ABSTRACT

Examining the Stability of Emotional Intelligence Among U.S. Adults
Before and After the Onset of the COVID-19 Pandemic

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Emotional Intelligence (EI) has been established as a critical skill with the ability to influence positive outcomes and mitigate challenging situations. Research connects EI to such benefits as better health, superior job performance, and psychological well-being. EI has also been shown to help moderate the negative impacts of stress. The recent COVID-19 pandemic is well-recognized as a source of unprecedented stress with implications for emotional well-being; however, continued research is needed to understand its impact on EI. We examined EI across both known and unknown subpopulations before and after the onset of the COVID-19 pandemic. Our purpose was to investigate the stability of EI among the general U.S. population ($n$ = 33,875) during this time. In addition, we investigated the measurement invariance of an EI instrument not previously examined in the literature. Our EI instrument demonstrated measurement invariance over time. In addition, EI did not vary meaningfully, either among known or unknown subgroups. These findings align with previous research in which EI is an independent variable that moderates or mediates other factors. This study contributes to

the theoretical understanding of EI and its stability, which is critical to the ongoing debate regarding the significance of EI. If substantial claims are to be made regarding the efficacy of EI, then evidence supporting its stability is needed to demonstrate that EI is usually the actor and not the variable acted upon by circumstances. This study provides important evidence of the stability of EI during highly stressful and chaotic circumstances.

Examining the Stability of Emotional Intelligence Among U.S. Adults
Before and After the Onset of the COVID-19 Pandemic

By

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A Dissertation

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DEDICATION

To my family: Phillip, Annalise, Israel, Malachi, and Isabelle. Thank you each for contributing to the laughter, compassion, and love that fill our home. I love you. TGGM.

# CHAPTER ONE

## Introduction

The study of Emotional Intelligence has captivated psychologists, educators, business leaders, and the public at large since the 1990s. Introduced first in the academic literature (Salovey & Mayer, 1990), it gained popular traction a few years later with the publication of Daniel Goleman's *New York Times* best-selling book (Goleman, 1995). Emotional Intelligence (EI) is defined broadly as the ability to understand and utilize emotions in daily life; different conceptual models divide EI into a variety of components such as awareness, regulation, perception, and expression. In the decades since its introduction, EI has been both hailed as a panacea and disparaged as hype. Despite its detractors, EI is now well-established in the research literature (Mancini et al., 2022), and, although it is certainly not a universal remedy, it has been shown to be a useful and relevant skill in a wide variety of contexts including education, business, and personal life.

EI research has taken the academic world by storm. A Google Search query for EI yields approximately 3,430,000 results (compared to 2,410,000 for IQ), and a recent meta-analysis documented 40 different EI measures, 24 in English, 16 in various other languages (Bru-Luna et al., 2021). Ongoing interest in EI is no doubt the result of the large number of studies linking high levels of EI to seemingly innumerable positive outcomes. These include better physical and mental health (Schutte et al., 2007), psychological well-being (Costa et al., 2013), job performance (Joseph et al., 2015;

O'Boyle et al., 2011), retail service quality (Miao et al., 2019), organizational commitment and job satisfaction (Doğru, 2022), entrepreneurial success (Allen et al., 2021), and academic performance (MacCann et al., 2020). A particular line of research, to be discussed later in greater detail, shows that EI can help moderate stress (Mikolajczak et al., 2009).

The ability of EI to support positive life outcomes and mitigate detrimental ones for individuals has the potential to also inform our theoretical understanding of the relationship between EI and events or crises that happen on a wider scale. The recent COVID-19 pandemic brought the issues of mental and emotional health to the forefront of both public and professional conversation. Research into the relationship between EI and the COVID-19 pandemic has begun, but much remains to be learned. Specific questions regarding this relationship are discussed in detail toward the end of this chapter.

Not all EI researchers are equally enthusiastic about its benefits, and critics of EI question whether its powers have been overstated. One meta-analysis reports a steady decline in effect sizes, suggesting that effect sizes in some original EI studies were overestimated (Gong & Jiao, 2019). In some cases, lack of control for cognitive ability or personality may have falsely inflated the amount of variance seemingly explained by EI (Ybarra et al., 2014). At a more fundamental level, some researchers have claimed that the traits grouped together as EI are only loosely affiliated, the EI construct "does not meet psychometric standards," and the yardstick by which EI is measured is constantly changing (Daus & Ashkanasy, 2003, p. 69). Attention and response to these critiques is important to help refine the definition and measurement of EI. Proponents of EI have responded with meta-analyses of their own to clarify the nomological network of EI and present more accurate information regarding its predictive validity (Joseph et al., 2015; Ybarra et al., 2014). While conceding that a continual improvement process is needed to refine and strengthen the validity argumentation of EI, there is widespread agreement among researchers that EI is a genuine, unique construct correlated with many positive outcome variables (Mancini et al., 2022). Despite the controversy, consensus around three basic principles can guide ongoing efforts: 1) emotions play a real and important role in daily life, 2) individuals vary in their abilities to understand and use these emotions, and 3) these variances are tied to specific, consequential outcomes in a variety of contexts (McCleskey, 2014).

### *Theoretical Frameworks of EI*

Some of the confusion and debate regarding EI stems from the fact that there are multiple theoretical frameworks for understanding EI. Although Salovey and Mayer (1990) are credited with introducing the term to the academic community, Reuven Bar-On was simultaneously conducting research on emotions, using the term *Emotional Quotient (EQ)* in his unpublished 1988 dissertation (Bar-On, 2006). Meanwhile, throughout the 1980s and early 1990s, as a Harvard graduate writing for the *New York Times,* Daniel Goleman was cataloguing research on emotions and the brain that would culminate in his best-selling book (Goleman, 1995). These three simultaneous yet separate streams of research yielded differing theories for understanding and explaining EI. A fourth framework, using the Five Factor Model of personality as a foundation (Petrides & Furnham, 2001), emerged later in an effort to target gaps in EI theory that had opened the door for criticism. Since it was not among the early EI frameworks, the

Petrides and Furnham theory of EI is not always included in EI taxonomies (e.g. Ashkanasy & Daus, 2005).

Most EI frameworks do not treat the construct as a strictly cognitive intelligence, even though it is called *emotional intelligence* and the term EQ highlights the comparison with IQ. Among the four theories described above, only the Mayer-Salovey-Caruso Emotional Intelligence Test (MSCEIT; Mayer et al., 2002) treats EI as a true ability, utilizing what is called a *maximum performance test* for assessment. Tests of maximum performance usually have right and wrong answers and assess the peak performance of an individual, as compared to assessments of typical performance, which measure how a person usually performs or behaves (Shultz et al., 2014). Every framework except that of Salovey and Mayer utilizes an assessment of typical performance, usually self-report, and some researchers group all three self-report models together (eg. Gong & Jiao, 2019). However, the three self-report EI frameworks can be better understood by sub-dividing them into *competence-based* and *trait-based models*. Both the Bar-On model (Bar-On, 2006) and the Goleman model (Goleman, 1995) treat EI as a constellation of social, emotional competencies. At times this type of EI has been called emotional self-efficacy (MacCann et al., 2020). In contrast, Petrides et al. (2007) conceptualize EI as a combination of personality traits.

There is a general leaning among academics to embrace the two models of EI that have emerged in the academic literature, ability and trait (Daus & Ashkanasy, 2003; Joseph et al., 2015; Tsaousis & Kazi, 2013; van der Linden et al., 2017), presumably because of their higher rigor in measurement. However, this preference is problematic because competency models have shown higher incremental validity in predicting outcomes over and above intelligence and personality (Joseph et al., 2015). In addition, viewing EI as either a trait or an ability suggests a greater degree of fixedness in the level of EI present within an individual. This would be appropriate if EI was understood to be a static construct, since traits and abilities are a somewhat more fixed construct of personality (McAdams & Pals, 2006). However, there is a substantial body of literature investigating the potential for change in EI. It is no surprise, considering the wide array of positive outcomes linked to EI, that many have sought to develop and document interventions to improve EI. Successful implementation of these EI interventions could demonstrate the malleability of EI. Although the degree and quality of change may vary based on the kind of intervention and the theoretical framework of EI, meta-analyses of the literature suggest that EI training can improve EI (Hodzic et al., 2018; Kotsou et al., 2019). Some of this research on EI interventions has been conducted based on trait and ability models, and EI has been shown to change, even as measured by trait and ability frameworks. However, conceptually, if one assumes EI is malleable, then conceiving of EI as a competency or skill makes more theoretical sense. In this study, we theorize EI to be a malleable construct; therefore, we treat EI as competency-based.

### *EI and Positive Outcomes*

As mentioned previously, possessing high levels of EI has been linked to numerous positive outcomes. Among the myriad benefits of high EI, a particular line of research has investigated the potential of EI to mitigate stress and burnout. EI has been shown to either moderate or mediate against stress and/or burnout among HR professionals (Santos et al., 2015), resettlement workers (Espinosa et al., 2019), undergraduate students (Mikolajczak & Luminet, 2008), nurses (Mikolajczak et al., 2007;

Sun et al., 2021; Szczygiel & Mikolajczak, 2018), and lawyers (Platsidou & Salman, 2012). EI was observed to negatively correlate with job burnout among medical interns (Weng et al., 2011); in other words, higher levels of EI correlated with less burnout. The mechanisms through which EI helps mitigate stress are varied. In some cases, individuals may be able to recognize and manage their own emotions more effectively. In other instances, emotionally intelligent people may be better able to draw upon social resources for assistance. Overall, EI is understood to be a protective factor against stress and/or burnout.

### *EI and Stress*

Although EI may at times help protect against stress, in other situations EI itself may be subject to the effects of stress, suggesting that the relationship between EI and stress is not unidirectional. The medical education literature, in particular, has long documented the decline of empathy, a component of EI, among medical students (Hojat et al., 2004; Newton et al., 2008; Rosenfield & Jones, 2004; Spencer, 2004). Empathy has also been shown to wane among dental students (Sherman, 2005). Researchers have questioned the reasons for this ironic decline because many students in medically related fields initially profess a deep desire to care for others and, in fact, may be drawn to the profession for empathetic and compassionate reasons. A need to provide a coping mechanism for both prolonged exposure to human suffering and the stressful environment of medical school erodes empathy (Spencer, 2004). Ironically, significant decreases in empathy often coincide with increased patient interaction (Sherman, 2005). The broader construct of EI decreased for occupational, physical, and speech therapy students during their final-year clinical placements (Gribble et al., 2017), and two dimensions of EI, attention to emotions and mood repair, decreased significantly for medical students between orientation and clerkship (Stratton et al., 2008). Limited research regarding the impact of stress on emotional intelligence and the component of empathy exists outside the medical literature, and more attention is warranted regarding the two-way relationship between EI and stress.

### *COVID-19 and Stress*

The COVID-19 pandemic has been a recent source of substantial and ongoing stress that has presented a significant threat to emotional well-being. A survey in China during the initial phases of the outbreak revealed that over half the participants experienced moderate to severe psychological impact as a result of the pandemic (Wang et al., 2020). Higher than normal levels of loneliness, depression, and suicidal ideation were reported among the American population (Killgore et al., 2020). Because high EI has been associated with better mental health (Schutte et al., 2007) and shown to moderate stress (Mikolajczak et al., 2009), possessing high EI may prove beneficial in mitigating the negative emotional impact of COVID-19. Indeed, a growing body of research demonstrates the benefits of EI during the COVID-19 pandemic. Those who participated in EI training immediately prior to the pandemic had lower depression, suicidal ideation, and state anxiety scores as compared to the control group (Persich et al., 2021). EI was shown to play a moderating role on work-related stress (Scherer, 2022), teacher-wellbeing (Nichols, 2021), the impact of stress on work performance (Sadovyy, Sánchez-Gómez, et al., 2021), and to mediate psychological harm (N. Li et al., 2021). In keeping with previous findings, EI beneficially moderated and/or mediated the impact of stress during the pandemic.

On the other hand, if the relationship between EI and stress is bi-directional, then the challenges of the pandemic may have impacted EI. Although the body of research investigating the impact of stress and crisis on EI is comparatively small, the medical education literature suggests that exposure to stress and human suffering can change EI. Whether the effects seen among medical students are unique to that population or whether similar changes in EI might generalize to other populations remains to be seen. That is, findings from studies conducted among health care professionals experiencing prolonged exposure to human suffering provide a theoretical basis for examining potential changes in EI among other populations during the COVID-19 pandemic.

The purpose of the present study is to examine whether or not EI remained stable throughout the duration of the COVID-19 pandemic. The stress of the COVID-19 pandemic has been unlike any other crisis in that it has been prolonged, pervasive of all aspects of life, and global in reach. The elements of the COVID-19 pandemic stress were unique enough to warrant the development of a specialized pandemic stress scale (Taylor et al., 2020). Therefore, the relationship between EI and the unique stress of the COVID-19 pandemic may be different from the relationship between EI and other crisis situations. Hence, more research is needed to understand the relationship between EI and the COVID-19 pandemic stress among medical professionals as well as the broader population.

## *Statement of the Problem*

The COVID-19 pandemic has been a recent source of consequential, prolonged stress, unique from any other stressful event in the last 100 years. While abundant research demonstrates that emotional well-being was compromised due to COVID-19

(Crabtree et al., 2021; Hoerger et al., 2014; Rossi et al., 2020; Shigemura & Kurosawa, 2020), we know little about the specific effects the pandemic may have had had on emotional intelligence. EI is known to be a useful moderator and/or mediator of the effects of stress and crisis and to correlate with many other beneficial outcomes. If EI changed during the COVID-19 pandemic, there may be other related effects that would be useful for researchers to anticipate and investigate. If EI remained stable during the COVID-19 pandemic, this would lend indirect support to the theory that EI serves as a buffer for stress. Before further research can take place, we need a better understanding about what happened to EI during the pandemic.

### *Significance of the Study*

EI has been established as a critical skill with the ability to influence positive outcomes and mitigate challenging situations. However less is known about the impact of ongoing stress on EI. Understanding the impact of COVID-19 pandemic stress on EI will likely update the general theoretical knowledge of EI. Furthermore, learning how EI might have changed could have practical implications for moving forward in the wake of COVID. On the other hand, if EI does not change, recognizing its stability would be an important theoretical principle for EI researchers.

### *Purpose of the Study*

The purpose of this study is to investigate whether Emotional Intelligence among the general U.S. population changed during the COVID-19 pandemic, and if so, to investigate how it changed, to what degree, and among which demographic group(s).

# CHAPTER TWO

## Literature Review

As explained in Chapter One, EI has been established as a critical skill with the ability to influence positive outcomes and mitigate challenging situations. However, the study of emotions, and the awareness of their significance, has not always been central to the study of psychology. Rather, understanding the importance of emotions is a relatively recent phenomenon. The first section of this chapter provides a historical overview of the study of emotions, culminating in the emergence of emotional intelligence as a unique construct. The second section describes and compares different theories of EI. Section three summarizes the literature highlighting beneficial outcomes of EI, while sections four and five, respectively, present the relationship between EI and stress. Next, the experience of the COVID-19 pandemic is described as a unique, unprecedented source of stress. Finally, the research questions of this study are presented.

### *Historical Overview of the Study of Emotions*

When psychology emerged as a unique field of study, the investigation of mental processes was a key area of focus, and the earliest, most imminent psychologists attempted to understand and explain the experience and function of emotions. Wilhelm Wundt, considered the founder of the science of psychology, undertook research in the 1890s to categorize emotions. William James also developed a theory of emotion, and E. B. Titchener created a periodic table of psychology that included sensation, images and feelings (Benjamin, 2014). One might consider these studies to be the earliest roots of the self-awareness and self-regulation components of EI, constructs we will discuss later in more detail. Early psychologists also sought to define the construct of social intelligence. John Dewey first used the term in describing his view of the moral and social responsibilities of schools to equip students to engage their social settings (Dewey, 1909). Dewey's conceptualization of social intelligence was somewhat different than our modern understanding, which connects more closely with a construct Edward Thorndike described a few years later. As Thorndike outlined both the progress and the gaps in intelligence research, he listed three overarching intelligences, which he called mechanical, social, and abstract (Thorndike, 1920). Social intelligence is defined as "the ability to understand and manage men and women, boys and girls—to act wisely in human relations (Thorndike, 1920 p. 228). Among the three intelligences, he said, the greatest progress to date had been made in understanding abstract intelligence, and he admitted that means of measuring social intelligence were hard to devise.

Although the study of emotions, feelings, and consciousness was introduced early in the study of psychology, these areas of focus did not gain prominence at that time. This was partly due to the challenge of measuring these constructs (Thorndike, 1920). As Thorndike famously said, "Whatever exists at all exists in some amount. To know it thoroughly involves knowing its quantity as well as its quality" (Thorndike, 1918). To a fledging field seeking to establish itself, areas of study that lent themselves better (at least seemingly) to empirical assessment were prioritized (either consciously or unconsciously) over subjects that were harder to measure or could only be studied through introspection. In Thorndike's estimation, the assessment of social intelligence was hard (Thorndike, 1920). One way to understand the sidelining of emotions is to consider two other areas of focus that did take center stage in the U.S. which, by their very nature, pushed emotions to the fringe.

One of earliest forces to emerge as a popular application of psychology was the mental testing movement of the early 1900s. In 1910, Henry Goddard translated an intelligence test developed in France five years earlier by Alfred Binet and Theodore Simon, and by 1915, more than 22,000 copies of the test, along with 88,000 response booklets, had been distributed (Lagemann, 2000). To early psychologists attempting to establish their field as genuine, reputable, and applicable, the appeal of these mental tests was considerable. In fact, the appeal was so great that an instrument designed to proactively identify students needing special assistance, was (for a time) used to identify those who should be removed from society and/or prevented from having children based on their status as “morons” (Strickland, 2000, p. 333). Goddard and his colleagues eventually recanted this viewpoint, and the Stanford-Binet tests (as they had come to be known) were limited to educational purposes. From that point until now, standardized tests of intelligence have become the benchmark of measurement, and cognitive abilities have been hailed as *the* key performance indicator. Cognitive tests are used to measure achievement throughout elementary and secondary school and to qualify for entrance into college, graduate schools, and some jobs. Indeed, to demonstrate the importance of emotional acuity, the most powerful comparison writers could make was to name it EQ and compare it to IQ (Gibbs, 1995).

Due to the apparent success of the mental testing movement among students, the test-makers were called upon during World War I to develop aptitude tests for adults (Fancher, 1985). Between 1917 and 1918, around 1,750,000 men were tested using the

Army Alpha and Army Beta tests. Although the trial was too short-lived to be measured in terms of success or failure, it put intelligence testing on America's mental radar and linked the study of psychology and intelligence in the popular mindset, for better or for worse. Wechsler, who helped administer the Army Alpha tests, went on to create his own measures of intelligence for both adults and children, and his instrument eventually surpassed the Stanford-Binet in use (Robinson, 1999). Weschler himself referred to non-intellective abilities which comprised intelligent behavior—including affective and conative ability—and suggested that psychologists should create global measures of intelligence measuring affective and conative abilities along with cognitive abilities (Wechsler, 1943). However, while his theory and his research recommendations accounted for these abilities, his instrument did not. Verbal homage was paid to the importance of emotions while practical activity sidelined them.

A second force that pushed emotions to the fringe of psychology was a movement historians call "the behaviorist revolution" (Benjamin, 2014, p. 140). Sparked by John Watson's speech at Columbia University in 1913, which bemoaned the failure of psychology to establish itself as a serious science, behaviorists called upon psychology to abandon the study of consciousness and introspection in favor of the more objective study of outward behaviors. Initiated by Watson, the behaviorist movement became almost synonymous with B.F. Skinner, a name familiar in both the scientific and general populations. Skinner believed psychology could function without referring to mental processes (Benjamin, 2014). The functions of the so-called mental black-box were unimportant to the behaviorists, and they studied emotion only in regard to the behavior it produced. Behaviorism, B. F. Skinner especially, remained a strong influence in American psychology until the 1970s.

When psychologists finally returned in earnest to the investigation of the mind's inner workings, it was through the lens of cognitive psychology. Cognitive psychologists, like behaviorists, used empirical means to investigate the human experience, but they believed that the observation of external behavior could provide clues about mental processes (Ormrod, 2016). Although it is overly simplistic to say that psychologists viewed the human mind as a mere machine, the advent of computing in the 1960s influenced the theory and vocabulary of psychology. Mental processes were described in terms of input and output, vocabulary made familiar through computer jargon. Information processing theory, a means of explaining how people process and store information, borrows computer terminology as well. The field of psychology had finally asserted the authority to investigate mental processes in addition to outward behaviors. But cognitivism was a functional, process-based lens by which to study the human mind, and the study of emotions was still excluded.

Shortly after cognitive psychology began to broaden psychological inquiry from behavior to mental processes, the preeminence of IQ was finally challenged as well. Although, as mentioned, both Thorndike and Wechsler had defined and described various intelligences, these other intelligences had been left by the wayside in the effort to perfect measurement of IQ. Finally, in the 1980s, sixty years after Thorndike's article on multiple intelligences, a champion of multiple intelligences emerged. Howard Gardner's *Frame of Mind* (1983) challenged the singular view of intelligence, listing eight different types, among them, intrapersonal and interpersonal intelligence. Intrapersonal intelligence is defined as the ability to understand oneself, and interpersonal intelligence is the ability to understand others. Gardner did not specifically reference emotional intelligence, and his goal was to challenge a singular view of intelligence, not to particularly highlight the importance of emotions. Critics of Gardner's theory claim his definition of intelligence is too broad, encompassing personality, traits, skills, and abilities (Klein, 1997). The use of the word *intelligence,* where others might say ability, aptitude, or skill was a problem for Gardner's critics that would plague future EI researchers as well. His inclusion of kinesthetic and musical aptitudes clearly moved his discussion of intelligence out of the purely cognitive realm. Although Gardner focused broadly on intelligence and not emotion, we can see in his multiple intelligence theory, particularly the personal intelligences, an early foundation for the emotional intelligence theories that emerged a few years later.

Most researchers credit Salovey and Mayer (1990) as the originators of the emotional intelligence movement. Theirs was the first major academic publication to use the term, although others used it before them (Beldoch, 1964; Leuner, 1966; Payne, 1986). The inspiration for Daniel Goleman's book title, *Emotional Intelligence*, the book that popularized the study of emotional intelligence and put it on the cover of *Time* magazine (Gibbs, 1995), came directly from the Salovey and Mayer article (Goleman, 1995). There is no doubt that the feature article on Goleman's book in *Time* was the watershed moment in the development of emotional intelligence. However, the term EQ, used as shorthand for *emotional intelligence* on the cover of *Time*, was purposefully never used by Goleman, even though his title makes a direct comparison between emotional intelligence and IQ (Gibbs, 1995). Ironically, the term EQ was first used in

*Mensa*, a magazine most recognized for its focus on IQ (Beasley, 1987). In addition, Reuven Bar-On had also used the appellation EQ to refer to emotional intelligence prior to its popularization in *Time* (Bar-On, 2006). As a result of these simultaneously developing streams, crediting one individual as the “creator” of EI is difficult.

Another closely related line of research that helped bring the study of emotions to the forefront of scientific inquiry was simultaneously being conducted by neuroscientist Antonio Damasio. In his work with patients who had suffered brain injuries, Damasio noted that damage to the frontal region of the brain that processes emotions disabled decision-making, a phenomenon that occurred repeatedly with numerous patients (Damasio, 1994). In other words, Damasio saw that impairment of emotion also impaired the function of reason in the brain, even when attention, memory, language, and general intelligence continued to function at pre-injury levels. Although Damasio’s research was conducted among patients with brain injuries, the implications for healthy patients were immense. Emotions, according to Damasio, should not be considered as undesirable or even secondary. On the contrary, the healthy functioning of emotions was a critical component of daily logic and reasoning. Damasio’s research provided much-desired empirical evidence to underscore the importance of emotions and their function.

By the late 1980s and early 1990s, the study of emotions and emotional intelligence was no longer a sidenote in psychology. The centrality of their function in the reasoning process had been established through neuroscience. The construct of emotional intelligence had been defined and described in the peer reviewed literature. And the link between EI and important life outcomes had been demonstrated in both academic and popular literature. In the following sections, we will investigate these definitions and linkages in greater detail.

## *Theories of Emotional Intelligence*

Because research on emotions was conducted simultaneously by several different individuals or teams, multiple theories of EI have emerged in the research literature. At the broadest level, EI refers to the ability to understand and use emotions. Within each of the various streams of EI research, broad EI abilities are subdivided into a variety of different subdomains, with different emphases; yet common themes emerge. EI involves recognizing, understanding, expressing, managing, and harnessing or channeling emotions for practical purposes such as motivation and goal achievement (Cherniss, 2004). As we examine each model of EI, we will investigate the sub-domains of EI each model defines and emphasizes, beginning with Salovey and Mayer (1990). Although they were not necessarily the first to conceptualize EI, they were the first to publish a peer-reviewed journal article defining, describing, and endorsing it.

### *The Salovey and Mayer Theory of EI*

*Theory development.* As the first to attempt to carve out a nomological space for the construct of EI, Salovey and Mayer (1990) spent the entirety of their initial EI article defining intelligence in general and then the specific components of emotional intelligence. Although they believed themselves to be identifying a new construct, they clearly described how the components of EI already existed in the research space. Therefore, their goal was to unify an existing body of research spread across multiple disciplines. This idea of EI as a unifying umbrella or framework for existing constructs is critical to understanding the construct. EI detractors argue that EI is an unrelated set of abilities and/or that, even if they are related, simply grouping pre-existing constructs under one heading is not a valid means of defining a construct since it defies parsimony (Joseph et al., 2015; Joseph & Newman, 2010; Mayer et al., 2008). In light of such ongoing criticism, it is important to note that the earliest definition of EI described it as "a set of conceptually related mental processes involving emotional information," research for which was, at the time, "scattered without a guiding framework" (Salovey & Mayer, 1990, p. 190). Salovey and Mayer (1990) believed the construct of EI provided that framework. However, the question of which traits and abilities should be grouped under the umbrella of EI is still a matter of ongoing debate, and researchers differ in their opinions about which are legitimate and which are "eclectic" or "grab bag" (Joseph & Newman, 2010, p. 59; Mayer et al., 2008, p. 503). Continuing to clarify the nomological network of EI is an important task of EI researchers and one for which consensus still seems challenging. In the heat of the debate, researchers should bear in mind that, from its inception, the purpose of defining EI as a construct has been to conceptually integrate disparate strands of research on emotion to maximize their contribution to psychology (Salovey & Mayer, 1990).

Salovey and Mayer (1990) initially conceived of EI as a subset of social intelligence, reaffirming this position in later research (Mayer et al., 2016). Figure 2.1 below illustrates their initial theory.

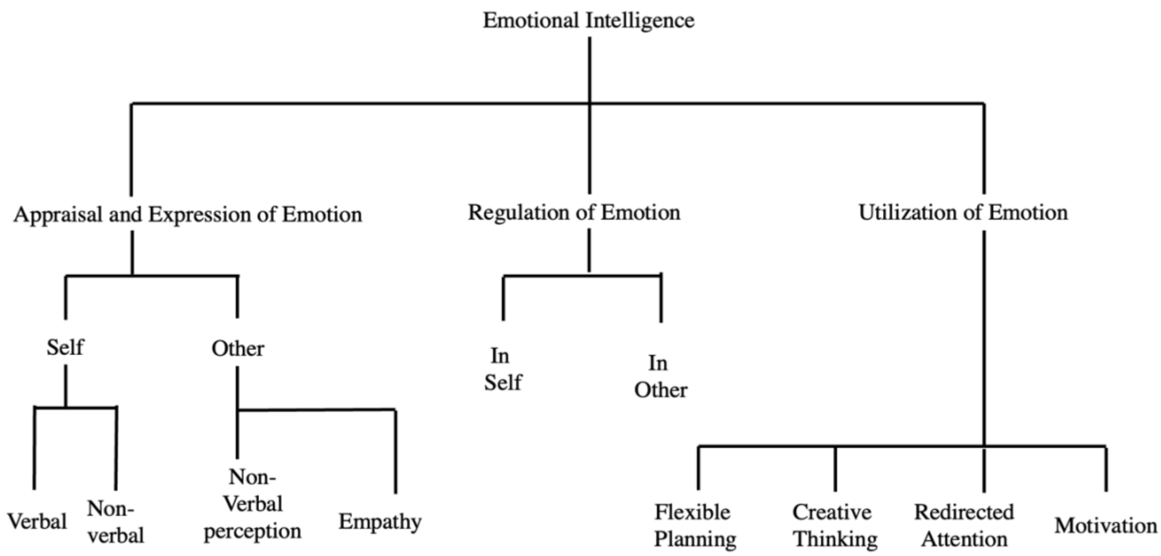



*Figure 2.1.* The Original Salovey-Mayer Model of Emotional Intelligence. This figure has been adapted from Salovey and Mayer (1990).

As mentioned before, while common themes emerge among the theories, the emphasis in each model is different. In the Salovey and Mayer (1990) original model, detailed attention was given to the EI branch of utilization, and it is subdivided into four subdomains, as shown in Figure 2.1. Although their original model evolved, the authors continued to emphasize the problem-solving function of EI (Mayer et al., 2016). A final key point to understand about Salovey and Mayer's initial concept of EI (1990) is that they believed differences in EI to be rooted in underlying skills that could be learned and/or improved.

