Emotion Regulation Therapy for Distressed Adults During The COVID-19 Pandemic:

Examining Trajectories and Predictors of Response Following a Blended Telehealth Intervention

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Abstract

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In March 2020, New York City became the epicenter of the COVID-19 pandemic. Waves of illness, uncertainty, isolation, disruption, and loss led to increased rates of emotional distress. To extend access to evidence-based mental health services, we initiated an open trial of emotion regulation therapy in the context of the pandemic (ERT-P), delivered via telehealth and "blended" with an internet and mobile intervention (IMI) to augment treatment (e.g., video modules, between-session exercises, mindful regulation practices). ERT-P is a brief, 9-session psychotherapy program that integrates principles from traditional and contemporary cognitive behavioral therapies and mindfulness-based interventions to well-sui motivational and regulatory mechanisms associated with distress. The current study sought to evaluate the efficacy of ERT-P, investigate the impact of COVID-19 severity on treatment response, and explore whether sociodemographic, clinical, and contextual patient characteristics predict differential patterns of treatment response. Patients (N =134) were distressed, treatment-seeking adults in New York State. At pre- and posttreatment, as well as 3-month and 9-month follow-ups, patients completed assessments of perseverative negative thinking (PNT; worry, rumination), symptoms of emotional distress, and indices of quality of life. Patients exhibited statistically significant, large-magnitude reductions in all outcomes of interest at posttreatment (*d*s 1.53 – 2.74), which were maintained during the follow-up period (*d*s 0.75 – 1.33). Those who enrolled in treatment when the pandemic was most severe (i.e., highest seven-day averages of cases, hospitalizations, and

deaths) demonstrated greater improvement in PNT at posttreatment compared to those who enrolled earlier and later, irrespective of vaccine availability. Longer-term trajectories of improvement were not impacted by enrollment date and COVID-19 severity. Exploring predictors of reliable improvement identified a mix of sociodemographic, clinical, and contextual characteristics associated with acute treatment response. Notably, parenthood was consistently associated with a decreased likelihood of reliable improvement in worry, rumination, and distress. Despite the study's open trial design, which precludes causal attributions, ERT-P demonstrated preliminary efficacy. Further, ERT-P was found to be feasible and acceptable, evidenced by high patient satisfaction ratings, perceived usability of the IMI platform, and low attrition rates (10.5%). The current trial succeeded in its clinical objective to rapidly mobilize and extend access to evidence-based mental health services to a diverse group of distressed adults amidst the evolving landscape of the COVID-19 pandemic.

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Dedication

"Take into account that great love and great achievements involve great risk."
-HHDL

This dissertation is dedicated those who have been there for the entire adventure. Milo, thank you for bringing me joy, nudging me to step away from my computer and go outside, and sticking by my side since my first day of undergrad—I love being your dog dad. Stephen, my love, thank you for your patience, lifting me up, and giving me something to look forward to. I can't wait to share life with you and embark on our next big adventures. Mom, Dad, and Justin: I couldn't have pivoted and achieved this without you. Thank you for encouraging my dreams unconditionally. Megan, thank you for being in my corner and showing me it could be done! Richard, thank you for being a guiding light and reminding me to ask, "What if it all worked out?" Joe, endless thanks for holding space through it all.

To my grandparents: You've been with me every day. I love you.

Chapter 1: Introduction

The first cases of sudden acute respiratory syndrome coronavirus 2 (SARS-CoV-2), the 2019 novel coronavirus disease now known worldwide as COVID-19, were documented in late December 2019 in Wuhan province, China (World Health Organization, 2020). In weeks, the virus spread across all provinces in the country, precipitating the earliest protective measures to slow human-to-human transmission, including strict region-wide lockdowns, mandatory face coverings, symptom screening, and border closures (Chappell, 2020). The world watched in shock as new outbreaks emerged around the globe and catastrophic death counts were reported day after day. The international scientific and medical communities mobilized to learn about the virus, its transmissibility, and the most effective treatments. By March 2020, COVID-19 was confirmed in 114 countries, cases surpassed 100,000, and the death toll climbed to 4,291, prompting the World Health Organization (WHO; 2020) to declare it a pandemic.

1.1 COVID-19 in the United States

At the time of this declaration, cases of COVID-19 had already been confirmed within the United States, prompting dire warnings from public health officials at the U.S. Center for Disease Control and Prevention (CDC) that the virus would cause drastic and overwhelming disruptions to daily life (CDC, 2020b). In late January 2020, the U.S. implemented travel restrictions to and from China, and soon, numerous other countries were added to the list, further escalating the sense of uncertainty and isolation (Grépin et al., 2021). On March 13, 2020, the U.S. declared a national state of emergency, leading many states to impose emergency public health measures. Among the first and most restrictive measures were “shelter-in-place” directives limiting person-to-person contact outside the home. However, despite these efforts, the virus continued its rapid spread, causing severe illness and death faster than governments and communities could respond and placing an unprecedented burden upon the healthcare system (Miller et al., 2020).

As hospitals and morgues reached capacity in New York City, the first U.S. epicenter of COVID-19, temporary health facilities were established within the city's convention center and erected in Central Park, with refrigerated trucks deployed as makeshift morgues (Bumsted & Sisak, 2020). Elective surgeries and non-emergency services were postponed prioritizing COVID-19 patients and to ease pressure on health institutions. Those who fell ill or tested positive for COVID-19 were instructed to isolate themselves, while individuals exposed to the virus were advised to quarantine. During the early stage of the pandemic, when less was known about the virus's transmissibility and incubation period, isolation and quarantine lasted as long as 14 days (Jernigan & Team, 2020).

Per shelter-in-place directives, Americans were counseled only to leave their homes to obtain food, receive medical care, or if their occupation was deemed "essential" for the continuity of critical infrastructure operations (Cybersecurity & Infrastructure Security Agency, 2020). By the first week of April 2020, 40 states and Washington D.C. had imposed statewide shelter-in-place orders (Raifman et al., 2020). Concurrently, other public health measures were enacted, including closures of on-premise dining, public spaces, and transportation services; social distancing (i.e., maintaining spatial separation from others); mandated mask-wearing (Guy et al., 2021); and prohibitions on social gatherings and events (Avena et al., 2021). Almost immediately, schools, businesses, institutions, and health service providers around the nation transitioned to online formats, with an estimated 71% of Americans working "remotely" during this period (Parker et al., 2020).

1.2 Economic and Societal Impacts

Policies intended to protect lives had profound and adverse socioeconomic repercussions, resulting in non-essential business closures, widespread worker layoffs, and a dramatic economic downturn (Ganie et al., 2022). In the early months of COVID-19, the U.S. unemployment rate increased by 10.3%, with a staggering 23.1 million Americans unemployed (U.S. Bureau of Labor Statistics, 2020). Further, those who remained employed experienced substantial wage decreases, marking the first statistically significant decline (2.9%) in median household income since 2011. The economic fallout brought by COVID-19 pushed 3.3 million Americans below the poverty line (i.e., a family income less than < $26,695), increasing the national poverty rate to 11.4% (Shrider et al., 2021). At the height of the economic collapse, 30 million Americans—equivalent to 14% of the U.S. population—reported food insecurity the preceding week.

While the impacts of COVID-19 reverberated across the nation, certain groups were disproportionally affected, exposing preexisting health and socioeconomic disparities. National data from the early months of the pandemic revealed that American Indian or Alaskan Native, Black, and Latino individuals were at higher risk of infection, hospitalization, and death (Hooper et al., 2020). Across several U.S. cities and states, the percentages of COVID-19 hospitalizations and deaths among Black and Hispanic or Latino populations far exceeded their respective proportions of the population (Tirupathi et al., 2020). For example, in New York City, while non-Hispanic Black individuals account for 22% of the population and Hispanic individuals account for 29%, they accounted for 28% and 34% of total COVID-19 deaths, respectively (New York State Department of Health, 2022).

These glaring racial and ethnic disparities in health outcomes underscore long-standing inequities and discriminatory policies that have perpetuated unequal socioeconomic opportunity and access to essential resources such as housing, education, quality healthcare, health insurance, and personal protective equipment (Holtgrave et al., 2020; Lee et al., 2020). Particularly for disadvantaged racial and ethnic groups, living in multifamily homes or urban areas reliant on public transportation, adherence to public safety guidelines was often infeasible. As aptly stated by Dr. Clyde Yancy (2020) of Northwestern University, "social distancing is a privilege." Moreover, remote work was not a viable option for many. Indeed, the ability to work from home was observed to vary as a function of income and education (Parker et al., 2020). Alarmingly, from 2019 to 2020, poverty rates saw the steepest increases among Hispanic (17% increase) and Black (19.5% increase) ethnic and racial groups (U.S. Census Bureau, 2022b).

Beginning in March 2020, federal and state governments in the U.S. launched emergency relief initiatives under the Coronavirus Aid, Relieve, and Economic Security (CARES) Act to avert further economic catastrophe and assist the most vulnerable segments of the American population. These efforts included augmenting unemployment insurance benefits, distributing economic relief payments directly to citizens, providing emergency rental assistance to individuals, and extending financial support to businesses to facilitate the rehiring of laid-off workers (U.S. Department of the Treasury, 2021). However, data compiled by the Social Policy Institute at Washington University in St. Louis revealed significant delays in the disbursement of economic relief payments to racial and ethnic minority households and those already earning low incomes, likely exacerbating economic anxiety (Roll & Grinstein-Weiss, 2020).

1.3 Psychological Impacts of COVID-19

The pandemic and its consequent societal and economic impacts adversely affected mental health worldwide, as highlighted by research (Liu et al., 2021). Early studies from researchers in China provided insight into the psychological responses to COVID-19, sounding the alarm in countries that had yet to face the virus (Wang et al., 2020; Wu et al., 2020). As the pandemic unfolded, numerous cross-sectional studies from international hotspots reported similar increases in distress as those observed in China (Bonati et al., 2021). A large, multi-country study conducted in 2020 reported concerning statistics, estimating a 25.6% increase in anxiety disorders and a 27.6% increase in depressive disorders compared to prevalence rates in 2013 (Santomauro et al., 2021). These researchers also observed a significant association between prevalence rates, rising COVID-19 case rates, and restricted mobility, with higher rates among females and younger adults.

Within the U.S., results from a large-scale survey of American adults conducted in late March 2020 showed that the highest rates of fear, worry, and threat were concentrated in Northeastern regions of the country, where confirmed COVID-19 cases were highest (Fitzpatrick et al., 2020). Subsequent studies conducted in the months following the onset of the pandemic corroborated these findings, demonstrating increased rates of anxiety, depression, and symptoms of acute and traumatic stress across the U.S. (Daly et al., 2021; Glowacz & Schmits, 2020; Kibbey et al., 2021; Killgore et al., 2021; Marroquín et al., 2020; McGinty et al., 2020). Accordingly, researchers endeavored to identify the individual, societal, and contextual factors contributing to adverse mental health outcomes associated with the pandemic.

Impact of COVID-19 Context

Early on, psychologists and mental health professionals warned of a “second wave of devastation” due to the complex, interrelated set of stressors that COVID-19 presented (Simon et al., 2020). Gruber and colleagues (2021) succinctly summarized the various aspects of the pandemic that could detrimentally affect mental health, emphasizing the threat, chronicity, and reach of the virus itself; the loss of life and disruptions to coping and routine; and the social, occupational, economic, and interpersonal ramifications of pandemic-related changes to daily life.

Study after study, researchers sought to disentangle the network of factors contributing to COVID-19 distress and to identify populations at higher risk for psychiatric illness. Indeed, differences in distress-related outcomes consistently emerged based on COVID-19 experiences. Concerning the impacts of the virus itself, several studies investigated the relationships between distress and contracting the illness, having a family member or close friend test positive or become ill, or losing a loved one to COVID-19. For instance, more severe symptoms of anxiety, depression, and traumatic stress were observed among individuals who contracted the virus (Mazza et al., 2020). A large-scale study of U.S. adults revealed that, among individuals with no prior psychiatric history, there was an increased probability of meeting criteria for a psychiatric condition in the two weeks to three months following a COVID-19 diagnosis (Taquet et al., 2021). Interestingly, Genereux and Landaverde (2022) observed similarly high rates of anxiety among individuals who contracted the virus and individuals who experienced COVID-like symptoms or had direct contact with a confirmed COVID-19 case—without a diagnosis. As such, continued research is needed to elucidate the extent to which distress conditions following COVID-19 illness are attributable to infection itself or the pandemic's socioeconomic consequences.

Additionally, loved ones of COVID-19 patients and family members of those who died from the virus have experienced negative mental health impacts. Due to visitation restrictions in hospitals and care facilities for older adults, families and friends were left to worry about their ill loved ones from a distance. Studies of relatives of confirmed COVID-19 patients revealed elevations in anxiety, depression, and traumatic stress, comparable in severity to the COVID-19 patients themselves (Amass et al., 2022; Dorman-Ilan et al., 2020). Further, many families and friends of severely ill hospitalized patients—whether due to COVID-19 or another illness—were unable to be present at their loved one's time of death. Social distancing measures and hospital safety protocols disrupted customary funeral practices, altering the grieving and adjustment process for many (Burrell & Selman, 2022; Eisma et al., 2020). Indeed, a 2021 study of bereaved adults found that individuals who experienced COVID-19-related bereavement endorsed more severe symptoms of prolonged grief and persistent complex bereavement compared to those who lost a loved one to natural causes (Eisma et al., 2021). Examining potential risk factors for dysfunctional grief following a COVID-19 death, Neimeyer and Lee (2021) found that the circumstantial factors (e.g., absence of a proper burial or memorial service, not being present at the time of death) accounted for 59% and 71% of the variance in functional impairment and dysfunctional grief symptoms, respectively.

Public health measures, particularly shelter-in-place and social distancing restrictions, were also linked to increased health anxiety, financial worries, loneliness, and emotional distress (Okruszek et al., 2020; Tull et al., 2020). An analysis by Ferwana & Varshney (2024) revealed that lockdown measures in the U.S. negatively impacted mental health, causing a surge in utilization of mental health services that extended through 2020; remarkably, this effect persisted even after controlling for regional COVID-19 case rates. Killgore & colleagues (2021) found higher prevalence rates of depression, anxiety, acute and posttraumatic stress, and suicidal ideation during the first three weeks of the pandemic compared to population estimates in the preceding ten years. Moreover, distress rates were 1.5-1.7 times higher among individuals who reported losing their jobs due to COVID-19 shutdowns. Indeed, job and income loss, which interfered with individuals' ability to provide for themselves and their families, emerged as a significant predictor of adverse mental health outcomes during the pandemic (Hertz-Palmor et al., 2021; Hu et al., 2021; McDowell et al., 2021).

Food insufficiency, considered the most severe form of food insecurity, has also been linked with poor mental health outcomes (Nagata, Ganson, Bonin, et al., 2021). Analyzing data from the U.S. Census Bureau, Berkowitz & Basu (2021b) observed an association between Federal Pandemic Unemployment Compensation and distress, such that reported symptoms of anxiety and depression increased when the program expired in July 2020. In a novel study conducted by Luk et al. (2022), latent class analyses revealed four distinct subgroups that differed in psychosocial impacts of COVID-19 (i.e., minimal impact, work impact, family and friends affected by COVID-19, severe financial stress). Interestingly, their findings suggest that those who identified economic stress as their primary COVID-related challenge experienced more severe anxiety and depression, increased loneliness, and decreased quality of life.

Impact of Sociodemographic and Psychosocial Characteristics

Various sociodemographic factors have been linked with higher risks of adverse mental health outcomes during the COVID-19 pandemic. Understandably, the emotional well-being of healthcare workers—at the frontlines of this challenging crisis—received considerable research attention (Marvaldi et al., 2021; Moitra et al., 2021; Serrano-Ripoll et al., 2020; Wu et al., 2020). Multiple studies have reported high rates of anxiety (Halperin et al., 2021), depression (An et al., 2020), insomnia (J. Lee et al., 2021), trauma-related stress (Benfante et al., 2020), burnout (Denning et al., 2021), and moral distress (Norman et al., 2021) among this group, which all have the potential to impede their ability to provide care effectively.

