kiddos, the kids" as the reason they stay in education.

Memo #8: *Operational Memo*
On the day/a few hours before Ms. Meyers' (PID #6) interview, she asked me if she could see the interview questions beforehand. I talked about it with Alison and we decided it wouldn't have too much of an impact and that comfort is the most important thing for the participating teachers. Therefore, I sent her the interview protocol approximately 2.5 hours before her interview began.

Memo #9: *Analytical Memo – Ms. Collins*
As far as interviews, this one also went well. She expressed that most of her challenge during math instruction comes from disruptions/classroom behaviors – especially in kindergarten. One of the more interesting things that emerged was her discussion of the ever-changing math curriculum. From my interpretation, it almost "restarts" their intrinsic load or possibly takes a lot of germane load to learn/teach. She mentioned that there is always an adjustment period with new curriculum. In addition, like all her peers thus far, expressed that she was "in it for the kids."
Small operational note: We had some connection issues. She got logged off at one point but came back shortly after.

Memo #10: *Analytical Memo – Ms. Myers*
Another great interview. Nothing too unusual/unique stands out to me. Once again, it seems classroom management needs seem to be the most distracting during math instruction. I will say

loss of valued alternatives cost really came through as she said she will leave teaching once she becomes a mother as she doesn't feel she can give 100% of attention to both. Frustration was her most common emotion described. One thing that most stands out to me from this interview is the lasting effect of cognitive load. That is, she expressed that it doesn't just end at the end of the lesson, for a while after she will think about: how did it go? What have gone better? What do I need to improve upon for tomorrow?
Small operational note: This teacher had the questions beforehand.

Memo #11: *Operational Memo*
My interviewee today canceled. She said she is going to reschedule, and I re-sent her the Calendly link to do so. I also had another teacher reach out to me today who did not originally sign up, ask if she could still participate. I told her yes and she signed up for 2/14/26.

Memo #12: *Analytical Memo – Ms. Klein*
A great interview with a teacher from school #1 in her 2nd year of teaching kindergarten. A few interesting takeaways: (a) she clearly has a lot of extraneous cognitive load or environmental distractions during instruction, (b) she talked a lot about how the math content itself is not that hard, but it's getting the abstract concepts of math across to students, (c) she expressed (as did Ms. Myers) that should doesn't think she'd be able to teach/do both once she becomes a mom in the future.

Memo #13: *Operational Memo*
A teacher signed up after not signing up after 3 contacts (PID #3). She mentioned she didn't realize that hours outside of school were available. She heard from another teacher who interviewed (PID #4) that she participated over the weekend and then decided to sign up.

Memo #14: *Analytical Memo – Ms. Hall*
Great interview. One thing that really stood out to me about this interview was her discussion of her learning disability (i.e., ADHD) and how that might change her teaching experiences slightly compared to a lot of her peers (i.e., often more overwhelmed by distractions). She also had lots of knowledge on trauma. She didn't seem super confident in teaching in general, though expressed that she is confident in math. It seems that teaching is a lot for her and that she will eventually leave the field to do something else.
Small operational note: I think I may be starting to arrive at data saturation.

Memo #15: *Analytical Memo – Ms. Baker*
This was a very refreshing interview. She was a veteran teacher (currently in Pre-K) and still had so much enthusiasm. There were a few things that stood out to me. First was her expanding "teacher toolbox" – she has so much in her toolbox at this point. Though, still sometimes things can get overwhelming. She explained how she has put up a shield of sorts against burnout and

that some people in her life can't help but be shocked by things she shares sometimes. In her personal life, she is always thinking about early childhood things, things for her classroom, and her students.

Memo #16: *Analytical Memo – Ms. Thomas*
Interesting interview, she is an upper-elementary teacher. This teacher said many similar things to other teachers (again pointing to data saturation). However, one interesting thing that emerged was that her cognitive load had a lot less to do with environmental factors and more to do with the need to scaffold/meet her students in many different spots (i.e., challenge of differentiation). I can now officially confirm that every single teacher responded "the students" to the question of what keeps them in the field – so inspiring!
Small operational note: this teacher only had about 30 minutes of her time to give, so some of the questions were slightly rushed. Though, we were able to get through all the questions.