*Refinement and instrument.* Having introduced an initial definition of EI, Salovey and Mayer, with colleagues, continued to refine and develop the construct. They revised their theory (Mayer & Salovey, 1997), and operationalized their model through an instrument called the Multifactor Emotional Intelligence Scale (MEIS; Mayer et al., 1999). After further research and pilot studies, the MEIS was revised to become the Mayer-Salovey-Caruso Emotional Intelligence Test (MSCEIT-RV1.1; Mayer et al., 2001), with a total of 292 items on 12 subscales. Further efforts to refine the MSCEIT produced the current version (MSCEIT 2.0; Mayer et al., 2003) which has 141 questions on 8 subscales, two scales for each of the following four branches: Perceiving Emotions, Facilitating Thought, Understanding Emotions, and Managing Emotions.

The questions on the MSCEIT consist of a variety of ability tasks. For example, participants are asked to rate emotional content in faces and pictures; to respond with how they feel toward fictional characters in various scenarios; to answer questions about blends of emotions; and to rate a variety of responses for their appropriateness in a series of brief, fictional vignettes. Consensus and expert scoring techniques are used to determine the accuracy of responses. Efforts to duplicate the reliability and validity studies of the authors have met with only partial success (Brannick et al., 2011; Gignac, 2005; Keele & Bell, 2008; Palmer et al., 2005; Rossen et al., 2008). These researchers all found consensus between normative and expert scoring but only partial support for the four-factor model due to the overestimation of fit by Salovey and Mayer. Both Palmer et al. (2005) and Brannick et al. (2011) found the most problems with the Facilitation branch and recommend a three-factor model. The MSCEIT authors admitted that mathematical evidence is lacking for the Facilitation branch but retain it based on theory (Mayer et al., 2016). Finally, an IRT examination of the MSCEIT suggested that it may not be appropriate for those with above average EI (Fiori et al., 2014). Only individuals with low levels of EI answered questions differently on the MSCEIT. Individuals with average and high levels of EI answered similarly, meaning that the MSCEIT was unable to distinguish between those with average and those with high levels of EI.

*Critique of other models.* Because the MSCEIT uses ability tasks to assess EI, its authors critique Bar-On and Goleman by name (models described in later sections) for including non-ability traits and dispositions within the EI framework. To describe these supposedly suboptimal frameworks, Mayer et al. (1999) introduce the term *mixed models*, suggesting that confounding variables have been mixed with pure EI, represented by their strictly ability-based model (p. 268). Interestingly, among the "confounding" components included by Bar-On and Goleman is motivation, which was part of Salovey and Mayer's own original model.

The term mixed model was picked up by later researchers trying to untangle the disparate threads of EI research, but not always in reference to the same cluster of EI theories, ironically perpetuating the confusion surrounding EI. We will further discuss the naming and classifying of EI theories at the end of this section. For now, it is useful to note that Salovey and Mayer (1990) are unique in linking EI to literal definitions of intelligence, arguing that any type of intelligence must be measured by performance and empirical standards and that self-report measures of EI are inappropriate.

*Strengths and limitations.* Both the strength and the limitation of the Salovey-Mayer model is that it relies on criterion measures of EI abilities, using items with right and wrong answers. By doing so, the researchers attempt to create as objective a measure of EI as is possible. However, there are still problems with this method of EI assessment. In the scenario-based EI examples, having one correct answer assumes that there is one best way of utilizing emotion in a given situation (Fiori et al., 2014). For example, suppressing anger may be a useful strategy for maintaining relationships, but it may not be effective if there is an underlying problem that needs to be addressed and is being ignored. The use of consensus and expert scoring is intended to provide a dependable standard against which to score individual respondents. However, the complexity of EI makes it difficult to determine with certainty which response is most accurate, because it is problematic to ignore the inherent subjectivity of emotion (Petrides, 2010). Unlike subjects such as math or spelling, EI is too complex for any assessment to be completely objective, no matter how much it attempts or claims to be.

*Additional insights.* The development of the MEIS and MSCEIT highlights another important point to keep in mind regarding EI: its definition, while mostly agreed-upon, is open to some degree of interpretation. Because EI is defined as a cluster of abilities drawn from a variety of disciplines (Salovey & Mayer, 1990), researchers are likely to differ somewhat in which abilities they cluster under the title of EI. Petrides and Furnham (2001) likened it to trying to determine which sports should be included in the Olympics: the question cannot be answered objectively. Critiques both within and without the camp of EI point to this divergence as de-ligitimizing EI as a whole or various streams (e.g. Waterhouse, 2006). The authors of the MSCEIT have been vocal in their criticism of other definitions of EI as being so “confounded” by non-EI variables as to “undercut the utility” of the constructs (Mayer et al., 1999, p. 268; Salovey & Mayer, 1990). Such a strict position is untenable. Although the variety of definitions is somewhat problematic, it should not cause researchers to throw out the baby with the bathwater, whether regarding EI as a whole or one of its prominent streams. It is true that consensus should be developed regarding the various labels given to kinds of EI, and researchers must clarify the nomological network in which EI is being situated. That said, even the most stringent of EI constructs has limitations and has undergone revision. Salovey and Mayer (1990) began with a three-branch model and revised it to a four-branch model, illustrating that, even in the minds of eminent EI researchers, the idea of what EI is and exactly what should be measured within its umbrella is not completely clear-cut. In addition, they initially included motivation and then criticized others for doing so (Mayer et al., 1999; Salovey & Mayer, 1990). Finally, as demonstrated above (and conceded by Mayer et al., (2016)) their current four-branch theory lacks empirical mathematical support for the Facilitation branch.

### *The Bar-On Theory of EI*

The Bar-On EQ-i is one of the most utilized workplace assessments of emotional intelligence (Bar-On, 2019). Bar-On's unpublished dissertation on EQ (1988) predates the publication of the Salovey and Mayer (1990) article that brought EI to the attention of the academic world.

*Theory development.* Reuven Bar-On began developing his theory of emotional intelligence during his doctoral work in South Africa (Bar-On, 1988). He credits the scholarship of Darwin, Thorndike, and Weschler as the theoretical foundation for his EI model. The role of Thorndike and Weschler in the general history of social and emotional intelligence has been discussed above. In addition, Bar-On extended Darwin's work on the need for emotional expression for survival and underscores the importance of emotion not just for surviving but also for thriving (Bar-On, 2010). A theoretical emphasis for

Bar-On is the connection between EI and psychological well-being, as indicated by the title of his dissertation (Bar-On, 1988). Over the years he continued to write about the connection between EI and facets of mental health (Bar-On, 2005, 2010). In addition, coping with daily demands and pressures is a key focus of Bar-On's theory, and this is borne out in the subdomains of his model: Two of five factors in his assessment are devoted to the use of emotion for daily life. The five factors are 1) intrapersonal EQ, 2) interpersonal EQ, 3) stress management EQ, 4) adaptability EQ, and 5) general mood EQ (Bar-On, 2000).

Although Bar-On at times uses the term emotional-social intelligence (ESI) (e.g. Bar-On, 2006), his instrument is called the Emotional *Quotient* Inventory (EQ-i, emphasis mine). Although Bar-On claims to have coined the name EQ in his dissertation (Bar-On, 2006), it was used previously by Mensa (Beasley, 1987). The term EQ became a household word when it was featured in the watershed *Time* magazine article (1995). The name is used frequently since it mirrors the familiar IQ and is often used interchangeably with EI. Bar-On defines EI this way, "[e]motional-social intelligence is an array of interrelated emotional and social competencies and skills that determine how effective individuals understand and express themselves, understand others and relate with them, and cope with daily demands, challenges, and pressures" (Bar-On, 2010, p. 57). What is important to note is that, while using the term *intelligence*, Bar-On describes EI as a set of competencies. Bar-On's intent was to measure emotionally and socially competent behaviors, not personality or cognitive abilities (Bar-On, 2000)

*Instrument.* The EQ-i is a 133-item self-report assessment, utilizing a five-point Likert-type response scale. Standardized scores are reported for overall EQ, five composite scales, and 15 sub-scales on a scale with 100 as the mean and a standard deviation of 15, to mirror the scores on IQ tests. Bar-On's model applies emotional abilities to both self and others, like the Salovey and Mayer (1990) model, and like them, he includes emotion recognition. Bar-On includes two "use" categories of adaptability and stress management, as compared to one branch that is subdivided in the Salovey and Mayer (1990) model.

*Strengths and limitations.* A strength of Bar-On's theory of EI is that it developed through practical interaction with clients in his work as a clinical psychologist, differentiating Bar-On's work from any of the other models described here. In addition to his work as a practitioner, Bar-On has committed considerable energy to research in support of his theory and instrument (Bar-On, 2000, 2006; Cherniss, 2004). Bar-On's assessment has received some attention in the academic literature, though less than the Salovey and Mayer model; a PsychInfo search for "Salovey and Mayer Emotional Intelligence" yields 1185 results as compared to 180 for "Bar-On Emotional Quotient Inventory."

### *The Goleman Theory of EI*

*Theory and goals.* As previously mentioned, Daniel Goleman's 1995 book *Emotional Intelligence* brought EI into the mainstream. Although Goleman earned a Ph.D. in psychology from Harvard University, he was not operating within the academic space at the time his book was published. Rather, he was working as a science reporter for the *New York Times*, writing about psychology for lay readers. As a scientist, Goleman grounded his book in empirical data; however, his goals were practitioner-focused rather than research-focused. Goleman wrote to address several confusing and/or dismaying trends. One of these was a global survey of parents and teachers showing a worldwide trend of emotional distress among children and teens. Another was what he calls the “disintegration of civility and safety” in the world, as witnessed by the number of public shootings, violence, and vandalism reported daily in the news. His imperative in writing was therefore first a moral one, and he wrote based on “growing evidence that fundamental ethical stances in life stem from underlying emotional capacities (Goleman, 1995, p. xxii). In other words, Goleman believed that a primary cause of the “disintegration of civility and safety” was a lack of “underlying emotional capacities.” He describes his purpose in writing as “a small gesture toward making the world a better place” (Goleman, 1995, p. xvii). To this same end, prior to writing his book, Goleman founded the Collaborative on Academic, Social, and Emotional Learning (CASEL), an organization working to facilitate social/emotional learning (SEL) among children. Goleman’s emphasis to this day remains on education and application, especially with children, arguing that the components of EI can be summarized in a single word: character. Finally, Goleman wrote to address the ironic truth that at times, those with high IQ do not achieve anticipated success while those with modest IQ accomplish surprising achievement. Goleman sought to account for this disparity, arguing that EI was often the differentiator.

It was this third goal that brought Goleman and EI notoriety. Over the years, claims about what EI can do have been misinterpreted, misrepresented, and often inflated. Along with other studies on IQ, Goleman cited Howard Gardner, who argued that the majority of a person’s life outcome is dependent on factors other than IQ.

According to Gardner (1995), only 20% of the variance in life situation can be accounted for by IQ; the remaining 80% is due to other factors. Although Goleman only claims that EI is *part* of the 80%, he is often quoted as saying EI accounts for the entire 80%, prompting him to make a direct disclaimer in the introduction to the twenty-fifth anniversary edition of his book. An additional claim of Goleman's regarding EI is that it can differentiate among those with high IQ. In other words, assuming that two employees are both above average in intelligence and skill, how can one account for differences in their achievement level? The answer, according to Goleman, is often EI.

*Model and instrument.* Goleman's model encompasses three levels: brain circuitry, domains of EI that emerge from the brain's circuitry, and competencies within those domains. In writing his book, Goleman relied, with permission, on research by Salovey and Mayer, most especially in using the title of their 1990 article as the title of his book (Paul, 1999). However, when listing the domains of EI, although he cited Salovey and Mayer (1990), he did not use their domains as shown in Figure 2.1. This tendency to draw on academic sources without strict adherence was, not surprisingly, a source of dismay for Salovey and Mayer (Paul, 1999), and it opened Goleman to much criticism from the academe, some justified and some extreme. Goleman outlined the following five categories of EI: 1) knowing one's emotions, 2) managing emotions, 3) motivating oneself, 4) recognizing emotions in others, and 5) handling relationships (Goleman, 1995, p. 43). In a *Harvard Business Review* article that is among their most-requested reprints, he updated the names of his categories: 1) self-awareness, 2) self-regulation, 3) motivation, 4) empathy, and 5) social skill (Goleman, 1998). In this article he defined the components as follows:

Self-Awareness: The ability to recognize and understand your moods, emotions, and drives, as well as their effect on others

Self-Regulation: The ability to control or redirect disruptive impulses and moods; the propensity to suspend judgment, to think before acting

Motivation: a passion to work for reasons that go beyond money or status; a propensity to pursue goals with energy and persistence

Empathy: the ability to understand the emotional makeup of other people; skill in treating people according to their emotional reactions

Social Skill: Proficiency in managing relationships and building networks; an ability to find common ground and build rapport

He eventually narrowed his five categories to four, with the parallel names of Self-Awareness, Self-Management, Social Awareness, and Relationship Management, subsuming motivation as a specific kind of self-management (Goleman, 2000). Although his primary intent was education, Goleman eventually developed an instrument, the Emotional Competence Inventory (ECI; Boyatzis et al., 1999), which measured 22 competencies. In 2007, the assessment was reconceptualized as the Emotional and Social Competency Inventory (ESCI), and the number of competencies assessed was reduced to 12; further edits were made in 2011 (Hay Group, 2011). The ECSI is a 360-degree assessment in which participants not only rate themselves but are also scored by peers and supervisors. Norms for the ECSI are drawn from a sample of 4,014 participants, rated by 42,092 respondents in 273 organizations.

Although Goleman's current model subsumes motivation within the other four categories, some who use Goleman's model retain motivation as a separate category.

There are a couple theoretical arguments for doing so. First, Goleman (1995) described EI as a kind of meta-ability, a skill that determines to what extent people can use their other abilities, such as intelligence. Likewise, motivation is to EI what EI is to other abilities. In other words, without motivation, someone may have self-regulation abilities but not use them. Because of its centrality to the function of EI, some researchers and practitioners have chosen to keep motivation separate, as Goleman did in his original model. In addition, motivation most strongly represents the achievement function of EI, as shown in the utilization branch of the Salovey and Mayer (1990) model or in the decision-making and stress management domains of the Bar-On Model (2006). Because motivation is sometimes a pre-cursor or facilitator of general self-regulation (Werner & Milyavskaya, 2019), some practitioners may feel that subsuming motivation into the self-regulation domain de-emphasizes its role in self-direction and goal-pursuit.

*Strengths and limitations.* One of the major strengths of Goleman's model is its simplicity. The simple repetition of "awareness" and "management" in the current domain names facilitates memory, which, despite being less important in research, is critical for application. Although basic, the categories also represent the major themes seen in the other models: recognizing, understanding, expressing, managing, and channeling emotion for practical purposes, such as motivation and goal achievement. Subdomains added into the four-branch model increase the level of specificity and detail. In addition, Goleman, like Bar-On, specifically identified the components of his model as competencies, which indicates the possibility that they can be taught and learned. In addition, the emphasis on EI as a behavior or competency drives practical application (Boyatzis, 2009, 2018). The primary limitation of this model is that it does not have as strong a representation in the academic literature as do the other models. Although based on research, its primary application has been in the business sector, where proprietary tools have limited the opportunity for scientific inquiry.

Opinion regarding Goleman's contribution to the field of EI is mixed. Some applaud his work, noting that the Salovey and Mayer (1990) article had received little attention until it was highlighted in Goleman's book. Others complain that turning EI into a household word has done it a disservice, muddying the construct definition and creating a cottage industry that impedes the progress of serious science. Regardless, Goleman provided a model that is accurate in essence and practical in application for practitioners with the requisite knowledge and skill.

### *The Petrides and Furnham Theory of EI*

*Theory and instrument.* The development of a fourth stream of EI research (Petrides, 2010) was based specifically on critiques of the ability and blended conceptualizations of EI. Petrides (2010) argued that ability EI, as defined by Salovey and Mayer (1990), ignored the subjective nature of emotions, while self-assessments of blended EI, such as the models proposed by Bar-On (2006) and Goleman (1995), could not be relied upon because they tapped self-perceptions rather than actual competencies. Instead, he says, EI facets should be viewed as personality traits, rather than cognitive abilities or social competencies. As such, EI facets may be assessed through self-report without violating psychometric principles. The operationalized assessment based on Petrides' EI theory is called the Trait Emotional Intelligence Questionnaire (TEIQue) and includes 15 traits: adaptability, assertiveness, emotion perception, emotion expression, emotion management, emotion regulation, impulsiveness (low), relationships, self-esteem, self-motivation, social awareness, stress management, empathy, happiness, and optimism (Petrides et al., 2007) . Using self-report items that tap into these 15 categories, the TEIQue is designed to support decisions about emotional self-efficacy. Its strength lies in its connection to an existing psychological taxonomy (the Big Five, or FFM) with a strong research base.

Petrides (2010) labels his theory of EI *trait EI*, in reference to the personality traits it encompasses. However, even though he conceptualized EI as trait-based and located it within the personality space, he also claimed EI encompasses self-perceived abilities (Petrides & Furnham, 2001). Furthermore, he argued that any assessment of EI that does not use a maximum-performance test is a measure of trait EI (as opposed to competency or ability), a description he contended encompassed every EI theory apart from Salovey and Mayer (1990) and most instruments except the MSCEIT. To illustrate his point, Petrides factor-analyzed Bar-On's EQ-i, demonstrating its correlation with the Five Factor Model of personality (Petrides & Furnham, 2001). In other words, according to Petrides and Furnham (2001), there are only two kinds of EI, ability and trait. Unfortunately, as with *mixed EI*, application of the term *trait EI* has not been uniform, in part because advocates of a competency-based model resist being labelled as a trait. We will return to the labeling and classification of EI streams at the end of this chapter.

Critics of trait EI argue that it does not offer additional information beyond personality. However, factor analysis of the TEIQue demonstrated that EI was a correlated yet unique factor from the Big Five (Petrides et al., 2007; Petrides & Furnham, 2001). As such, it theoretically does not represent a completely new construct but rather a lower order composite (Petrides and Furnham, 2001). In addition, the TEIQue demonstrated incremental predictive validity over and above the Big Five (Petrides, 2010, 2011; Petrides et al., 2007).

*Strengths and limitations.* The strength of Petrides' model lies in its efforts to address previous limitations and to situate EI within a known taxonomy. However, characterizing EI as a trait is problematic because EI presumably involves more than personality. Even the authors of trait EI theory nod to the ability stream by including "self-perceived abilities" within the scope of their theory (Petrides & Furnham, 2001, p. 425). In subsequent publications, Petrides et al. (2007) drop the word *abilities* and simply say "self-perceptions" (p. 273), perhaps recognizing the incongruity of using the word *ability* in a trait-only model. However, the shift they make is merely semantic because they continue to assess the same 15 traits.

An additional challenge with a trait-based approach to EI is that traits, including the Big Five, are understood to be expressed across a range of situations over a long period of time (McAdams & Pals, 2006). In their model of personality, McAdams & Pals (2006) describe three levels: dispositional traits, characteristic adaptations, and life narratives. Whereas traits are understood to be more stable over time, characteristic adaptations include qualities such as motivation, goal-orientation, and other social-cognitive adaptations. Characteristic adaptations are influenced by a person's traits but are more open to change. Indeed, they are shaped by and respond to "the social ecology of everyday life" (McAdams & Pals, 2006, p. 209). Based on this prominent theory of personality, it is our conclusion that EI is better categorized as a characteristic adaptation, rather than a trait.

*Classifying EI Streams*

There have been a variety of efforts to clarify and label the disparate strands of EI research. As mentioned above, Petrides and Furnham (2001) narrow the groupings to two types: ability and trait. Mayer et al. (1999) also list two types, their own ability EI model, and everything else, which they call "mixed." (Note that their classification was made prior to the 2001 publication of Petrides' trait EI Theory.) The *Encyclopedia of Applied Psychology* names three theoretical frameworks of EI: 1) Salovey-Mayer, 2) Goleman, and 3) Bar-On—a classification that does not include the Petrides and Furnham trait approach (Cherniss, 2004). Another three-stream classification of EI also leaves out trait EI (Ashkanasy & Daus, 2005), describing the following three classifications: 1) maximum-performance ability EI, 2) self-reported ability EI, and 3) mixed EI. The omission of trait EI in the latter two instances is perhaps because these reviews followed too closely on the heels of the Petrides and Furnham (2001) article for a research body to have been established. However, some later analyses continue to overlook trait EI or combine it with other approaches (e.g. Joseph et al., 2015). Proponents of ability EI and trait EI tend to be particularly critical of each other and of blended models of EI.

Given the diversity of theories and classification schemes, it is no wonder that critics of EI claim the construct lacks clarity or coherence and that even proponents of EI despair of reaching consensus regarding the nature of EI. Because of its blended nature, defining EI is a challenge: EI can be operationalized in terms of mental processes, behaviors, and outcomes (Matthews & Zeidner, 2000). However, as explained throughout this section, despite the differences in labeling and organizing the components of EI, there are coherent themes that emerge in all the theories. Recall the original objective of Salovey and Mayer (1990): to draw together the disparate strands of research on emotion into one coherent body that can impact the study of psychology. Although the definitive boundaries of EI may be fuzzy, a few core tenants are clear. Ongoing research is needed to continue clarifying the definition and nomological network of EI.

To help sort out the differences among strands of EI research and theory, some have suggested that new words be used. For example, models of EI that do not closely adhere to the traditional definition of intelligence might be relabeled as emotional competency or emotional efficacy (Joseph et al., 2015; Petrides & Furnham, 2001). Another suggestion is the term EQ, which is already familiar to many and is often used interchangeably with EI. However, since the terms *emotional intelligence* and *EQ* are commonly thought to refer to the same construct, it is unlikely the labels can be parsed in the public mind, even if researchers were to differentiate them. Still, developing consensus for vocabulary among researchers would be useful. Because traits are considered relatively stable and EI is considered trainable, we do not embrace the universal application of the term *trait EI* that Petrides and Furnham (2001) recommend; instead, we limit trait EI to their model alone. However, we do include their model in our classification, even though it is not in the *Encyclopedia of Applied Psychology* (Cherniss, 2004). For EI that draws on a variety of characteristics, we suggest the term *blended* is less pejorative than *mixed* and implies a sense of intentionality, which is in fact the case, for most blended EI researchers. Our classification of EI theories (often called *streams*) is shown in Table 2.1.

Table 2.1

*Classification of EI streams*

| Author(s) | Year | Instrument | Type | Response |
|---|---|---|---|---|
| Mayer, Salovey, & Caruso | 1990 | MSCEIT | Ability | Scored |
| Goleman | 1995 | ESCI | Blended | Self-report; 360 |
| Bar-On | 1997 | Bar-On EQ-i | Blended | Self-report |
| Petrides & Furnham | 2001 | TEIQue | Trait | Self-report |

*Note.* MSCEIT = Mayer-Salovey-Caruso Emotional Intelligence Test; ESCI = Emotional and Social Competency Inventory; EQ-i = Emotional Quotient Inventory; TEIQue = Trait Emotional Intelligence Questionnaire

### *Selecting an EI Theory*

In this study we will be using the Goleman (1995) model of EI. We have chosen this model for three primary reasons. First, as we will discuss in detail in Chapter 3, our population is the working community, with whom the Goleman model has most often been used and with whom its simplicity resonates. Second, because EI operates on such a variety of levels, including mental processes, behaviors, and outcomes (Matthews & Zeidner, 2000), a blended approach arguably best represents the construct. Finally, our view of EI is that it is malleable, a characteristic we will discuss more later in this chapter. Because EI is malleable, a blended EI model best fits this assertion theoretically, because cognitive abilities and traits are known to be more stable (i.e., less malleable). Researchers who embrace the concept of EI as a constellation of personality traits must sacrifice the idea that EI is malleable (McCrae, 2000). The disadvantage of selecting the Goleman model is that the reference body of peer-reviewed literature is smaller than for other models. However, this study will help contribute to that literature. Interestingly, the two streams with the strongest support in the academic literature are the ability and trait models, which most closely connect EI to IQ and personality. Given that EI has been criticized at times for offering little incremental validity over and above IQ and personality, it is ironic that more research attention and support have not been given to blended models. Research is needed on blended EI that can form a stronger foundation for it within the academic literature.

*Emotional Intelligence Correlates with Positive Life and Work Outcomes*

Following Goleman's bold claims about the importance of EI, numerous studies have explored the connection between high levels of EI and favorable outcomes in both life and work. As noted previously, a Google Search query for EI yields approximately 3,430,000 results. Several meta-analyses have been conducted to analyze and categorize this vast body of literature.

Much of the research on EI concerns its relationship with job outcomes. In a meta-analysis of 55 primary studies of EI and supervisor-rated job performance, both mixed EI and ability EI demonstrated a moderate positive correlation with job performance (Joseph et al., 2015). Mixed EI demonstrated a slightly larger correlation ($\hat{\rho}$=.29, *SD* =.13) than ability EI ($\hat{\rho}$=.20, *SD*=.03). According to the authors, this finding may be because ability EI captures more of the true intelligence aspect of EI, whereas mixed EI taps into a constellation of qualities and competencies known to correlate highly with job performance. EI is also connected with other means of assessing of job performance not included in the above meta-analysis, such as financial performance (Boyatzis, 2006), success in debt collection (Bachman et al., 2000a), client service in call centers (Higgs, 2004), client service among front-line retail service providers (Miao et al., 2019), leadership potential (Higgs & Aitken, 2003), and restaurant management performance as measured by performance ratings, satisfaction of the team, profit output, and customer satisfaction (Langhorn, 2004). EI can facilitate successful job outcomes in numerous ways. The ability to recognize and manage difficult emotions can help one navigate stressful and challenging assignments. Self-management toward goals can be helpful in accomplishing personal and company objectives. The ability to recognize and manage emotions in others is useful both in building relationships with peers as well as leading and managing direct reports.

Other research has explored the relationship between EI and academic outcomes, which has been an area of special interest due to Goleman's claim that EI can matter more than IQ in some cases (Goleman, 1995). A meta-analysis of 1276 effect sizes drawn from all streams of EI research revealed a small but significant relationship between EI and academic outcomes (MacCann et al., 2020). EI was among the top three predictors of academic achievement, after cognitive ability and conscientiousness. The overall test for the heterogeneity of effect sizes was significant ($p < .001$). Ability EI ($\hat{\rho}$=.24, 95% CI [.18, .30]) was a stronger predictor of academic performance than self-report ($\hat{\rho}$=.12, 95% CI [.07, .18]) or mixed EI ($\hat{\rho}$=.19, 95% CI [.15, .22]); however, after accounting for intelligence and personality, total ability EI and self-report ability EI provided very little incremental explanatory power. Only mixed EI and the understanding and management branches of ability EI provided incremental validity of EI over intelligence and personality; respectively, these explained an additional, 2.3%, 3.9%, and 3.6% of the variance. The authors suggest that the different outcomes for the various types of EI may be because the mechanisms for each type of EI work differently. The suggested mechanisms by which EI facilitates stronger academic performance are 1) management of challenging emotions such as boredom, overwhelm, or test anxiety, 2) facilitation of social relationships with teachers and peers that facilitate learning, and 3) emotion content knowledge.

EI has been associated with health and well-being outcomes as well. A meta-analysis of 44 effect sizes based on responses from 7898 participants demonstrated that high EI correlates with better health (Schutte et al., 2007). The weighted effect sizes were moderate and positive for physical health ($r=.22$, $SE= 0.070$, $p =.002$), mental health ($r=.29$, $SE= 0.026$, $p < .001$), and psychosomatic health ($r=.31$, $SE=0.038$, $p < .001$). These studies were conducted across a wide range of participants, including both men and women and both young people and adults. An extension of the above meta-analysis, adding 46 studies and 63 effect sizes, reported similar but slightly larger correlations for all three branches of health (Martins et al., 2010). EI encompasses the capacity to recognize, understand, and manage emotions, and these abilities may help avert mental health problems. These abilities may also impact the degree to which psychosomatic symptoms are experienced. EI has also been shown to correlate with subjective well-being (Sánchez-Álvarez et al., 2016). This is likely due to a twofold benefit whereby EI reduces the frequency and duration of negative emotions while increasing the frequency and duration of positive emotions. Although the relationship between EI and health outcomes is now well-established, more work needs to be done to investigate the incremental validity of EI over other factors, such cognitive abilities (Martins et al., 2010).

The benefits of EI have been demonstrated across the lifespan, from the teenage years to old age. A meta-analysis of 41 studies investigating EI and subjective well-being among adolescents revealed a moderate, positive relationship between EI and both affective and cognitive well-being (Llamas-Díaz et al., 2022). In the analysis, effect sizes from 24 articles regarding affective well-being were analyzed using a random effects model (estimated effect size = .35, *SE* = 0.03, $p < .001$; although most of the articles reviewed reported correlations, these authors do not report a specific type of effect in their meta-analysis). In addition, effect sizes from 23 articles regarding cognitive well-being were analyzed, again using a random effects model (estimated effect size = .27, *SE* = 0.02, $p < .001$). Every study in the analysis that utilized an EI self-report ability model or a self-report mixed model indicated a significant positive relationship with subjective wellbeing, but none of the studies using a performance-based ability model showed a significant correlation. At the opposite end of the lifespan continuum, EI skills increased life satisfaction and resilience among older adults (Delhom et al., 2020). EI has also been linked with greater romantic relationship satisfaction (Jardine et al., 2022).