Despite being at the highest risk for severe COVID-19 illness and death, older adults demonstrated psychological resilience, although increases in loneliness were reported (Palgi et al., 2020; Vahia et al., 2020). Conversely, prevalence rates for anxiety and depression rose from pre-pandemic levels among adults aged 18-59 (Kessler, Chiu, et al., 2022), with the most pronounced increases in distress observed among young adults aged 18-29, as well as those with annual incomes lower than $35,000 (McGinty et al., 2022). In a separate study, individuals with chronic health conditions (e.g., obesity, diabetes, asthma, chronic lung disease), more vulnerable to COVID-19 illness and death, reported significantly greater anxiety, depression, and stress than those without pre-existing medical problems (Wang et al., 2020). Notably, Wang and colleagues observed significant increases in symptoms of distress among White individuals with chronic conditions but not for other racial or ethnic groups.

Examining mental health trends during the pandemic, Cai and colleagues (2021) found that men, young adults, and Americans with lower incomes, as well as individuals who identified as racial or ethnic minorities reported higher levels of psychological distress. During the first year of the pandemic, prevalence rates of anxiety and depression increased to 30.3% among Hispanic and 29.3% among Black adults, compared to 24.8% among White adults (Kessler, Ruhm, et al., 2022).

Against the backdrop of the global pandemic, in the summer of 2020, protests for racial justice and chants of "I can't breathe" erupted around the country, following the police killing of George Floyd, an unarmed Black man (Hagemann & Neuman, 2020). According to analysis of longitudinal Gallup data, significant spikes in negative emotion, particularly sadness and anger, were reported among U.S. adults following George Floyd's death. In addition, since the start of the pandemic, Asian individuals of all ethnicities have reported increased instances of discrimination, stigmatization, and violence and increased psychological distress, likely fueled by xenophobic politicization of the virus and its origins in China (Hahm et al., 2021). Prior research has indicated that experiences of discrimination engender increased physiological stress responses and are associated with worse physical and mental health outcomes (Carter et al., 2017; Pascoe & Richman, 2009).

Impact of Pre-existing Psychological Symptoms and Clinical Factors

Researchers have also examined the impact of prior mental health conditions on the impact the psychological distress during COVID-19. Findings from a meta-analysis of international studies indicate that individuals with pre-exiting psychiatric diagnoses reported significantly more psychiatric symptoms and higher rates of anxiety, depression, stress, and sleep disturbance during the pandemic (Neelam et al., 2021). Examining distress among U.S. adults during the initial five months of COVID-19, Tsai and colleagues (2021) found further evidence that pre-existing mental health conditions exacerbated psychological outcomes. Specifically, after adjusting for several other covariates, including sociodemographic and psychosocial characteristics, the presence of a pre-existing mental health condition was uniquely and strongly associated with an increased likelihood of screening positive for major depressive disorder and generalized anxiety disorder. Notably, this association was even more pronounced than reporting personal or familial COVID-19 illness. Importantly, Taquet and colleagues (2021) found that individuals diagnosed with COVID-19, compared to other health events such as influenza or a respiratory tract infection, were twice as likely to be diagnosed with a psychiatric condition—most commonly an anxiety or mood disorder— in the 14-90 day period following a COVID-19 diagnosis. These researchers also observed that individuals diagnosed with a psychiatric condition in the year before the onset of the COVID-19 pandemic were 65% more likely to test positive for the virus (Taquet et al., 2021). Moreover, in a prospective study of over 3,500 North American adults, pre-pandemic depression and heightened COVID-related worry and loneliness emerged as risk factors for COVID-19 hospitalization, after controlling for demographic characteristics and health related risk factors (e.g., asthma, hypertension, high cholesterol; Wang et al., 2023).

In the context of rising alcohol and substance use, Holingue and colleagues (2020) identified a link between substance consumption and pandemic-related distress. Their research revealed that increased frequency of past-week alcohol or cannabis use significantly predicted anxiety and depressive symptoms amidst the COVID-19 crisis. Relatedly, separate investigations have found that increased alcohol and substance use—and newly initiated use during the pandemic—were linked to emotional distress (Roberts et al., 2021).

Previous research has emphasized the association between mental health conditions and suicidal risk, finding that 98% of individuals who completed suicide had at least one psychiatric disorder, most commonly a mood disorder (Bertolote et al., 2004). While suicide rates declined during the first year of the pandemic, there was a marked increase in drug overdoses in the general population and suicide attempts among adolescents (Friedman & Hansen, 2022; Yard et al., 2021). Exploring the relationship between suicidal ideation and behavior, Ammerman and colleagues (2021) observed that 43% of individuals reporting suicidal ideation in the past month explicitly attributed these thoughts to COVID-19. Concerningly, a small but notable group of participants in this study (n = 67, 7.4% of the sample), who were more likely to identify as male and as a racial or ethnic minority, reported intentionally exposing themselves to COVID-19 with suicidal intent. Together, these findings demonstrate the importance of considering pre-existing mental health factors and psychiatric characteristics when identifying those most vulnerable to adverse mental health outcomes during the COVID-19 era.

1.4 The "New Normal"

Long after COVID-19 was declared a public health emergency and the end of its acute phase, the virus continued to profoundly impact lives. Across the country, multiple variants of COVID-19 emerged, leading to recurrent surges and resurgences of infection, hospitalization, and death (L. Lin et al., 2021). Pre-symptomatic and asymptomatic spread of the virus fueled outbreaks (Moghadas et al., 2020). Efforts to re-open society were bolstered by vaccinations, which were rapidly developed and disseminated beginning in December 2020 following Emergency Use Authorization from the U.S. Food and Drug Administration (FDA, 2021b). Additionally, a number of COVID-19 boosters were developed and recommended to provide protection from new virus mutations and to restore waning immunity, especially for individuals with compromised immune systems (CDC, 2022b). In December 2021, the U.S. FDA approved an antiviral medication that demonstrated 88% efficacy in reducing the likelihood of hospitalization and death (FDA, 2021a). By 2022, Americans could order free rapid antigen tests through the U.S. Postal Service, with significant improvements in the accuracy of these tests compared to 2020 (Center for Medicaire & Medicaid Services, 2022).

At the societal level, polls showed that political views were related to vaccine refusal, as widespread misinformation, COVID-19 and vaccine conspiracy theories, and politicization of the government's response to the virus continued (Bolsen & Palm, 2021). Americans reported increasing "pandemic fatigue" and began taking fewer precautions and more risks (Haktanir et al., 2022). Vaccine hesitancy was also documented, most notably in the Black community, likely due to understandable and historical mistrust of medical community deriving from a history of exploitation (Warren et al., 2020). However, data suggested that rates of vaccine hesitancy and mistrust among Black Americans declined over time (Padamsee et al., 2022). Americans slowly returned to the workforce, working in-person, remotely, or a “hybrid” of the two formats, as the unemployment rate returned to pre-pandemic levels (U.S. Bureau of Labor Statistics, 2022). During the second year of the pandemic, data collected by the U.S. Census Bureau’s (2022a) Household Pulse Survey, showed that 39.1% of adults opted to work from home, while 23.5% made the decision specifically due to COVID-19.

Over time, the challenges shifted, and the “monster” was, for the most part, being kept at bay. And yet, hundreds and thousands of Americans were still dying of COVID-19 each day through the second year of the pandemic. The initial U.S. surge of COVID-19 was without question the most harrowing due to the shocking onset, overwhelming illness and death, and never-before-experienced restrictions placed on daily lives. However, in terms of severity, the country saw even worse in the years after 2020, with peaks of illness and death in both 2021 and 2022. As of Spring 2024, nearly 775 million individuals have been diagnosed with COVID-19 and over 7 million have died from the virus around the world (WHO). According to WHO data, the U.S. currently accounts for over one-sixth of the global total confirmed cases and deaths (i.e., over 100 million cases, over 1 million deaths).

On May 11, 2023, the U.S. Department of Health and Human Services (HHS) officially ended the COVID-19 Public Health Emergency (HHS, 2023). However, COVID-19 and its aftermath continue to impact lives, prompting the question: “How has the nation adapted?” Kessler and colleagues (2022) highlight the challenges of collecting data to address this query, questioning the reliability of previously-reported, exceptionally high prevalence rates of emotional distress. Nonetheless, using data from the CDC’s Behavioral Risk Factor Surveillance System (BRFSS), Kessler et al. observed statistically significant increases in anxiety and depression during the first year of the pandemic. Notably, these increases varied alongside

COVID-19 death rates and among different racial and ethnic groups. Similarly, Le & Nguyen (2021) found that a 0.01% increase in COVID-19 mortality rate was associated with higher daily reports of anxiety, worry, anhedonia, and depression.

According to 2019 estimates from the National Health Inventory Survey, average prevalence rates for anxiety, depression, and anxiety or depression were 8.1%, 6.5%, and 10.8%, respectively (Terlizzi & Schiller, 2022). By May 2020, rates surged dramatically, with 30.8% of American adults reported symptoms of anxiety, 23.5% reported symptoms of depression, and 35.9% reported symptoms of an anxiety or a depression (CDC, 2022a). Elevated rates of distress persisted through August 2022, with 28.3% of American adults reporting anxiety, 22.0% reporting symptoms of depression, and 32.3% reporting of anxiety or depression (CDC, 2022a). CDC data from August 2022 study shed light on the variability in the population, revealing that the highest rates of distress were observed among specific demographic groups, including respondents aged 18-29, individuals with disabilities, those identifying as female, individuals with lower levels of education, members from sexual and gender minorities, and persons identifying as “other” or “multiple” racial categories.

Longitudinal studies examining trajectories of distress during COVID-19 have yielded mixed findings, with researchers identifying patterns of decreasing, stable, and increasing distress, particularly among vulnerable demographic groups. For example, Daly and Robinson (2021) analyzed three months of data from the Understanding America Study (UAS) and showed emotional distress peaking from March to April 2020 but returning to baseline by June 2020. Another longitudinal study focusing on depression symptoms among U.S. adults between March-April 2020 and March-April 2021 found that symptoms increased over this year-long period, with a 5% increase in prevalence rates (Ettman et al., 2022). Ettman and colleagues observed the worst outcomes among individuals with lower household income, unmarried status, and those reporting multiple concurrent COVID-related stressors. McGinty and colleagues (2022), examined trajectories from early April 2020 through late July 2022, using data from Johns Hopkins COVID-19 Civic Life and Public Health Survey, and found that prevalence rates of distress remained stable, with no significant change between April 2020 (13.6%) and July 2020 (13%). In this study, and at both time points, distress prevalence was highest among young adults, those with an annual income less than $35,000, and Hispanic individuals. Lastly, Kim and colleagues' (2023) longitudinal study of U.S. adults, which utilized data from the Health Information National Trends Survey, observed increasingly poor mental health from the first to third years of the pandemic, with significantly higher rates of distress in 2022 compared to 2020. In this study, respondents reporting food insecurity, housing instability, and lower income exhibited increased risk of negative mental health outcomes.

To fully grasp its impact on mental health and well-being, further analysis of data spanning the entire duration of the pandemic is imperative. Seminal work by George Bonanno and colleagues (2004) suggests that following potentially traumatic events, a large proportion of individuals exhibit resilience—a pattern characterized by minimal disruption in functioning, followed by normative, stable functioning. Indeed, a 2018 meta-analysis of 54 studies examining response trajectories following potentially traumatic events found the pooled prevalence rate for the resilience to be 65.7%, while a "chronic" trajectory (i.e., consistently high rates of stress or distress) constituted 10.6% of responses across populations (Galatzer-Levy et al., 2018). In a systematic review of 28 longitudinal studies examining resilience during COVID-19, Schäfer and colleagues (2022) replicated these findings, with the resilience trajectory being most prevalent (pooled prevalence 66.0%, range 29.0 – 88.9%). "Delayed" distress and chronic distress trajectories were also observed, with prevalence rates of 11.6% (range 3.5% - 35.5%) and 11.2% (range 3.9 – 53.1%), respectively. Included in this systematic review was a study by Chen et al. (2022) examining trajectories of anxiety, depression, and posttraumatic stress symptoms among Chinese participants in Hubei, China, between April and October 2020. Their findings revealed that the majority of individuals demonstrated resilient trajectories for anxiety (58%), depression (87%), and posttraumatic stress symptoms (93%). Conversely, 37%, 8%, and 7% demonstrated chronic trajectories for anxiety, depression, and posttraumatic stress symptoms, respectively. Notably, worry emerged as the most robust predictor of both resilience and chronicity of anxiety and depression, such that worry negatively predicted resilience and positively predicted chronicity of symptoms.

It is encouraging that most individuals will exhibit resilience or eventually adapt and recover when faced with life's stressors, including the pandemic and the challenges it posed. However, it is essential for the field of clinical psychology to be proactive in addressing the needs of those whose suffering persists, does not fully remit, or emerges long after the initial impacts of COVID-19.

1.5 Telepsychological Treatment for Emotional Distress

According to the earliest data collected by the U.S. Census Bureau in August 2020, 21% of American adults who had positive screen for anxiety or depression reported unmet needs for mental health services in four weeks (CDC, 2020a). Subsequent polling indicated that the reported lack of access to mental healthcare remained high or increased in subsequent years, with rates reaching 26.1% in March 2021 and 28.5% in March 2022.

Even before the pandemic, individuals in distress faced a variety of barriers to receiving mental healthcare in the U.S., including lack of financial resources or insurance (Rowan et al., 2017), limited availability of treatments (Walker et al., 2015), a shortage of mental health providers (Andrilla et al., 2018; Thomas et al., 2009), and stigma (Corrigan et al., 2014). Moreover, access to mental health services has historically been limited for racial and ethnic minority groups (Cook et al., 2017), low resource communities (Mongelli et al., 2020), and individuals living in rural areas (Morales et al., 2020). To bridge gaps in mental health treatment access, the field has turned to technology to deliver and/or augment standard forms of clinical care (Ralston et al., 2019).

Telepsychology, as defined by the American Psychological Association (APA), is "the provision of psychological services using telecommunication technologies…telephone, mobile devices, interactive videoconferencing, e-mail, chat, text, and Internet" (Joint Task Force for the Development of Telepsychology Guidelines for Psychologists, 2013). Over the past ten years, access to the internet and ownership of technology (e.g., computers, smartphones, internet-connected devices) has steadily increased. According to polling data from Pew Research Center in 2021, 96% of Americans aged 18-49, 95% of Americans aged 30-49, and 83% of Americans aged 50-64 owned a smartphone with internet access (Faverio, 2022). As is the case with health and mental health outcomes, it is of upmost importance to consider disparities in access to technology (e.g., lack of reliable internet, no computer in the home). Encouragingly, polling data suggests that 76% of Americans with annual household incomes below $30,000 own a smartphone with internet access—up from 71% in 2019 (Anderson, 2019; Vogels, 2021). Given this trend in steadily increasing access to remote technology, it is essential to leverage these resources to provide clinical services to those in need.

During the pandemic, government agencies swiftly responded to increase access to mental health services. The Security and Privacy rule of the Health Insurance Portability and

Accountability Act (HIPAA) was temporarily relaxed to allow the use of telecommunication technologies (e.g., Zoom) for service delivery (U.S. Department of Health and Human Services, 2020). Additionally, Medicare and Medicaid insurance programs agreed to provide reimbursement for "tele-visits" (Center for Medicaire & Medicaid Services, 2020), while states eased jurisdictional and licensing policies, allowing clinicians to provide services across state lines (U.S. Department of Health and Human Services, 2021).

The utilization of "teletherapy," or "telehealth" psychotherapy delivered via video, surged from 7.1% before COVID-19 to 85.5% during the pandemic (Pierce et al., 2020). Meta-analytic findings indicate that the efficacy of teletherapy for mental health conditions is comparable to in-person psychotherapy, with no significant differences in attrition rates between modalities (Giovanetti et al., 2022; Greenwood et al., 2022; T. Lin et al., 2021; Scott et al., 2022). Indeed, research from open trials and RCTs conducted during the pandemic suggests that video-based psychotherapy was efficacious for reducing emotional distress (Alawi et al., 2021; Sanilevici et al., 2021; Shabahang et al., 2021; Simonsson et al., 2021). Moreover, studies indicated that the transition from in-person therapy to teletherapy during COVID-19 was largely successful, resulting in increased attendance and fewer cancellations, likely attributed to increased flexibility (Appleton et al., 2021; Cuthbert et al., 2022).