Memo #17: *Operational Memo*
I am officially finished with interviews and have closed off Calendly. I ended up with a total of 10 completed interviews.

Memo #18: *Analytical Memo*
I have been transcribing interviews and decided it would be good to list any trends I am noticing thus far:

- Frustration – over constantly changing curriculum
- Differentiation – adds to the difficulty of math instruction
- Anxiety about readiness for next grade/appropriate grade level
- Shifting generation of students
- Each group/class is completely different
- Supportive admin really makes a difference
- Teaching doesn't just turn off after the lesson ends – constantly thinking about the next steps, how they can improve, what they need to do tomorrow, etc.
- Teaching is tiring – mentally and physically
- Lack of math self-efficacy seems to link to math not being their favorite subject and/or their personal ability beliefs in math
    - More common to be not very confident in math

Memo #19: *Coding Memo*
Up to this point in my thematic analysis I've completed:

- Phase 1: gained a thorough understanding of the data
    - Memos throughout data collection
    - Transcribing interviews
    - Additional read through

- Phase 2: generated initial codes
    - Added any codes or patterns I saw as I read through the transcriptions again
    - Coded all data (besides my own talking)
    - Coded extracts inclusively
        - After phase 2 I ended up with 68 total codes

Memo #20: *Coding Memo*
Following Phase 1 and 2 of my thematic analysis, I now have completed:

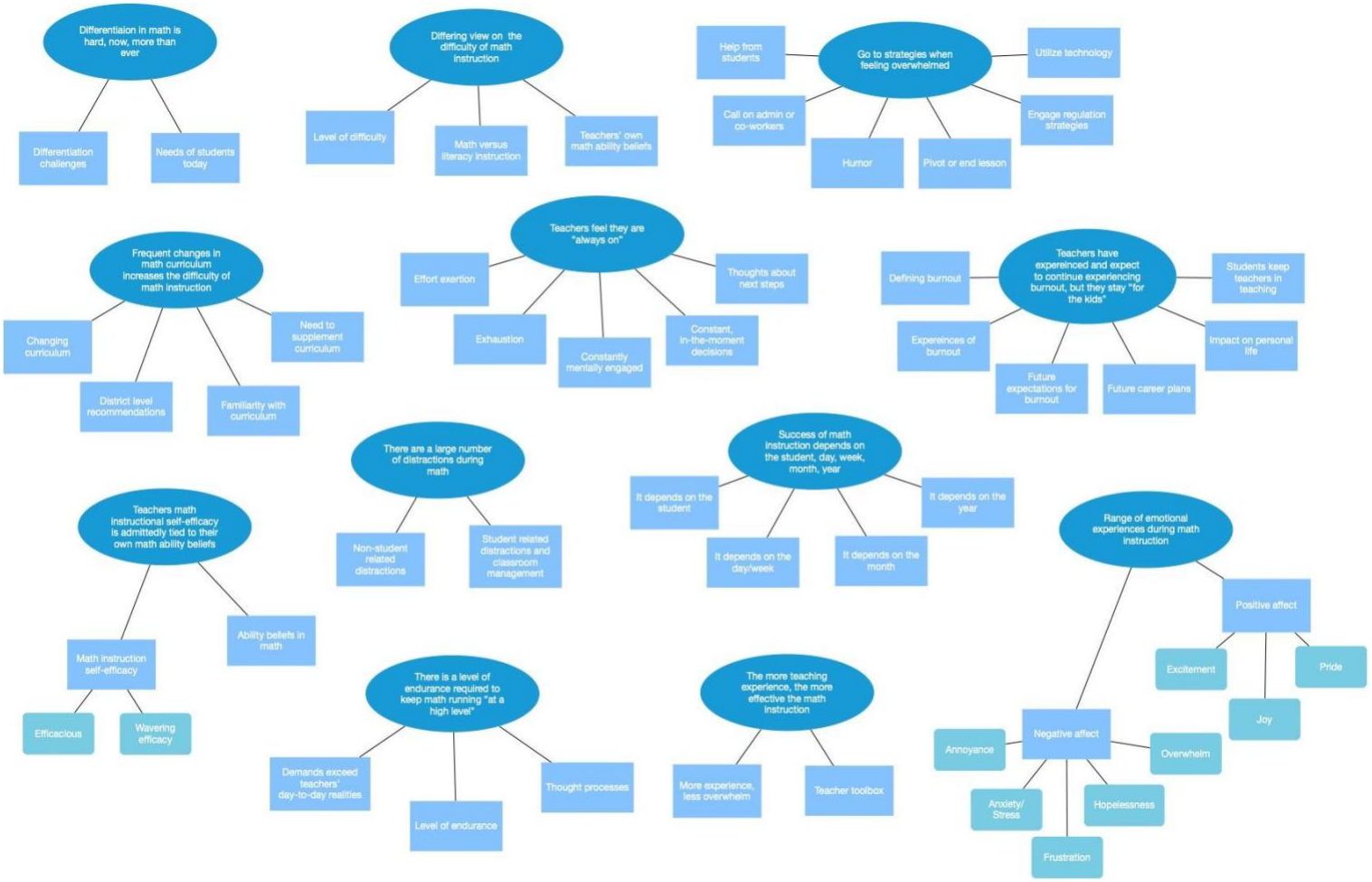
- Phase 3: Searching for themes
    - I began to group all the different codes into categories or themes.
    - Many codes were merged at this point if they were highly similar to another code.
        - I ended up with 12 themes and 52 codes after this phase