### *Emotional Intelligence Can Mitigate Stress and Burnout*

EI not only correlates with multiple positive outcomes, it also helps mitigate a variety of negative outcomes such as stress and burnout. Considering the research cited above linking EI and mental health, it is unsurprising that the role of EI in buffering stress has been investigated. This relationship between EI and stress has been studied in both experimental and contextual situations, and there is a considerable body of research demonstrating the benefits of EI for mitigating stress. In fact, meta-analyses and systematic reviews have examined EI as a protective factor against negative outcomes. A systematic review of 16 peer-reviewed reports in the medical literature highlighted two studies linking higher EI and effective coping with organizational pressures and leadership (Arora et al., 2010). In one study, there was a significant negative relationship between EI and perceived stress in the workplace ($r$ = -0.23, $p < .001$, no S.E. reported) as well as a negative correlation with depression ($r$ = -0.28, $p < .001$, no S.E. reported). In another study, EI correlated significantly with coping ability ($r$ = 0.319, $p < .01$, no S.E. reported). Another systematic review compiled research on resilience to emotional distress in response to failure, investigating EI along with several other factors, such as self-esteem, attributional style, perfectionism, and reappraisal. Of the 46 studies in the review, two highlighted EI, with partial evidence for the role of emotional intelligence in bolstering resilience to failure (Johnson et al., 2017). A review of 36 studies targeting EI in sport did not report effect sizes; however, the authors concluded that high EI can serve a protective role against stress among athletes (Laborde et al., 2016). A systematic review of 45 studies investigated two aspects of stress response: 1) immediate reactivity during the stressful event and 2) ability to recover after the stressful event (Lea et al., 2019). Mixed results were found in the level of reactivity to stress, depending on the type of stressor and the type of EI being measured (trait or ability). Trait EI was useful in buffering reactivity to sports-based stressors but did not buffer physiological response to cognitive stressors. Relatively few studies investigating ability EI were found, and in most cases ability EI was non-significant in buffering stress reactivity. However, regardless of the type of stress or EI, those with high EI were seen to recover more quickly from the stress-inducing situations (Lea et al., 2019).

Medical professionals have been a group of ongoing interest and concern for EI researchers, and a variety of individual studies have been conducted following the above-cited meta-analysis. In an investigation of the protective effects of EI among nurses, trait EI was negatively associated with burnout and somatic complaints (Mikolajczak et al., 2007). EI explained 34% of the burnout variance and demonstrated incremental validity over and above the Five Factor Model (FFM) of personality, adding 4-8% to the FFM predictions. Demonstrating the incremental predictive validity of EI over personality is an important piece of evidence supporting the unique construct validity of EI, especially since some detractors consider EI to be nothing more than an aspect of personality. In another study, a moderated hierarchical regression analysis was performed to investigate the relationship between EI, burnout, and emotions for 188 female nurses in Poland (Szczygiel & Mikolajczak, 2018). Anger-related emotions predicted greater burnout among nurses with low-trait-EI ($\beta = 0.56$, $p < .01$, no S.E. reported), but not among nurses with high trait-EI ($\beta = 0.15$, $p = .37$, no S.E. reported). Similarly, greater burnout was predicted by sadness-related emotions among nurses with low trait-EI ($\beta = 0.66$, $p < .001$, no S.E. reported) but not among nurses high in trait EI ($\beta = -0.08$, $p = .65$, no S.E. reported). These results suggest that the relationship between negative emotions and burnout may be buffered by higher levels of EI. Among a group of 110 medical interns, self-reported EI was significantly related to lower burnout ($\varphi = -.73$, $p < .001$, no S.E. reported) and greater job satisfaction ($\varphi = .52$, $p < .01$, no S.E. reported) (Weng et al., 2011).

The relationship between EI and stress has been investigated among workers in other high-intensity roles as well. A study of occupational distress among refugee resettlement workers, a job recognized as being emotionally taxing, found that EI had significant direct and indirect effects on stress and burnout, moderated by an individual's choice of coping mechanism (Espinosa et al., 2019). Similarly, a regression analysis of responses from 80 police officers in India showed a negative relationship between emotional intelligence and operational stress EI ($\hat{\beta}$= -0.354, $p < .01$).

To isolate the effects of EI and minimize confounding variables, the relationship between EI and stress has been investigated experimentally. In a series of three lab studies, participants in the experimental condition were assessed for negative and positive affect, along with EI, then asked to perform a stress-inducing task such as public speaking or test-taking. In the pooled results, there was a significant interaction effect between trait EI and both positive affect ($F_{(1, 183)} = 8.15$, $p < .01$, adjusted $R^2 = .60$) and negative affect change ($F_{(1, 179)} = 14.50$, $p < .001$, adjusted $R^2 = .64$) (Mikolajczak et al., 2009). The experimental study used effective stress manipulation, controlled for confounding variables, and assessed both positive and negative affect.

The studies above demonstrate EI's potential for protecting against stress and burnout. There are most likely several mechanisms by which EI facilitates resilience to stress. First, better self-awareness through EI may provide the opportunity for a person to intervene at an early stage in their emotional response, before stress has built to an unmanageable level. In addition, self-regulation, the ability to manage one's own emotions, generally includes knowledge of a variety of coping strategies, both physical and mental, which can ameliorate both bodily and cognitive stress responses. The EI factor of social awareness can help those with higher EI recognize how others around them are coping—especially important if the stressor impacts a group, not just the individual—and prevent the person from being blindsided by unexpected emotions and responses from peers. Finally, the ability to socially regulate others may help mitigate stress by enabling an individual to de-escalate stress brought on by other people. In addition, facility with social skills may enable those with high EI to seek help from those around them.

Fortunately, some of these mechanisms have been tested. EI may improve self-efficacy during stressful events (Mikolajczak et al., 2009). Both during and after a stressful event, the ability to reframe one's perspective may help reduce stress. Those with high levels of EI may be better able to delay gratification (Fiori et al., 2014), which may be necessary during periods of intense stress. High levels of EI are associated with the ability to build social relationships in a variety of contexts (MacCann et al., 2020); therefore, those with high levels of EI may be better able to draw upon social support during times of stress. And EI likely facilitates efficacious choice of coping strategy (Matthews & Zeidner, 2000).

*Potential Impact of Stress on EI*

Although abundant research exists demonstrating the buffering effect of EI on stress, there are some cases in which stress may adversely impact EI. Particularly in the medical education context, EI may decrease under certain circumstances. An investigation of EI among 64 students at the University of Kentucky College of Medicine showed that two dimensions of EI, attention to feelings (4.12 [T1], 3.97 [T2], $p \leq .05$, no S.E. reported) and mood repair (4.19 [T1], 3.90 [T2], $p < .001$, no S.E. reported), were significantly lower during the third year of medical school than they were during the first (Stratton et al., 2008). These results are important because third-year medical students take part in clinical placements; in other words, in the third year, students begin interacting with patients, a critical threshold when EI is of uttermost importance. In another study, scores for empathy, one component of EI, decreased significantly, on average, for 125 third-year medical students between testing at the beginning and end of the academic year ($d = 0.29$, $p < .05$), (Hojat et al., 2004). A longitudinal study assessed the visceral empathy (as compared with cognitive empathy) of four cohorts of medical students at the beginning of each of their four years of medical school and then once after graduation (Newton et al., 2008). Visceral empathy was, on average, significantly lower ($p < .001$) at the start of the senior year ($M = 34.38$, $SD = 29.07$) than it was at the start of the freshman year ($M = 46.25$, $SD = 24.82$), a change which included both men and women, core and non-core specializations. A similar decrease in empathy was seen among dental students when assessed across their four years of medical training (Sherman, 2005). EI has also been shown to decrease for students in other health care professions. In a study investigating the EI of 109 therapy students (occupational, physical, and speech) during clinical placements, several aspects of EI declined (Gribble et al., 2017). Although only one aspect (assertiveness) declined in a statistically significant way, none of the students' EI scores increased, and scores in five categories decreased by more than five points for at least one-third of the students. In addition to the high levels of stress and anxiety experienced during medical school, the experience of fluctuating social relationships, isolation, long hours, continued exposure to human suffering, and the disparity between the idealized version of doctors in the media and the reality experienced in school may contribute to the decline in empathy and overall EI (Newton et al., 2008; Spencer, 2004).

Though limited in scope, the above research highlights an important principle of EI. While EI is most often seen to provide a protective effect against stress, there are at least some situations in which the reverse may happen. In the case of health care students, the changes in empathy occurred in extremely high-stress situations characterized by long hours, changing social relationships, isolation, and the ongoing reality of human suffering. While we cannot generalize the above findings to other populations, the results provide a rationale for asking questions about EI and its potential for change. If the situational factors cited above were imposed on another population, what might happen to EI? The events of 2019 and 2020 created an extremely similar crucible for the general population.

### *The COVID-19 Pandemic*

The outbreak of COVID-19 and the ensuing pandemic created a crisis unparalleled for a century in scope, breadth, and duration. Globally, the entire population endured multiple sources of mental threat and distress. First was the fear of getting sick, both for oneself and for loved ones. As businesses shut down, many experienced the loss of a job, and others feared they would. As a result of protective measures, the population experienced isolation from friends and society. Ongoing quarantine produced challenges at home. For some, being isolated continuously with the same small group of people was a source of stress, and constant togetherness took a toll on some marriages. Those who continued to work experienced a lack of separation between work and personal life. Some people reported working longer hours because the lack of separation made it easy to slide back into emails and calls in the evening. While working from home, some were trying to take care of preschoolers while others were suddenly “home schooling” older children. Those in apartments or small houses did not have space to separate these activities; therefore, two adults and multiple students might all be on video or telephone calls in the same room. Many experienced confusion and fear because of the differences of opinion of various medical experts, politicians, and peers. And tragically, for many, the ultimate loss of a loved one was a devastating reality.

These conditions, while not identical to those experienced by the medical students in the studies cited above, present some striking similarities. These include isolation, fluctuating social relationships, prolonged stress, ongoing exposure to human suffering, and potential disillusionment when experts are recognized as being flawed humans rather than immutable heroes. These factors had the potential to interrupt the mechanisms described above by which EI helps to mitigate stress. For example, the ability to self-regulate may have been impacted when the choice of coping strategies was limited by the lockdown. Individuals typically high in social awareness may have struggled to maintain this awareness during social distancing. Similarly, strategies for effective relationship management that worked in person prior to the pandemic may have been less effective when connecting through technology. In each of these instances, the interruption of familiar mechanisms may have had an impact on EI. There is some research into the relationship between COVID and emotional well-being, but more is needed. In particular, there is limited research on the relationship between COVID and emotional intelligence.

### *Research Questions*

While the COVID-19 pandemic is well-recognized as a source of unprecedented stress with implications for emotional well-being, continued research is needed to understand the specific effects. Particularly, more research is needed to understand the relationship between the pandemic and EI. In our analysis, we will explore the variance in EI across both known and unknown subpopulations. The guiding research questions for this study are exploratory in nature. They are as follows:

1) Does EI differ before and after the onset of the COVID-19 pandemic?
2) Are there identifiable latent, homogenous groups of working adults on the basis of EI profiles?
3) Are there differences in the demographic characteristics in latent profile membership before and after the onset of the COVID-19 pandemic?

*Summary*

In this chapter, we have provided an overview of how the study of emotions moved from the sideline to the center of psychological inquiry. We have described the major streams of EI research and their theories. EI is now a well-established construct in the academic literature, even though there are a variety of definitions and conceptualizations. In addition, EI has been linked to a variety of positive life outcomes. In particular, EI has been shown to mitigate the effects of stress and burnout. However, in at least one population, prolonged stress has adversely impacted EI. These disparate outcomes illustrate the need for ongoing research into the relationship between EI and stressful conditions.

The recent COVID-19 created a crisis unique in scope, breadth, and duration. Understanding the relationship between COVID-19 pandemic stress and EI will likely update the general theoretical knowledge of EI. Furthermore, learning how EI might have changed could have practical implications for moving forward in the wake of COVID. On the other hand, if EI does not change, recognizing its stability would be an important theoretical principle for EI researchers.

In our study, we will be using the Goleman model of EI to examine the relationship between the COVID-19 pandemic and EI. Because our population may contain unobserved heterogeneity, we will utilize finite mixture modeling to examine EI both before and after the onset of the COVID-19 pandemic.

# CHAPTER THREE

## Method

The problem addressed in this study is the lack of information regarding the relationship between the recent COVID-19 pandemic and EI. Previous research shows that EI correlates with positive outcomes and mitigates some potential negative outcomes such as the impact of stress and burnout. At the same time, stress has been shown to impact EI in at least one population, in educational settings for specialized medical degrees (e.g., physicians, dentists, physical therapists). The decrease in EI experienced by medical students may stem, at least in part, from prolonged intense stress and ongoing exposure to human suffering, conditions experienced on a global scale during the COVID-19 pandemic. Because the COVID-19 pandemic was an unprecedented source of stress, research attention is needed to understand more about its relationship to mental health and EI. In this chapter, we provide a description and justification for the methodology employed in this investigation of potential differences in EI before and after the onset of the pandemic among both known and unknown populations.

### *Research Questions*

The guiding research questions for this study are:

1) Does EI differ before and after the onset of the COVID-19 pandemic?
2) Are there identifiable latent, homogenous groups of working adults on the basis of EI profiles?

3) If latent profiles are detected, are there differences in the demographic characteristics in latent profile membership before and after the onset of the COVID-19 pandemic?

To answer these research questions, the following research objectives must also be met:

1) establish the dates of usable data and data considered to be onset of COVID-19 pandemic;
2) investigate and establish invariance in the latent factor structure of EI dimensions across time, which extended before and after the onset of the COVID-19 pandemic;
3) examine the frequency and distributional forms of underlying latent profiles on the basis of EI domains;
    a. depending on the latent profile enumeration, investigate and establish invariance in the latent profile structure of EI before and after the onset of the COVID-19 pandemic.

### *Dates for Sample Inclusion & COVID-19 Onset*

To complete this study, we used a survey design with data provided by the test developer, Target Training International (TTI). When conducting survey research, collecting responses that represent the underlying population(s) is an important component of research design to ensure high quality data (Kapteyn et al., 2020). To this end, we partnered with TTI because of the broad scope of their data collection and wide range of demographic populations assessed in previous samples.

The start date for our analytic sample was predetermined by the availability of demographic data, which began in April 2018 and continued until December 2022.

Determining which date constituted post-pandemic-onset was not a straightforward decision. The World Health Organization officially declared a pandemic (Ghebreyesus, 2020) on March 11, 2020. However, the true nature of crisis was arguably not fully evident on March 11, and changes in EI would not have been instantaneous. Between March and May of 2020, closures and social distancing were seen as efforts to "flatten the curve," with multiple states beginning "phased re-openings" throughout May. Phased re-openings led to a resurgence in COVID-19 cases (Berger, 2020; Bosman & Smith, 2020). Schools began announcing a continuation of online instruction for the fall ("School Districts' Reopening Plans," 2020), and many businesses postponed returning to the office (Dienst, 2020). In June 2020, the CDC found that U.S. adults reported considerably worse mental health than in previous years (Czeisler, 2020). We contend here that the time between March and August could all be reasonably considered as the period during which the onset was experienced. For reporting purposes, we collapsed time into 6-month time blocks, with the block from March to August of 2020 considered as the onset of COVID-19. Using a six-month block as the *onset* allows time for the optimism of a quick solution to have passed and the reality of the ongoing nature of the COVID-19 pandemic to have set in. More detail on how time was modeled is provided in the Data Analysis section.

### *Analytic Sample*

The population of interest in this study is the working-age population of the United States. The analytic sample consisted of participants who responded to the TTI EQ survey between April 30, 2018 and December 31, 2022. The rationale for selecting these dates is that they provide opportunity for a wide range of responses (i.e., approximately 30 months) both before and after the onset of the COVID-19 pandemic. All response data were de-identified by TTI prior to transmission to the research team. Additionally, these data were stored in an encrypted online data storage directory with dual-authentication log-in requirements. The Baylor University IRB has reviewed the research plan and data security plan, and the research has been classified as "Exempt" (Reference # 2011402). The demographic variables provided by TTI included year born, employment status, ethnicity, veteran status, disability status, education level, ZIP code, industry, and gender. We were also interested in examining the potential differences on the basis of geography. To conduct this analysis, the urbanicity codes for each U.S. ZIP code were obtained from the most current available U.S. Census Bureau (i.e., 2010). The urbanicity codes for rural, suburban, and urban were matched to the ZIP codes in the file obtained from TTI.

### *Inclusion and Exclusion Criteria*

The file received from the test developer contained the observations from 108,982 respondents; however, only the data that met the inclusion criteria were analyzed. To be included, cases must have met the following criteria: (1) complete data for all items, (2) a participant aged 18 or older, and (3) have a valid U.S. ZIP code. Additionally, cases for whom the birth year was prior to 1923 were excluded. After applying these criteria, final analytic sample included 33,875 cases.

### *Analysis of Excluded Cases*

Before proceeding with the statistical analyses of the analytic sample, we compared the EI domains of the observations that were excluded against those that were included. In light of the volume of data, even very small, practically trivial differences in EI domain means were expected to be statistically significant (i.e., $p < .05$). Therefore, effect size estimates using Cohen's *d* were examined.

### *Sample Demographics*

Descriptive analyses were conducted to describe the sample using IBM SPSS Statistics Version 28.0.1.1. A univariate frequency distribution was generated for the following demographic variables of interest: age, ethnicity, employment status, education level, gender, industry, and urbanicity (see Table 4.2). Demographic information on disability and veteran status was collected but not reported because the group size was small and not of interest in this study.

Table 3.1

*Demographic Characteristics of the Analytic Sample*

| Demographic Group | *n* | % |
|---|---|---|
| Age | | |
| 18-24 | 1584 | 4.7% |
| 25-34 | 7254 | 21.4% |
| 35-44 | 9665 | 28.5% |
| 45-54 | 8781 | 25.9% |
| 55-64 | 5443 | 16.1% |
| 65 and over | 1148 | 3.4% |
| Employment Status | | |
| Employed | 29178 | 86.1% |
| Self-Employed | 3300 | 9.7% |
| Not employed, looking | 616 | 1.8% |
| [a]Not employed, not looking | 277 | 0.8% |
| Student | 504 | 1.5% |
| Ethnicity | | |
| African American | 1840 | 5.4% |
| Native American or Alaskan Native | 149 | 0.4% |
| Asian | 1311 | 3.9% |
| Caucasian | 26323 | 77.7% |
| Hispanic or Latino | 2511 | 7.4% |

| Demographic Group | *n* | % |
|---|---|---|
| Pacific Islander | 69 | 0.2% |
| Two or More Races | 888 | 2.6% |
| Other | 784 | 2.3% |
| Education | | |
| [b]Less than a high school diploma | 218 | 0.6% |
| High school | 1995 | 5.9% |
| [c]Some college | 7669 | 22.6% |
| Bachelor’s degree | 13954 | 41.2% |
| Master’s degree | 7203 | 21.3% |
| Professional or doctoral degree | 2836 | 8.4% |
| [d]Gender | | |
| Male | 17442 | 51.5% |
| Female | 16433 | 48.5% |
| Urbanicity | | |
| Urban | 30771 | 90.8% |
| Large rural | 1728 | 5.1% |
| Small rural | 603 | 1.8% |
| Isolated | 439 | 1.3% |
| [e]N/A | 334 | 1.0% |
| Industry/Occupation | | |
| Architecture and Engineering | 1549 | 4.6% |
| Arts, Design, Entertainment, Sports, and Media | 1003 | 3.0% |
| Building and Grounds Cleaning and Maintenance | 220 | 0.6% |
| Business and Financial Operations | 4944 | 14.6% |
| Community and Social Service | 1103 | 3.3% |
| Computer and Mathematical | 1805 | 5.3% |
| Construction and Extraction | 1348 | 4.0% |
| Education, Training, and Library | 1757 | 5.2% |
| Farming, Fishing, and Forestry | 101 | 0.3% |
| Food Preparation and Serving Related | 335 | 1.0% |
| Healthcare Practitioners and Technical | 2876 | 8.5% |
| Healthcare Support | 1012 | 3.0% |
| Installation, Maintenance, and Repair | 522 | 1.5% |
| Legal | 480 | 1.4% |
| Life, Physical, and Social Science | 538 | 1.6% |
| Management | 6028 | 17.8% |
| Military Specific | 36 | 0.1% |
| Office and Administrative Support | 1815 | 5.4% |
| Personal Care and Service | 262 | 0.8% |
| Production | 805 | 2.4% |
| Protective Service | 403 | 1.2% |
| Sales and Related | 4293 | 12.7% |
| Transportation and Material Moving | 630 | 1.9% |
| None of the above | 10 | 0.0% |

[a]Includes the following responses: out of work, not looking; homemaker; retired; unable to

[b]Includes the following responses: no schooling, nursery school to 8th grade; 9th, 10th, or 11th grade; 12th grade, no diploma
[c]Includes the following responses: some college credit but less than 1 year; 1 or more years of college, no degree; associate degree or certifications
[d]Prior to July 2022, male and female were the only options offered by the assessment provider for the gender pronouns. Beginning July 2022, participants were asked to report their preferred gender pronouns (i.e., he/his, she/her, they/their). Because most of our data collection occurred prior to July 2022, we opted to utilize only these two categories. Future studies could utilize the provider's more inclusive gender demographics.
[e]334 participants reported all demographic data except zip and were included because they comprised only 1% of the sample. Zip codes were categorized according to the USDA Rural-Urban Commuting Area Codes.

### *Instrumentation*

The TTI EQ instrument (Gehrig & Bonnstetter, 2019) is based on Goleman's (1995) EI theory and consists of the following dimensions: Self-Awareness (SA), Self-Regulation (SR), Social Awareness (SoA), Social Regulation (SoR), and Motivation (M). The content validity of the instrument was addressed by using subject matter experts (SMEs) on test development internal to TTI and SMEs on emotional intelligence from outside the organization. Definitions for each of these dimensions are as follows:

Self-Awareness (SA)—The ability to recognize and understand your moods, emotions, and drives, as well as their effect on others

Self-Regulation (SR)—The ability to control or redirect disruptive impulses and moods and the propensity to suspend judgment and think before acting

Social Awareness (SoA)—The ability to understand the emotional makeup of other people and how your words and actions affect others

Social Regulation (SoR)—The ability to influence the emotional clarity of others through a proficiency in managing relationships and building networks

Motivation (M)—A passion to work for reasons that go beyond the external drive for knowledge, utility, surroundings, helping others, power, or methodology and are based on an internal drive or propensity to pursue goals with energy and persistence

The TTI EQ instrument consists of 40 items that each use a six-point Likert-type response scale, on which participants are asked to rate the degree to which each statement describes them. Responses range from 1 to 6, with 1 being “very inaccurate” and 6 being “very accurate.” Statements like the following are included on the survey (note that these are not actual items on the TTI EQ instrument): “I can recognize how my emotions impact my performance,” and “When a friend or co-worker experiences intense emotion, I can offer support.”

The TTI EQ instrument is administered and scored online on both standard and mobile platforms. A composite EQ score ranging from 0-100 is calculated based on all 40 responses. In addition, subscores are tallied for each of the five dimensions, based on eight items each. Results are distributed to participants by TTI associates who are certified in EQ theory, meaning they have attended EQ training and passed a certification exam. The scoring algorithms are proprietary, but we will estimate latent trait scores on the EI dimensions from confirmatory factor analysis.

Numerous reliability and validity studies been conducted on the TTI EQ instrument by their internal research team. The most recent internal analysis (Gehrig & Bonnstetter, 2019) was based on 27,000 responses. The item-total correlations for the Self-Awareness dimension ranged from .40 to .59 with an internal consistency estimate ($\alpha$) of .77. The item-total correlations for the Self-Regulation dimension ranged from .31 to .59 with an internal consistency estimate ($\alpha$) of .75. The item-total correlations for the Motivation dimension ranged from .41 to .58 with an internal consistency estimate ($\alpha$) of

.79. The item-total correlations for the Social Awareness dimension ranged from .32 to .56 with an internal consistency estimate ($\alpha$) of .78. The item-total correlations for the Social Regulation dimension ranged from .46 to .62 with an internal consistency estimate ($\alpha$) of .78. All these estimates were considered acceptable. Generalizability theory was used to estimate test-retest reliability using the generalizability and dependability indices (see Table 3.2).

Table 3.2

*Test-Retest Reliability, TTI Emotional Quotient, 12/16/2014 to 05/07/2018*

| Scale | Generalizability | Dependability |
|---|---|---|
| Self-Awareness | 0.71 | 0.69 |
| Self-Regulation | 0.70 | 0.62 |
| Motivation | 0.71 | 0.68 |
| Social Awareness | 0.75 | 0.71 |
| Social Regulation | 0.75 | 0.71 |

## *Data Analysis*

### *Descriptive Analyses*

Descriptive analyses were first conducted to describe the sample. The EI domain scores were each described using the mean, standard deviation, skewness, and kurtosis. Next, we conducted basic item analysis based on classical test theory (CTT), including estimation of the item means, item-total correlations, and reliability coefficients (i.e., coefficient $\alpha$). These analyses were performed with the entire analytic sample using IBM SPSS Statistics (Version 28).

*Confirmatory Factor Analysis*

Following the descriptive analysis, we investigated the structural validity of the instrument through confirmatory factor analysis (CFA) using the entire analytic sample. Reviewing the fit from the entire sample was an important first step to understanding the dimensional structure of the instrument before proceeding to subsequent analyses. CFA is a means of testing a measurement theory by comparing a theoretical model to reality (i.e., the sample data) (Hair, 2010). Mathematically, this is accomplished by using the hypothesized model to recreate the variance-covariance matrix of the data, and then comparing the fit using a variety of indices. Because each of the fit indices has strengths and drawbacks, it is recommended that several be used in tandem, with the following recommendation: comparative fit index (CFI) $\geq .95$, root mean square error of approximation (RMSEA) $\leq .06$, and standardized root mean residual (SRMR) $\leq .08$ (Hu & Bentler, 1999). Although $\chi^2$ is the traditional measure of model fit, it is known to be inflated by sample size (Brown, 2015). Because of our large sample size, $\chi^2$ results were interpreted in light of the statistic's limitations. It should be noted that the CFA fit index performance has not been systematically investigated in samples as large as the analytic sample for this study, so the conventional interpretive guidelines cited above may not apply.

The CFA model contained the five EI dimensions, each of which was measured by eight items. Given the ordinal nature of the item-level data, we used a categorical estimator (e.g., DWLS) that has been shown to yield trustworthy fit statistics and estimates of parameters and standard errors (DiStefano & Morgan, 2014). The covariances between the five EI dimensions were included in the model. We reported the standardized and unstandardized solutions from the CFA model. These analyses were conducted using Mplus (version 8.8; Muthén & Muthén, 2017), and the factor scores were saved from the CFA model for use in subsequent analyses.

*Measurement Invariance*

In light of the high confidence placed in EI as a critical skill with the power to mediate negative outcomes and influence positive outcomes, evidence for the measurement invariance of the instruments used to assess EI is critical. Evidence of measurement invariance supports decisions about an instrument performing similarly across groups or time because any observed differences between groups or across time due to the instrument can be ruled out. In other words, an instrument with evidence supporting its invariance evidence can more confidently be used to make comparisons about constructs across groups or across time. When the measurement properties of an instrument are invariant, the data collected with the instrument can be inferred to reflect the same underlying constructs and reflect them equally strongly and, ideally, with the same amount of error. For the current study, establishing invariance of the TTI EQ instrument was critical in order to determine if EI and its dimensions changed before and after the onset of the COVID-19 pandemic.

Given the continuous nature of data collection across nearly four years, the more common method of multigroup CFA (Vandenberg & Lance, 2000) with a small number of groups was not tenable. Instead, we specified a CFA model that included a random effect for each of the model parameters to capture the variability of the model parameters across each the 57 months of data collection. To execute this analysis, we employed the following steps. First, the cumulative month of data collection was recorded and saved.

For example, April 2018 was coded “1,” May 2018 was coded “2”, and so on, through December 2022 coded “57.” Second, the CFA model was then modeled within a multi-level framework where the factor structure was specified within each cumulative month but allowed to vary across time. Due to the complexity of this parameterization, Bayesian estimation was employed using the default priors from *Mplus*. To verify and supplement the findings from the CFA invariance model, months were also recoded into six-month blocks, where the block from March to August 2020 was coded as “0.” Time blocks preceding COVID-19 were given negative values, and time blocks following COVID-19 were given positive values. This coding scheme could allow for comparisons of potential differences in factor structure based on proximity to COVID-19 onset. Using the recoded time blocks, we, third, freely estimated the five-factor CFA model in each of the 10 time blocks and reported the variability in the model parameter estimates.