These changes that enabled the continuation of mental health services were particularly beneficial to individuals already engaged in therapy. However, as population distress increased, so did the demand for services, placing considerable strain on the mental health system and individual providers (APA, 2021). Consequently, many individuals struggling with distress during the pandemic found themselves on waitlists, tirelessly chasing referrals, or left without needed help.

Mobile Mental Health Apps

Mobile mental health apps (MMHAs) offer accessible support via smartphone or other portable device and can be effective tools for individuals in distress, particularly when in-person services are limited, unavailable, or out of reach. To increase access, many MMHAs temporarily suspended subscription fees during the pandemic (onemindpsyberguide.org, 2020). Presently, the marketplace hosts hundreds of thousands of MMHAs, available for free and for purchase (Neary & Schueller, 2018). However, a 2017 systematic review of MMHAs for anxiety found significant shortcomings: few MMHAs relied on any theoretical framework, 96.2% did not provide outcome or efficacy data, and only 3.8% had been empirically evaluated (Sucala et al., 2017). Nevertheless, separate meta-analyses of tested MMHAs have demonstrated their effectiveness, showing substantial and significantly greater reductions in symptoms of depression (Firth, Torous, Nicholas, Carney, Pratap, et al., 2017) and anxiety (Firth, Torous, Nicholas, Carney, Rosenbaum, et al., 2017) compared to control conditions.

COVID Coach is a free and publicly available MMHA, developed and launched by the U.S. Veteran Affairs in April 2020, at the height of the pandemic. COVID Coach offered "evidence-informed tools for coping with stress and anxiety, information about how to stay well, stay connected, and navigate challenges, self-monitoring mental health symptoms and goals, and resources to discover and connect with various types of verified and vetted support" (Jaworski et al., 2021). Engagement data indicated that the COVID Coach was downloaded 143,097 times in the first six months of the pandemic, with users most frequently seeking tools to manage their stress (53.2%). However, no outcome data have been published to date.

To examine the use of MMHAs and MMHA preferences, Mata-Greve and colleagues (2021) surveyed 2,000 healthcare workers and individuals who lost their job during COVID-19.

Although roughly 75% of respondents reported clinically significant symptoms (i.e., above the clinical cut-off for anxiety, depression, substance use disorder, or suicidal risk), only 14% reported using an MMHA to help manage their distress. In the study, respondents were also asked to identify the MMHA components they would include if they could build their own app. Among respondents with elevated emotional distress, the most desired components were mindfulness (65.3%), psychoeducation (62.7%), tools for distraction (i.e., puzzles, music; 60.4%), and symptom tracking (60.2%). Discouragingly, of the distressed group, 37.2% reported not using an MMHA because they felt it would not be of benefit.

Unguided and Guided Internet-delivered Interventions

For the past two decades, researchers have sought to adapt empirically supported treatments into internet-delivered interventions, which hold the potential for scalability and wide dissemination to the public (Andersson, 2018). Unguided internet interventions most resemble bibliotherapy or MMHAs in that they are self-administered. During COVID-19, several unguided interventions were tested to address the needs of individuals reporting symptoms of anxiety and depression (Riboldi et al., 2022). One unguided internet-delivered CBT (iCBT) program, which consisted of psychoeducation and CBT-based worksheets, resulted in small but significant reductions in anxiety and depression at posttreatment (*d*s .36 and .28, respectively), compared to adults in the control condition (Egan et al., 2021). Separately, an RCT of a brief, unguided dialectical behavioral therapy skills intervention for COVID-19 distress found that the online intervention led to decreases in negative affect and increases in reported tolerance of negative emotion (Rizvi et al., 2022). For individuals who experienced the death of a loved one due to COVID-19, Reitsma, and colleagues' (2022) unguided internet intervention demonstrated significantly greater reductions in symptoms of depression, persistent complex bereavement, and posttraumatic stress compared to the waitlist comparator group. While these and prior studies have shown that unguided interventions are efficacious in reducing distress-related symptoms, easily scalable, and cost-effective, they often exhibit higher dropout rates, poor adherence, and more significant non-usage attrition (Sieverink et al., 2017).

Conversely, guided internet-delivered interventions involve therapist support, aiming to provide feedback and encouragement, minimize attrition, and promote adherence to self-guided components of the treatment (Hadjistavropoulos et al., 2017; Lindner et al., 2014; Mohr et al., 2011; Schueller et al., 2017). Across a spectrum of mental health conditions, guided internet interventions have demonstrated that they are as effective as face-to-face (F2F) therapy, result in significant, moderate-to-large effect size reductions in distress-related symptoms, and are superior to control conditions (Andersson, Carlbring, Titov, et al., 2019; Andersson et al., 2014; Spek et al., 2007; Svärdman et al., 2022).

Previous meta-analyses have underscored that guided interventions are superior to unguided interventions for depression (Karyotaki et al., 2021), whereas guided and unguided formats show comparable effectiveness for anxiety (Pauley et al., 2023). Studies examining the import of therapist guidance in internet interventions during COVID-19 have yielded mixed results. In a meta-analysis of iCBT trials conducted during the pandemic, Komariah and colleagues' (2022) showed that guided iCBT was more effective for depression, consistent with prior findings, whereas unguided iCBT outperformed guided iCBT for anxiety. Conversely, in a separate meta-analysis of online CBT and mindfulness-based intervention (MBI) trials, Chi and colleagues (2022) observed that guided interventions were superior to unguided ones for anxiety, with no significant differences observed for depression or stress.

These findings emphasize the importance of further research to determine which individuals and conditions benefit most from unguided or guided interventions. Additionally, it is essential to recognize the variability in type (i.e., synchronous, asynchronous) and frequency (e.g., scheduled, as-needed; Hadjistavropoulos et al., 2017) of guidance, as well as the differences in who provides guidance (e.g., licensed psychologist, trainee therapist, "coach," "technician";Titov et al., 2010) and the mode of communication used (e.g., e-mail, text message, phone, video; Renfrew et al., 2020) in the existing literature. Still, therapist involvement inherently compensates for some of the limitations of unguided internet-delivered interventions (Baumeister et al., 2014).

Blended Interventions

Interventions that integrate F2F therapy and internet- and mobile-based intervention (IMI) components are called "blended interventions" (Erbe et al., 2017). Blended interventions have often been described as a "best of both worlds" approach to treatment (Wentzel et al., 2016) aiming to retain and maximize the benefits of standalone F2F therapy and IMIs. However, due to vague operational definitions and the many ways technology can be incorporated into therapy, "blended interventions" are somewhat challenging to define. As classified by Erbe et al. (2017), interventions can be "blended" by simultaneously integrating F2F and IMI components (i.e. "integrated-blended") or chronologically ordering the components (i.e., "sequential-blended"). Further, integrated-blended interventions may emphasize either the F2F or IMI component, using the other to augment treatment.

Regardless of design, research has consistently shown that the use of technology to supplement standard F2F psychotherapy enhances treatment outcomes (Lindhiem et al., 2015). A 2017 systematic review attests to the feasibility and clinical benefit of blended interventions

(Erbe et al., 2017), which have been implemented across various clinical settings including primary care and outpatient psychiatric clinics (Høifødt et al., 2013; Schuster et al., 2020). Despite this, research on blended interventions remains limited, especially in comparison to trials testing standalone, unguided and guided internet-delivered interventions. There is also an absence of studies directly comparing the efficacy of unguided, guided, and blended interventions. As such, further research, including dismantling studies, multi-arm RCTs, and meta-analyses, is needed to understand how F2F and IMI components contribute to therapeutic improvement (López-López et al., 2019).

Still, several trials have been conducted, explicitly integrating F2F therapy and IMI components. For instance, in their study testing a blended intervention for depression (i.e., 12 sessions F2F therapy integrated with CBT-based IMI) versus 12 sessions of F2F therapy, Berger et al (2018) found that the blended intervention was superior at posttreatment, with a medium-magnitude advantage ($d = 0.51$). A 2021 investigation of a blended intervention in a different format—six F2F therapy sessions with six modules of CBT-based IMI (B-CBT)—found that patients who received the blended intervention demonstrated significantly greater reductions in depression at posttreatment ($d = .36$) and 6-month follow-up ($d = .31$) compared to patients who received 12 F2F therapy sessions (Mathiasen et al., 2022). Using an integrated-blended format (i.e., alternating F2F and IMI) for anxiety disorders, Romijn and colleagues (2021) found no significant differences in efficacy at posttreatment or one-year follow-up between blended CBT and F2F therapy, despite the blended group receiving half the number of F2F sessions. Further, in an open trial design, Lungu et al. (2020) tested a video-based CBT augmented with an IMI and observed large-magnitude reductions in anxiety ($d = 1.50$) and depression ($d = 1.49$) after six weeks, the average length of treatment.

Particularly given the diverse impacts of COVID-19, personalized treatment is crucial. Clinicians delivering F2F therapy within a blended intervention maintain the flexibility to tailor treatment to the patient's unique context and narrative and provide culturally responsive care, shown to improve treatment outcomes (Huey et al., 2023; Thompson-Hollands et al., 2014). Additionally, therapists can encourage between-session engagement with IMI components, as greater completion of these components has been associated with optimized treatment outcomes (Lungu et al., 2022). Collectively, these findings underscore the potential utility of blended interventions in the treatment of emotional distress.

1.6 Stress, Emotion Regulation and Dysregulation

Since its emergence in 2020, the pandemic has taken form as both an acute and chronic stressor, characterized by sudden "spikes" and cumulative negative impacts unfolding over time. Stressors, as defined by Wheaton and Montazer (2010), are "conditions of threat, challenge, demand, or structural constraint that, by the very fact of their occurrence or existence, call into question the operating integrity of the organism." From a biological perspective, humans have evolved to respond to stressful events, to optimize survival and promote adaptation (i.e., "allostasis"). However, when a stressor is extreme, persistent, or multifaceted and/or efforts to achieve stability (i.e., homeostasis) are insufficient or disrupted, physiological dysfunction often ensues (McEwen, 2004). While McEwen's biological model elucidates adaptive physiological responses to adverse events, it is aligns with contemporary theories of self-regulation and, more specifically, emotion regulation (Renna et al., 2020).

From a functional emotion regulation perspective, optimal regulation is attained through the deployment and valuation of attentional, cognitive, and behavioral strategies to modify an unfolding emotional response and to achieve a contextually or personally relevant objective

(Gross, 2015). However, when a stressor is severe or enduring, or when strategies to navigate stress are unavailable or ineffectual, emotional suffering and mental anguish may soon follow—akin to the physiological consequences of "allostatic overload." Indeed, when faced with life's stressors, the inability to efficiently regulate emotional experience can exacerbate and/or prolong suffering, resulting in distress.

Distress is characterized by intense emotionality (Kotov et al., 2017; Watson, 2005) upon activation of biologically-rooted motivational systems signaling threat and reward/loss (Mennin & Fresco, 2015) and ineffective or maladaptive attentional, cognitive, and/or behavioral efforts to dampen the intensity of emotional experience. Researchers estimate that up to 80% of major depressive episodes are temporally preceded by a chronic stressor (Hammen, 2005), hypothesized to be related to disruptions in reward processing (Pizzagalli, 2014). Relatedly, the uncertainty generated by the pandemic, risks of exposure and loss, and drastic life changes can increase the salience of attentional cues for threat and safety, contributing to anxiety (Ferber et al., 2021; Jowett et al., 2021). Prior research indicates that distressed individuals demonstrate attentional rigidity and can become overly engaged with, have difficulties disengaging from, and/or demonstrate attentional avoidance of interoceptive and exteroceptive emotional stimuli (Armstrong & Olatunji, 2012; Barry et al., 2015; Etkin & Schatzberg, 2011; Goodwin et al., 2017; Hayes et al., 2008; Keller et al., 2019; Peckham et al., 2013). Theorized to serve an avoidance function, reduce uncertainty, and/or create predictability in the context potential threats, losses, or conflicting motivational states (Borkovec & Roemer, 1995; Newman & Llera, 2011; Nolen-Hoeksema & Watkins, 2011; Olatunji et al., 2013), perseverative negative thinking (PNT; i.e., worry, rumination, self-criticism, loneliness) is a commonly utilized cognitive strategy among individuals in distress. Indeed, PNT has been conceived of as a transdiagnostic process that contributes to the development and maintenance of distress-related conditions, such as anxiety and depression (Mansueto et al., 2022; McEvoy et al., 2013; Mennin & Fresco, 2013; Watkins & Roberts, 2020). To alleviate distress following failed regulation attempts, distressed individuals may also engage in maladaptive behaviors (e.g., physical avoidance or withdrawal, compulsive, repetitive behavior, alcohol and drug use, emotional eating, reassurance-seeking, and self-injury).

These attentional, cognitive, and behavioral responses to emotional distress are perceived to or function to temporarily reduce the intensity of negative emotion and discomfort. Conversely, however, these strategies often perpetuate distress and, over time, become increasingly difficult to disengage, impeding consideration of more flexible and adaptive responding.

1.7 Emotion Regulation Therapy

Emotion regulation therapy (ERT) was specifically designed to treat emotional distress by directly targeting PNT, which both exacerbates and is exacerbated by deficits in self-regulation. ERT is a brief psychotherapy that utilizes an affective science framework and draws on theoretical principles from traditional and contemporary CBTs and MBIs to target the motivational mechanisms (i.e., safety system, reward system) and regulatory mechanisms (i.e., attention, metacognition) that lead to short-term, maladaptive coping behaviors (e.g., avoidance, compulsive behaviors, reassurance seeking) and long-term contextual learning consequences (i.e., threat generalization, diminished reward sensitivity, behavioral inflexibility).

ERT has been delivered in 20-, 16-, and 8-session formats and has demonstrated strong efficacy for the treatment of disorders characterized by anxiety, depression, and PNT (Mennin et al., 2018; Mennin et al., 2015; Renna et al., 2018), as well as in the context of distressing life events (i.e., informal caregiving of cancer patients; Applebaum et al., 2018; O’Toole et al., 2019). Additionally, preliminary evidence suggests that clinical gains achieve in ERT are driven by and temporally preceded by changes in its hypothesized regulatory mechanisms, attention and metacognitive regulation, consistent with its theoretical model (Mennin et al., 2018; O'Toole et al., 2019; O’Toole et al., 2021; Renna et al., 2023). Further, these mechanisms frequently emerge as mediators of improvement in a variety of CBTs (Gómez Penedo et al., 2020; Johannsen et al., 2022) and MBIs (Goldberg, 2022).

The positive impacts of attention regulation (Shi et al., 2019; Wang et al., 2024), and metacognitive regulation (King & Fresco, 2019; Kraiss et al., 2020; MacBeth & Gumley, 2012; Naragon-Gainey & DeMarree, 2017; Riepenhausen et al., 2022) on emotional distress and psychological well-being have been extensively researched. During COVID-19, Bardeen and colleagues (2022) found that attention regulation moderated the link between COVID-specific stress and anxiety symptoms, suggesting that the ability to shift and sustain attention serve as a buffer against distress. Additionally, Mann and Walker (2022) showed that higher self-reported openness and receptiveness towards experience (i.e., equanimity), akin to sustained nonjudgmental attention, mediated the relationship between perceived social isolation and increased distress during the pandemic. Tatar & Papies’s (2022) demonstrated the utility of decentering (i.e., the metacognitive ability to observe objects that arise in the mind as transient internal events and from a healthy psychological distance; Fresco et al., 2007), finding that momentary implementation during a COVID-related worry induction resulted in lower state anxiety compared to a control condition. The capacity to generate alternative perspectives and interpretations of an event (i.e., cognitive reappraisal) was found to moderate the associated between COVID-19 impact and distress (Kuhlman et al., 2021), in addition to mediating the relationships between loneliness and depression (Lv et al., 2022) and COVID-19 worries and anxiety (Muñoz-Navarro et al., 2021). Liang and colleagues' (2022) concluded that the ability to generate self-validating perspectives differentiated psychological response to the COVID-19 pandemic and was associated with a decreased likelihood of chronic and/or worsening trajectories of anxiety and depression.