Memo #21: *Coding Memo*
Following Phase 3 of my thematic analysis, I now have completed:

- Phase 4: Reviewing Themes
    - I began to further refine themes and realized that some were highly related and should be sub-themes of broader overarching ones.
        - One way I did this was by developing a concept map which then allowed me to better visualize their connections
    - I ended with 5 themes, 8 subthemes, and 44 codes

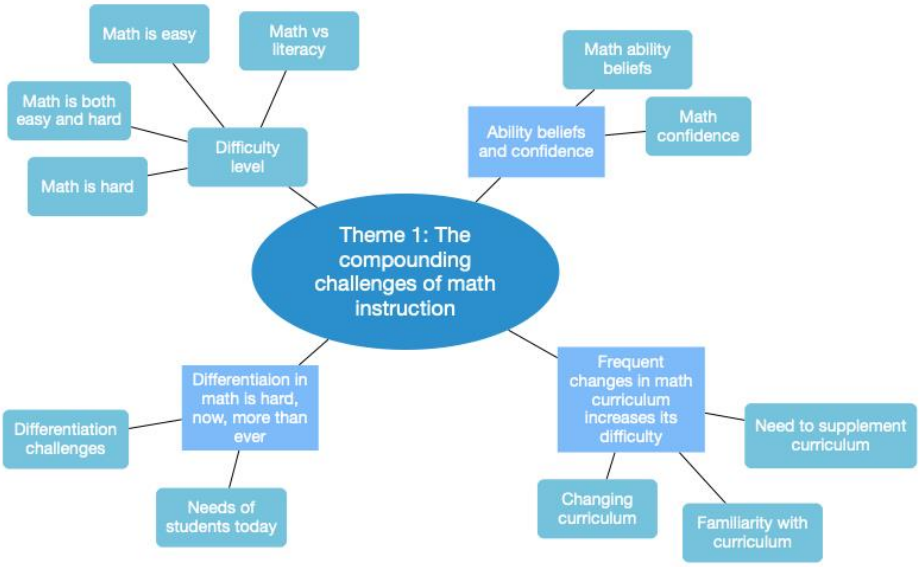
Appendix X

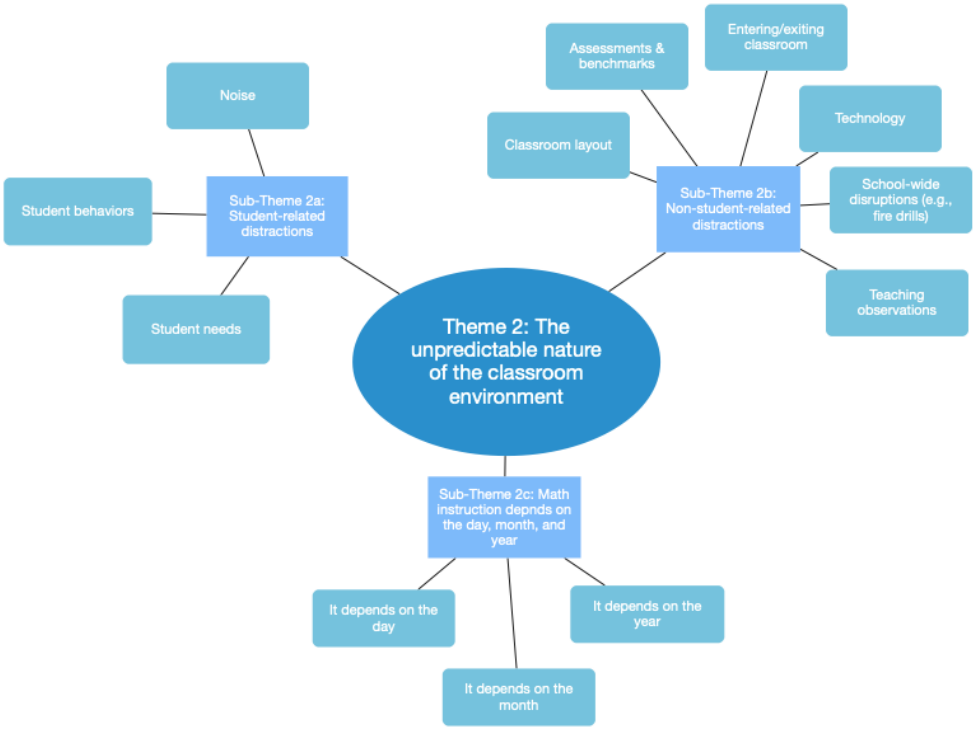
Thematic Analysis: Thematic Map (Step 3)