### *Latent Profile Analysis*

After evaluating the invariance of the instrument, we examined the possibility of unobserved heterogeneity within the sample. In behavioral research, there are often a variety of subgroups, or subpopulations, that are known, such as the demographic groups outlined above, or control and experimental groups in clinical trials. When groups are known *a priori,* statistical methods such as *t*-tests or MANCOVA can be used to compare them (Field, 2018). However, sometimes these subgroups are not known beforehand, a condition known as unobserved heterogeneity. In the case of unobserved heterogeneity, we cannot use *t*-tests or MANCOVA because they are powerless to find subgroups; they can only compare known groups. Because responses of various subgroups are likely to vary, regardless of whether the groups are known beforehand or not, having research methodology to identify the subgroups is essential for understanding the differences within a large population with multiple subgroups. In addition, because the pandemic was global in breadth, it impacted many subpopulations, the responses of which, in terms of EI, probably varied widely. It was our goal to investigate differences among subpopulations, both known and unknown.

One common way of investigating unobserved heterogeneity is with finite mixture models. Mixture modeling is a method used when we assume there are a variety of populations, finite in number, which are not known a priori (Morgan & Beaujean, 2014). Mixture modeling allows researchers to analyze unobserved heterogeneity by treating group membership as a latent variable (Morgan & Beaujean, 2014), as compared to *t* tests and ANOVA in which group membership must be known and specified a priori. Using mixture modeling, the different sub-populations can be identified by means, variance, item responses, or other parameters. Latent variable models performed cross sectionally using continuous indicators of latent category membership may be referred to as latent profile analysis (LPA), which we will employ in this study. The general LPA model can be expressed:

$$f(\boldsymbol{y}) = \sum_{k=1}^{K} \pi_k f(\boldsymbol{y}|\mu_k, \Sigma_k),$$

where $f(\boldsymbol{y})$ is a mixture of profile-specific densities, $\pi_k$ is the mixing weight (i.e., profile prevalence) for the *k*th profile and $\sum_{k=1}^{K} \pi_k = 1$, $\pi_k \geq 0$, for $k = 1,\ldots,K$, $\mu_k$ is the mean vector for profile *k*, and $\Sigma_k$ is the covariance matrix of profile indicators for profile *k*. Conceptually, LPA can be used to correctly identify the optimal number of profiles on the basis of differences in means and covariances of the profile indicators such that observations within a latent profile are similar while being as different as possible from observations between latent profiles.

A major benefit of LPA as a model-based approach to examining population heterogeneity is the availability of fit indices to aid in model selection. The fit indices we examined are Akaike information criterion (AIC), Bayesian information criterion (BIC), and adjusted BIC (aBIC). When comparing between final models, we also used Lo-Mendell-Rubin likelihood ratio test (LMR) and the bootstrapped likelihood ratio test (BLRT). Models with relatively lower AIC, BIC, and aBIC values fit better. The BIC, aBIC, and ICL-BIC have been shown to be more trustworthy than AIC in determining profile enumeration (Morgan, 2015; Nylund, 2007). The LMR and BLRT test the null hypothesis that the *k*-profile solution fits better than a solution with *k*-1 profiles, and it yields a *p*-value. With a maximum Type I error rate of 5%, the best fitting model is the one where *k* profiles yields a *p*-value greater than .05. The final model was selected on the basis of statistical fit information along with interpretability.

For the LPA in this study, the factor scores of the EI domains were used as the indicators of latent profile membership. As a model-based approach to clustering/classification, LPA offers greater flexibility and control to researchers in choosing how to parameterize their desired models. Therefore, four alternative parameterizations of the profile-specific covariance matrix ($\Sigma_k$) were explored. The first parameterization constrained the variances of the EI domains to equal across profiles and fixed all covariances to zero. The second parameterization allowed the EI domain scores to vary across profiles but fixed all covariances to zero. The third parameterization constrained the variances and covariances of the EI domains to equal across profiles. The fourth parameterization allowed the EI domain score variances and covariances to vary across. The respective parameterizations can be expressed

$$\begin{pmatrix} \sigma_{SA}^2 & 0 & 0 & 0 & 0 \\ 0 & \sigma_{SR}^2 & 0 & 0 & 0 \\ 0 & 0 & \sigma_M^2 & 0 & 0 \\ 0 & 0 & 0 & \sigma_{SoA}^2 & 0 \\ 0 & 0 & 0 & 0 & \sigma_{SoR}^2 \end{pmatrix},$$

$$\begin{pmatrix} \sigma_{SAk}^2 & 0 & 0 & 0 & 0 \\ 0 & \sigma_{SRk}^2 & 0 & 0 & 0 \\ 0 & 0 & \sigma_{Mk}^2 & 0 & 0 \\ 0 & 0 & 0 & \sigma_{SoAk}^2 & 0 \\ 0 & 0 & 0 & 0 & \sigma_{SoRk}^2 \end{pmatrix},$$

$$\begin{pmatrix} \sigma_{SA}^2 & \sigma_{12} & \sigma_{13} & \sigma_{14} & \sigma_{15} \\ \sigma_{21} & \sigma_{SR}^2 & \sigma_{23} & \sigma_{24} & \sigma_{25} \\ \sigma_{31} & \sigma_{32} & \sigma_M^2 & \sigma_{34} & \sigma_{35} \\ \sigma_{41} & \sigma_{42} & \sigma_{43} & \sigma_{SoA}^2 & \sigma_{45} \\ \sigma_{51} & \sigma_{52} & \sigma_{53} & \sigma_{54} & \sigma_{SoR}^2 \end{pmatrix}, \text{ and}$$

$$\begin{pmatrix} \sigma_{SAk}^2 & \sigma_{12k} & \sigma_{13k} & \sigma_{14k} & \sigma_{15k} \\ \sigma_{21k} & \sigma_{SRk}^2 & \sigma_{23k} & \sigma_{24k} & \sigma_{25k} \\ \sigma_{31k} & \sigma_{32k} & \sigma_{Mk}^2 & \sigma_{34k} & \sigma_{35k} \\ \sigma_{41k} & \sigma_{42k} & \sigma_{43k} & \sigma_{SoAk}^2 & \sigma_{45k} \\ \sigma_{51k} & \sigma_{52k} & \sigma_{53k} & \sigma_{54k} & \sigma_{SoRk}^2 \end{pmatrix}.$$

We determined the number of latent profiles for each parameterization by estimating a model with only one profile and then consecutively increasing the number of profiles until the model no longer converged. Prior to running the LPA, we randomly selected 10,000 observations from the analytic sample, and used 7,500 as the calibration sample to identify an LPA solution. Then we used the remaining 2,500 observations as a validation sample to provide supporting evidence for the selected model.

*Reporting of Selected Model*

Following the identification and supporting evidence for the selected model, we examined the EI domains across time and demographic groups. We paid specific attention to the demographic variables that were hypothesized to have been most impacted by COVID-19 pandemic. The demographic variables of interest include age, gender, ethnic/racial background, education, industry, and urbanicity.

## *Summary*

The purpose of this study was to investigate whether Emotional Intelligence among the general U.S. population changed after the onset of the COVID-19 pandemic, and if so, to investigate how it changed, to what degree, and among which demographic group(s). To this end, we used a survey design with data provided by the test developer TTI. After various descriptive analyses, we used the CFA framework to evaluate the overall model fit as well as to collect evidence to support decisions about the invariance of the EI dimensional structure across time. After measurement invariance had been established, we used mixture modeling to investigate unknown heterogeneity and examined differences in EI by reported demographic group membership.

# CHAPTER FOUR

## Results

The problem addressed in this study is the lack of information regarding the relationship between the recent COVID-19 pandemic and EI. The guiding research questions were:

1) Does EI differ before and after the onset of the COVID-19 pandemic?
2) Are there identifiable latent, homogenous groups of working adults based on EI profiles?
3) Are there differences in the demographic characteristics in latent profile membership before and after the onset of the COVID-19 pandemic?

To answer these research questions, the following research objectives were met:

1) establish the dates of usable data and data considered to be onset of COVID-19 pandemic;
2) investigate and establish invariance in the latent factor structure of EI dimensions before and after the onset of the COVID-19 pandemic;
3) investigate and establish invariance in the latent profile structure of EI before and after the onset of the COVID-19 pandemic (discussed in Analysis Plan subsection).

Below are the results of the data analysis conducted to address the questions and objectives described above.

*Delimitations and Preliminary Analyses*

The original sample received from TTI contained 108,982 observations. Due to the size of the sample and the large number of demographic groups, it was beyond the scope of this study to investigate all possible sources of variance. These present possible directions for future study, which are discussed in Chapter Five. We delimited our focus to respondents aged 18 and above living in the United States for whom complete demographic data was available. All survey respondents who did not fit these criteria were removed from the data before analysis, resulting in an analytic sample of 33,875. Appropriate measures of central tendency, variability, and shape were generated for quantitative variables (see Table 4.1).

Table 4.1

*Measures of central tendency, variability, and shape*

| | *M* | *SD* | Skewness | | Kurtosis | |
|---|---|---|---|---|---|---|
| | | | Statistic | SE | Statistic | SE |
| Self-Awareness | 76.06 | 4.31 | .095 | .013 | -.074 | .027 |
| Self-Regulation | 69.32 | 4.78 | .037 | .013 | -.079 | .027 |
| Motivation | 75.93 | 4.87 | .012 | .013 | -.106 | .027 |
| Social Awareness | 72.41 | 3.75 | -.041 | .013 | .030 | .027 |
| Social Regulation | 70.73 | 5.63 | -.045 | .013 | -.082 | .027 |

In addition, we conducted basic item analysis using classical test theory (CTT), estimating item means, item-total correlations, and reliability coefficients. These are reported in detail in the appendix. The item means for Self-Awareness ranged from 3.34 to 4.06. The estimated alpha was .73. The item means for Self-Regulation ranged from 2.24 to 4.02. The estimated alpha was .78. The item means for Motivation ranged from 3.69 to 4.35. The estimated alpha was .78. The item means for Social Awareness ranged from 2.82 to 4.08. The estimated alpha was .77. The item means for Social Regulation ranged from 3.34 to 4.06. The estimated alpha was .73.

### *Analysis of Excluded Cases*

Before proceeding with the statistical analyses of the analytic sample, we compared the EI domains of the observations that were excluded against those that were included. In light of the volume of data, even very small, practically trivial differences in EI domain means were expected to be statistically significant (i.e., $p < .05$). Therefore, effect size estimates using Cohen's *d* were examined. The standardized mean differences for Self-Awareness, Self-Regulation, Motivation, Social Awareness, and Social Regulation were, respectively, -.05, .03, .05, -.03, and .00. Each of these effect size estimates are considered practically meaningless.

### *Confirmatory Factor Analysis*

To investigate the structural validity of the instrument, Confirmatory Factor Analysis (CFA) was conducted on the entire sample using MPlus (version 8.8; Muthén & Muthén, 2017). The model tested contained the five EI dimensions, each of which is measured by eight items. Due to the ordinal nature of the items, the categorical estimator DWLS was used because it has been show to yield trustworthy results with noncontinuous data (DiStefano & Morgan, 2014). The results of the CFA are presented in Table 4.2. The model $\chi^2$ value was 159,401.6 (df = 730, $p < .001$), which suggests that the model does not fit the data. However, due to the well-known sensitivity of the $\chi^2$ with large samples, we relied on the other fit indexes. The estimated CFI was .78, RMSEA was .08 ($CI_{90}$ = .08, .08), and SRMR was .06. The RMSEA and SRMR are estimates of absolute model-data fit, and the values reported above are considered good or, at minimum, adequate (Hu & Bentler, 1999). The standard set by Hu and Bentler (1999) for CFI was not met. It should be noted that the Hu & Bentler (1999) criteria were established with a simple two-factor model that may be challenging to achieve with highly complex models such as the one used in this study. For more complex models, a more nuanced interpretation of the fit indexes may be useful, specifically with relative fit indexes. van Laar and Braeken (2021) contend that the base $\chi^2$ value should be considered when interpreting a model's CFI estimate. CFI is the relative improvement of the model under consideration compared against the base model, which in this case is the null or independence model. As such, design factors like number of variables, degree of multivariate dependencies, and sample size each influence the performance of CFI. For the current analysis, the noncentrality of the baseline model is large. That is, the $\chi^2$ value for the null model is 721,545.7 ($df = 780$). For the five-factor model under investigation, the relative improvement is nearly 80%. Said another way, the CFI metric space for this particular model is very large, so strict adherence to the CFI > .95 criterion may be too strict because more absolute misspecification is allowed. As a reminder, the indexes of absolute model fit (i.e., RMSEA, SRMR) indicated acceptable model-data fit. Taken together, the fit of the model was considered acceptable. The standardized parameter estimates are presented in Table 4.2.

Table 4.2A

*Results of CFA on the entire analytic sample, Standardized Factor Loadings*

| Item* | Self-Awareness | Self-Regulation | Motivation | Social Awareness | Social Regulation |
|---|---|---|---|---|---|
| 1 | .48 | .48 | .49 | .47 | .56 |
| 2 | .61 | .37 | .64 | .78 | .36 |
| 3 | .65 | .53 | .54 | .46 | .64 |
| 4 | .63 | .66 | .67 | .78 | .52 |
| 5 | .50 | .60 | .68 | .46 | .63 |
| 6 | .72 | .46 | .72 | .61 | .58 |
| 7 | .61 | .61 | .65 | .63 | .64 |
| 8 | .52 | .59 | .67 | .71 | .54 |

* Item number indicates first through eighth item on each respective factor. Items 1-8 reflect Self-Awareness, Items 9-16 reflect Self-Regulation, Items 17-24 reflect Motivation, Items 25-32 reflect Social Awareness, Items 33-40 reflect Social Regulation.

Table 4.2.B

*Results of CFA on the entire analytic sample, Standardized Factor Correlations*

| | Self-Awareness | Self-Regulation | Motivation | Social Awareness | Social Regulation |
|---|---|---|---|---|---|
| Self-Awareness | (.81) | | | | |
| Self-Regulation | .50 | (.77) | | | |
| Motivation | .53 | .68 | (.84) | | |
| Social Awareness | .57 | .23 | .13 | (.83) | |
| Social Regulation | .62 | .46 | .47 | .79 | (.79) |

*Note*. Values in parentheses on the diagonal of the factor correlation matrix are reliability estimates indexed by $\omega$.

### *Measurement Invariance*

As reported in Chapter Three, the more common method of multigroup CFA (Vandenberg & Lance, 2000) with a small number of groups was not tenable given the continuous data collection from 2018 to 2022. To examine the invariance of the CFA model across each month of the data collection period, a random effect for each of the model parameters was added to capture the variability of the model parameters across each the 57 months of data collection. To estimate the model as parameterized, the items were treated as continuous, which yielded estimates of their intercepts, loadings, and residual variables. The model was estimated using Bayesian estimation with default, uninformative priors (i.e., inverse gamma [IG(0, ∞)]). The point estimate for each parameter was the median of the posterior distribution, although it should be noted that the between-month parameter variance of each parameter was the outcome of interest. In general, the parameter estimates followed the same pattern as the previously reported CFA from the entire sample; the variance of each parameter was less than .001. The implication of this model was that the parameter estimates varied minimally across time, thus providing evidence for the invariance of the model.

To provide additional support for the invariance and confirm the interpretation from the CFA model with random effects, we also estimated a CFA for each model independently based on 6-month blocks. Each model was estimated using DWLS, and only configural invariance was imposed on the data structure. Again, across all 10 time blocks, the parameter estimates varied minimally. The largest variance observed was for Item 10, which was .0014. The smallest variance observed was for Item 24, which was .00005. The output from the two analytic approaches to investigating measurement invariance concur and support the invariance of the CFA model across time. As such, the factor means and (co)variances were considered comparable and were submitted to LPA.

### *LPA Calibration and Validation*

LPA was conducted using a random subset of 7,500 from the analytic sample. The factor scores of the EI domains were used as the indicators of latent profile membership. Four alternative parameterizations of the profile-specific covariance matrix

($\Sigma_k$) were explored. The first parameterization constrained the variances of the EI domains to equal across profiles and fixed all covariances to zero. The second parameterization allowed the EI domain scores to vary across profiles but fixed all covariances to zero. The third parameterization constrained the variances and covariances of the EI domains to equal across profiles. The fourth parameterization allowed the EI domain score variances and covariances to vary across profiles. Each of these parameterizations was estimated for 1, 2, 3, 4, and 5-profiles, for a total of 20 models. Selected fit statistics are presented in Table 4.3.

For each of the indexes presented in Table 4.3, values closer to zero indicated relatively better fitting models. Clearly, the models that allow within-profile covariances between the EI domain scores (i.e., Models 3 and 4) fit the data better those models that constrained the within-profile covariances to zero. Generally, the parameterization that constrained the variances and covariances to be equal across profiles were better fitting with AIC identifying the five-profile solution, BIC identifying the two-profile solution, and sample-size adjusted BIC identifying the three-profile solution. Upon review of each of these solutions, none was theoretically meaningful or interpretable. As a result, the one-profile was selected.

Table 4.3

*LPA Fit Statistics, Calibration Sample*

| Model | Classes | LogLik | AIC | BIC | SABIC |
|---|---|---|---|---|---|
| 1 | 1 | -19,859 | 39,739 | 39,808 | 39,776 |
| 1 | 2 | -13,542 | 27,115 | 27,226 | 27,175 |
| 1 | 3 | -11,322 | 22,687 | 22,839 | 22,769 |
| 1 | 4 | -10,503 | 21,062 | 21,255 | 21,166 |
| 1 | 5 | -9,481 | 19,030 | 19,265 | 19,157 |
| 2 | 1 | -19,859 | 39,739 | 39,808 | 39,776 |
| 2 | 2 | -13,528 | 27,098 | 27,244 | 27,177 |
| 2 | 3 | -11,219 | 22,502 | 22,724 | 22,622 |
| 2 | 4 | -10,152 | 20,390 | 20,688 | 20,551 |
| 2 | 5 | -9,118 | 18,343 | 18,717 | 18,545 |
| 3 | 1 | -3,288 | 6,616 | 6,755 | 6,691 |
| 3 | 2 | -3,061 | 6,204 | 6,487 | 6,357 |
| 3 | 3 | -2,995 | 6,114 | 6,543 | 6,346 |
| 3 | 4 | -2,973 | 6,112 | 6,687 | 6,423 |
| 3 | 5 | -2,910 | 6,028 | 6,748 | 6,417 |
| 4 | 1 | -3,288 | 6,616 | 6,755 | 6,691 |
| 4 | 2 | -3,271 | 6,594 | 6,774 | 6,691 |
| 4 | 3 | -3,256 | 6,577 | 6,798 | 6,696 |
| 4 | 4 | -3,235 | 6,546 | 6,809 | 6,688 |
| 4 | 5 | -3,182 | 6,451 | 6,756 | 6,616 |

Note. LogLik = Log-Likelihood value; AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion; SABIC = sample size-adjusted Bayesian Information Criterion. Model 1 = Equal variances, Covariances constrained to zero; Model 2 = Profile-specific variables, Covariances constrained to zero; Model 3 = Profile-specific variances and covariances; Model 4 = Equal variances and covariances.

Following estimation with the calibration sample, the analysis was performed again using the validation sample, using the parameterizations that allowed within-profile covariances between EI domain scores. The fit indexes from the validation sample are presented in Table 4.5. Consistent with the calibration sample output, the AIC identified the five-profile solution. The BIC identified the one-profile solution, and the sample-size adjusted BIC identified the two-profile solution. Again, we reviewed the model parameter estimates from these models and reached the same conclusion. Only the single profile solution was interpretable or theoretically meaningful.

Table 4.4

*LPA Fit Statistics Using Validation Sample*

| Model | Classes | LogLik | AIC | BIC | SABIC |
|---|---|---|---|---|---|
| 3 | 1 | -1,010 | 2,060 | 2,177 | 2,113 |
| 3 | 2 | -931 | 1,944 | 2,183 | 2,053 |
| 3 | 3 | -905 | 1,933 | 2,294 | 2,097 |
| 3 | 4 | -877 | 1,920 | 2,403 | 2,139 |
| 3 | 5 | -854 | 1,916 | 2,521 | 2,191 |
| 4 | 1 | -1,010 | 2,060 | 2,177 | 2,113 |
| 4 | 2 | -1,007 | 2,065 | 2,217 | 2,134 |
| 4 | 3 | -984 | 2,033 | 2,219 | 2,117 |
| 4 | 4 | -951 | 1,978 | 2,200 | 2,079 |
| 4 | 5 | -940 | 1,968 | 2,224 | 2,084 |

Note. Model 3 = Profile-specific variances and covariances; Model 4 = Equal variances and covariances.

Because the model with only one latent profile was selected, latent profile comparisons could not be made. However, comparisons of demographic groups over time were appropriate, based on the results of measurement invariance.

### *Analysis of EI Trends*

Overall, EI proved relatively stable over time. However, there were slight differences in EI among demographic groups over time. These differences were small but may be of interest in future research. The observed differences are described below, and directions for future research are discussed in Chapter Five.

*Age.* Although the results were significant due to sample size, age explained very little of the variance in self-awareness ($F_{(5,\ 33869)} = 10.68$, $p < .001$, $\eta^2 = .002$), self-regulation ($F_{(5,\ 33869)} = 42.22$, $p < .001$, $\eta^2 = .006$), motivation ($F_{(5,\ 33869)} = 20.56$, $p < .001$, $\eta^2 = .003$), social awareness ($F_{(5,\ 33869)} = 18.78$, $p < .001$, $\eta^2 = .003$), and social regulation ($F_{(5,\ 33869)} = 6.68$, $p < .001$, $\eta^2 = .001$). The trend lines by age did not vary by more than five or six points overall (see Figure 4.1). However, some interesting patterns emerged. The 65-and-over group trended toward the top of the self-scales (self-awareness, self-regulation, and motivation) during the onset of the COVID-19 pandemic and immediately afterward. However, 18 months after the pandemic, the average score on all five subdomains dipped by one or two points. Investigating what may have happened among this population 18 months after the onset of the pandemic could be of interest. In addition, while most trend lines did not change in a major way during the onset of COVID-19, the average Social Awareness and Social Regulation for the 18-24 age group dropped by two points during this time. It seems plausible that emerging adults, who are generally highly social, would have been greatly impacted by the social disruption and distancing of the pandemic. However, specific research regarding EI and emerging adults during the pandemic would be needed to support this hypothesis.

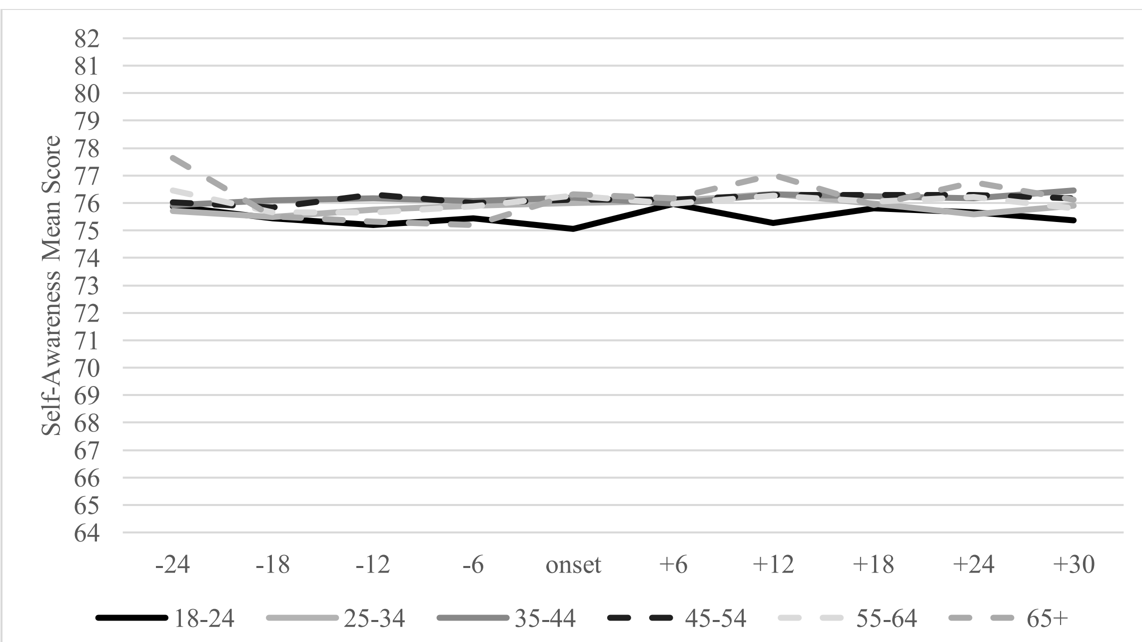



*Figure 4.1.A.* Trend lines for self-awareness over time by age.

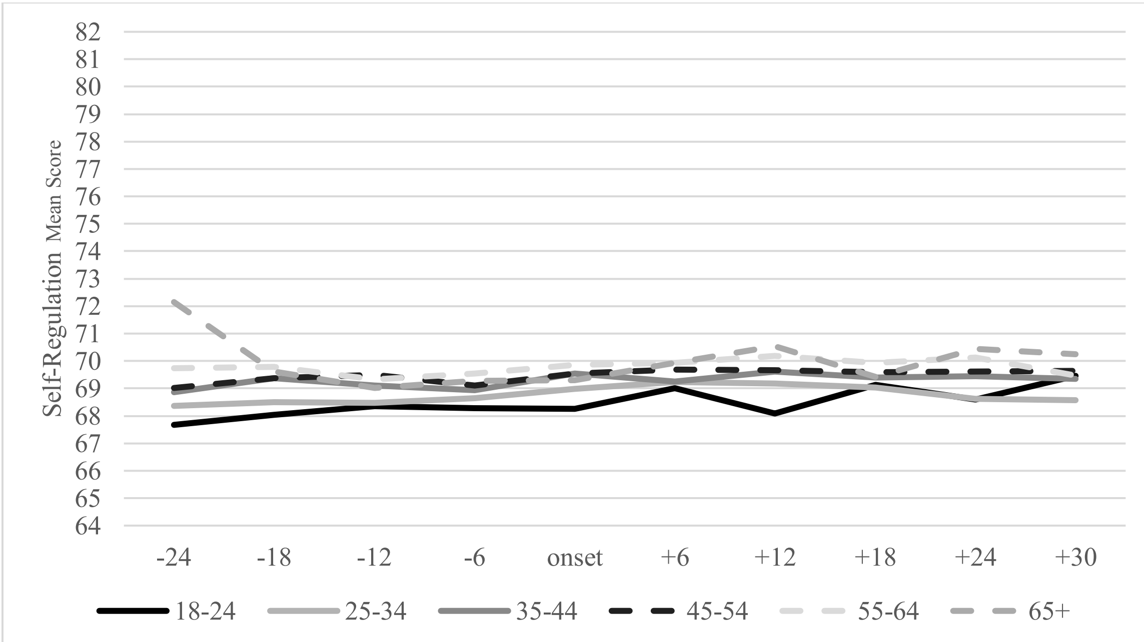



*Figure 4.1.B.* Trend lines for self-regulation over time by age.

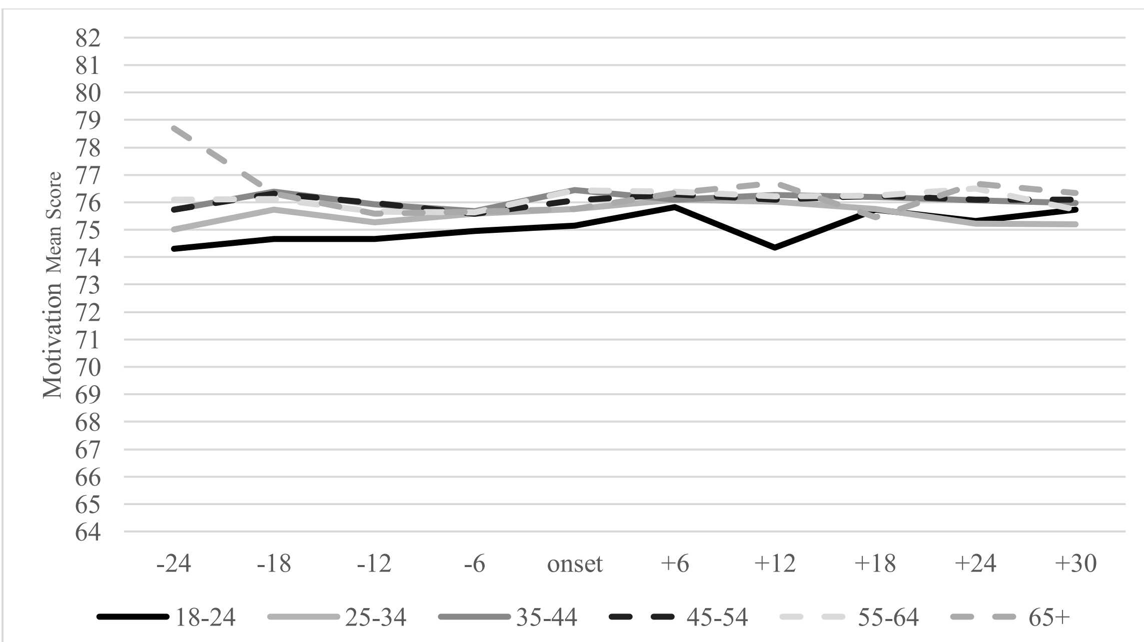



*Figure 4.1.C.* Trend lines for motivation over time by age.