These studies, alongside decades of research in affect science and previously reported efficacy findings, suggest that ERT may be an especially suitable intervention for individuals in distress during the COVID-19 global crisis.

1.8 The Current Study

ERT-Pandemic (ERT-P) was specifically adapted for emotional distress within the context of COVID-19 and designed as a blended telehealth intervention, integrating synchronous teletherapy sessions and IMI components (e.g., video modules, mindful regulation skill practices, between-session exercises). The current study sought to 1) examine the capacity of ERT-P to effectively treat emotional distress during the COVID-19 pandemic, investigate the impact of COVID-19 severity on treatment response, and explore whether sociodemographic, clinical, and contextual patient characteristics predict differential patterns of treatment response. The aims and research questions are as follows:

1. **To determine whether ERT-P was efficacious in improving primary (i.e., worry, rumination, distress), secondary (i.e., anxiety, depression), and tertiary (i.e., functional impairment, life satisfaction, meaning and purpose) during the acute period and through follow-up.** I hypothesized that ERT-P patients would exhibit statistically significant improvement in all outcomes 1) from pre- to posttreatment and 2) from pretreatment through follow-up.

2. **To test whether the status of the pandemic, at each participant's baseline, predicts treatment response during the acute period and through follow-up.** Given that participant enrollment occurred over the course of two years (i.e., different phases of the pandemic), I used regional COVID-19 data (i.e., cases, hospitalizations, deaths, vaccinations), corresponding to each participant's enrollment date, to derive subgroups of "Pandemic Status" employing a categorical latent variable approach. I hypothesized that the "Pandemic Status" variable would differentially predict treatment response during the acute period and through follow-up for primary outcomes of worry, rumination, and distress.
3. **To investigate patient characteristics as predictors of differential patterns of treatment response.** I examined sociodemographic, clinical, and contextual patient characteristics as predictors of reliable improvement in primary outcomes, without specific a priori hypotheses. As an exploratory aim, I also investigated subgroups of longitudinal response and predictors of distinct trajectories classes. Results and discussion of these exploratory analyses are included in Appendix A.

Chapter 2: Method

The present study utilized an open trial design to provide immediate access to evidence-based treatment for individuals experiencing distress and living in the U.S.'s first epicenter of COVID-19. Study procedures were approved by the university's Institutional Review Board, and the trial was registered at clinicaltrials.gov (NCT0615416). Patients were screened and enrolled in treatment between May 2020 and May 2022. Those interested in participating provided informed consent before completing a screening interview and before study enrollment.

2.1 Participants

Treatment-seeking adults who met full study inclusion criteria, described in detail below, were eligible to participate. Potentially eligible patients were recruited through online public advertisements and bulletins, listservs, posted flyers, mail and e-mail announcements, social media, and direct referrals from local organizations and health professionals. Screening for the current study included two phases: "pre-screening," to assess eligibility for a screening interview, and "screening," to assess eligibility for the full study.

2.2 Pre-Screening

First, individuals interested in participating in the study and receiving treatment completed a brief online survey to determine eligibility for a screening interview. This pre-screening survey consisted of various questions related to sociodemographic and eligibility criteria. Specifically, patients were required to be between the ages of 18-65, reside in New York State (i.e., permanent and current address in New York State), not currently enrolled in another form of psychotherapy, able to read and understand English, and have at least one device with internet and video-conferencing capabilities.

Also included in the prescreening survey were the Distress Thermometer (DT; Applebaum et al., 2018), a single-item visual analog scale of psychological distress; the three-item version of the Penn State Worry Questionnaire (PSWQ-3; Berle et al., 2011); three items from the rumination subscale of the Rumination/Reflection Questionnaire (RRQ-3; Trapnell & Campbell, 1999); and the Coronavirus Impact Scale (CIS; Stoddard et al., 2021). Individuals were asked to rate their worry, rumination, and distress at two time points: before COVID-19 and in the past week. Individuals who endorsed the following were eligible for a screening interview: elevated worry, rumination, and distress in the past week (i.e., PSWQ-3 or RRQ-3 $\geq$ 12 and DT $\geq$ 4); an increase in worry, rumination, and distress (i.e., $\geq$ 1 point) from before COVID-19 to the past week; "moderate" to "severe" stress related to the COVID-19 pandemic (i.e., CIS item 7); and a "severe" rating on one additional CIS item, reflecting disruption within a specific domain (e.g., income/employment, access to social supports, access to medical care). These additional criteria were implemented to ensure that the sample was comprised of individuals experiencing elevated distress attributable to the COVID-19 context.

2.3 Screening

Individuals who met pre-screening eligibility criteria and wished to complete the screening interview provided informed consent. The Mini International Neuropsychiatric Interview-Version 7.0.2 (Sheehan et al., 1998), a brief structured interview aligned with the Diagnostic and Statistical Manual of Mental Disorders-Fifth Edition (American Psychiatric Association, 2022) and the International Classification of Diseases and Related Health Problems-Tenth Revision (WHO, 2016), was used to assess psychiatric diagnoses. The screening interview was conducted via secure web-conferencing software and administered by masters-level research assistants extensively trained on the instrument. During the screening interview, diagnostic interviewers confirmed eligibility criteria, administered the MINI to assess ineligibility criteria based upon current and past diagnostic history. Diagnoses reaching clinical thresholds were assigned a clinical severity rating according to criteria adapted from the Anxiety Disorders Interview Schedule for DSM-V (ADIS-5; Brown & Barlow, 2014). Clinical severity ratings range from 0 to 8, with higher scores indicating greater severity of diagnosis (e.g., number and frequency of symptoms, associated distress and impairment).

Individuals were deemed ineligible for the study if they met criteria for bipolar I disorder (i.e., current or past manic episode), lifetime symptoms of psychosis, a primary alcohol or substance use disorder, or probable primary diagnosis of borderline or narcissistic personality disorder, as assessed by select items from the Structured Clinical Interview for DSM-5 Screening Personality Questionnaire (First et al., 2016). Additionally, individuals who reported active suicidal ideation with intent or plan were referred to more acute services. Links to online therapist directories, digital mental health resources, and the phone numbers for emotional support hotlines were provided to all individuals deemed ineligible at the pre-screening phase. A comprehensive list of referrals was provided to individuals who completed a screening interview but were deemed ineligible during the screening phase. Refer to Figure 1 for a flowchart of participant screening and enrollment.

2.4 Study Procedures

Prior to enrollment, all eligible individuals were required to provide informed consent to participate in the full study and receive treatment. Enrolled patients completed a full battery of questionnaires at pretreatment and posttreatment, as well as 3-month, 9-month, and 2-year follow-up timepoints. Upon completion of each assessment, patients received $20 compensation (i.e., eGift Card). Stratification was implemented to ensure that the sample was representative of

New York City in terms of racial and ethnicity; however, patients were recruited and enrolled from other cities within New York State. These sampling procedures have been increasingly used in psychological research to ensure that findings are not overgeneralized to minority populations previously underrepresented within clinical trials (Bornstein et al., 2013). Permuted blocks that matched the racial composition of NYC, based on 2020 Census data (see Figure 2), were created. Allocation into blocks was based on participants' self-reported racial and ethnic identity, collected from the pre-screening survey. After a participant completed the screening interview, was deemed eligible for the study, and provided informed consent, they were assigned to a block. In the event that a participant was lost to contact or did not provide informed consent, they were removed from the block to allow for enrollment of another participant.

2.5 Measures

Primary Outcomes

Worry. The Penn State Worry Questionnaire (Meyer et al., 1990) is a widely used self-report measure of pathological worry. The PSWQ consists of 16 Likert-scale items (e.g., "Once I start worrying, I cannot stop."), ranging from 1 ("Not at all typical of me") to 5 ("Very typical of me"). Scores on the PSWQ range from 16-80, with higher scores indicating more severe worry. Internal consistency of the PSWQ was excellent (Cronbach's α = .90).

Rumination. The rumination subscale of the Rumination-Reflection Questionnaire (Trapnell & Campbell, 1999) was used to measure past-focused, perseverative negative thinking consistent with rumination. The RRQ-Rumination subscale consists of 12 items (e.g., "My attention is often focused on aspects of myself I wish I'd stop thinking about.") scored on a 5-point Likert scale (1 = "Strongly Disagree" to 5 = "Strong Agree"). Scores on the RRQ range from 12 to 60, with higher scores indicating greater rumination. The RRQ demonstrated good internal consistency (Cronbach's α = .85).

Distress. The Mood and Anxiety Symptoms Questionnaire-30 item (Wardenaar et al., 2010), is a brief adaptation of the 90-item MASQ that measures dimensions of the tripartite model of anxiety and depression (Watson et al., 1995). The MASQ-D30 is comprised of three subscales, each consisting of 10 items: general distress (GD), anxious arousal (AA), and anhedonic depression (AD). Each item is rated on a 1 ("not at all") to 5 ("extremely") Likert scale, with subscale scores ranging from 10 to 50 and higher subscale scores indicating more severe distress, depression, and anxiety. The GD subscale assesses a range of non-specific symptoms associated with negative affect and emotional distress (e.g., "Felt irritable", "Felt hopeless"). Internal consistency for the distress subscale was good (Cronbach's α = .84).

Secondary Outcomes

Depression and Anxiety. The AD subscale of the MASQ-D30 consists of reverse-scored items assessing decreased positive affect and symptoms associated with depression, such as lack of pleasure and low energy (e.g., "Felt like I was having a lot of fun," "Felt like I had a lot to look forward to"). The AA subscale of the MASQ-D30 assesses symptoms associated with anxiety, such as bodily tension and hyperarousal, (e.g., "Startled easily," "Heart was racing or pounding"). Higher scores on the AD and AA subscales indicate increased severity of symptoms of depression and anxiety, respectively. Internal consistency was excellent for depression (Cronbach's α = .90) and acceptable for anxiety (Cronbach's α = .78).

Tertiary Outcomes

Functional Impairment. The Sheehan Disability Scale (Sheehan et al., 2010) is a 3-item measure of functional impairment within the domains of work/school, social life/leisure, and family life/home responsibilities. For each item (e.g., "Because of my problems, my social life/leisure was impaired…"), respondents rate their impairment on a scale from 0 ("Not at all) to 10 ("Very Severely"). Scores on the SDS range from 0 to 30, with higher scores indicating greater disability in the assessed life domains. The SDS demonstrated acceptable internal consistency (Cronbach's α = .71).

Life Satisfaction. The Brief Multidimensional Students' Life Satisfaction Scale (Seligson et al., 2003) is a 5-item measure of life satisfaction that asks respondents satisfaction in five life domains: family, friends, school, self, and living environment. In the current study, the school item was adapted to also included work. Each item is on a Likert-type scale, with responses ranging from 1 ("Terrible") to 6 ("Delighted"). Scores on the BMSLSS range from 6 to 30, with higher scores indicating greater life satisfaction. Internal consistency of the BMSLSS was acceptable (Cronbach's α = .73).

Meaning and Purpose. The 4-item version of the Patient-Reported Outcomes Measurement Information System Meaning and Purpose (PROMIS M&P-4; Salsman et al., 2020) assesses respondents' sense of meaning, purpose, and well-being. Each item of the PROMIS M&P-4 (e.g., "I experience deep fulfillment in my life") is rated on a Likert scale from 1 ("Not at all") to 5 ("Very much"). Scores range from 4 to 20, with higher scores signifying a greater sense of purpose in life. The PROMIS M&P-4 demonstrated good internal consistency (Cronbach's α = .85).

Feasibility, Acceptability, and Satisfaction

Satisfaction. The Client Satisfaction Questionnaire-8 (Nguyen et al., 1983) was administered posttreatment to assess patients' evaluation of the intervention as a whole (i.e., teletherapy, IMI). To limit patient burden, four items were selected to measure overall satisfaction (“In an overall, general sense, how satisfied are you with the services you received?”), satisfaction with the quality and amount of services received (”How would you rate the quality of services you have received?” and “How satisfied are you with the amount of help you have received?”), and likelihood of recommending the intervention to others (“If a friend were in need of similar help, would you recommend our program?”). Each item is rated on a Likert scale from 1 (e.g., “Poor”) to 4 (“Excellent”), with higher scores indicating greater satisfaction with services.

At posttreatment, patients were also asked to rate the usefulness of ERT-P psychoeducational and session summary videos on a scale from 1 (“Not at all useful”) to 5 (“Extremely Useful”) and respond to the following questions specifically related to teletherapy sessions: 1) “Prior to ERT, had you ever used telehealth/teletherapy/telemedicine?” (“Yes” or “No”); 2) “How would you rate your telehealth sessions?” (1 = “Poor” to 4 = “Excellent”); 3) “I felt comfortable communicating with my clinician using the videoconferencing software.” (1 = “Strongly disagree” to 5 = “Strongly agree”); and 4) “I would consider using telehealth separate from the current COVID-19 circumstances.” (1 = “Strongly disagree” to 5 = “Strongly agree”).

Usability. The System Usability Scale (SUS; Brooke, 1993) (SUS) was administered posttreatment to assess the usability of the IMI platform. The SUS consists of 10 items (e.g., “I found the system very cumbersome to use”) rated on a 5-point Likert scale ranging from “Strongly Disagree” to “Strongly Agree.” The SUS score, calculated by multiplying the total item score by 2.5, ranges from 0 to 100, with higher scores indicating greater acceptability of the platform. The SUS demonstrated good internal consistency (Cronbach’s α = .89).

Patient Characteristics

Sociodemographic Characteristics. The following sociodemographic information was collected from the pre-screening survey and screening interview: age, gender identity, race, ethnicity (i.e., Hispanic/Latino), sexual orientation, country of birth, relationship status, parent status, student status, employment in healthcare, living arrangement (i.e., alone/not alone), highest level of education, pre-existing medical conditions, personal income, current employment status, currently exercising, and current frequency of alcohol and marijuana use (i.e., not at all, daily, weekly, monthly).

Clinical Characteristics. The following information was collected during the screening interview: total number of DSM-5 diagnoses; clinical severity rating (0 – 8) of primary diagnosis or co-primary diagnoses; the MINI Assessment of Impairment of Functioning/Disability total score (0 – 120), currently taking psychotropic medication, and engagement in prior mental health treatment.

Contextual Characteristics. The Coronavirus Impact Scale (Stoddard et al., 2023) was used to assess the extent of life changes attributable to COVID-19. The CIS is comprised of 11 items, rated on a 4-point Likert scale (i.e., No Change, Mild, Moderate, Severe). Items 1-8 inquire about pandemic-related changes in routines, family income/employment, access to food, access to medical healthcare, access to mental health treatment, access to social support, experience of stress, and familial discord. Personal diagnosis of COVID-19 and the severity of illness (i.e., symptoms effectively managed at home, severe symptoms and required brief hospitalization, severe symptoms and required ventilation) are assessed by Item 9. For items 10 and 11, respondents are asked whether immediate and extended members contracted COVID-19 and to rate the severity of symptoms (i.e., symptoms effectively managed at home, severe symptoms and required brief hospitalization, severe symptoms and required ventilation, death) for the immediate and extended family member whose illness was most severe. Patients were also asked during the screening interview if they lost their job due to COVID-19.

2.6 Intervention

ERT-P consisted of nine individual, 60-minute therapy sessions delivered via telehealth, occurring on a twice-weekly basis. An introductory session was added to a previously tested 8-session version of ERT (Renna et al., 2022) to provide an opportunity for patients to share their COVID-19 experience and for therapists to introduce the IMI platform. The subsequent eight sessions of treatment are divided into two phases. The first phase focuses on increasing emotional and motivational clarity in moments of distress and the cultivation of mindful regulation skills. Skills are presented in order from least elaborative (i.e., attention regulation skills) to most elaborative (i.e., metacognitive regulation skills), targeting different points in the temporal cascade of emotion. Patients are first introduced to attention regulation skills to strengthen the ability 1) to shift and broaden attention (i.e., orienting) and 2) to sustain attention on all aspects of their emotional experience (i.e., allowing). Next, patients are introduced to metacognitive regulations skills to promote the capacities 3) to observe aspects of their emotional experience as temporal events, from a healthy psychological distance (i.e., decentering) and 4) to alter the emotional significance of these percepts, through validation of emotional pain and the addition of perspectives to facilitate courage and compassion (i.e., reappraisal). The overarching goal of the mindful regulation skills is to strengthen the client's abilities to notice arising emotional and motivational (e.g., approach, avoid) cues and to promote more adaptive responding to internal experiences and contextual stressors. Skill development is achieved through formal mindful regulations skills practices (e.g., guided practice recorded by the therapist) and momentary implementation of skills during day-to-day instances of emotional reactivity.