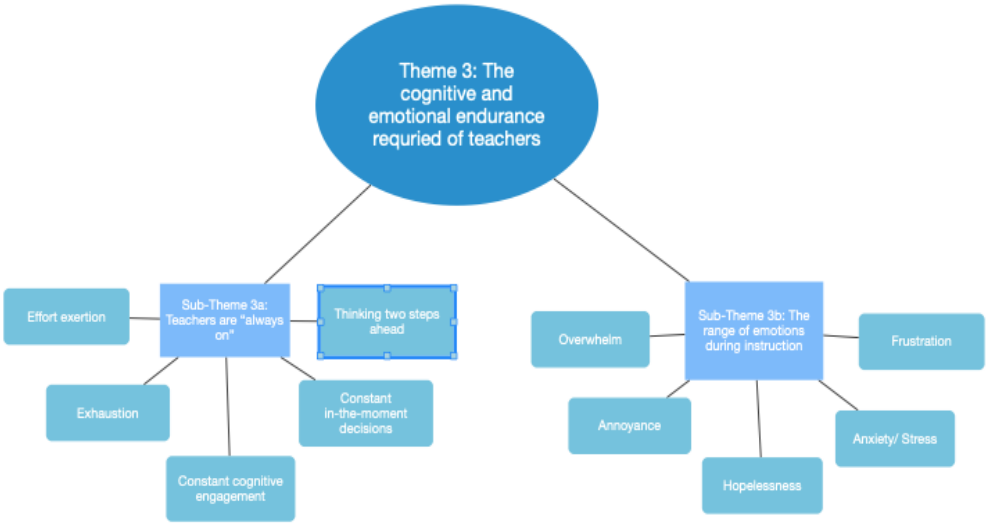


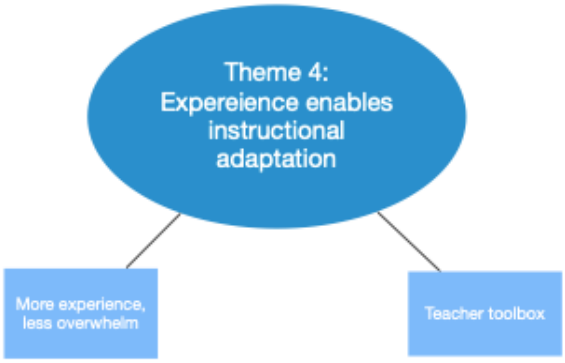
Appendix Y

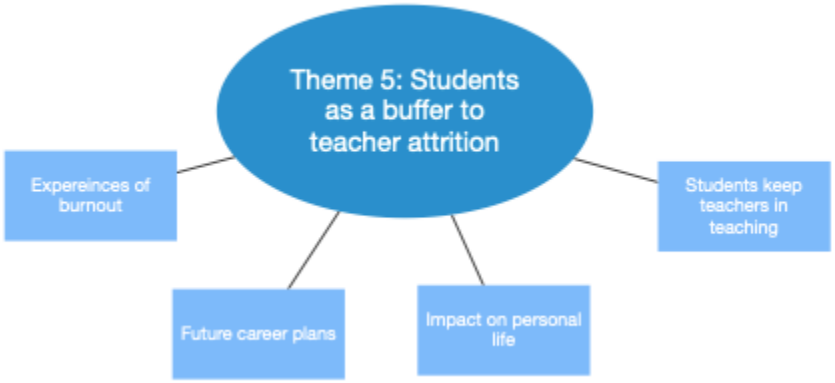
Thematic Analysis: Theme 1-5 Thematic Map (Step 4)






Theme 3: The cognitive and emotional endurance requried of teachers
Effort exertion
Sub-Theme 3a: Teachers are "always on"
Thinking two steps ahead
Exhaustion
Constant cognitive engagement
Constant in-the-moment decisions
Overwhelm
Sub-Theme 3b: The range of emotions during instruction
Frustration
Annoyance
Hopelessness
Anxiety/ Stress


Theme 4: Expereience enables instructional adaptation
More experience, less overwhelm
Teacher toolbox


Theme 5: Students as a buffer to teacher attrition
Expereinces of burnout
Students keep teachers in teaching
Future career plans
Impact on personal life

Appendix Z

Qualitative Codebook

Theme	Definition	Codes	Example Quote	Frequency, *n* (%)
Theme 1: The compounding challenges of math instruction	Teachers' perceptions of the level of difficulty of the math instruction they provide, including person, student, and district level factors that exacerbate its level of challenge.	Math is easy Math is both easy and hard Math is hard Math versus literacy	"...it's [math] pretty challenging because now math is taught where they want the kids to know multiple ways to show math. And so with one skill, we're showing like four different methods. And to me, that is very difficult."	*9* (90%); 66 references
Sub-Theme 1a: Differentiation in a shifting educational landscape	The need to tailor instruction to meet the different academic levels of students, of whom have needs that are perceived by teachers as heightened in today's classroom contexts.	Differentiation challenges Needs of students today	"In the last 30 year period… you might have a challenging student or a student with really high needs once every three to four years. And now you have four [students with high needs] every year. So the level of support needed… I mean, you've got to work a lot of areas to be able to keep this [math instruction] running at a high level."	*7* (70%); 31 references