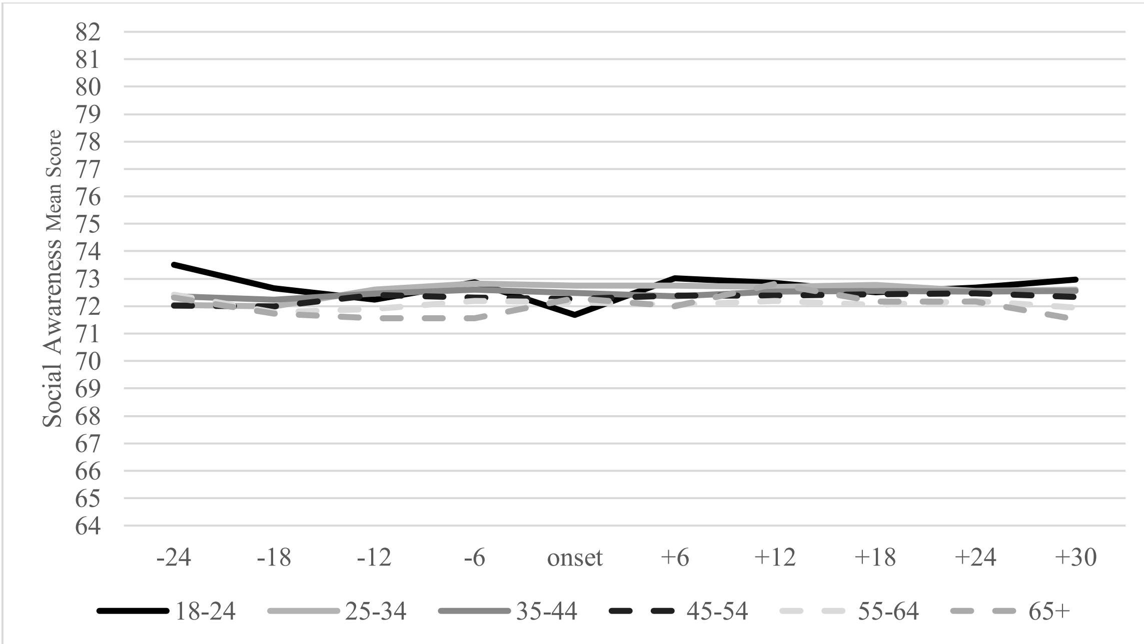
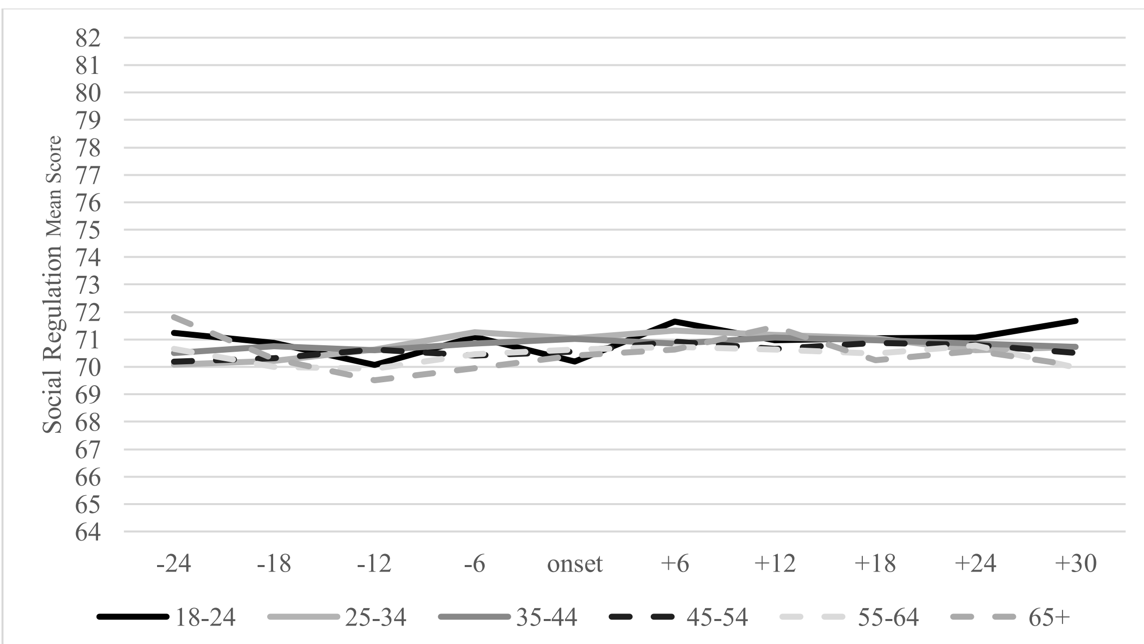



*Figure 4.1.D.* Trend lines for social awareness over time by age.




*Note.* Onset of the pandemic refers to the time between March and August 2020. The 6-month time blocks preceding the onset are designated as -6, -12, -18, and -24. The time blocks following the onset continue the same pattern with positive numbers.

*Figure 4.1.E.* Trend lines for social regulation over time by age.

*Ethnicity.* No meaningful trends were observed based on ethnicity (see Figure 4.2). Perceived variability among Native American or Alaskan Native and Pacific Islander groups is assumed to be an effect of the small sample size ($n$ < 150). Although the results were significant due to sample size, ethnicity explained very little of the variance in self-awareness ($F_{(7, 33867)} = 25.39$, $p <.001$, $\eta^2 = .005$), self-regulation ($F_{(7, 33867)} = 14.05$, $p <.001$, $\eta^2 = .003$), motivation ($F_{(7, 33867)} = 13.64$, $p <.001$, $\eta^2 = .003$), social awareness ($F_{(7, 33867)} = 6.11$, $p <.001$, $\eta^2 = .001$), and social regulation ($F_{(7, 33867)} = 3.95$, $p <.001$, $\eta^2 = .001$).

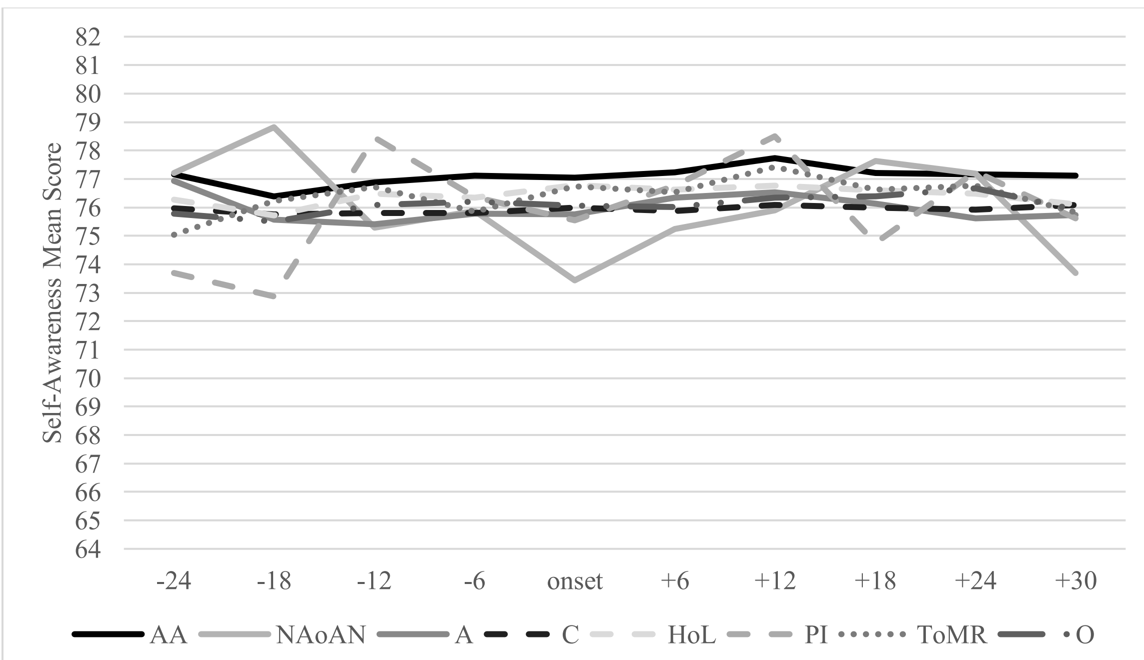



*Figure 4.2.A.* Trend lines for self-awareness over time by ethnicity.

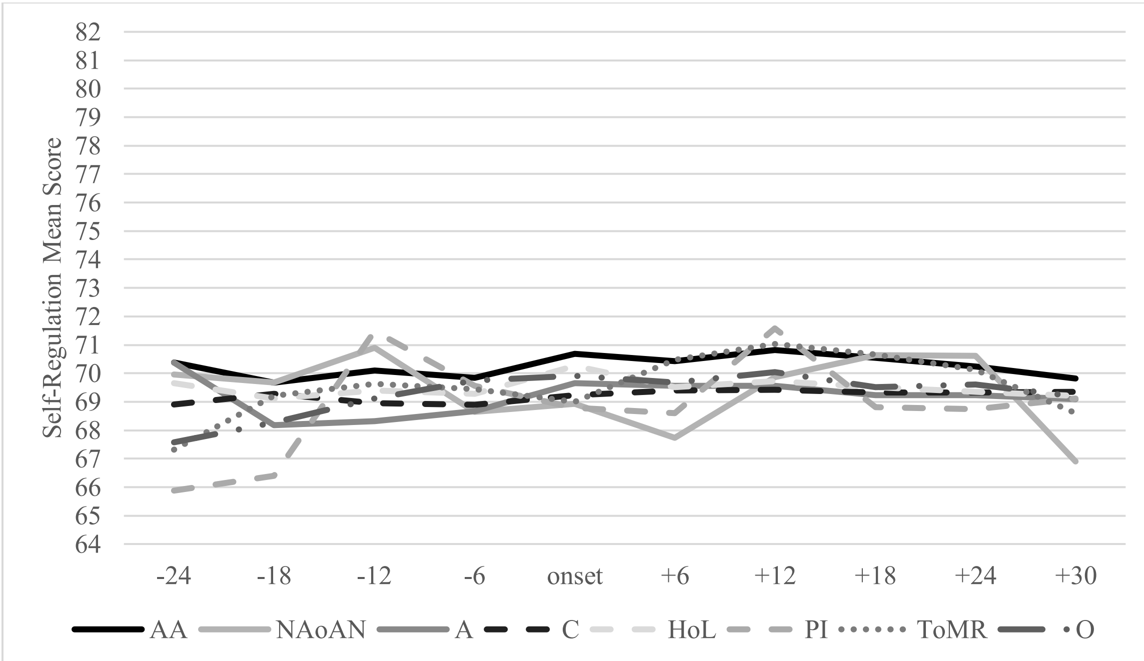



*Figure 4.2.B.* Trend lines for self-regulation over time by ethnicity.

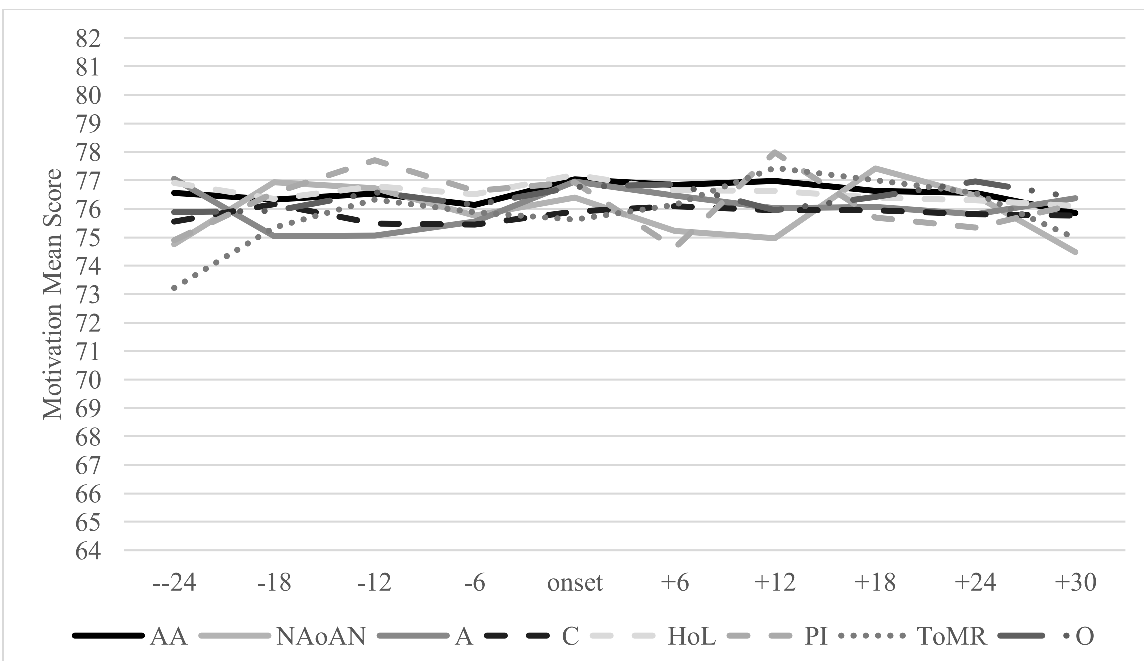



*Figure 4.2.C.* Trend lines for motivation over time by ethnicity.

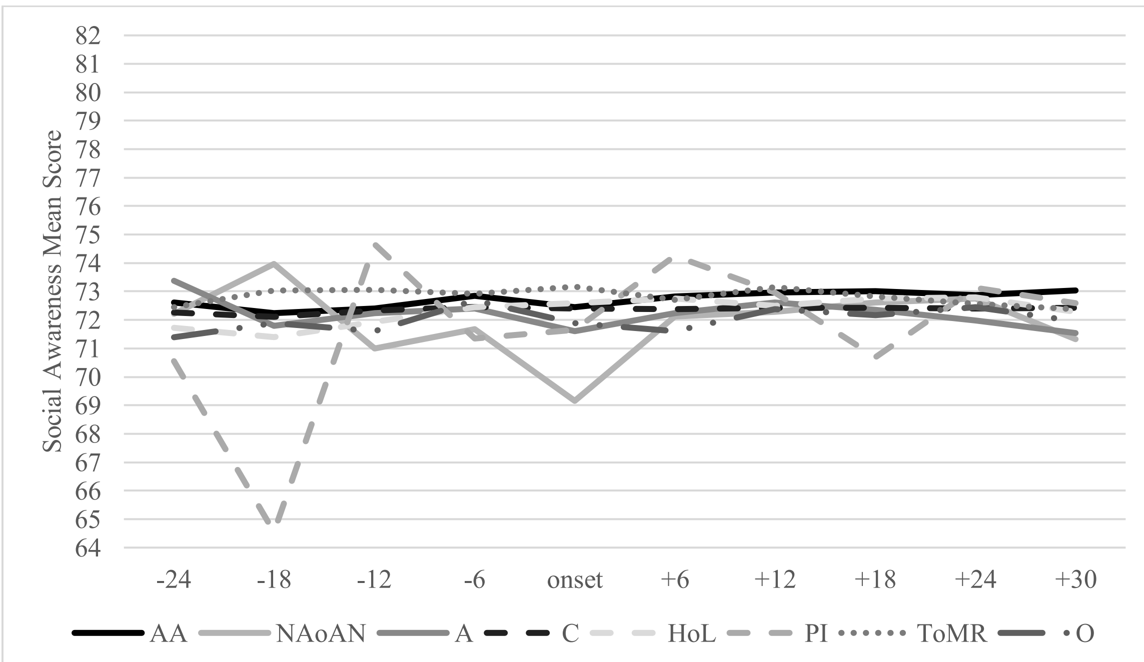
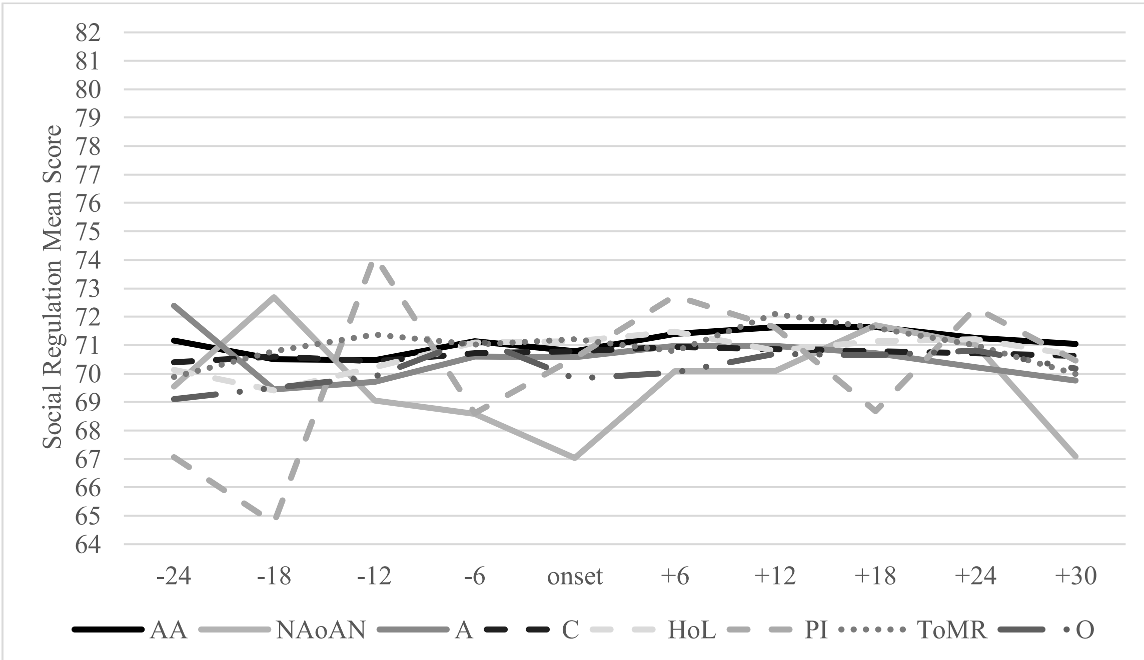



*Figure 4.2.D.* Trend lines for social awareness over time by ethnicity.




*Note.* AA=African American, NAoAN=Native American or Alaskan Native, A=Asian, C-Caucasian, HoL=Hispanic or Latinx, PI=Pacific Islander, ToMR=Two or More Races, O=Other. Onset of the pandemic refers to the time between March and August 2020. The 6-month time blocks preceding the onset are designated as -6, -12, -18, and -24. The time blocks following the onset continue the same pattern with positive numbers.

*Figure 4.2.E.* Trend lines for social regulation over time by ethnicity.

***Education.*** Although the results were significant due to sample size, education explained very little of the variance in self-awareness ($F_{(5, 33869)} = 36.95$, $p$ <.001, $\eta^2$= .005), self-regulation ($F_{(5, 33869)} = 53.19$, $p$ <.001, $\eta^2$= .008), motivation ($F_{(5, 33869)} = 42.53$, $p$ <.001, $\eta^2$= .006), social awareness ($F_{(5, 33869)} = 39.76$, $p$ <.001, $\eta^2$= .006), and social regulation ($F_{(5, 33869)} = 56.93$, $p$ <.001, $\eta^2$= .008). Those with some college, a bachelor's degree, a master's degree, and a professional or doctoral degree all trended within one or two points of each other on all subdomains for the duration of data collection. Those with a professional or doctoral degree trended above the other groups for Self-Regulation and Motivation, those with a master's degree trended higher than other groups on Self-

Awareness and Social Regulation, and the bachelor's and master's groups together trended higher than other groups for Social Awareness. To reiterate, each of these trends was very minor, varying by less than two points. The group with less than a high school education appears to show the most variability. This is most likely due to a smaller sample size for this group ($n$ = 218). Even while varying, average scores for this group were within four to five points of the other groups. No trends related to specific events of the COVID-19 pandemic were evident based on education level (see Figure 4.3).

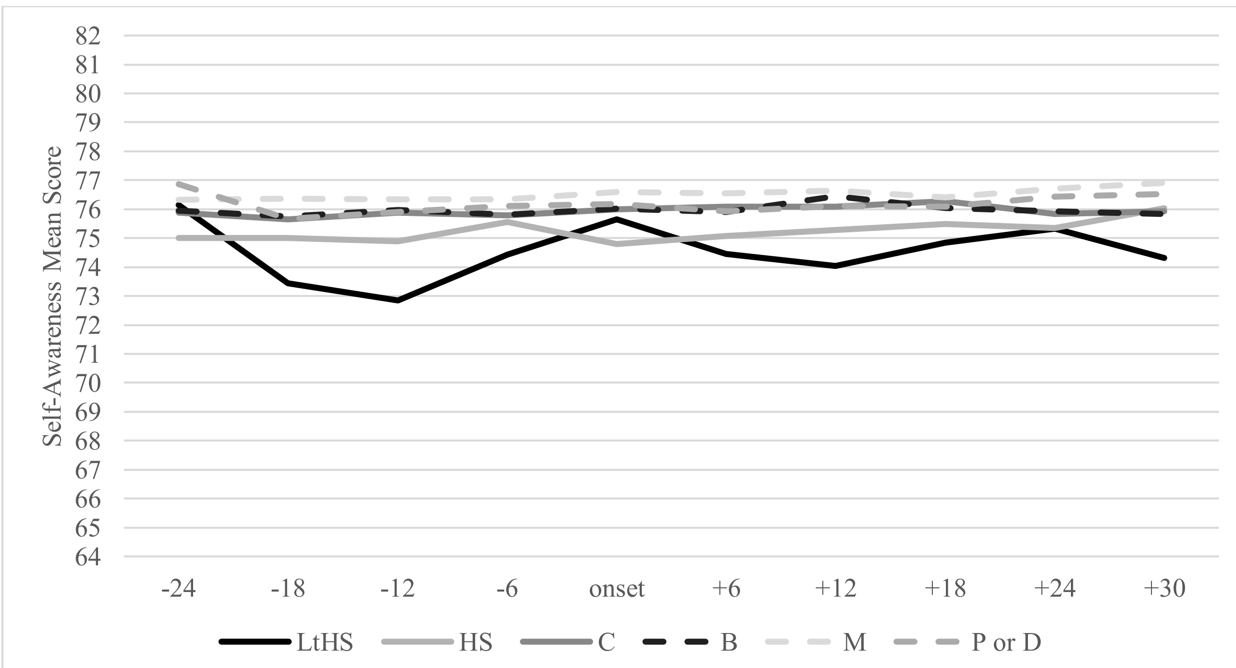



*Figure 4.3.A.* Trend lines for self-awareness over time by education level.

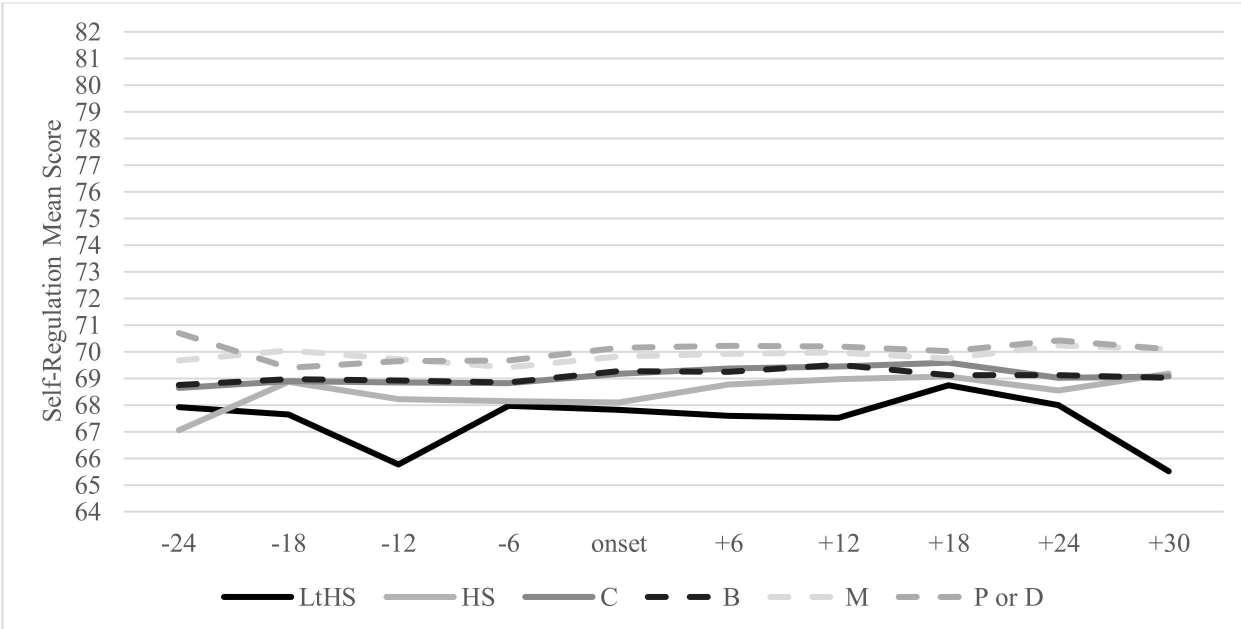



*Figure 4.3.B.* Trend lines for self-regulation over time by education level.

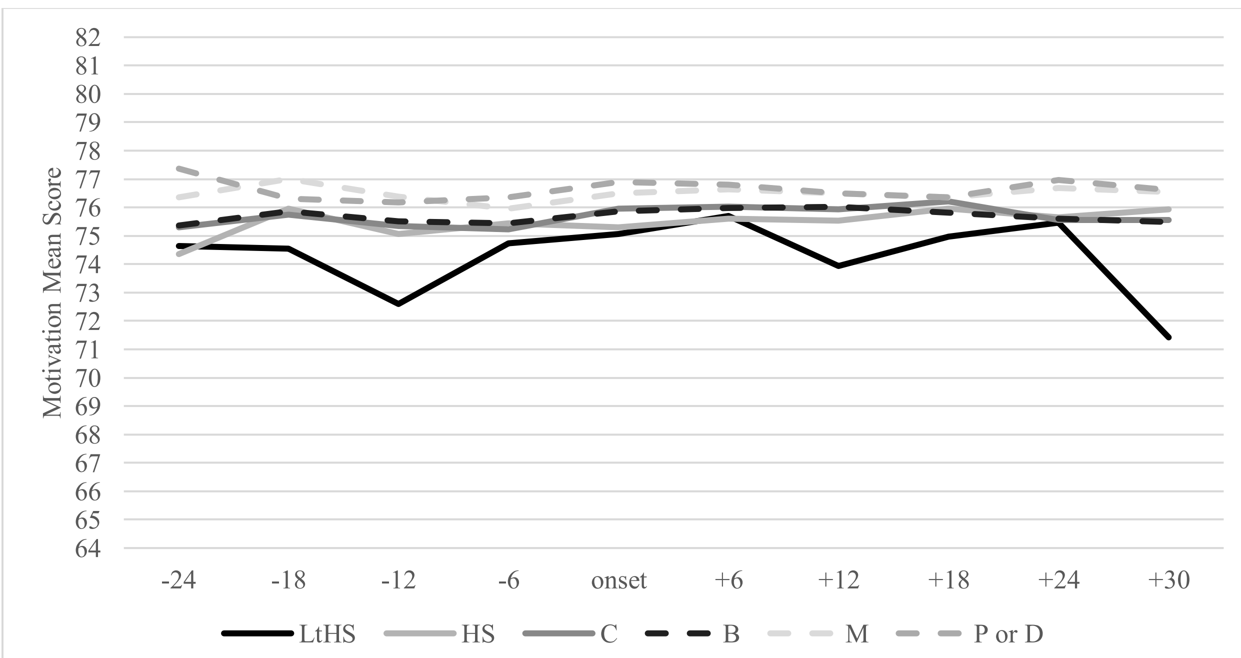



*Figure 4.3.C.* Trend lines for motivation over time by education level.