The second phase of ERT-P focuses on empowering patients to pursue behavioral goals aligned with what they find meaningful and rewarding in their lives. Between sessions, patients commit to taking actions that involve some degree of motivational conflict (e.g., actions that elicit strong "pulls" for safety, reward/loss, or both), in service of living in accordance with their values. In-session activities, such as imaginal exposures and conflict dialogue tasks, are conducted to prepare for potential challenges, utilizing mindful regulation skills to attend to and resolve motivational conflicts, as they commit to expanding their behavioral repertoires. The treatment culminates in a review of mindful regulation skills to be deployed in moments of distress (i.e., "being counteractive") and/or in the pursuit of meaningful life goals (i.e., "being proactive"), as well as discussion of treatment progress and relapse prevention. The ERT model and treatment components are more fully described in previous publications (Mennin & Fresco, 2014; Renna et al., 2017).

Clinicians were licensed psychologists or doctoral students in clinical or counseling psychology, extensively trained to administer ERT-P. Group supervision was held weekly and consisted of didactics and a review of active cases. Therapists completed a treatment adherence checklist for each session, which was reviewed during each supervision.

In addition to telehealth sessions, patients were invited to use the IMI platform, created to facilitate between-session engagement with ERT-related content. This content included animated psychoeducational and summary video modules, which included further elaboration on session content, case vignettes, a review of assigned between-session activities, and tips for navigating the IMI platform. Handouts of session content were also made available in the event that the patient preferred to read the material. Along with video modules, patients had access to mindful regulation skill practices audio-recorded by their therapist and digital exercises to practice self-monitoring of emotions, facilitate mindful regulation skill use, and record and reflect on between-session exposures. At the end of each session, therapists assigned activities to be completed between sessions via the IMI platform. No email or text feedback was provided. Links to emergency resources (e.g., National Suicide Prevention Lifeline) and technical support were visible on every page of the IMI. Continued access to the IMI platform was available to all patients after treatment. Refer Table 1 for IMI content included as part of each ERT-P session.

2.7 Analytic Plan

All analyses were conducted according to intention-to-treat (ITT) principles and included patients who discontinued ERT-P or failed to complete posttreatment or follow-up assessments. The collection of two-year follow-up data is ongoing. As such, analyses only included pretreatment, posttreatment, 3-month follow-up, and 9-month follow-up timepoints.

Aim 1

Linear mixed modeling (LMM) was employed to determine whether ERT-P was efficacious in improving outcomes during the acute period (i.e., from pre- to posttreatment) and from pretreatment through 9-month follow-up. The LMM approach is well-suited for repeated outcome measurements of the same individual (i.e., nonindependence). All LMMs were two-level models, where time (level 1) was nested within individuals (level 2). An additional benefit of LMM is the ability to accommodate missing data, which allows all patients to be retained in analysis. All models included a random intercept at the individual level to account for variability at pretreatment and used restricted maximum likelihood estimation (REML). The parameter of interest was the fixed effect of time (i.e., regression coefficient) to determine change in outcome during both periods of interest. Cohen's *d* was derived for all outcomes ($d = 2 \times \sqrt{[F/df]}$) with effect sizes of .20, .50, and .80 denoting small, medium, and large effects, respectively (Cohen, 1988). These analyses were conducted in IBM SPSS version 29 using the MIXED procedure.

Aim 2

The next aim was to test whether the status of the pandemic, at the time of each participant's baseline, was related to treatment response during the acute and follow-up periods for the primary outcomes of worry, rumination, and distress. First, a dataset including all patients and their respective baseline dates was created. Next publicly available, government-source COVID-19 data for the region was extracted, corresponding to each participant's baseline date (i.e., pretreatment assessment). These data included: the number of days since March 1, 2020, when the first case of COVID-19 was confirmed in NYC (Goldstein & McKinley, 2020); seven-day averages of cases, hospitalizations, and deaths in NYC (New York City Department of Health and Mental Hygiene, 2022); enrollment before or after the first vaccine was administered in the region, on December 14, 2020 (Ferre-Sadurni & Goldstein, 2020).

Using these data as indicators, latent profile analysis (LPA) was conducted to partition the sample into subgroups capturing the changing pandemic dynamics between May 2020 and May 2022. LPA is a probabilistic modeling approach used to categorize individuals within a heterogeneous population to form more homogenous subgroups that are mutually exclusive and exhaustive (Spurk et al., 2020). Each participant was assigned to the profile with the highest probability for membership (i.e., 95% likelihood of membership to Profile 1 [e.g., highest cases, hospitalizations, death; vaccines not available] vs 5% likelihood of membership to Profile 2 [e.g., lowest cases, hospitalizations, deaths; vaccinations available]). MPlus version 8 was used for LPA analysis.

To investigate the predictive role of "Pandemic Status" on treatment response, dummy-coded variables representing different levels of "Pandemic Status" were created. Subsequently, LMMs were employed, testing the interaction effect of "Time" by "Pandemic Status" on outcomes during the acute period and through follow-up. Significant interactions were probed by computing simple slopes for corresponding "Pandemic Status" groups. These analyses were conducted using the MIXED procedure in IBM SPSS version 29.

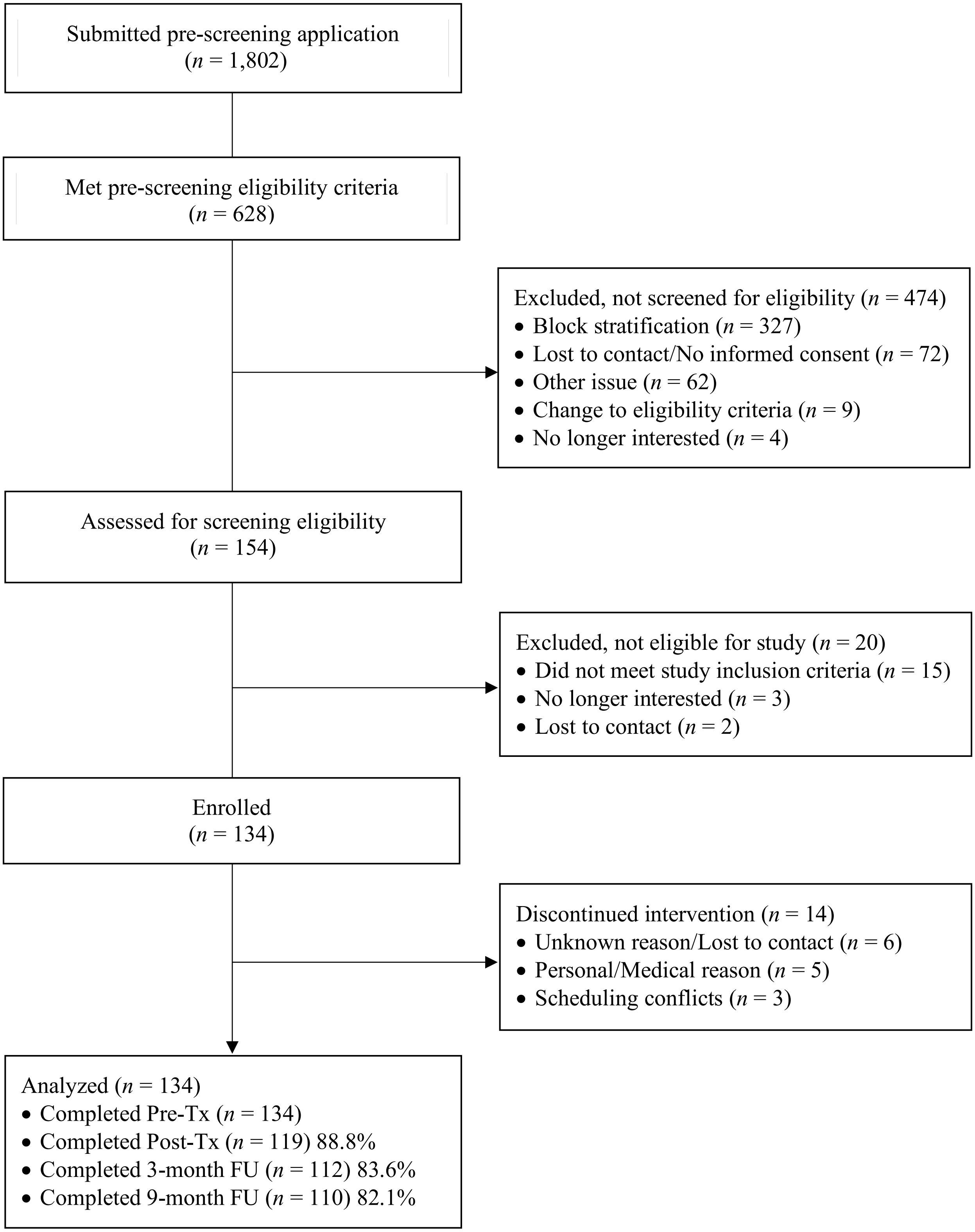
Aim 3

To explore subgroups of treatment response in the outcomes of worry, rumination, and distress at posttreatment, I used the reliable change index (RCI), which represents a change from pre- to posttreatment that is large enough to not be attributed to measurement error (Jacobson & Truax, 1991). The RCI is calculated by dividing the difference between pretreatment and posttreatment scores by the standard error of the difference (i.e., $[x_2 - x_1]/s_{diff}$), which is computed using the standard deviation and reliability of the measure (i.e., $s_{diff} = \sqrt{2}[S_E]^2$, where $S_E = sd\sqrt{1} - r_{xx}$). An RCI ≤ -1.96 represents "Reliable improvement" (RI) while an RCI ≥ 1.96 indicates "Reliable Deterioration" (RD) at $p < .05$. Patients who do not demonstrate RI or RD were classified as demonstrating "Indeterminate Change" (i.e., indeterminate improvement, 0 > RCI > -1.96; the same scores at pre- and posttreatment signifying no change; indeterminate deterioration, 0 < RCI < 1.96). These analyses were conducted in IBM SPSS version 29.

Missing values were imputed using K-nearest neighbor (KNN) imputation (i.e., personal income). To aid interpretation, categorical predictors with more than two levels were separated in separate dichotomous variables (e.g., relationship status [i.e., "single," "unmarried in a relationship," "married"]) and some variables were collapsed (e.g., sexual and gender minority

[SGM; i.e., patients identifying as gender non-binary, gay/lesbian, bisexual, pansexual, asexual]). See Appendix A.1 for further description of handling of predictor variables in LASSO models.

Lastly, to explore whether patient characteristics (i.e., sociodemographic, clinical, contextual) predicted treatment response, I implemented least absolute shrinkage and selection operator regression (Tibshirani, 2011). LASSO regression is well-suited for feature selection, identifying the most influential predictors from a large set of potentially multicollinear variables. This is accomplished by adding a shrinkage penalty, which reduces the coefficients of uninfluential predictors to zero, based upon a regularization parameter, λ. To determine the optimal value for λ and to minimize the risk of model overfitting, 10-fold cross-validation was performed with three repetitions. Up-sampling with replacement was used to improve class imbalance in instances where < 30% of observations belonged to the minority class. Using the optimal regularization parameter, λ, models were subsequently refitted to obtain regression coefficients of the included predictors and quantify their relative importance (0 – 100). LASSO model performance was evaluated using the area under the curve (AUC) and categorized into five levels: fail (.50–.59), poor (.60–.69), fair (.70–.79), good (.80–.89), and excellent (.90 – 1.00; Safari et al., 2016). Bias-corrected 95% confidence intervals of the AUC, sensitivity (i.e., how well the model identifies relevant features), and specificity (i.e., how well the model identifies irrelevant features) were also calculated. As a final step, features selected by LASSO models were entered in unregularized, multivariable logistic regressions to obtain odds ratios for predictors of posttreatment response for the primary outcomes. In both regularized and unregularized regressions, positive and negative coefficients denote increased and decreased likelihood of subgroup membership, respectively. LASSO analyses were conducted using the *caret* package in R. Unregularized logistic regressions were conducted in IBM SPSS version 29.



Note. Tx = treatment, FU = follow-up.

Figure 1: Flowchart of participant screening and enrollment.

Population by Race/Hispanic Origin*
New York City, 2010 and 2020

	2010		2020		Change	
	Number	Percent	Number	Percent	Number	Percent
Total Population	**8,175,133**	**100.0**	**8,804,190**	**100.0**	**629,057**	**7.7**
Not Hispanic						
White	2,722,904	33.3	2,719,856	30.9	-3,048	-0.1
Black	1,861,295	22.8	1,776,891	20.2	-84,404	-4.5
Asian	1,028,119	12.6	1,373,502	15.6	345,383	33.6
Some Other Race	78,063	1.0	143,632	1.6	65,569	84.0
Two or More Races	148,676	1.8	299,959	3.4	151,283	101.8
Hispanic	2,336,076	28.6	2,490,350	28.3	154,274	6.6

Source: U.S. Census Bureau, 2010 and 2020 Census Redistricting Data (Public Law 94-171) Summary Files
Population Division, New York City Department of City Planning

Figure 2: New York City census data.

Table 1: Overview of ERT-P and IMI platform activities.

Sx	Brief Summary	IMI Activities
0	Patients share their COVID-19 experience, are introduced to the flow and format of ERT-P. Therapy rationale and expectations reviewed. Patients are oriented to the IMI platform.	**Video:** *Welcome to ERT* **Handout:** *Distress Experiences*
	Phase I: Being Counteractive and Skills Training in Mindful Regulation Sessions begin with a review of between session activities and a therapist-led mindful regulation skill practice, beginning after Session 1.	
1	Introduction to the emotion regulation perspective and treatment, "reactive responding," cue detection and self-monitoring, and mindful regulation skills. 1st attention regulation skill: orienting.	**Video:** *Session 1 Recap* **Exercises:** Orienting skill practice, CYR 1 **Handouts:** *Understanding Your Emotions, Emotion Regulation Therapy Model, Reactive Responding, Attention Regulation: Orienting*
2	Introduction to motivations (security/reward), "being counteractive" and utilizing emotions/motivations to take "counteraction." 2nd attention regulation skill: allowing.	**Video:** *Session 2 Recap* **Exercises:** Allowing skill practice, CYR 2 **Handouts:** *Emotions Signal Motivations, Attention Regulation: Allowing*
3	Introduction to "in-the-moment" skills use, metacognitive regulation. 1st metacognitive regulation skill: distancing (i.e., decentering).	**Video:** *Session 3 Recap* **Exercises:** Distancing skill practice, CYR 3 **Handouts:** *Metacognitive Regulation: Distancing*

Table 1 (continued).