Sub-Theme 1b: Frequent changes to math curriculum	The challenges associated with recurring changes to the curriculum used to teach math.	Changing curriculum Familiarity with curriculum Need to supplement curriculum	"...it's [former math curriculum] already in my mind, it's in my back pocket. I've taught it many times, and I can do it basically standing on my head. I can navigate everything. But if I get a new curriculum all the time, and it changes the way to do it [teach math], I'm more likely to use my old	*8* (80%); 23 references

Theme	Definition	Codes	Example Quote	Frequency, *n* (%)
			method of teaching the same thing the new curriculum wants me to teach, because it's the same standard. Because then I can do everything else. So I think constant curriculum change can really add to the load."	
Sub-Theme 1c: Teachers' personal ability beliefs in math	Teachers' own beliefs about their math ability level and its influence on how challenging they perceive their math instruction to be.	Math ability beliefs Math confidence	"I feel a lot more confident doing the younger grades than the older grades. I have a daughter in seventh grade right now. She is doing algebra… and she's in advanced math. She has to get that from her daddy – numbers guy."	*6* (60%); 12 references
Theme 2: The unpredictable nature of the classroom environment	The unexpected and everchanging occurrences that happen in and around the classroom during math instruction, particularly those that are not related to the instructional materials themselves.	Student-related distractions Non-student related distractions It depends	"...well, it's me in a room with 15, five and six year olds, and so what they're distracted by, I'm pretty distracted by because my goal is to get them focused up on the… board and so I myself can lose track pretty easily."	*10* (100%); 135 references
Sub-Theme 2a: An unlimited number of student distractions	The high frequency of disruptions that occur during math instruction due to student needs, behaviors, or other miscellaneous happenings that could occur within the context of an elementary classroom.	Noise Student behaviors Student needs	"Not very well. I don't have ADHD, but I sure feel like it when I teach math instruction… I can't even get one sentence out about the lesson without being like, I need you to be quiet. I need you to focus. Are you looking this way? Cross-cross, mountain, or mermaid? Are you	*10* (100%); 62 references