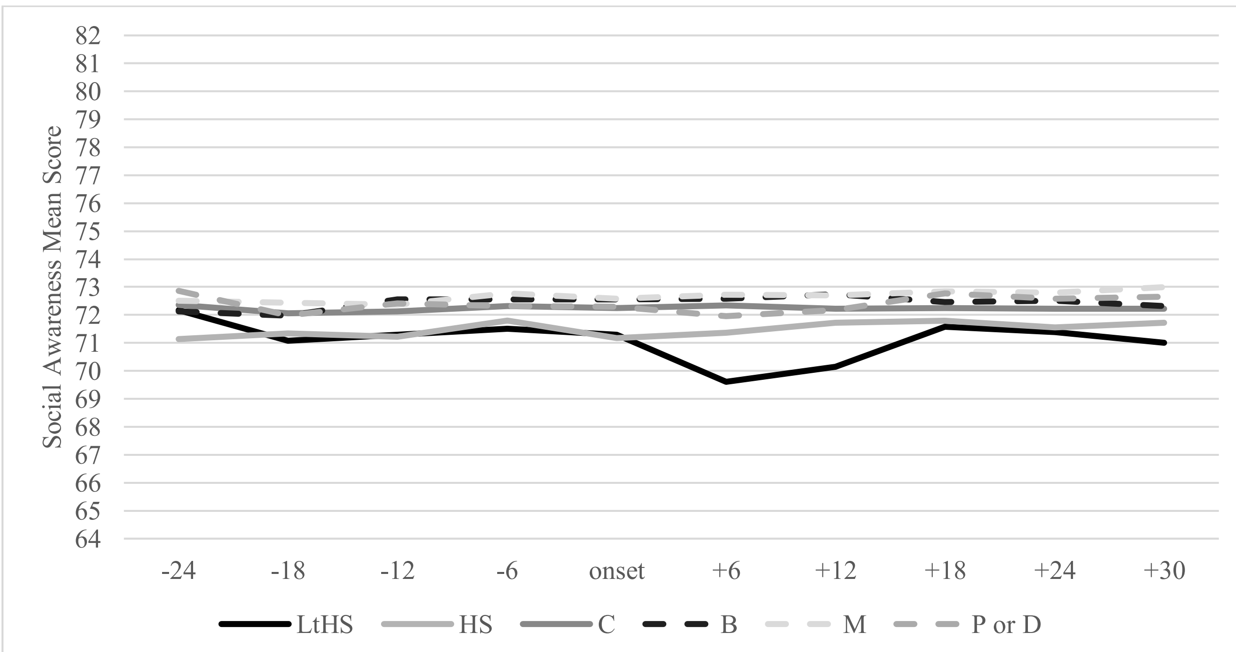
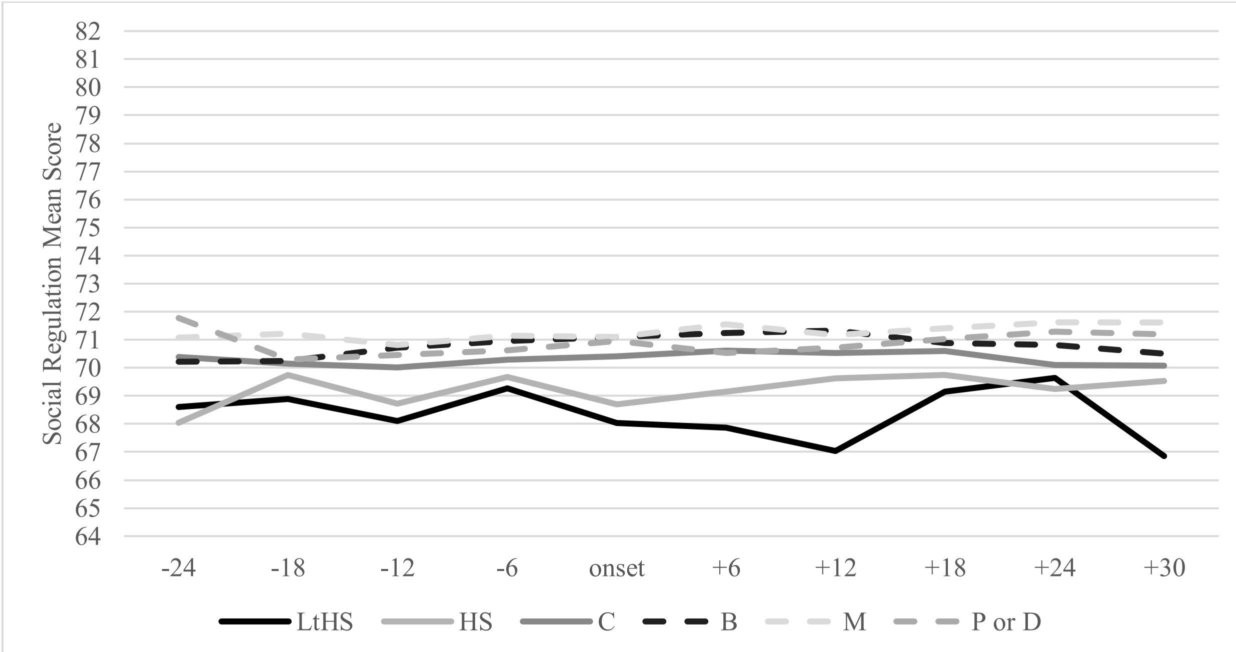



*Figure 4.3.D.* Trend lines for social awareness over time by education level.




*Note.* LtHS=less than high school; HS=high school; C=some college but less than one year, one year of college, and those with an associate's degree; B=bachelor's degree; M=master's degree; P or D=professional or doctoral degree. Onset of the pandemic refers to the time between March and August 2020. The 6-month time blocks preceding the onset are designated as -6, -12, -18, and -24. The time blocks following the onset continue the same pattern with positive numbers.

*Figure 4.3.E.* Trend lines for social regulation over time by education level.

*Gender.* Although the results were significant due to sample size, gender explained very little of the variance in self-awareness ($F_{(1, 33873)} = 443.15$, $p$ <.001, $\eta^2$= .013), self-regulation ($F_{(1, 33873)} = 361.99$, $p$ <.001, $\eta^2$= .011), motivation ($F_{(1, 33873)}$ = 217.09, $p$ <.001, $\eta^2$= .006), social awareness ($F_{(1, 33873)} = 1344.19$, $p$ <.001, $\eta^2$= .038), and social regulation ($F_{(1, 33873)} = 120.85$, $p$ <.001, $\eta^2$= .004). There were very small differences in social awareness, based on gender. Trend lines by gender were among the stable over the course of data collection and most similar (to each other) in terms of point-spread (see Figure 4.4). There were no trends seen among males or females that corresponded to COVID-19 events.

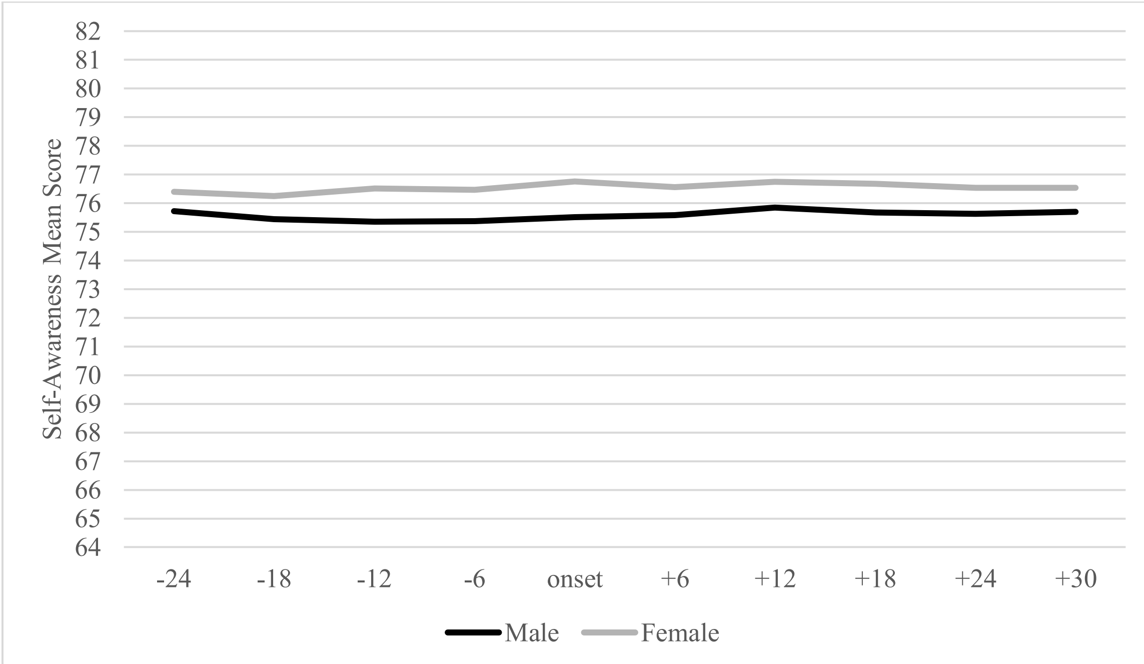



*Figure 4.4.A.* Trend lines for self-awareness over time by gender.

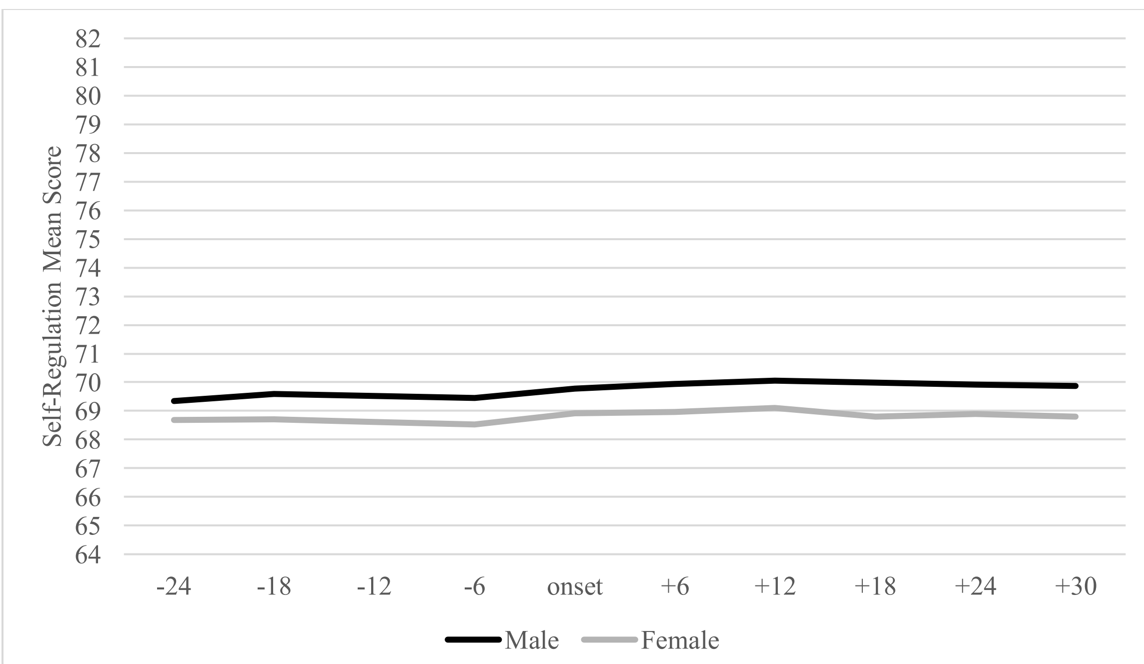



*Figure 4.4.B.* Trend lines for self-regulation over time by gender.

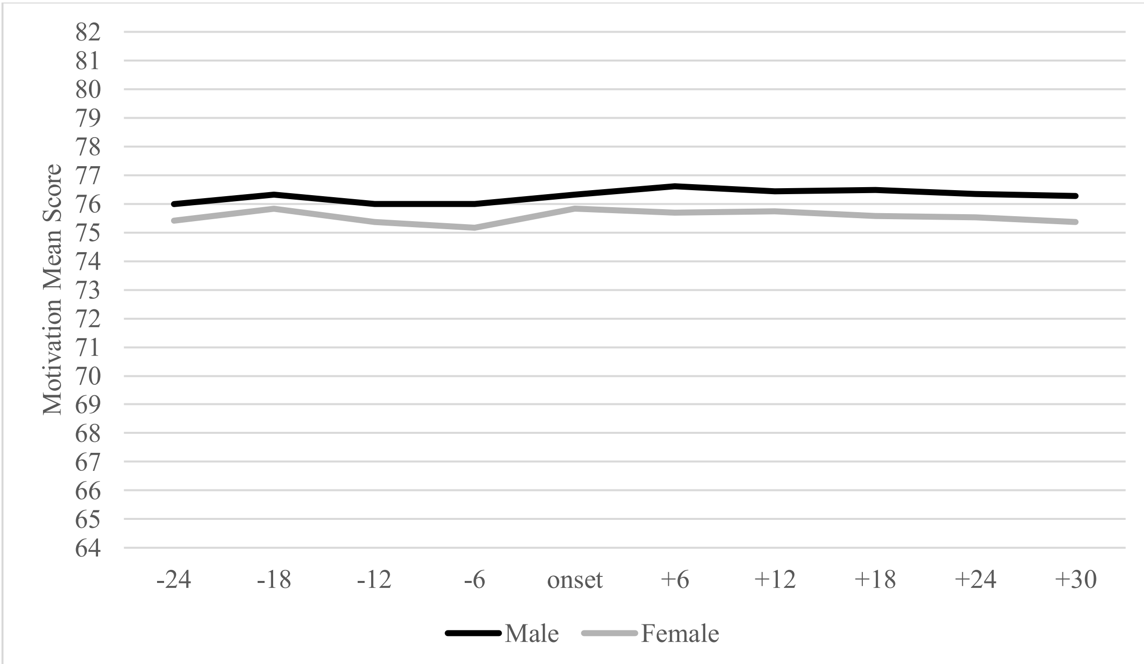



*Figure 4.4.C.* Trend lines for motivation over time by gender.

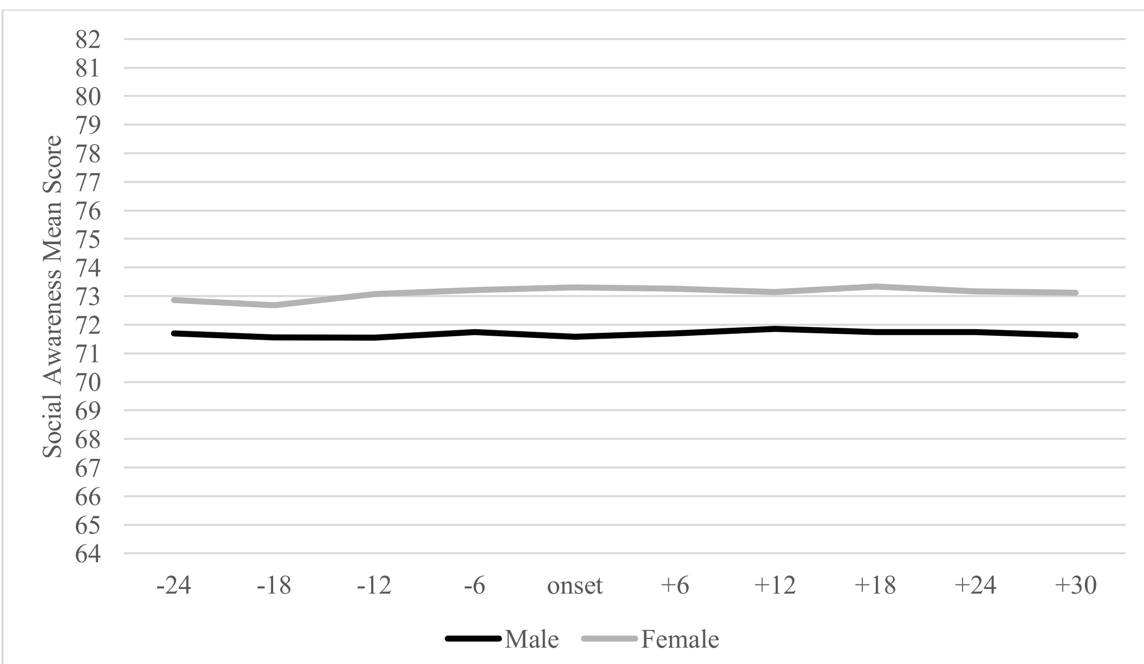
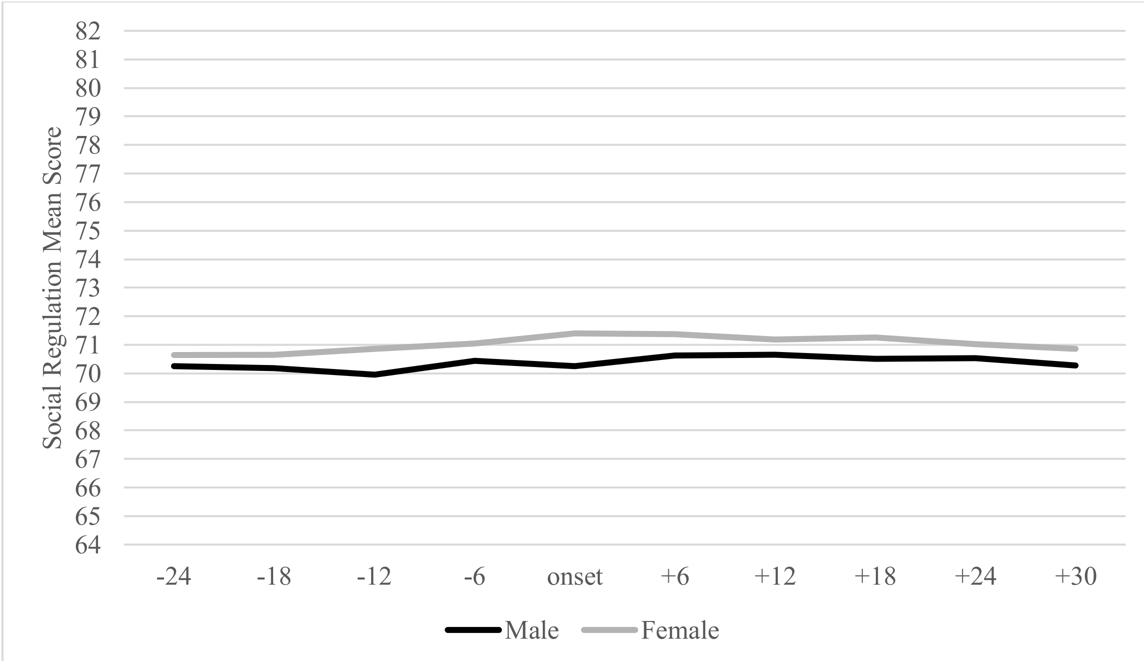



*Figure 4.4.D.* Trend lines for social awareness over time by gender.




*Note.* Onset of the pandemic refers to the time between March and August 2020. The 6-month time blocks preceding the onset are designated as -6, -12, -18, and -24. The time blocks following the onset continue the same pattern with positive numbers.

*Figure 4.4.E.* Trend lines for social regulation over time by gender.

*Urbanicity.* Although some of the results were significant due to sample size, urbanicity explained very little of the variance in self-awareness ($F_{(3,\ 33537)} = 10.39$, $p < .001$, $\eta^2 = .001$), self-regulation ($F_{(3,\ 33537)} = 2.00$, $p = .029$, $\eta^2 = .000$), motivation ($F_{(3,\ 33537)} = 2.99$, $p = .030$, $\eta^2 = .000$), social awareness ($F_{(3,\ 33537)} = 13.21$, $p < .001$, $\eta^2 = .001$), and social regulation ($F_{(3,\ 33537)} = 17.50$, $p < .001$, $\eta^2 = .002$). Although the differences are very slight, those in Urban and Large Rural areas trend slightly higher than those in Small Rural and Isolated until the onset time stamp, after which the trend lines intersperse (see Figure 4.5). This tendency, though slight, could suggest that more research regarding the interaction between the COVID-19 pandemic, urbanicity, and EI might be of interest.

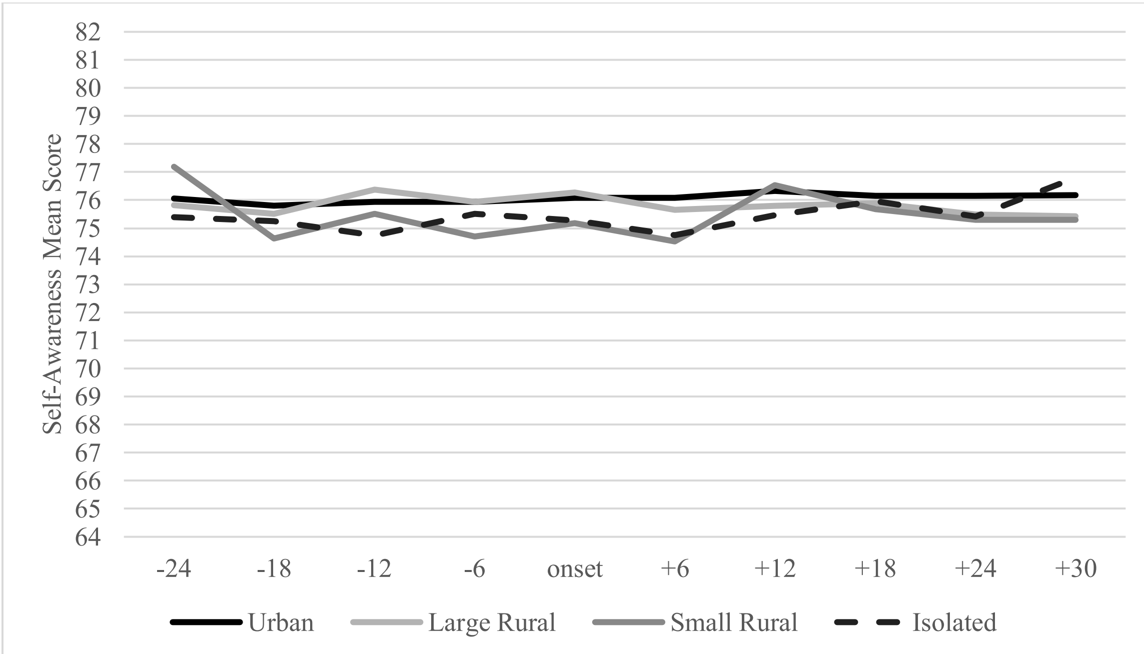



*Figure 4.5.A.* Trend lines for self-awareness over time by urbanicity.

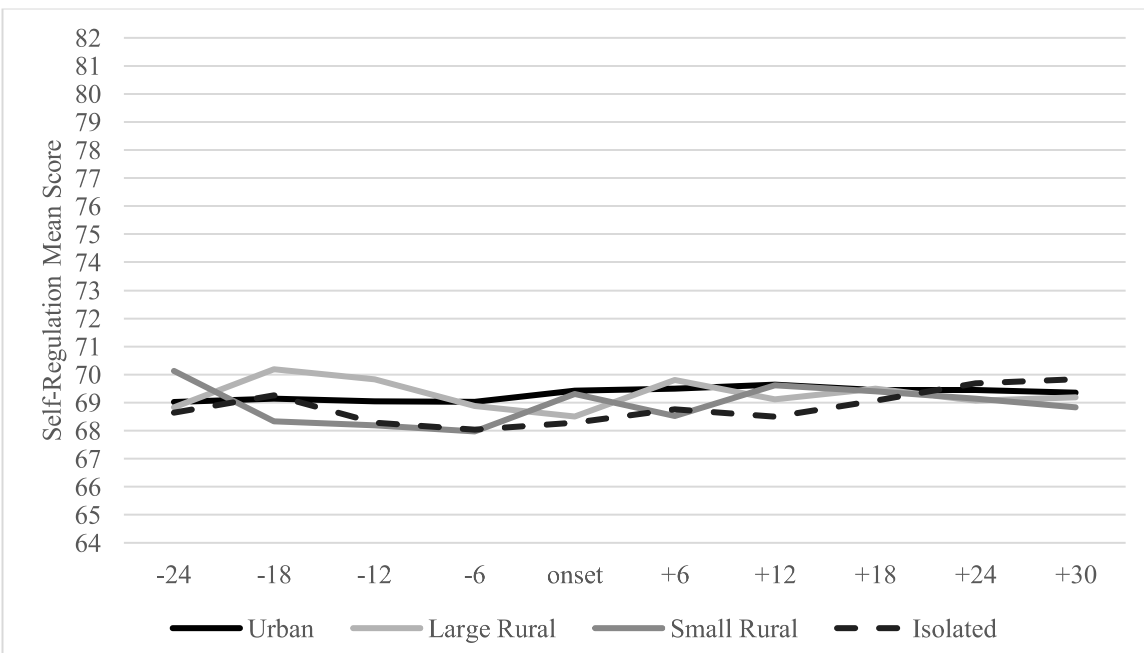



*Figure 4.5.B.* Trend lines for self-regulation over time by urbanicity

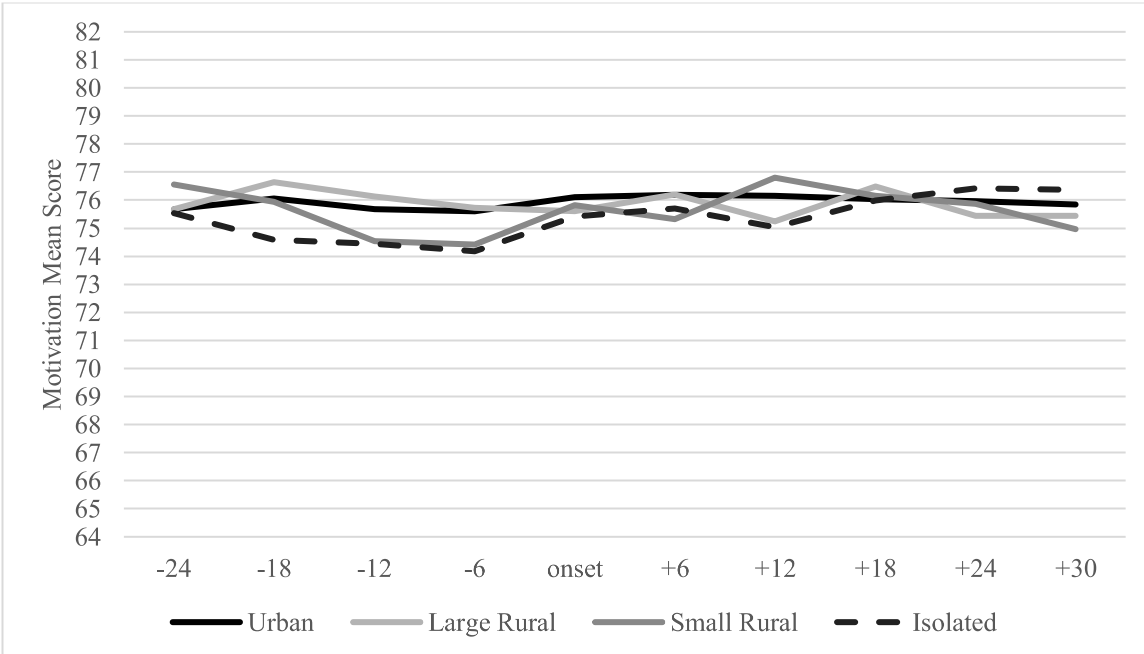



*Figure 4.5.C.* Trend lines for motivation over time by urbanicity.

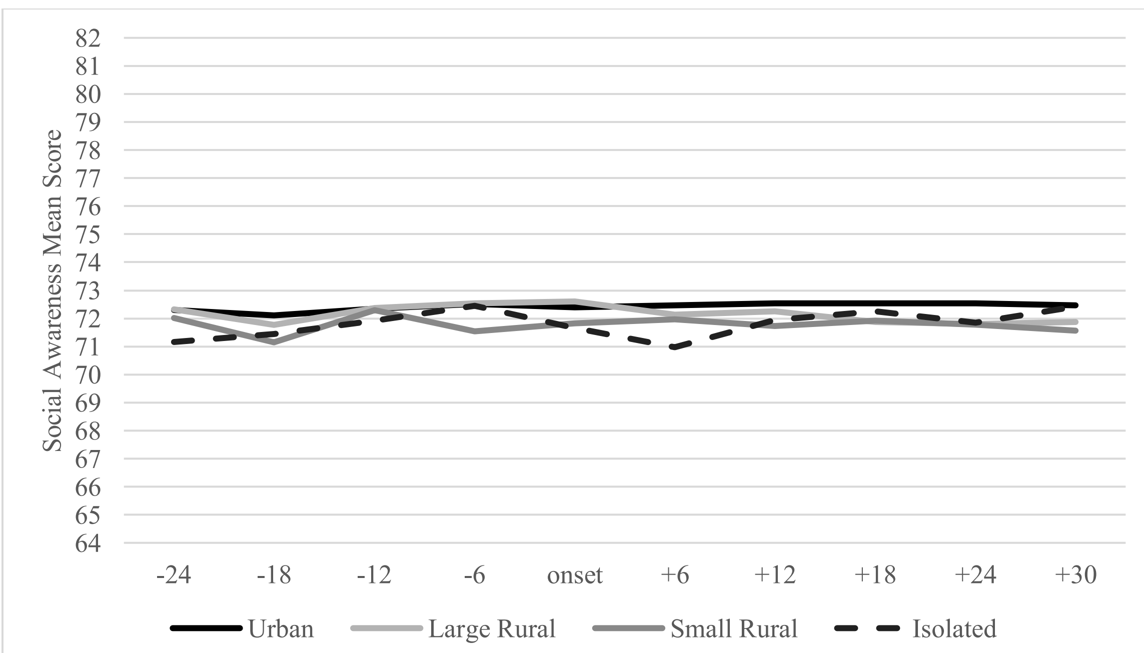
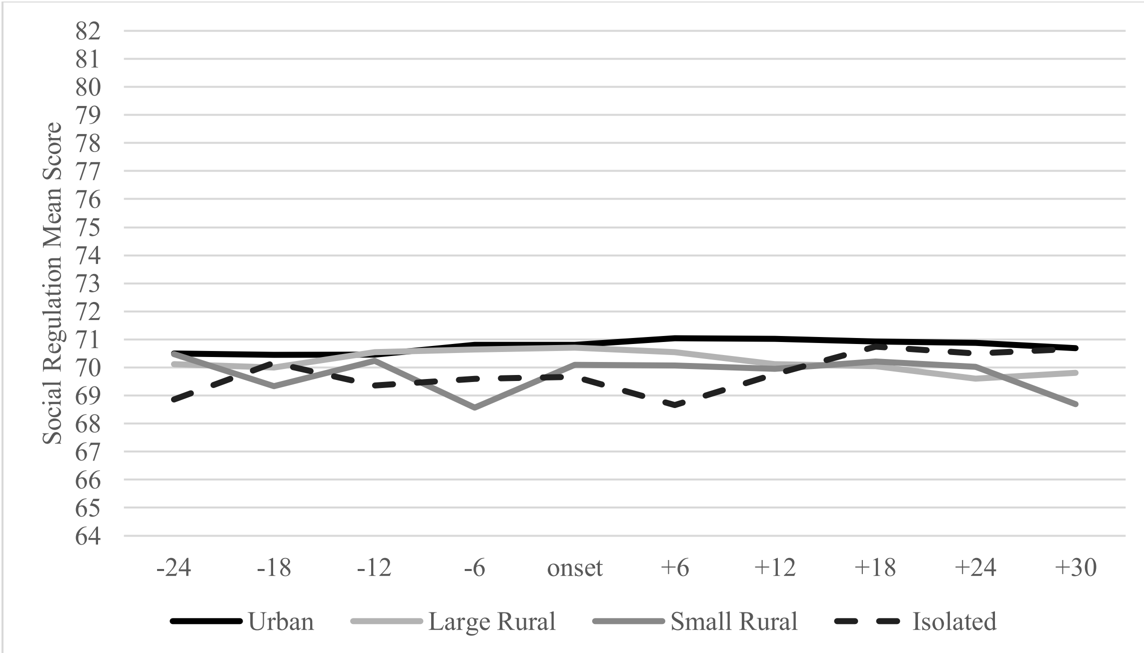



*Figure 4.5.D.* Trend lines for social awareness over time by urbanicity.