4	2nd metacognitive regulation skill: reframing (i.e., reappraisal) with courage and compassion. Review mindful regulation skills, contextualizing counteractive skills use.	**Video:** *Session 4 Recap* **Exercises:** Reframing skill practice, CYR 4 **Handouts:** *Metacognitive Regulation: Reframing, Reframing: Courageous and Compassionate Statements, ERT Skills Toolbox*
	Phase II: Experiential Exposure and Proactive Living Sessions begin with a review of between session activities and a therapist-led mindful regulation skill practice of the patient's choosing.	
5	Introduction to Phase II and "proactive" living, through balancing momentary motivations and values. Committing to valued action via SYA-Preparation (SYA-P).	**Video:** *Session 5 Recap* **Exercises:** Skill practice, CYR 5, SYA: Debriefing (SYA-D) **Handouts:** *Being Proactive, Values Identification*
6	Experiential exposure (imaginal rehearsal) rehearsal of taking "proactions" (i.e., values-based behavioral goals), confronting emotional challenges with skills. SYA-P.	**Video:** *Session 6 Recap* **Exercises:** Skill practice, CYR 6, SYA: D **Handouts:** *Envisioning Proaction and Engaging Internal Conflict*
7	Experiential exposure (conflict dialogue) transforming emotional meaning of emotional challenges and motivational conflicts, facilitating engagement of "proactions." SYA-P. Introduction to termination.	**Video:** *Session 7 Recap* **Exercises:** Skill practice, CYR 7, SYA: D **Handouts:** *Anticipating the Transition Out of Therapy*
8	Consolidating therapy gains. Review of ERT themes (i.e., reactivity, counteraction, proaction) and relapse prevention. Encouragement to continue practicing mindful regulation skills and reflecting on "taking larger steps" with regards to proactive living.	**Video:** *Session 8 Recap* **Handouts:** *Consolidating Therapy Gains*

Note. Sx = Session, IMI = internet and mobile intervention, CYR = "Catch Yourself Reacting," SYA = "See Yourself Acting."

Chapter 3: Results

3.1 Patient Characteristics

Sociodemographic Characteristics

Table 2 provides a comprehensive overview of sociodemographic descriptive statistics for the sample. The mean age of enrolled patients (N = 134) was 34.84 years (SD = 10.76, range = 18 - 62). Patients identifying as female comprised the majority of the sample (n = 91, 67.9%), while 27.6% (n = 37) identified as male and 4.5% (n = 6) identified as non-binary. Examining race, 31.3% (n = 42) identified as White, 23.9% (n = 36) as Black or African American, 17.2% (n = 42) as Hispanic or Latino(a), 15.7% (n = 21) as Asian, 9.7% (n = 13) as Mixed Race, and 2.2% (n = 3) as another race. No patients identified as American Indian or Alaskan Native or Native Hawaiian or Pacific Islander. More than one-third of the sample (n = 46, 34.3%) identified as ethnically Hispanic or Latino(a). Regarding sexual orientation, a majority identified as heterosexual (n = 93, 70.2%), with the remainder identifying as gay or lesbian (n = 12, 9.0%), bisexual (n = 12, 9.0%), "unsure/don't know" (n = 10, 7.5%), pansexual (n = 3, 2.2%), asexual (n = 2, 1.5%), or preferred not to answer (n = 1, 0.8%). Roughly one third of the sample was born outside of the United State (n = 33, 24.6%). Concerning relationship status, 46.3% of patients were single (n = 62), while the rest reported being unmarried in a relationship (n = 35, 26.1%), married (n = 34, 25.4%), or "other" (n = 3, 2.2%). Twenty-seven patients (20.2%) reported having children and 30 patients reported living alone (22.4%).

More than one quarter of the sample (n = 38, 28.4%) reported earning less than $25,000 per year; twenty-one patients (15.7%) left this item missing or selected "prefer not to answer." With regards to education, 77.6% of the sample earned a bachelor's degree (n = 55, 41.0%) or completed graduate school (i.e., master's or doctoral degree; n = 49, 36.6%) and fourteen patients (10.5%) reported being a current student. Seventeen patients (12.7%) identified as healthcare workers, while nearly one third of the sample (*n* = 43, 32.1%) reported being unemployed at the start of treatment.

Pertaining to physical health, nearly half of the sample (48.5%) reported having a non-psychiatric, chronic medical condition. More than half of the sample reported that they were exercising at the start of treatment (*n* = 87, 64.9%). Regarding current alcohol use, the majority of patients reported drinking alcohol monthly (*n* = 46, 34.3%), with the remainder reporting weekly alcohol use (*n* = 43, 32.1%) or no alcohol use (*n* = 39, 29.1%). Six individuals reported daily alcohol use (4.5%). The vast majority of patients reported no current marijuana use (*n* = 94, 70.2%), with the remainder reporting daily (*n* = 21, 15.7%), weekly (*n* = 12, 9.0%), or monthly (*n* = 7, 5.2%) use. Seven patients (5.2%) reported current use of other substances (e.g., ecstasy, LSD, cocaine, ketamine) or drugs for which they did not have a prescription (e.g., Adderall, Percocet, Vicodin).

Clinical Characteristics

Clinical characteristics of the sample are presented in Table 3. Of the 134 enrolled patients, 127 patients (94.8%) met criteria for one or more DSM-5 diagnoses as assessed by the MINI. The mean number of diagnoses was 2.3 (*SD* = 1.34); 42 patients (31.3%) met criteria for more than one primary diagnoses (i.e., coprimary). The mean clinical severity rating (0-8) of primary and coprimary diagnoses was 5.28 (*SD* = 0.98). The most frequently assigned diagnoses were generalized anxiety disorder (GAD; *n* = 70, 52.2%) and major depressive disorder (MDD, *n* = 65, 48.5%). Roughly one-quarter of the sample reported never receiving any kind of treatment (e.g., psychotherapy, psychiatric medication management) for a mental health condition (*n* = 34, 25.4%). Thirty-one patients (23.1%) reported taking one or more psychiatric medications. The sample mean MINI Assessment of Impairment of Functioning/Disability (0-120) was 50.04 (*SD* = 21.15).

Contextual Characteristics

Table 4 displays descriptive statistics of items from the CIS and other contextually relevant characteristics. Disruption of routines (CIS 1: $M = 2.84$, $SD = 0.41$) and family stress and discord (CIS 8: $M = 2.59$, $SD = 0.49$) received the highest ratings, indicating “moderate” to “severe” pandemic-related changes within these domains. Disruptions in access to food received the lowest ratings, reflecting “no change” to “mild” changes patients’ in ability to obtain food. Means for other items fell in the “mild” to “moderate” ranges. Thirty-two patients (23.9%) reported contracting COVID-19, with most patients reporting mild symptoms. More than half the sample ($n = 70$, 52.2%) reported having an immediate and/or extended family member diagnosed with COVID-19. Twenty-eight patients (20.9%) reported ≥ 1 COVID-19 diagnosis within their immediate family, while 55 patients (44.0%) reported having ≥ 1 extended family member diagnosed with COVID-19. Twenty-four patients (17.9%) reported a death in their immediate and/or extended family due to COVID-19: more patients reported a death in their extended family ($n = 19$) than in their immediate family ($n = 4$). One patient (1.7%) reported a COVID-19 death in both their immediate and extended family. One-third of the sample ($n = 45$, 33.6%) reported losing their job as a direct result of COVID-19.

3.2 Baseline Correlations

See Figure 3 for a correlogram displaying strength and significance of correlations among sociodemographic, clinical, context characteristics, and baseline measures.

3.3 Baseline Differences by Gender, Race, Ethnicity

Significant gender differences in baseline worry ($F[1,132] = 6.23$, $p = .01$) and anxiety ($F[1,132] = 4.72$, $p = .03$) were observed, such that female patients reported greater worry (M = 65.96, SD = 9.34) and anxiety (M = 61.44, SD = 10.03), compared to all other patients (worry: M = 19.59, SD = 6.44; anxiety: M = 17.16, SD = 5.08). A one-way ANOVA indicated statistically significant differences in baseline life satisfaction scores across racial groups, $F(5,128) = 5.54$, $p < .001$. Subsequent Tukey's post hoc tests revealed that Black patients reported significantly lower baseline life satisfaction (M = 15.48, SD = 4.92) compared to both White (M = 19.70, SD = 3.54, $p < .001$) and Asian patients (M = 18.93, SD = 4.20, $p = .03$). Additionally, Hispanic patients (M = 15.62, SD = 3.50), reported significantly lower baseline life satisfaction compared to White patients ($p < .01$). No other notable differences between race and baseline measures were discerned (ps > .20).

Further analyses revealed statistically significant differences in baseline anxiety ($F[1,132] = 4.79$, $p = .03$), functional impairment ($F[1,132] = 6.22$, $p = .01$), and life satisfaction ($F[1,132] = 7.49$, $p < .01$) between patients identifying as ethnically Hispanic/Latino and those who did not. Specifically, patients who identified as ethnically Hispanic/Latino reported higher levels of baseline anxiety (M = 20.39, SD = 6.89) and functional impairment (M = 20.15, SD = 5.91) and significantly lower levels of life satisfaction (M = 16.26, SD = 4.27) compared to their non-Hispanic/Latino counterparts (anxiety: M = 17.99, SD = 5.56; functional impairment: M = 17.42, SD = 6.08; and life satisfaction: M = 18.42, SD = 4.38).

3.3 Attrition

Fourteen of the 134 enrolled patients (10.5%) did not complete ERT-P. Specifically, three patients dropped out directly after the introductory session (21.4%), nine dropped out during Phase I (35.7%), and six dropped out during Phase II (42.9%). Pretreatment outcome measures did not differ between patients who completed ERT-P and those who did not (ps > .29).

Patients who identified as SGM accounted for a significantly greater proportion of treatment drops compared to their non-SGM identifying counterparts (57.1% vs. 18.3%; $\chi^2[1] = 10.87$, $p < .01$). Additionally, patients who dropped out of treatment reported significantly higher scores on CIS item 3 ($t[132] = -2.41$, $p <.01$), assessing disruptions in access to food ($M_{\text{drop}} = 1.36$, $SD = 1.01$; $M_{\text{completer}} = 0.81$, $SD = 0.78$), and CIS item 4 ($t[132] = -2.53$, $p <.01$) assessing disruptions in access to medical healthcare ($M_{\text{drop}} = 2.07$, $SD = 1.00$; $M_{\text{completer}} = 1.37$, $SD = 0.99$). Other differences between treatment completers and drops were not statistically significant (ps >.08).

3.4 Feasibility, Acceptability, and Satisfaction

With regard to patient satisfaction, 71.3% of the sample reported being "Very satisfied" with the services they received. Additionally, most patients rated the quality of services as "Excellent" (86.1%) and reported feeling "Very satisfied" (60.0%) with the amount of help they received. Only three patients (2.2%) reported feeling "Quite dissatisfied" with the amount of help they received, while the remaining patients reported feeling "Mostly satisfied" (28.4%) or "Indifferent or mildly dissatisfied" (3.7%). Encouragingly, 70.4% of patients stated that they would "definitely" recommend ERT-P to a friend in need of similar support.

The mean SUS score ($M = 79.70$, $SD = 18.04$) corresponds to an "A-" rating (85-89$^{\text{th}}$ percentile) based on established benchmarks (Lewis et al., 2018), suggesting ERT-P patients perceived the IMI platform to be usable and high quality. Patient ratings of the usefulness of ERT-P psychoeducational and session summary videos were as follows: 33.0% "Very useful," 27.0% “Extremely useful,” 25.2% “Moderately useful,” 13.0% “Slightly useful,” and 1.7% “Not at all useful.”

Slightly more than half of patients (52.2%) reported having never used the telehealth format before ERT-P, while 71.3% of patients (“Strongly agree”) stated they would use telehealth separate from the circumstances of COVID-19. A majority of patients (85.2%) rated telehealth ERT-P sessions as “Excellent,” with the remainder selecting “Good” (13.0%) and Fair (1.7%). No patients rated telehealth ERT-P sessions as “Poor.” Regarding use of videoconferencing software for therapy, 82.6% of patients (“Strongly Agree”) endorsed feeling comfortable communicating with their clinician in this modality.

3.5 Aim 1

Descriptive statistics of primary, secondary, and tertiary outcomes at pretreatment, posttreatment, 3-month follow-up, and 9-month follow-up are displayed in Table 5.

Acute Treatment Phase

Statistically significant improvements were observed across all outcomes of interest from pre- to posttreatment. Patients demonstrated large magnitude reductions in primary outcomes of worry, ($F[1,125.96] = 180.92$, $p < .001$, $d = -2.40$), rumination ($F[1,127.33] = 164.94$, $p < .001$, $d = -2.28$), and distress ($F[1,123.97] = 233.39$, $p < .001$, $d = -2.74$) and secondary outcomes of depression ($F[1,122.46] = 94.21$, $p < .001$, $d = -1.75$) and anxiety ($F[1,121.34] = 71.05$, $p < .001$, $d = -1.53$). Effect sizes of gains in tertiary outcomes were also large for functional impairment, ($F[1,112.18]$)= 128.35, $p < .001$, $d = -1.87$), life satisfaction ($F[1,121.57] = 78.35$, $p < .001$, $d = -1.61$), and meaning and purpose ($F[1,122.93] = 74.26$, $p < .001$, $d = -1.55$). The results of these analyses are presented in Table 6.

Longitudinal Trajectory

Statistically significant improvement persisted from pretreatment through the 9-month follow-up period. Effect sizes of reductions in primary outcomes were large (worry: $F[1,358.92] = 157.95$, $p < .001$, $d = -1.33$; rumination: $F[1,358.88] = 155.43$, $p < .001$, $d = -1.32$; distress: $F[1,358.09] = 104.11$, $p < .001$, $d = -1.08$). Despite patients demonstrating decreases in symptoms of both anxiety and depression through follow-up, effect sizes of improvements differed. Specifically, reductions in depression were of large magnitude ($F[1,356.01] = 78.96$, $p < .001$, $d = -0.94$), whereas reduction in anxiety ($F[1,352.73] = 17.91$, $p < .001$, $d = -0.45$) were of small-to-medium effect size (i.e., $d < 0.50$). Large magnitude improvements in functional impairment ($F[1,360.49] = 116.27$, $p < .001$, d = -0.94) were observed through the 9-month follow-up period, while gains in the other tertiary outcomes pertaining to quality of life (life satisfaction: $F[1,351.80] = 50.62$, $p < .001$, d = -0.76; meaning and purpose: $F[1,353.72] = 50.16$, $p < .001$, d = -0.75) were moderate-to-large magnitude. Table 7 displays the results of these analyses.

3.6 Aim 2

"Pandemic Status"

Latent profile analysis was conducted using publicly available, government-source COVID-19 data for the region (i.e., seven-day average cases, hospitalizations, deaths; vaccination availability; days since the first confirmed COVID-19 case in the region), corresponding to each patient's baseline. Seven-day averages of COVID-19 cases, hospitalizations, and deaths were log-transformed using a base of 10. Model fit information is presented in Table 8.

One- to five-class solutions were examined. The *p*-values of the LMR-LRT and BLRT were significant for one- to four-class models, whereas the *p*-value for the LMR-LRT became non-significant with the introduction of a fifth class. The three-class solution had the highest entropy (.997) and revealed the most distinction between classes when examining scatterplots of cases, hospitalizations, and deaths by days since the first COVID-19 case. As such, the three-class model was selected as the most parsimonious representation of the data. Of note, logit thresholds for the "Vaccination Availability" indicator were fixed to 0 ("Vaccines Not Available") or 1 ("Vaccines Available"), to increase stability of model estimation and interpretation of classes. Posterior probabilities were .999, .999, and 1.00 for Class 1, Class 2, and Class 3, respectively, indicating excellent classification. Refer to Table 9 for descriptive statistics of each class, estimated by the LPA and observed within the sample.

Class 1 ("Earliest, Vaccines Not Available"; 45.5%) consisted of patients who began treatment earliest within the overall sample, when COVID-19 vaccinations were not yet available. Patients in Class 2 ("Most Severe"; 29.1%) began treatment when the pandemic was most severe, evidenced by the highest seven-day averages for cases, hospitalizations, and deaths. Patients in Class 3 ("Latest, Vaccines Available": 25.4%) began treatment latest within the overall sample when vaccines were publicly available and seven-day averages for hospitalizations and deaths were lowest. Pretreatment scores for worry ($F(2, 131) = 0.39$, $p = .68$), rumination ($F(2, 131) = 1.31$, $p = .27$), and distress ($F(2, 131) = 0.17$, $p = .84$) were not significantly different across the three "Pandemic Status" classes.

"Pandemic Status" as Predictor of Treatment Trajectory

To investigate the impact of "Pandemic Status" on change in primary outcomes from pre- to posttreatment, the three-level categorical variable, "Pandemic Status," was recoded into two dummy variables (i.e., “Class 2 vs Class 1,” “Class 2 vs Class 3”), with "Pandemic Status" Class 2 ("Most Severe") serving as the reference group. All models included a linear effect of “Time” and a random intercept. Results are displayed in Table 10.