Theme	Definition	Codes	Example Quote	Frequency, *n* (%)
			looking this way? And I have super strong classroom management. I've been doing this a long time."	
Sub-Theme 2b: Non-student related distractions	The high frequency of disruptions that occurred in and around the classroom during math instruction did not stem from the students themselves.	Classroom layout Assessments and benchmarks Entering/exiting the classroom Technology School-wide disruptions Teaching observations	"...with all the demands and all the pressures from parents and administration and higher up people in education, and just how fast everything moves to get kids ready for the next grade, but also like college ready and job ready. We all have that in the back of our minds, so it's like, ahhh!"	*8* (80%); 37 references
Sub-Theme 2c: Math instruction depends on the day, month, and year	The everchanging and evolving nature of the classroom environment; the reality that no one day is the same as the next.	Depends on the day Depends on the month Depends on the year	"It [success of math instruction] depends on the day. And that's what I loved seeing about the little surveys. Like, some days I was like, yeah, I made a change in the world today. Other days, I was like I did nothing. And it wasn't really the content. It was more like just how the kids come in some days."	*10* (100%); 36 references
Theme 3: The Cognitive and Emotional Endurance Required of Teachers	The unrelenting cognitive and emotional demands that teachers endure throughout instruction	Feeling "always on" Emotional demands	"Yeah and with-itness, as a teacher, you got to make sure that you're always scanning and know and thinking about all those things, so that helps a whole lot."	*10* (100%); 83 references

Theme	Definition	Codes	Example Quote	Frequency, *n* (%)
Sub-Theme 3a: Teachers are "always on"	The consistent cognitive engagement required of teachers to remain aware, alert, and responsive during instruction.	Constant cognitive engagement Effort exertion Exhaustion In-the-moment decisions Thinking two steps ahead	"You definitely have to be on it and paying attention. And like I said before, problem solving in the moment. So it's not like you can just be like 'okay, two plus two' and then passively listen. You have to be paying attention, or [asking yourself] are they getting this, looking at you kids, noticing their body cues, their body language… so you have to be on it and paying attention."	*9* (90%); 39 references
Sub-Theme 3b: The range of emotions during instruction	The wide-variation in affective states that teachers experience throughout math instruction.	Frustration Overwhelm Anxiety/stress Hopelessness Annoyance	"...sometimes frustrated. Out of like, I know that you can do this, but it's like, if you would just listen for a little bit, then I can show you how. And some, they just don't want to engage at all. And even in a small group setting, I'm like, that's okay. I can't control that. But it does build."	*10* (100%); 44 references
Theme 4: Experience enables instructional adaptation	The perception that math instruction, including the handling of various environmental inputs, gets easier with time and experience.	More experience, less overwhelm Teacher toolbox	"...as I've taught over the years, and I've kind of honed in on my craft, I've figured out how to adjust in the moment… or how to let things go. That's been, I think, a big shift in it for me."	*9* (90%); 40 references
Theme 5: Students as a buffer to teacher	Teachers' beliefs that students keep them in the field of teaching despite the demands	Burnout experiences Future career plans	"For me, it's the kids… I love the children… It's like my heart and soul, like I am the weirdo that misses them	*10* (100%); 11 references

Theme	Definition	Codes	Example Quote	Frequency, *n* (%)
attrition	of the profession.	Impact on personal life Students keep teachers in	over break or misses being with kids over the summer. They're just they're my people. They make more sense to me. You know, where you stand with kids. You know? They find joy in the most mundane, tiny things. And I think that's how I've stayed in the classroom so long. I find joy every day in what I do, maybe not all day, maybe not more than once a day. But there's at least one moment a day that's really joyful and meaningful to me…"	

Note. "References" refer to the number of times a particular code related to a given theme appeared throughout the qualitative dataset