*Note.* Onset of the pandemic refers to the time between March and August 2020. The 6-month time blocks preceding the onset are designated as -6, -12, -18, and -24. The time blocks following the onset continue the same pattern with positive numbers.

*Figure 4.5.E.* Trend lines for social regulation over time by urbanicity.

*Industry and Occupation.* Although the results were significant due to sample size, industry explained very little of the variance in self-awareness ($F_{(23, 33851)} = 19.95$, $p < .001$, $\eta^2 = .013$), self-regulation ($F_{(23, 33851)} = 20.23$, $p < .001$, $\eta^2 = .014$), motivation ($F_{(23, 33851))} = 26.82$, $p < .001$, $\eta^2 = .018$), social awareness ($F_{(23, 33851)} = 51.72$, $p < .001$, $\eta^2 = .034$), and social regulation ($F_{(23, 33851)} = 49.86$, $p < .001$, $\eta^2 = .027$). There were very small differences in social awareness and social regulation, based on industry. However, the overall trend lines based on industry and occupation do not show significant changes over the course of data collection (see Figure 4.6). Because there are 23 industries represented, viewing individual lines is difficult. However, the difficulty in viewing individual lines due to overlap highlights the lack of difference between the individual lines. The one trend line that shows observable variance is in military occupations (*n* =36) where individual variation would greatly impact the trend line. In addition, the Farming and Fishing group appears to vary but also has a smaller sample size than other industries (*n* = 101).

The stability of EI among health care professionals was of special interest, due to the literature showing that EI fluctuated among health care students, and because the COVID-19 pandemic put specific stress on the health care industry. Although small changes of one or two points were seen, there were no large-scale changes seen among medical professionals and support staff. Trend lines for the health care industry are found in the appendix, and further discussion of these results is found in Chapter Five.

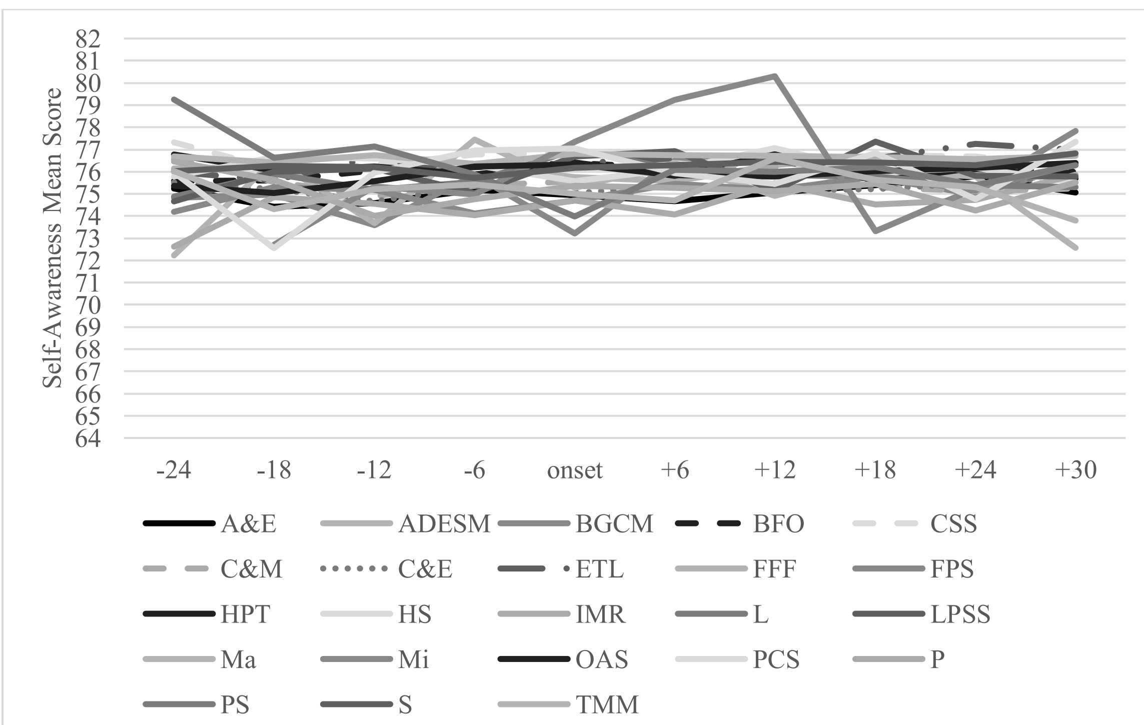



*Figure 4.6.A.* Trend lines for self-awareness over time by industry.

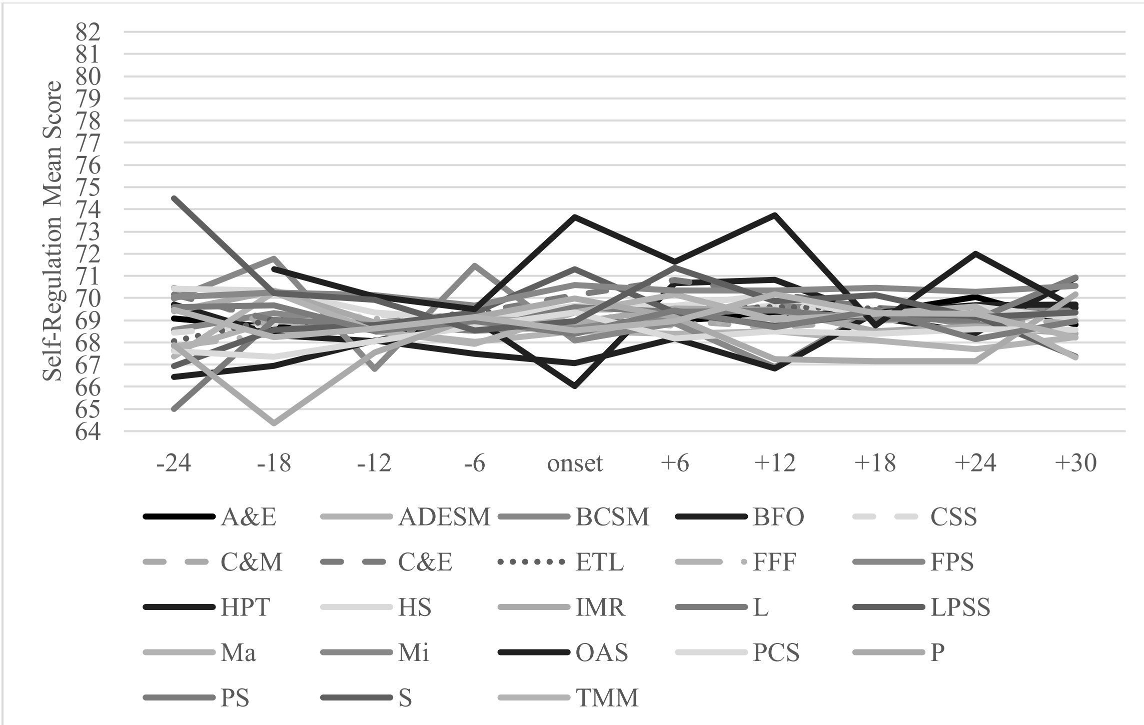



*Figure 4.6.B.* Trend lines for self-regulation over time by industry.

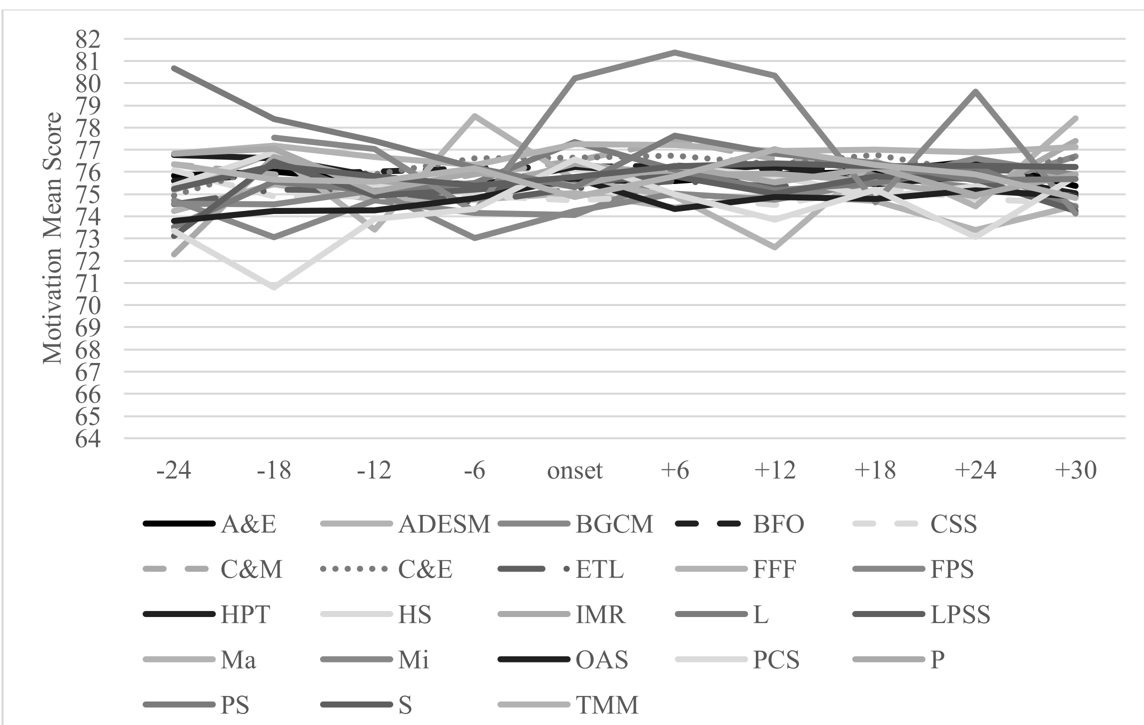



*Figure 4.6.C.* Trend lines for motivation over time by industry.

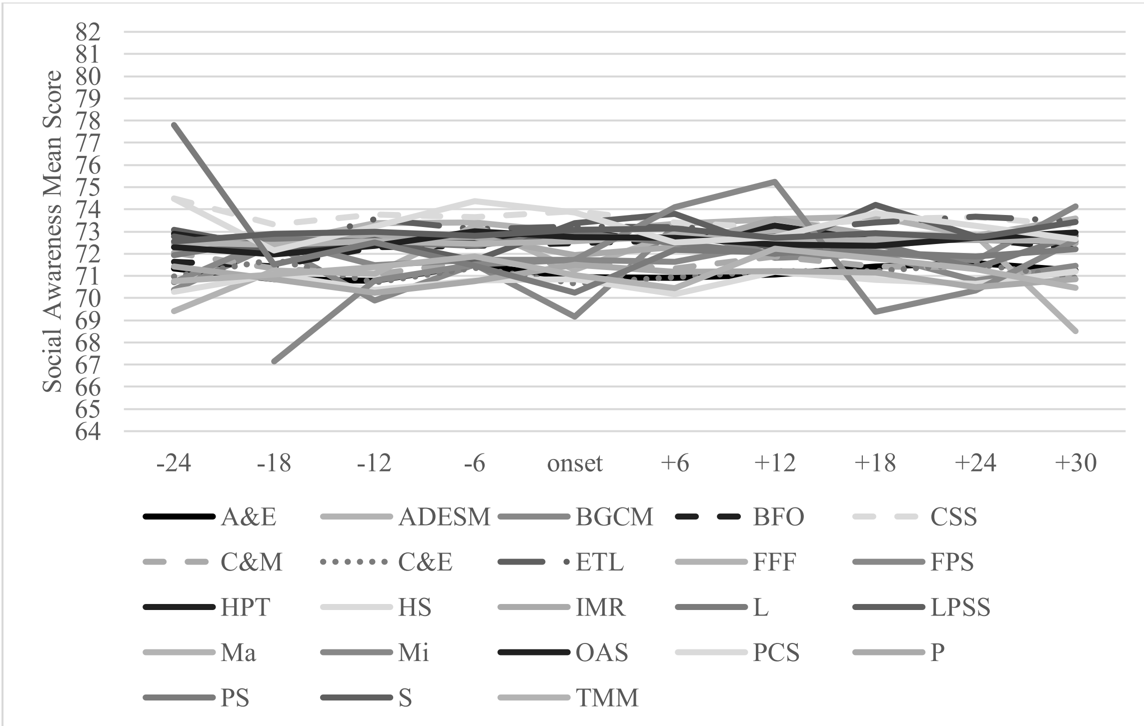
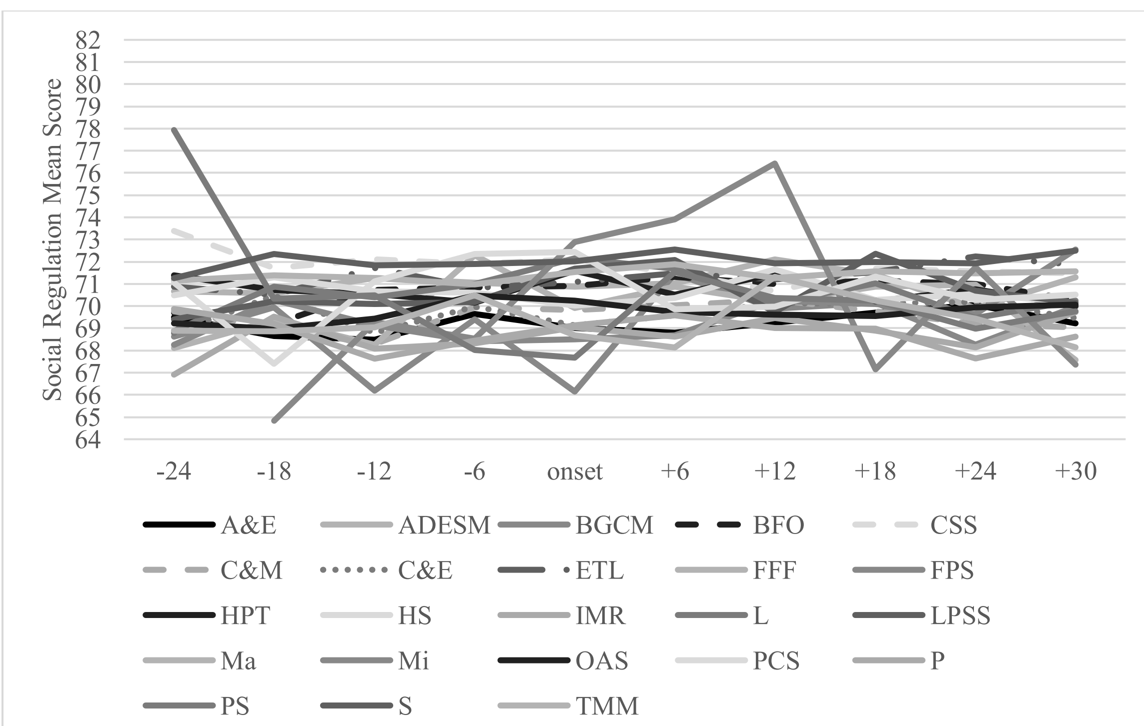



*Figure 4.6.D.* Trend lines for social awareness over time by industry.




*Note.* A&E=Architecture and Engineering Occupations; ADESM=Arts, Design, Entertainment, Sports, and Media Occupations; BGCM=Building and Grounds Cleaning and Maintenance Occupations;

BFO=Business and Financial Operations Occupations; CSS=Community and Social Service Occupations; C&M=Computer and Mathematical Occupations; C&E=Construction and Extraction Occupations; ETL=Education, Training, and Library Occupations; FFF=Farming, Fishing, and Forestry Occupations; FPS=Food Preparation and Serving Related Occupations; HPT=Healthcare Practitioners and Technical Occupations; HS=Healthcare Support Occupations; IMR=Installation, Maintenance, and Repair Occupations; L=Legal Occupations; LPSS=Life, Physical, and Social Science Occupations; Ma=Management Occupations; Mi=Military Specific Occupations; OAS=Office and Administrative Support Occupations; PCS=Personal Care and Service Occupations; P=Production Occupations; PS=Protective Service Occupations; S=Sales and Related Occupations; TMM=Transportation and Material Moving Occupations. Onset of the pandemic refers to the time between March and August 2020. The 6-month time blocks preceding the onset are designated as -6, -12, -18, and -24. The time blocks following the onset continue the same pattern with positive numbers.

*Figure 4.6.E.* Trend lines for social regulation over time by industry.

### *Major Findings*

Regarding the research questions, it was found that, when considering the overall U.S. adult population, there were no significant group changes in EI between April 2018 and December 2022. Additionally, there were no latent groups based on EI profiles. These findings were based on the delimitations of the study, and directions for future research will be discussed in Chapter 5. Regarding the research objectives, we established a defensible and feasible method for parameterizing time over more than two or three timepoints, in order to investigate the possibility of change in EI over time. In addition, we provided evidence for the measurement invariance of the TTI EQ instrument over time, establishing a foundation for group comparisons (whether latent or observed) over time.

# CHAPTER FIVE

## Discussion

Emotional intelligence is now widely recognized as a critical skill in business, education, and personal contexts. The study of emotions, sidelined for much of psychology's first century of research, has now attained center stage, as evidenced by the number of Google Search citations for EI (3,430,000) as compared to IQ (2,410,000). EI has been connected to multiple positive outcomes such as academic success (MacCann et al., 2020), health and well-being (Martins et al., 2010; Sánchez-Álvarez et al., 2016; Schutte et al., 2007), and better job performance (Bachman et al., 2000b; Boyatzis, 2006; Higgs, 2004; Higgs & Aitken, 2003; Joseph et al., 2015; Langhorn, 2004; Miao et al., 2019). EI has also been shown to help mitigate potential negative outcomes such as stress and burnout (Arora et al., 2010; Johnson et al., 2017; Laborde et al., 2016; Lea et al., 2019).

However, despite its wide recognition, some still dismiss the concept of EI as an overused buzzword. Even among the majority who recognize its importance, research is still needed to understand precisely what EI is (intelligence, trait, skill, or a combination of these); how it functions; and how it impacts and may be impacted by events, circumstances, and direct interventions. These needs underscore the importance of ongoing research into EI, despite the large extant body of literature on the subject.

A specific body of research, among medical students in a variety of fields, provided a theoretical basis for further investigation of the relationship between EI and stress. EI and/or empathy (a component of EI) was shown to decline among students in a variety of health-care professions (Gribble et al., 2017; Hojat et al., 2004; Newton et al., 2008; Rosenfield & Jones, 2004; Sherman, 2005; Spencer, 2004), causing some researchers to question how resilient EI is to prolonged stress and exposure to human suffering. The recent COVID-19 pandemic created similar circumstances among the general population, providing an opportunity to examine the stability of EI in the face of a sustained, global crisis.

This study investigated EI among U.S. adults aged 18 and over before and after the onset of the COVID-19 pandemic. While abundant research demonstrates that emotional well-being was compromised due to COVID-19 (Crabtree et al., 2021; Hoerger et al., 2014; Rossi et al., 2020; Shigemura & Kurosawa, 2020), we have, up to now, known little about the specific effects the pandemic may have had had on emotional intelligence. In this study, EI was measured using the TTI EQ instrument which follows the Goleman (1995) model of EI. Data were collected from April 2018 through December 2022. To examine EI over multiple years, time was parameterized in six-month blocks before and after the onset of the COVID-19 pandemic, with the time-period from March 2020 to August 2020 labelled as the *onset* of the COVID-19 pandemic. Measurement invariance over time was first investigated, utilizing confirmatory factor analysis with time as a random effect. The TTI-EQ model of EI was shown to be invariant over time. Once measurement invariance was established, an LPA was conducted to investigate the possibility of latent EI profiles. Finally, trend lines for EI by demographic were examined. No significant changes in EI were seen that could be contributed to the COVID-19 pandemic.

Although EI is well-recognized as a critical skill across personal, educational, and business contexts, less has been known about the impact of crisis and stress on EI. Although EI has been shown to mitigate stress and burnout, in some instances, EI has been shown to change in the face of prolonged stress and suffering. The current study contributes to the general theoretical knowledge about EI by demonstrating its stability in the face of a global pandemic with a broad scope and long-lasting impact.

### *Measurement Model*

Before meaningful comparisons of EI over time could be made, the measurement invariance of TTI's EI model (called *EQ*) had to be established. Because the sample was not truly longitudinal, it was necessary to treat time as a random variable in the CFA. The results of the multi-level CFA showed that the EQ model functioned in the same way across time. The implications of this invariance are important for those who work with EI, particularly those who utilize the TTI EQ instrument. Two primary implications for future practice and research emerge from our testing of the measurement model. First, the structure of the instrument held across a time-period when unprecedented change was happening. If the measurement model was stable across the chaotic period surrounding the COVID-19 pandemic, one could reasonably expect it to maintain its stability in other volatile time periods as well. In addition, the unique method used for establishing measurement invariance with a random effect contributes to the literature on measurement invariance testing by presenting an option for invariance testing when a true longitudinal design is not possible.

*LPA Investigation*

The LPA did not reveal unobserved latent groups based on EI profiles, meaning that EI is not functioning as a typology. Rather, within the population at large, each individual subdomain of EI varied independently. The independent function of the EI subdomains supports the measurement of separate domains, even though they are correlated.

Although typologies did not emerge among the general population, latent profiles could potentially exist based on industry or other demographic characteristics. That investigation was beyond the scope of the current study—as has been noted previously, it was impossible to examine all potential sources of variance due to the breadth of data collection. In the future, researchers could investigate whether patterns of EI that appear within individuals exist as typologies within demographic groups. For example, a group might score high on the three Self domains (Awareness, Regulation, and Motivation) but low on both Social domains (Awareness and Regulation). The reverse pattern (high social, low self) might also be seen. Alternatively, a group might be high in both aspects of Awareness but low on Regulation. This potential provides an opportunity for future research, which we will discuss at the end of this chapter.

*Stability of EI*

Overall, our results revealed little change in EI over time. The general stability of EI in our study aligns with previous research in which EI is an independent variable that moderates or mediates other factors. As mentioned previously, numerous studies have demonstrated a positive correlation between EI and beneficial life outcomes while many others have highlighted a negative correlation between EI and detrimental conditions such as stress and burnout. An oft-unstated assumption of this type of research is that an individual's EI must possess a certain level of strength and stability in order to be the moderator or mediator rather than the variable being acted upon. The results of the present study support such a theoretical understanding of EI. However, the question of whether EI, generally, could or would remain stable in the face of an unprecedented crisis such as the COVID-19 pandemic had not been explored. This study provides important information about the relative stability of EI in the U.S. adult population over the course of a widespread, prolonged crisis, specifically the COVID-19 pandemic.

Furthering our theoretical understanding of the stability of EI is critical to the ongoing debate regarding EI and its significance. First, if substantial claims are to be made regarding the efficacy of EI, then evidence supporting its stability is important: EI must usually be the actor and not the variable acted upon by circumstances. This study provides important evidence of the stability of EI during highly stressful and chaotic circumstances. At the same time, many—perhaps most—who tout the important of EI also claim that it can be improved through a variety of means such as teaching, training, and coaching. If EI is resistance to circumstantial changes, then understanding whether it can be changed at all, and if so, by which mechanisms, becomes increasingly important. We will discuss this further below when we examine potential directions for future research.

The literature presents a variety of mechanisms by which EI may help to mitigate stress, anxiety, and burnout. EI may improve one's ability to soothe distressed feelings (Goleman, 1995), delay gratification (Fiori, 2009), and select efficacious coping strategies (Matthews & Zeidner, 2000). EI may improve self-efficacy during stressful events (Mikolajczak et al., 2009), and it generally helps people counter negative self-talk and reframe their perspective (Goleman, 1995). High levels of EI correlate with the ability to build social relationships in a variety of contexts (MacCann et al., 2020). During the COVID-19 pandemic, each of these mechanisms would have been a powerful resource with which to manage the uncertainty and change. For example, those with the EI skill of building social relationships in a variety of contexts might have still found ways to build and maintain social relationships when traditional means were shut down due to social distancing. Those with the EI skill of selecting efficacious coping strategies might have utilized those skills, even when some coping strategies were unavailable due to COVID-19 lockdowns. The EI skills of soothing distressed feelings and delaying gratification would have been useful tools when goods and services were unavailable during the height of the COVID-19 pandemic. In each case, EI competencies may have served as a buffer against the stressful conditions of the COVID-19 pandemic. Indeed, a growing body of literature has begun to demonstrate the benefits of high EI in managing pandemic-related stress (J. Li et al., 2021; Nichols, 2021; Persich et al., 2021; Sadovyy, Sanchez-Gomez, et al., 2021; Scherer, 2022). The current study supports previous research by demonstrating that, overall, EI itself remained unchanged.

### *Understanding EI and negative mental health outcomes*

The negative impact of the COVID-19 pandemic on mental health is well-documented (Killgore et al., 2020; Wang et al., 2020). Therefore, a word about the relationship between EI and mental health, and what our results do and do not mean regarding mental health, is appropriate. EI is not a measure of depression, anxiety, or stress. EI is a measure of how readily a person *recognizes* their depression, anxiety, and stress (among other emotions) and to what degree they have tools to regulate these emotions. But EI is not a measure of these states. Therefore, research demonstrating that EI remained stable does not contradict research showing that the U.S. experienced a mental health crisis in relationship to COVID-19. In fact, to some degree, high levels of EI can contribute to heightened awareness of negative emotions. What may be true, based on both pre-and post-COVID literature regarding the relationships between anxiety, stress, and EI, is that, for those with high levels of EI, it served as a buffer for the stress of the pandemic. This hypothesis provides an opportunity for future research, which is discussed below.

### *Malleability of EI*

A similar comment regarding previous research demonstrating the malleability of EI is in order. Does the current study refute previous studies demonstrating that EI can be changed? We suggest that it does not. First, most studies which seek to investigate the changeability of EI are conducted in a controlled context, with a specific training intervention designed to increase EI. Though not experimental in design, the present study investigated whether EI could withstand circumstantial stress, not a targeted intervention. Therefore, we can neither make nor refute any claims regarding the malleability of EI in response to targeted training. In addition, as we will discuss further in our limitations, this study is not truly longitudinal; therefore, we cannot make claims about the specific effects on an individual person. However, as mentioned above, the results of the current study do point to the need for further research regarding targeted efforts to change EI through teaching and training. If EI is generally stable, then understanding if, when, and how it can be changed is critically important. Measuring the efficacy of training interventions is challenging (Leone, 2014), but the mandate to so is weightier when one considers how important EI is but how unlikely it is to change on its own.

Another important factor when discussing the malleability of EI is the population under consideration. The population of the current study was delimited to adults 18 and over. Therefore, we can make no claims regarding the malleability of EI among children and teens. Developmental psychology reveals that certain skills, such as language and reading, are developed more readily during childhood. The malleability of EI may likewise differ between adults and children. Although Goleman's (1995) model of EI has been widely accepted in the working world, his original emphasis was on education, and a solid body of literature exists regarding EI among children and teens. Considering the current study and the lack of change seen among EI in adults, understanding the efficacy of EI training among children becomes even more important.