Acute Treatment Phase. Regarding worry, the difference in the magnitude of improvements between the “Most Severe” class and “Latest, Vaccines Available” was statistically significant ($F[1,128.90] = 4.16$, $p = .04$) and of small-to-medium effect size ($d = -0.36$). Simple slope analysis revealed greater reductions in worry in the “Most Severe” class ($b = -16.81$, SE = 1.60, $p < .001$, $d = -3.54$) compared to the “Latest, Vaccines Available” class ($b = -11.14$, SE = 2.00, $p < .001$, $d = -2.04$). A small magnitude difference, though not statistically significant, was observed between the “Most Severe” and “Earliest, No Vaccines Available” classes ($F[1,125.68] = 2.68$, $p = .10$, $d = -0.29$).

Statistically significant, small-to-medium effect size differences were observed in reductions in rumination between the “Most Severe” class and both the “Earliest, Vaccines Not Available” ($F[1,127.74] = 5.45$, $p = .02$, $d = -0.41$) and the “Latest, Vaccines Available” ($F[1,130.89] = 6.12$, $p = .01$, $d = -0.44$) classes. Simple slope analyses revealed robust reductions in rumination in all classes, though the effect size within the “Most Severe” class ($b = -12.58$, SE = 1.06, $p < .001$, $d = -3.97$) was markedly larger than the “Earliest, Vaccines Not Available” ($b = -8.62$, SE = 1.06, $p < .001$, $d = -2.11$) and “Latest, Vaccines Available” ($b = -7.52$, SE = 1.74, $p < .001$, $d = -1.53$) classes.

For distress, the slope of the “Most Severe” class was not significantly different from the other two classes: “Earliest, Vaccines Not Available” ($F[1,123.75] = 1.32$, $p = .25$, $d = -0.21$) and “Latest, Vaccines Available” ($F[1,126.62] = 0.02$, $p = .89$, $d = -0.03$).

Longitudinal Trajectories. There were no significant trajectory differences in primary outcomes between groups when comparing the "Most Severe" class to the "Earliest, Vaccines Not Available" (worry: $F[1,360.14] = 0.07$, $p = .79$, $d = -0.03$; rumination: $F[1,360.20] = 0.00$, $p = .99$, $d = 0.00$; distress: $F[1,359.04] = 2.58$, $p = .11$, $d = -0.17$) and "Latest, Vaccines Available" (worry: $F[1,360.78] = 0.47$, $p = .49$, $d = -0.07$; rumination: $F[1,360.53] = 1.91$, $p = .17$, $d = -0.15$; distress: $F[1,359.06] = 0.02$, $p = .90$, $d = -0.02$) classes. Results of these analyses are displayed in Table 11.

3.7 Aim 3

The following section provides the percentages of patients achieving "Reliable Improvement" (RI), "Reliable Deterioration" (RD), and "Indeterminate Change" (IC) based on the full sample. Fifteen patients (11.19%) had missing posttreatment data, including 12 patients who dropped out of treatment and three patients who completed all sessions of ERT-P.

For worry, an RCI exceeding -1.96 corresponded to a reduction in PSWQ score greater than -8.55 points: 76 patients achieved RI (56.7%), while two showed RD (1.5%), and 41 exhibited IC (30.6%). Among patients classified as IC in worry, the majority demonstrated indeterminate improvement ($n = 29$, 21.6%) while eight showed indeterminate deterioration (6.0%) and four exhibited no change (3.0%).

Regarding rumination, an RCI exceeding -1.96 signified a reduction in RRQ score greater than -6.90 points: 75 patients demonstrated RI (56.0%) in rumination, while three showed RD (2.2%) and 41 exhibited indeterminate change (30.6%). Among patients classified as IC in rumination, the majority demonstrated indeterminate improvement ($n = 29$, 21.6%), while nine patients showed indeterminate deterioration (6.7%) and three exhibited no change (2.2%).

Concerning distress, an RCI exceeding -1.96 indicated a reduction in MASQ-D30-GD score greater than -8.38 points: 66 patients achieved RI (49.3%) in distress, whereas one patient showed RD (0.8%), and 52 patients were classified as IC (38.8%). The majority of patients classified as IC in distress demonstrated indeterminate improvement (n = 45, 33.6%), while 7 patients (5.2%) exhibited indeterminate deterioration.

LASSO Model Performance and Variable Importance (Posttreatment)

LASSO models were built to predict RI in primary outcomes at posttreatment, against all other categories (i.e., RD, IC, drop, missing data). LASSO models predicting RI demonstrated "poor" predictive accuracy for worry (AUC = .63, 95% CI [.58, .68]), rumination (AUC = .64, 95% CI [.59, .70]), and distress (AUC = .63, 95% CI [.57, .68]). Performance metrics of LASSO models are displayed in Table 12. Coefficients for variables predicting reliable improvement in LASSO models are displayed in Table 13.

Refer to Figure 4 for plots of predictors retained in individual LASSO models in descending order of importance. Of the five predictors retained in the LASSO model predicting RI worry, being single was identified as the most important feature and negatively associated with RI in worry. Of the 18 variables retained in the LASSO model predicting RI in rumination, being a parent was identified as the most important feature and negatively associated with RI in rumination. Of the 28 variables retained in the LASSO model predicting RI in distress, reporting increased family stress and discord was identified as the most important feature and positively associated with RI in distress.

Unregularized Logistic Regressions (Posttreatment)

Table 14 displays the results of unregularized binary logistic regressions with features selected by LASSO models.

Worry. The model predicting RI in worry correctly classified 71% of cases and was statistically significant, χ^2 (5) = 31.44, $p < .001$, Nagelkerke $R^2 = 0.28$. Four of the five retained predictors were statistically significant, of which three were associated with decreased odds of achieving reliable improvement in worry: being a parent (OR = 0.19 [0.07, 0.55], $p < .01$, d = 0.98), being single (OR = 0.20 [0.09, 0.49], $p < .001$, d = 0.89), and reporting greater reductions in access to medical healthcare (b = -0.43, SE = 0.21, OR = 0.65 [0.43, 0.98], $p = .04$, d = 0.25). Belonging to "Pandemic Status" Class 2 ("Most Severe") was associated with increased odds of achieving RI in worry (OR = 2.78 [1.13, 6.84], $p = .03$, d = 0.56).

Rumination. The model predicting RI in rumination correctly classified 78% of cases and was statistically significant, χ^2 (18) = 55.13, $p < .001$, Nagelkerke $R^2 = 0.45$. Three of the 18 retained variables were statistically significant predictors of RI in rumination. Being a parent (OR = 0.18 [0.05, 0.81], $p < .05$, d = -0.95) and reporting a chronic medical condition (OR = 0.36 [0.14, 0.94], $p = .04$, d = -0.56) were associated with decreased odds while engaging in mental health treatment for the first time was associated with increased odds (OR = 4.84 [1.51, 15.52], $p < .01$, d = 0.87) of RI in rumination.

Distress. The model predicting RI in distress correctly classified 75% of cases and was statistically significant, χ^2 (28) = 61.35, $p < .001$, Nagelkerke $R^2 = 0.49$. Being a parent (OR = 0.09 [0.02, 0.48], $p = .03$, d = -1.33), being born outside the U.S. (OR = 0.26 [0.08, 0.89], p = .03, d = -0.74), and reporting greater reductions in access to medical healthcare (b = -0.62, SE = 0.29, OR = 0.54 [0.31, 0.94], $p = .03$, d = -0.34) were significantly associated with decreased odds of achieving RI in distress. Conversely, being a healthcare worker (OR = 6.33 [1.20, 33.52], $p = .04$, d = 1.02), reporting more severe changes to family income and employment (b = 1.12, SE = 0.38, OR = 3.07 [1.47, 6.41], $p < .001$, d = 0.62), and reporting greater family stress and discord (b = 0.97, SE = 0.35, OR = 2.65 [1.34, 5.22], p = .01, d = 0.54) were significantly associated with increased odds of achieving RI in distress

Table 2: Descriptive statistics of sociodemographic characteristics (N = 134).

	n	**%**	***M* (*SD*)**
Age			34.84 (10.76)
Gender			
Female	91	67.9	
Male	37	27.6	
Non-Binary	6	4.5	
Race			
White	42	31.3	
Black or African American	32	23.9	
Hispanic or Latino Race	23	17.2	
Asian	21	15.7	
Mixed Race	13	9.7	
Other Race	3	2.2	
Hispanic/Latino Ethnicity	46	34.3	
Sexual Orientation			
Heterosexual	94	70.2	
Gay or Lesbian	12	9.0	
Bisexual	12	9.0	
Unsure/Don't Know	10	7.5	
Pansexual	3	2.2	
Asexual	2	1.5	
Prefer Not to Answer	1	0.8	
Born Outside of the United States	33	24.6	
Relationship Status			
Single	62	46.3	
Unmarried in a Relationship	35	26.1	
Married	34	25.4	
Other	3	2.2	
Parent	27	20.2	
Living Alone	30	22.4	
Personal Income			
$0 - $24,999	38	28.4	
$25,000 - $49,999	18	13.4	
$50,000 - $74,999	23	17.2	
$75,000 - $99,999	18	13.4	
$100,000 +	16	11.9	
Prefer Not to Answer	13	9.7	
Missing	8	6.0	
Level of Education			
< 4-Year College Degree	30	22.4	
Some High School	1	0.7	
High School Graduate	2	1.5	
Some College	22	16.4	
Trade/Technical/Vocational Training	1	0.7	
Associate Degree	4	3.0	

Table 2 (continued).

4-Year College Degree	55	41.0	
Bachelor's Degree	55	41.0	
Graduate School	49	36.6	
Master's Degree	34	25.4	
Doctoral Degree	15	11.2	
Student	14	10.5	
Healthcare	17	12.7	
Not Currently Working	43	32.1	
Chronic Medical Condition	65	48.5	
Currently Exercising	87	64.9	
Frequency of Alcohol Use (0-3)			0.70 (1.16)
Frequency of Marijuana Use (0-3)			1.12 (0.89)
Frequency of Substance Use (0-3)			0.06 (0.27)

Note. n = number of patients, % = percentage of sample, *M* = mean, *SD* = standard deviation.

Table 3: Descriptive statistics of clinical characteristics (*N* = 134).

	n	**%**	***M* (*SD*)**
DSM-5 Diagnosis	127	94.8	
Primary or Coprimary DSM-5 Diagnoses [a]	94	70.2	
GAD	70	52.2	
MDD	65	48.5	
SAD	14	10.5	
PTSD	7	5.2	
AGOR	7	5.2	
OCD	5	3.7	
PD	4	3.0	
SUD (coprimary)	3	2.2	
BED	3	2.2	
BN	1	0.8	
AUD (coprimary)	1	0.8	
Number of DSM-5 Diagnoses			2.29 (1.34)
Primary or Coprimary Clinical Severity (0-8)			5.28 (0.98)
No Prior Mental Health Treatment	34	25.4	
Taking Psychiatric Medication	31	23.1	
Antidepressants	19	14.2	
Anxiolytics	8	6.0	
Stimulants	10	7.5	
Antipsychotics	2	1.5	
Mood Stabilizer	1	0.8	
MINI Functioning/Impairment			50.04 (21.15)

Note. *n* = number of patients, % = percentage of sample, *M* = mean, *SD* = standard deviation, GAD = generalized anxiety disorder, MDD = major depressive disorder, SAD = social anxiety

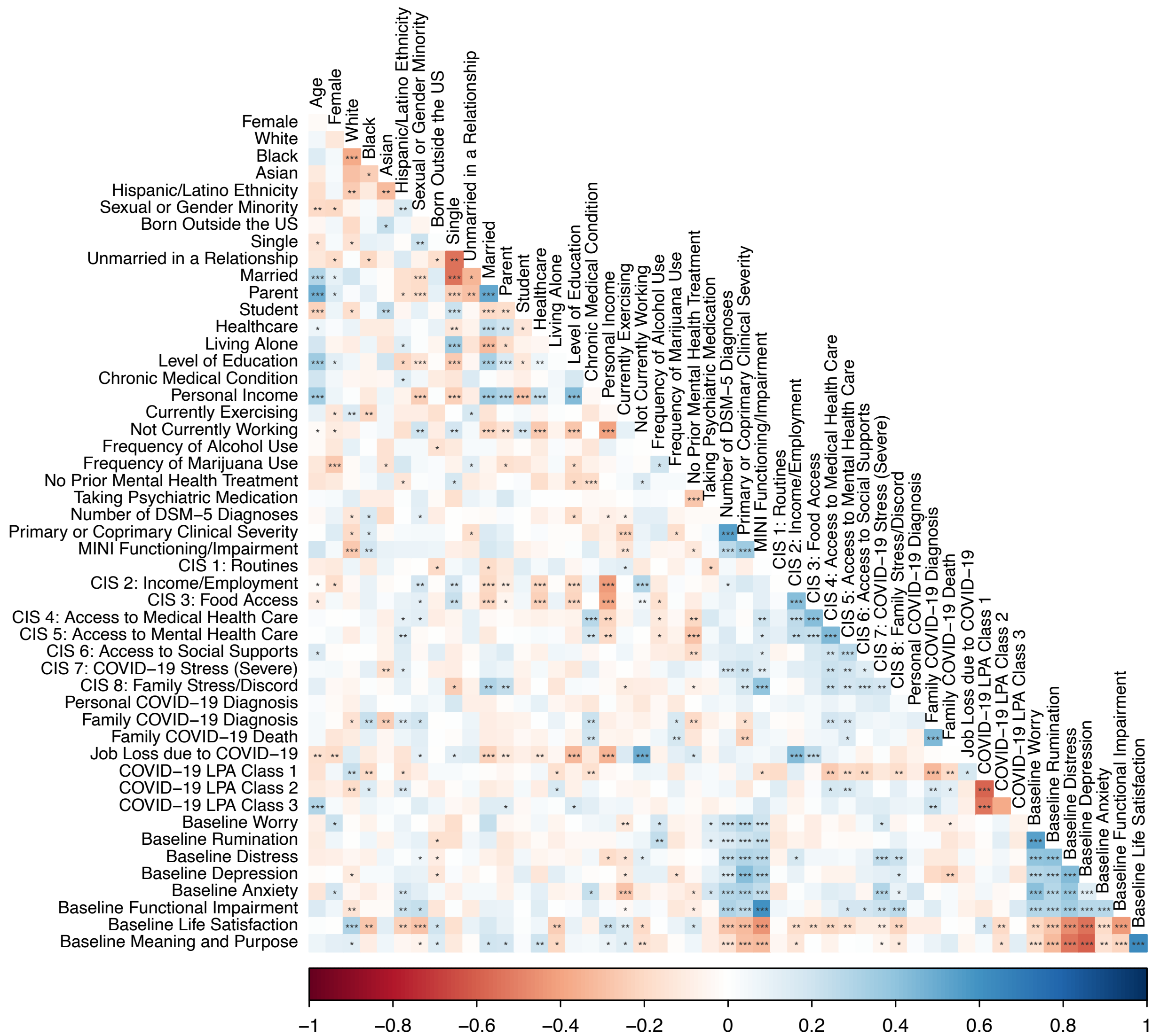
Table 3 (continued).

disorder, PTSD = post-traumatic stress disorder, AGOR = agoraphobia, OCD = obsessive compulsive disorder, PD = panic disorder, SUD = substance use disorder, BED = binge eating disorder, BN = bulimia nervosa, AUD = alcohol use disorder. [a] Primary or Coprimary Diagnoses represent individuals who had both a single and multiple primary diagnoses. Thus, the total value may exceed 100%. MINI = Mini International Neuropsychiatric Interview.