Finally, the question of EI's malleability holds implications for our theoretical understanding of the construct in general. As discussed in the literature review, three disparate streams of EI theory emerged concurrently (Bar-On, 2006; Goleman, 1995; Salovey & Mayer, 1990), with a fourth, trait-based, stream emerging in response to perceived gaps in the other three (Petrides & Furnham, 2001). Researchers who conceptualize EI as a constellation of personality traits must sacrifice the idea of its malleability (McCrae, 2000). One may ask if the reverse holds true as well: Does research supporting the stability of EI create an imperative to embrace a trait-model of EI? EI researchers must address this question; however, we suggest that saying EI is stable is not the same as saying it is trait-based or fixed. As explained above, the results of this study suggest that EI is resilient to circumstantial stressors but cannot speak to the efficacy, or lack thereof, of targeted EI interventions. The investigation of EI's malleability would be a fertile area for further discussion and would inform our theoretical understanding of the EI construct.

### *EI and Medical Education*

The decrease in empathy and EI seen in the medical education literature served as a theoretical framework for investigating potential change in EI due to the COVID-19 pandemic. Because prolonged stress and exposure to human suffering were the mechanisms for decreased EI among students across a range of medical professions, it was hypothesized that the same effect might be seen in the larger population. However, this did not occur. One possibility is that, although the general population was exposed to greater degrees of human suffering than is usual for the U.S., it still did not reach the level and frequency of what is experienced by the medical community. More research is warranted into the exact causes of EI decline among medical students.

### *Differences in EI by demographic groups*

Although EI proved relatively stable over time, there were slight differences in EI among demographic groups over time. These differences were small but may be of interest in future research. Of particular interest to the COVID-19 question is that, among emerging adults, the average score for both Social Awareness and Social Regulation experienced a slight dip between March 2020 and August 2020. In our study, this was a relatively small demographic group, comprising 4.7% of the sample ($n$ = 1584). Investigating the impact of the COVID-19 pandemic on the EI of emerging adults would be a useful subject for future research. In addition, 18 months after the onset of the pandemic, those 65 and above experienced a slight drop in all five subdomains of EI. Investigating the circumstances surrounding this drop could be of research interest. Regarding urbanicity, the average scores for urban and large rural areas trended higher than small rural and isolated areas up until the onset of the COVID-19 pandemic, at which point the trend lines were more mixed. The disparate impact of the pandemic on urban versus rural EI is another potential direction for future research.

### *Limitations and Delimitations*

Despite the large sample size, this research study was limited by the fact that it was not truly longitudinal. No within-person changes could be observed. In addition, the sample was limited to those who responded to the TTI instrument. Although it was large enough to be considered representative, it was not truly random. One further limitation of the study is that it utilized only one model and one measure of EI. Meta-analyses of EI research have demonstrated diverse outcomes for various conceptualizations of EI. It is possible that another measure of EI might reveal change when this instrument did not.

In addition to the above limitations, we purposefully delimited our research to participants aged eighteen and above, with a U.S. address, and full demographic information. We also delimited our research to EI, without comparing it to other variables such as stress or personality. We delimited our LPA by investigating the entire population without including demographics as predictors. In some cases, these delimitations provide opportunities for future research.

### *Future Research*

Due to the size of the research sample, it was beyond the scope of the current study to investigate every possible source of variance within the data. Therefore, there are numerous opportunities for further research, simply within the existing sample, based on the delimitations mentioned above. Notably, all non-U.S. observations were excluded, even those with demographic information. Exploring the trends for EI among participants in other countries and on other continents is of significant research interest. In addition, research among those under age 18 is recommended.

Beyond the scope of the current sample, the following research directions could be explored. First, the method of testing measurement invariance used in this study is unique, due to the nature of the sample. Further research could and should be done to explore the benefits and limitations of this model. Simulation studies would be especially useful in this regard. In addition, although the LPA conducted on the entire sample did not reveal more than one group, conducting an LPA by industry or other demographic might reveal different latent profiles. Understanding how EI varies by industry could be of use for those already working in the various industries, for those seeking to enter the various occupations, and for those who train and hire professionals in these occupations and industries.

One of the limitations of this study is that, while the stress of the pandemic was assumed, no specific measures of stress were included along with EI. Accessing scores of participants who completed an EI assessment before the onset of the pandemic and then a stress assessment after the onset would be useful in providing insight into a more direct relationship between EI and stress. Based on the literature regarding the buffering effect of EI on stress, one could hypothesize that those with higher levels of EI before the onset of the pandemic might have lower levels of stress during and after the onset. However, research is needed to either support or challenge this hypothesis.

Based on the stability of EI observed in the general population during and after the onset of the COVID-19 pandemic, the changes in EI seen among medical students in other studies stand out as even more unique. One important clarification is that the instrument used in this study was not used in any of the medical education studies. In addition, although this study assessed health care practitioners, technicians, and support staff, it did not target medical students. Future research utilizing the TTI-EQ instrument among medical students would be useful, to see if the same changes in EI were observed. In general, more research among medical students regarding EI is needed. On the one hand, the current body of literature regarding EI among medical students is relatively small. However, while small, the literature all points in the same direction: students across a wide variety of medical fields experience a decline in empathy and/or EI, especially as they engage in more direct interaction with patients. Research is needed to confirm these results and guide efforts to counter them.

Although this study can neither confirm nor refute the results of studies that show EI responds to training interventions, the relative stability of EI in such a large population during an unprecedented crisis highlights the need for more research on the malleability of EI. Multiple studies have shown that teaching and training can improve EI, and in fact, Daniel Goleman's entire purpose in writing his now famous book was to help train the public, especially children, in EI skills. If EI is indeed a relatively stable characteristic, then understanding the specific circumstances and mechanisms that will change it is critically important. In addition, understanding the degree of fixedness or malleability in EI has important implications for our theoretical understanding of the construct, currently a point of much debate within the literature.

Finally, the small changes in EI among the various demographic groups present opportunities for future research. Qualitative research among emerging adults would be useful to help understand their changes in social awareness and social regulation during the onset of the pandemic. And an investigation of the experience of those 65 and over during the period 18 months after the onset of COVID-19 might help explain the small dips observed for them in all five EI subdomains.

### *General Summary and Conclusion*

This study investigated the stability of EI among those over 18 in the U.S. before and after the onset of the COVID-19 pandemic. Between April 2018 and December 2022, the measurement model for the TTI EQ instrument demonstrated measurement invariance. No latent profiles based on EI were found; rather, EI domains were seen to vary independently among the population. In addition, EI scores demonstrated relative stability before, during, and after the onset of the COVID-19 pandemic, which aligns with previous research on EI. Although EI is known to be a critical skill across personal, educational, and business contexts, less is understood regarding the impact of crisis and stress on EI. Although EI has been shown to mitigate stress and burnout, in some instances, EI has been shown to change in the face of prolonged stress and suffering. The current study makes an important contribution to the general theoretical knowledge of EI by demonstrating its stability in the face of a global pandemic with a broad scope and long-lasting impact.

APPENDICES

APPENDIX A

Classical Test Theory Analysis

Table A.1

*CTT Scale Reliability and Item Parameters*

| | *M* | *SD* | *ρ* | α |
|---|---|---|---|---|
| **Self-Awareness** | | | | **.73** |
| SA.1 | 3.68 | 1.089 | .375 | |
| SA.2 | 3.78 | 1.084 | .483 | |
| SA.3 | 3.75 | .785 | .484 | |
| SA.4 | 3.87 | .866 | .378 | |
| SA.5 | 4.06 | .763 | .399 | |
| SA.6 | 3.88 | .739 | .559 | |
| SA.7 | 3.34 | .880 | .438 | |
| SA.8 | 3.55 | 1.008 | .396 | |
| **Self-Regulation** | | | | **.72** |
| SR.1 | 3.19 | 1.158 | .412 | |
| SR.2 | 2.24 | 1.374 | .391 | |
| SR.3 | 2.81 | 1.241 | .526 | |
| SR.4 | 3.66 | .936 | .429 | |
| SR.5 | 3.66 | .935 | .452 | |
| SR.6 | 4.02 | 1.012 | .322 | |
| SR.7 | 3.83 | 1.036 | .471 | |
| **Motivation** | | | | **.78** |
| M.1 | 4.06 | .894 | .405 | |
| M.2 | 4.01 | .939 | .484 | |
| M.3 | 3.60 | 1.222 | .409 | |
| M.4 | 4.35 | .724 | .486 | |
| M.5 | 3.94 | .883 | .494 | |
| M.6 | 3.69 | .975 | .567 | |
| M.7 | 3.75 | .946 | .535 | |
| **Social Awareness** | | | | **.77** |
| SoA.1 | 3.89 | 1.005 | .433 | |
| SoA.2 | 3.91 | .970 | .514 | |
| SoA.3 | 4.08 | 1.009 | .394 | |
| SoA.4 | 3.89 | .886 | .483 | |
| SoA.5 | 3.47 | 1.194 | .409 | |

| | *M* | *SD* | *ρ* | α |
|---|---|---|---|---|
| SoA.6 | 2.82 | 1.405 | .464 | |
| SoA.7 | 3.30 | 1.154 | .583 | |
| **Social Regulation** | | | | **.73** |
| SoR.1 | 3.99 | .857 | .476 | |
| SoR.2 | 2.91 | 1.504 | .404 | |
| SoR.3 | 3.67 | .875 | .337 | |
| SoR.4 | 4.14 | .852 | .470 | |
| SoR.5 | 3.56 | 1.112 | .443 | |
| SoR.6 | 3.68 | .753 | .411 | |
| SoR.7 | 3.76 | .999 | .571 | |
| SoR.8 | 3.38 | 1.009 | .386 | |

APPENDIX B

Confirmatory Factor Analysis

Table B.1

*Results of CFA across six-month time blocks, Standardized Factor Loadings* Table B.1

| Item | 24 Mos. Prior | 18 Mos. Prior | 12 Mos. Prior | 6 Mos. Prior | Onset | 6 Mos. Post | 12 Mos. Post | 18 Mos. Post | 24 Mos. Post | 30 Mos. Post |
|---|---|---|---|---|---|---|---|---|---|---|
| SA1 | .51 | .49 | .45 | .48 | .46 | .44 | .49 | .47 | .51 | .52 |
| SA2 | .62 | .62 | .61 | .61 | .62 | .60 | .62 | .62 | .66 | .63 |
| SA3 | .65 | .66 | .64 | .66 | .65 | .68 | .64 | .65 | .70 | .57 |
| SA4 | .60 | .62 | .65 | .64 | .62 | .66 | .66 | .64 | .60 | .63 |
| SA5 | .52 | .46 | .52 | .49 | .48 | .52 | .49 | .50 | .53 | .54 |
| SA6 | .73 | .72 | .72 | .73 | .73 | .72 | .70 | .72 | .71 | .73 |
| SA7 | .65 | .59 | .61 | .60 | .60 | .63 | .58 | .61 | .60 | .57 |
| SA8 | .51 | .52 | .52 | .55 | .51 | .53 | .51 | .50 | .48 | .51 |
| SR1 | .47 | .50 | .49 | .50 | .46 | .47 | .48 | .46 | .47 | .49 |
| SR2 | .36 | .38 | .41 | .37 | .36 | .42 | .36 | .32 | .36 | .45 |
| SR3 | .53 | .53 | .54 | .53 | .50 | .57 | .56 | .51 | .50 | .60 |
| SR4 | .65 | .64 | .67 | .66 | .65 | .65 | .67 | .67 | .66 | .64 |
| SR5 | .63 | .59 | .58 | .59 | .58 | .61 | .61 | .59 | .62 | .58 |
| SR6 | .48 | .46 | .47 | .43 | .45 | .49 | .43 | .49 | .45 | .47 |
| SR7 | .60 | .64 | .63 | .61 | .59 | .63 | .60 | .61 | .65 | .63 |
| SR8 | .58 | .59 | .60 | .57 | .60 | .62 | .58 | .61 | .57 | .63 |
| M1 | .51 | .50 | .52 | .49 | .50 | .47 | .49 | .49 | .46 | .44 |
| M2 | .62 | .67 | .64 | .66 | .64 | .65 | .63 | .63 | .61 | .67 |
| M3 | .56 | .55 | .55 | .53 | .56 | .55 | .52 | .50 | .54 | .52 |
| M4 | .65 | .66 | .64 | .66 | .68 | .68 | .68 | .67 | .63 | .66 |
| M5 | .64 | .69 | .69 | .68 | .67 | .69 | .67 | .65 | .68 | .70 |
| M6 | .70 | .72 | .71 | .71 | .72 | .73 | .72 | .71 | .68 | .73 |
| M7 | .63 | .66 | .65 | .65 | .64 | .67 | .63 | .66 | .65 | .70 |
| M8 | .68 | .66 | .68 | .66 | .67 | .67 | .67 | .68 | .67 | .68 |
| SOA1 | .50 | .47 | .50 | .49 | .46 | .43 | .45 | .44 | .43 | .44 |
| SOA2 | .78 | .81 | .78 | .78 | .76 | .82 | .76 | .79 | .80 | .76 |
| SOA3 | .48 | .47 | .47 | .46 | .45 | .46 | .45 | .46 | .40 | .42 |
| SOA4 | .80 | .79 | .78 | .76 | .77 | .81 | .78 | .78 | .79 | .75 |
| SOA5 | .49 | .45 | .50 | .48 | .46 | .44 | .44 | .43 | .42 | .48 |
| SOA6 | .64 | .62 | .60 | .59 | .63 | .65 | .59 | .61 | .59 | .62 |
| SOA7 | .63 | .64 | .63 | .62 | .62 | .62 | .62 | .62 | .64 | .63 |
| SOA8 | .70 | .72 | .71 | .72 | .71 | .72 | .69 | .71 | .69 | .72 |

| Item | 24 Mos. Prior | 18 Mos. Prior | 12 Mos. Prior | 6 Mos. Prior | Onset | 6 Mos. Post | 12 Mos. Post | 18 Mos. Post | 24 Mos. Post | 30 Mos. Post |
|---|---|---|---|---|---|---|---|---|---|---|
| SOR1 | .58 | .55 | .55 | .57 | .56 | .56 | .54 | .55 | .58 | .50 |
| SOR2 | .39 | .37 | .37 | .35 | .35 | .39 | .35 | .36 | .38 | .36 |
| SOR3 | .68 | .62 | .63 | .60 | .62 | .64 | .62 | .67 | .69 | .60 |
| SOR4 | .54 | .54 | .55 | .52 | .52 | .52 | .52 | .50 | .54 | .51 |
| SOR5 | .66 | .64 | .63 | .65 | .62 | .66 | .63 | .61 | .58 | .63 |
| SOR6 | .56 | .57 | .55 | .60 | .60 | .60 | .59 | .61 | .56 | .61 |
| SOR7 | .67 | .65 | .65 | .65 | .66 | .64 | .61 | .64 | .66 | .62 |
| SOR8 | .51 | .55 | .52 | .54 | .56 | .59 | .52 | .54 | .54 | .55 |

Table B.2

*Results of CFA across six-month time blocks, Standardized Factor Correlations*

| Item | 24 Mos. Prior | 18 Mos. Prior | 12 Mos. Prior | 6 Mos. Prior | Onset | 6 Mos. Post | 12 Mos. Post | 18 Mos. Post | 24 Mos. Post | 30 Mos. Post |
|---|---|---|---|---|---|---|---|---|---|---|
| SR-SA | .49 | .50 | .50 | .49 | .52 | .50 | .50 | .48 | .52 | .53 |
| M-SA | .51 | .54 | .54 | .53 | .54 | .49 | .55 | .52 | .55 | .53 |
| M-SR | .67 | .67 | .67 | .65 | .69 | .67 | .72 | .68 | .71 | .70 |
| SoA-SA | .54 | .59 | .59 | .57 | .57 | .57 | .58 | .57 | .56 | .59 |
| SoA-SR | .19 | .26 | .23 | .23 | .24 | .22 | .22 | .22 | .23 | .24 |
| SoA-M | .12 | .16 | .13 | .11 | .12 | .11 | .14 | .12 | .16 | .14 |
| SOR-SA | .62 | .62 | .63 | .63 | .6 | .60 | .62 | .63 | .62 | .63 |
| SoR-SR | .46 | .46 | .45 | .45 | .45 | .44 | .45 | .47 | .49 | .52 |
| SoR-M | .43 | .46 | .46 | .46 | .39 | .47 | .48 | .49 | .52 | .49 |
| SoR-SoA | .81 | .80 | .80 | .79 | .82 | .79 | .79 | .79 | .78 | .81 |

APPENDIX C

Emotional Intelligence Trend Lines for Health Care Professions

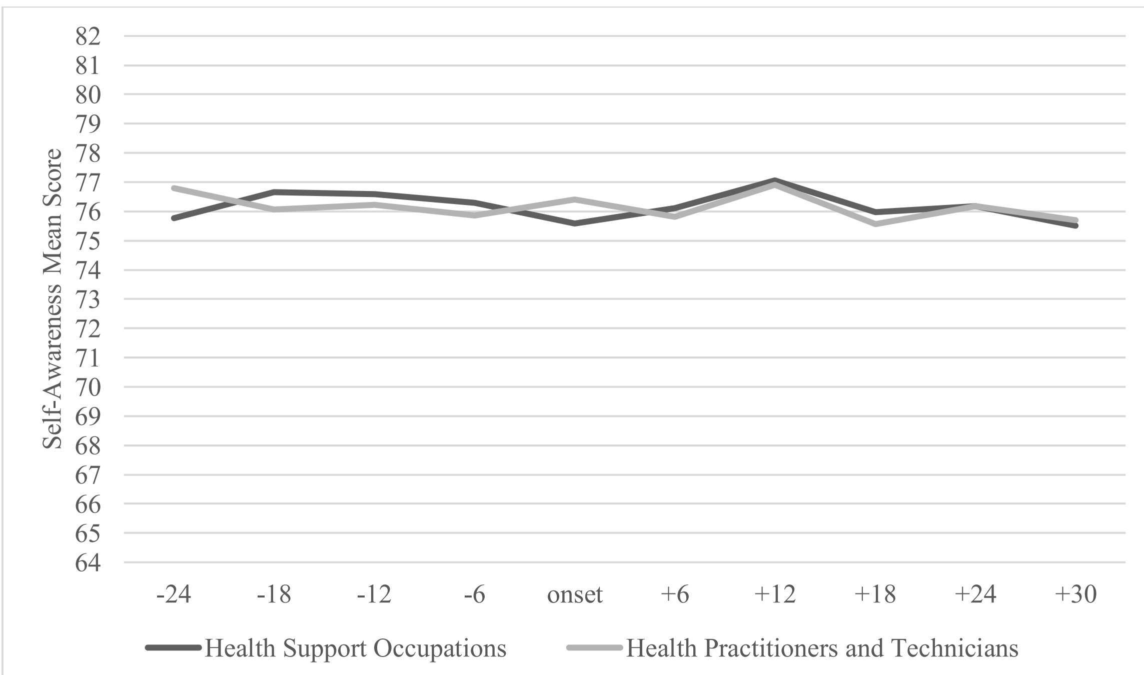



*Figure C.1.A.* Trend lines for self-awareness over time by health care industry.

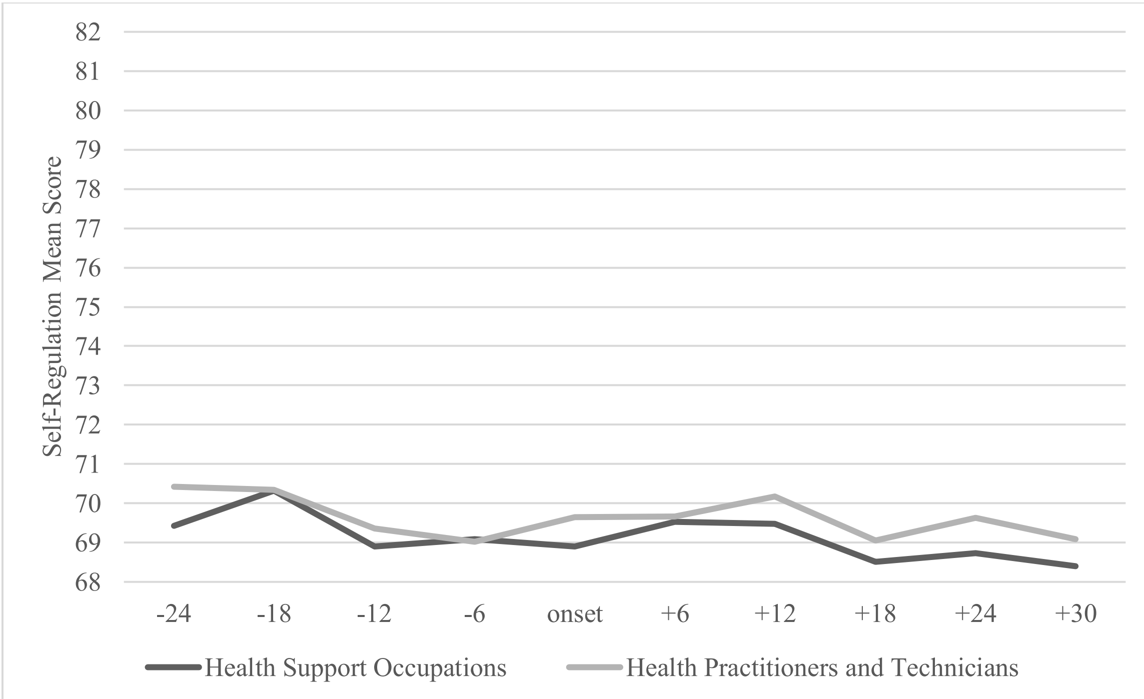



*Figure C.1.B.* Trend lines for self-regulation over time by health care industry.

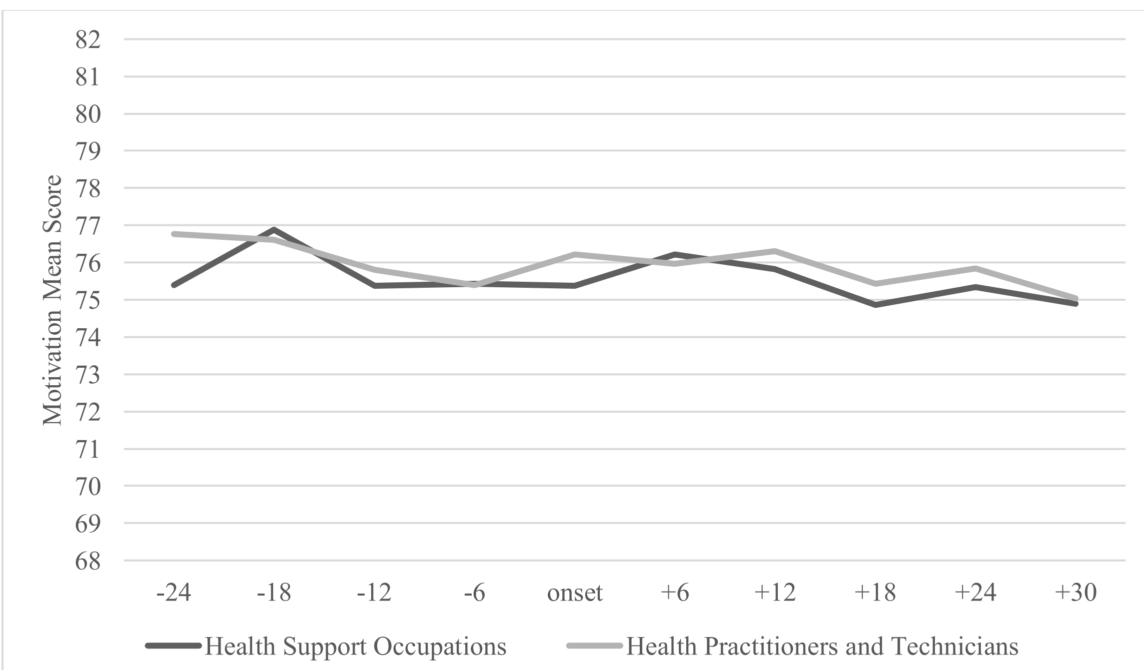



*Figure C.1.C.* Trend lines for motivation over time by health care industry.

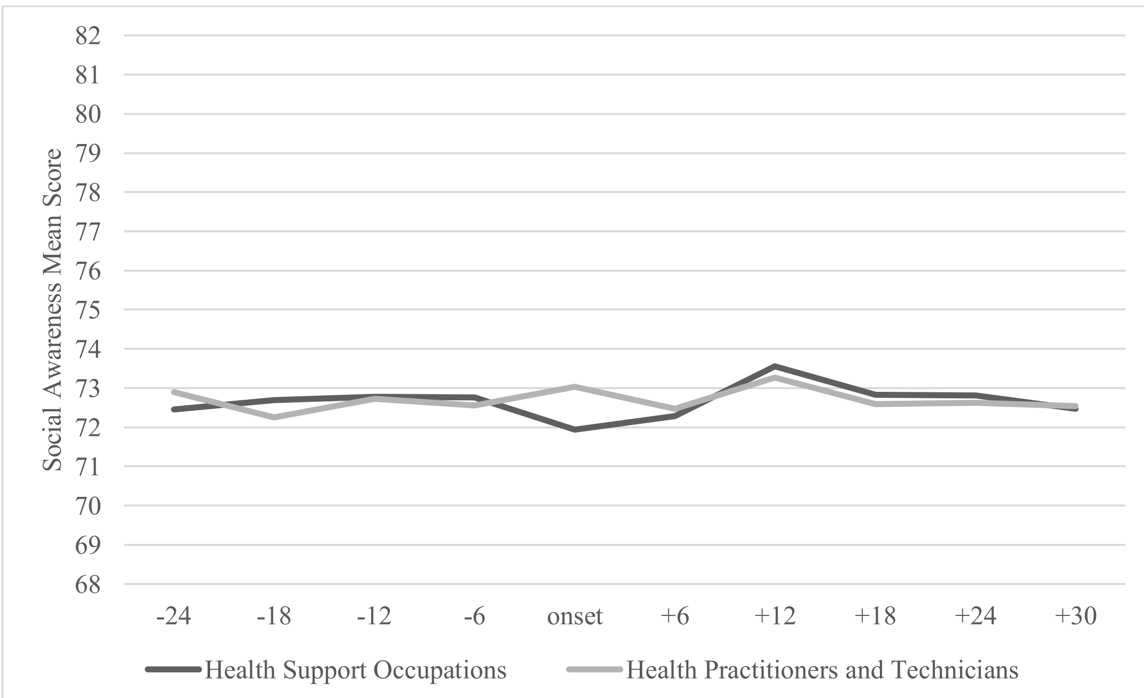
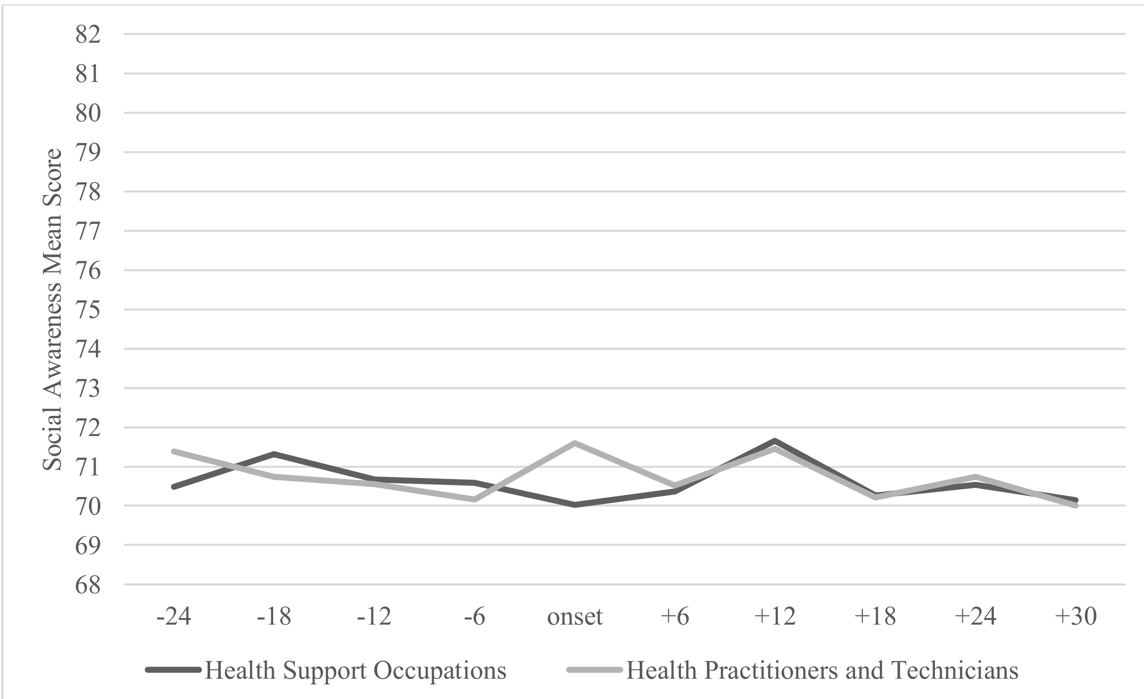



*Figure C.1.D.* Trend lines for social awareness over time by health care industry.




*Note.* Onset of the pandemic refers to the time between March and August 2020. The 6-month time blocks preceding the onset are designated as -6, -12, -18, and -24. The time blocks following the onset continue the same pattern with positive numbers.

*Figure C.1.E.* Trend lines for social regulation over time by health care industry.

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