Table 4: Descriptive statistics of contextual characteristics (*N* = 134).

	n	**%**	***M* (*SD*)**
CIS 1: Routines			2.84 (0.41)
CIS 2: Income/Employment			1.66 (0.88)
CIS 3: Food Access			0.87 (0.82)
CIS 4: Access to Medical Healthcare			1.44 (1.09)
CIS 5: Access to Mental Healthcare			1.25 (1.24)
CIS 6: Access to Social Supports			1.91 (0.70)
CIS 7: COVID-19 Stress			2.59 (0.49)
CIS 8: Family Stress/Discord			1.28 (0.86)
CIS 9: Personal COVID-19 Diagnosis	32	23.9	
Mild Symptoms	27	20.2	
Moderate Symptoms	3	2.2	
Severe Symptoms	2	1.5	
CIS 10: Immediate Family COVID-19 Diagnosis	28	20.9	
Mild Symptoms	18	13.4	
Moderate Symptoms	3	2.2	
Severe Symptoms	2	1.5	
Death	5	3.7	
CIS 11: Extended Family COVID-19 Diagnosis	59	44.0	
Mild Symptoms	25	18.7	
Moderate Symptoms	11	8.2	
Severe Symptoms	3	2.2	
Death	20	14.9	
Any Family COVID-19 Diagnosis	70	52.2	
Any Family COVID-19 Death	24	17.9	
Job Loss due to COVID-19	45	33.6	

Note. *n* = number of patients, % = percentage of sample, *M* = mean, *SD* = standard deviation.



Note. Missing values of "Personal Income" values were imputed using K-nearest neighbor (KNN) imputation.
* $p < .05$, ** $p < .01$, *** $p < .001$

Figure 1: Correlogram of relationships among sociodemographic, clinical, and contextual characteristics and baseline outcome measures (N = 134).

Table 5: Means and standard deviations of outcomes from pretreatment through follow-up.

Measure	Pre-Tx (N = 134)	Post-Tx (N = 119)	3-mo FU (N = 112)	9-mo FU (N = 110)
Primary Outcomes				
Worry	64.44 (9.75)	50.90 (9.62)	49.85 (11.11) [b]	50.60 (11.17)
Rumination	46.31 (6.43)	36.82 (8.00)	35.25 (9.10)	36.26 (8.90)
Distress	31.60 (7.56)	20.92 (6.90)	21.92 (7.31)	22.42 (8.30)
Secondary Outcomes				
Depression	39.96 (6.63)	33.05 (8.91)	33.58 (8.32)	32.68 (8.50)
Anxiety	18.81 (6.13)	14.73 (4.63)	15.72 (5.13)	16.28 (6.04)
Tertiary Outcomes				
Functional Impairment	18.36 (6.14)	11.84 (6.35)	10.14 (6.28)	11.10 (6.61)
Life Satisfaction	17.68 (4.45)	20.57 (3.92) [a]	20.44 (4.13)	20.70 (4.76)
Meaning and Purpose	9.90 (3.64)	12.58 (3.94) [a]	12.46 (3.95)	12.50 (4.34)

Note. Tx = treatment, FU = follow-up. Worry = Penn State Worry Questionnaire; Rumination = Rumination Reflection Questionnaire; Distress = MASQ-D30-General Distress; Depression = MASQ-D30-Anhedonic Depression; Anxiety = MASQ-D30-Anxious Arousal; Functional Impairment = Sheehan Disability Scale; Life Satisfaction = Brief Multidimensional Students' Life Satisfaction Scale; Meaning and Purpose = Patient Reported Outcomes Measurement Information System-Meaning and Purpose.

[a] N = 116 (3 patients with incomplete data)

[b] N = 113 (1 patient with incomplete data)

Table 6: Linear mixed models for outcomes from pre- to posttreatment.

	b	SE	p	95% CI	d
Primary Outcomes					
Worry	-13.58	1.01	<.001	[-15.57, -11.58]	-2.40
Rumination	-9.50	0.74	<.001	[-10.97, -8.04]	-2.28
Distress	-10.61	0.69	<.001	[-11.99, -9.23]	-2.74
Secondary Outcomes					
Depression	-7.06	0.73	<.001	[-8.50, -5.62]	-1.75
Anxiety	-4.10	0.49	<.001	[-5.06, -3.14]	-1.53
Tertiary Outcomes					
Functional Impairment	-6.48	0.61	<.001	[-7.69, -5.27]	-1.87
Life Satisfaction	2.87	0.32	<.001	[2.23, 3.52]	1.61
Meaning and Purpose	2.71	0.31	<.001	[2.09, 3.33]	1.55

Note. b = unstandardized regression coefficient, SE = standard error, p = significance value, 95% CI = 95% confidence interval [lower limit, upper limit], d = Cohen's d effect size. Worry = Penn State Worry Questionnaire; Rumination = Rumination Reflection Questionnaire; Distress = MASQ-D30-General Distress; Depression = MASQ-D30-Anhedonic Depression; Anxiety = MASQ-D30-Anxious Arousal; Functional Impairment = Sheehan Disability Scale; Life Satisfaction = Brief Multidimensional Students' Life Satisfaction Scale; Meaning and Purpose = Patient Reported Outcomes Measurement Information System-Meaning and Purpose. All models were fitted with linear effect of Time and included random intercept.

Table 7: Linear mixed models for outcomes from pretreatment through 9-month follow-up.

	b	SE	*p*	95% CI	*d*
Primary Outcomes					
Worry	-4.47	0.36	<.001	[-5.17, -3.77]	-1.33
Rumination	-3.28	0.26	<.001	[-3.79, -2.76]	-1.32
Distress	-2.79	0.27	<.001	[-3.33, -2.25]	-1.08
Secondary Outcomes					
Depression	-2.25	0.25	<.001	[-2.74, -1.75]	-0.94
Anxiety	-0.70	0.16	<.001	[-1.03, -0.38]	-0.45
Tertiary Outcomes					
Functional Impairment	-2.40	0.22	<.001	[-2.84, -1.96]	-1.14
Life Satisfaction	0.87	0.12	<.001	[0.63, 1.11]	0.76
Meaning and Purpose	0.81	0.11	<.001	[0.58, 1.03]	0.75

Note. *b* = unstandardized regression coefficient, SE = standard error, *p* = significance value, 95% CI = 95% confidence interval [lower limit, upper limit], *d* = Cohen's *d* effect size. Worry = Penn State Worry Questionnaire; Rumination = Rumination Reflection Questionnaire; Distress = MASQ-D30-General Distress; Depression = MASQ-D30-Anhedonic Depression; Anxiety = MASQ-D30-Anxious Arousal; Functional Impairment = Sheehan Disability Scale; Life Satisfaction = Brief Multidimensional Students' Life Satisfaction Scale; Meaning and Purpose = Patient Reported Outcomes Measurement Information System-Meaning and Purpose. All models were fitted with linear effect of Time and included random intercept.

Table 8: Fit indices for latent profiles of COVID-19 data at baseline.

#	LL	AIC	BIC	ssaBIC	Entropy	LMR-LRT (*p*)	BLRT (*p*)	Smallest
1	-1228.44	2474.88	2500.96	2472.49				
2	-1073.32	2176.64	2220.11	2172.66	.980	<.001	<.001	31.3%
3	**-960.16**	**1962.31**	**2023.16**	**1956.74**	**.997**	**<.001**	**<.001**	**25.4%**
4	-898.41	1850.82	1929.06	1843.66	.978	.01	<.001	20.9%
5	-864.28	1794.57	1890.20	1785.81	.981	.20	<.001	4.5%

Note. # = Number of classes, LL = log likelihood value, AIC = Aikaike information criterion; BIC = Bayesian information criterion; ssaBIC = sample-size adjusted Bayesian information criterion; LMR-LRT = Lo–Mendell–Rubin likelihood ratio test; BLRT = bootstrap likelihood ratio test, *p* = significance value, Smallest = percentage of patients in the smallest class.

Table 9: Descriptive statistics of three "Pandemic Status" classes.

#		*n* (%)	Days [a]	Vaccines [b]	Cases [c]	Hosp [c]	Deaths [c]
1	Est.	61 (45.5%)	148.32	0%	2.70	1.74	1.20
	Obs.		154.37 (74.97)	1.6%	573.75 (350.23)	59.56 (24.81)	22.62 (19.51)
2	Est.	39 (29.1%)	400.62	92%	3.57	2.47	1.74
	Obs.		400.64 (125.71)	92.3%	5,575.31 (6,353.78)	312.82 (95.38)	53.51 (20.89)
3	Est.	34 (25.4%)	616.71	100%	2.90	1.70	0.99
	Obs.		616.74 (111.77)	100%	1,022.79 (747.54)	55.85 (25.55)	11.09 (7.44)

Note. # = class, *n* = number of patients in class, Est. = estimated by LPA model, Obs. = means and standard deviations (in parentheses) of continuous variables observed within current sample.
[a] Days since first COVID-19 case in the region (March 1, 2020)
[b] Vaccines = vaccines available in the region (before/after December 14, 2020)
[c] Seven-day averages of cases, hospitalizations, and deaths (base 10 log-transformed)

Table 10: "Pandemic Status" as a predictor of primary outcomes from pre- to posttreatment.

	b	SE	*p*	95% CI
Worry				
Intercept	65.38	1.54	<.001	[62.36, 68.41]
Time	-16.78	1.87	<.001	[-20.47, 13.09]
Class 1	3.84	2.35	.10	[-0.81, 8.50)]
Class 2 [a]	-	-	-	-
Class 3	5.60	2.74	.04	[0.17, 11.04]
Rumination				
Intercept	47.54	1.14	<.001	[45.30, 49.78]
Time	-12.62	1.36	<.001	[-15.31, -9.94]
Class 1	4.00	1.71	.02	[0.61, 7.39]
Class 2 [a]	-	-	-	-
Class 3	4.98	2.00	.01	[1.02, 8.94]
Distress				
Intercept	32.21	1.16	<.001	[29.93, 34.48]
Time	-11.58	1.30	<.001	[-14.16, -9.01]
Class 1	1.88	1.64	.25	[-1.36, 5.13]
Class 2 [a]	-	-	-	-
Class 3	0.26	1.92	.89	[-3.53, 4.06]

Note. b = unstandardized regression coefficient, SE = standard error, *p* = significance value, 95% CI = 95% confidence interval [lower limit, upper limit]. Worry = Penn State Worry

Table 10 (continued).

Questionnaire; Rumination = Rumination Reflection Questionnaire; Distress = MASQ-D30-General Distress. Class 1 = "Earliest, Vaccines Not Available, Class 2 = "Most Severe," Class 3 = "Latest, Vaccines Available." Class 1 = Time * dummy variable (Class 2 vs Class 1) interaction. Class 3 = Time * dummy variable (Class 2 vs Class 3) interaction. All models were fitted with linear effect of Time and included random intercepts.
[a] Class 2 ("Most Severe") served as reference group.

Table 11: "Pandemic Status" as predictor of longitudinal change in primary outcomes from pretreatment through follow-up.

	b	**SE**	***p***	**95% CI**
Worry				
Intercept	60.72	1.62	<.001	[57.53, 63.92]
Time	-4.54	0.66	<.001	[-5.84, -3.24]
Class 1	-0.22	0.84	.79	[-1.88. 1.44]
Class 2 [a]	-	-	-	-
Class 3	0.67	0.97	.49	[-1.24, 2.57]
Rumination				
Intercept	44.21	1.26	<.001	[41.73, 46.69]
Time	-3.52	0.49	<.001	[-4.48, -2.56]
Class 1	-0.01	0.62	.99	[-1.23, 1.21]
Class 2 [a]	-	-	-	-
Class 3	0.98	0.71	.17	[-0.42, 2.39]
Distress				
Intercept	28.82	1.18	<.001	[26.51, 31.15]
Time	-2.34	0.50	<.001	[-3.33, -1.35]
Class 1	-1.04	0.65	.11	[-2.31, 0.23]
Class 2 [a]	-	-	-	-
Class 3	0.10	0.74	.90	[-1.36, 1.55]

Note. *b* = unstandardized regression coefficient, SE = standard error, *p* = significance value, 95% CI = 95% confidence interval [lower limit, upper limit]. Worry = Penn State Worry Questionnaire; Rumination = Rumination Reflection Questionnaire; Distress = MASQ-D30-General Distress. Class 1 = "Earliest, Vaccines Not Available," Class 2 = "Most Severe," Class 3 = "Latest, Vaccines Available." Class 1 = Time * dummy variable (Class 2 vs Class 1) interaction. Class 3 = Time * dummy variable (Class 2 vs Class 3) interaction. All models were fitted with linear effect of Time and included random intercepts.
[a] Class 2 ("Most Severe") served as reference group.

Table 12: Model performance of LASSO logistic regression models predicting reliable improvement in primary outcomes at posttreatment.

Outcome	AUC [CI]	Sensitivity [CI]	Specificity [CI]	λ
Reliable Improvement vs. No Reliable Improvement				
Worry	.63 [.58, .68]	.41 [.34, .46]	.74 [.76, .79]	.063
Rumination	.64 [.59, .70]	.50 [.42, .58]	.68 [.61, .75]	.029
Distress	.63 [.57, .68]	.62 [.56, .68]	.50 [.43, .58]	.015

Note. AUC = area under curve, λ = lambda tuning parameter. CI = 95% confidence interval [lower limit, upper limit].

Table 13: LASSO coefficients predicting reliable improvement in primary outcomes.

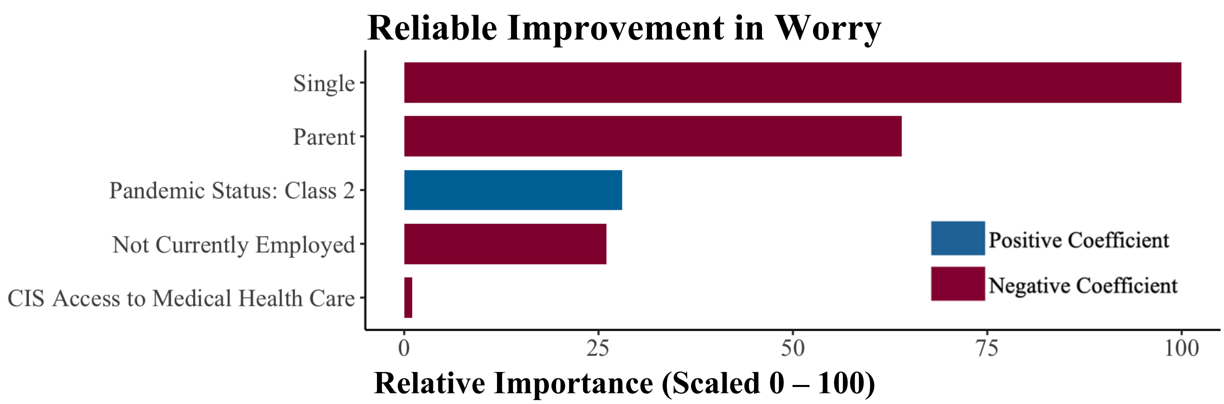
Predictor	Worry	Rumination	Distress
Age	-	-0.156	-
Female	-	-0.051	-0.090
White	-	0.157	0.168
Black	-	-	-0.112
Asian	-	-0.230	-
Hispanic/Latino Ethnicity	-	-	-
Sexual or Gender Minority	-	-	-
Born Outside the US	-	-	-0.319
Single	-0.318	-0.239	-0.077
Unmarried in a Relationship	-	0.014	-
Married	-	-	0.025
Parent	-0.204	-0.373	-0.544
Student	-	-	0.190
Healthcare	-	0.067	0.408
Living Alone	-	0.079	-0.021
Level of Education	-	-	-0.097
Chronic Medical Condition	-	-0.269	-
Personal Income	-	0.121	-
Currently Exercising	-	-	-0.071
Not Currently Working	-0.085	-0.187	-0.119
Frequency of Alcohol Use	-	0.214	0.010
Frequency of Marijuana Use	-	-	-
No Prior Mental Health Treatment	-	0.281	0.106
Taking Psychiatric Medication	-	-	-
Number of DSM-5 Diagnoses	-	0.023	-
Primary or Coprimary Clinical Severity	-	-	-
MINI Functioning/Impairment	-	-	0.156
CIS 1: Routines	-	0.078	-0.142
CIS 2: Income/Employment	-	-	0.539
CIS 3: Food Access	-	-	-
CIS 4: Access to Medical Healthcare	-0.005	-	-0.338

Table 13 (continued).

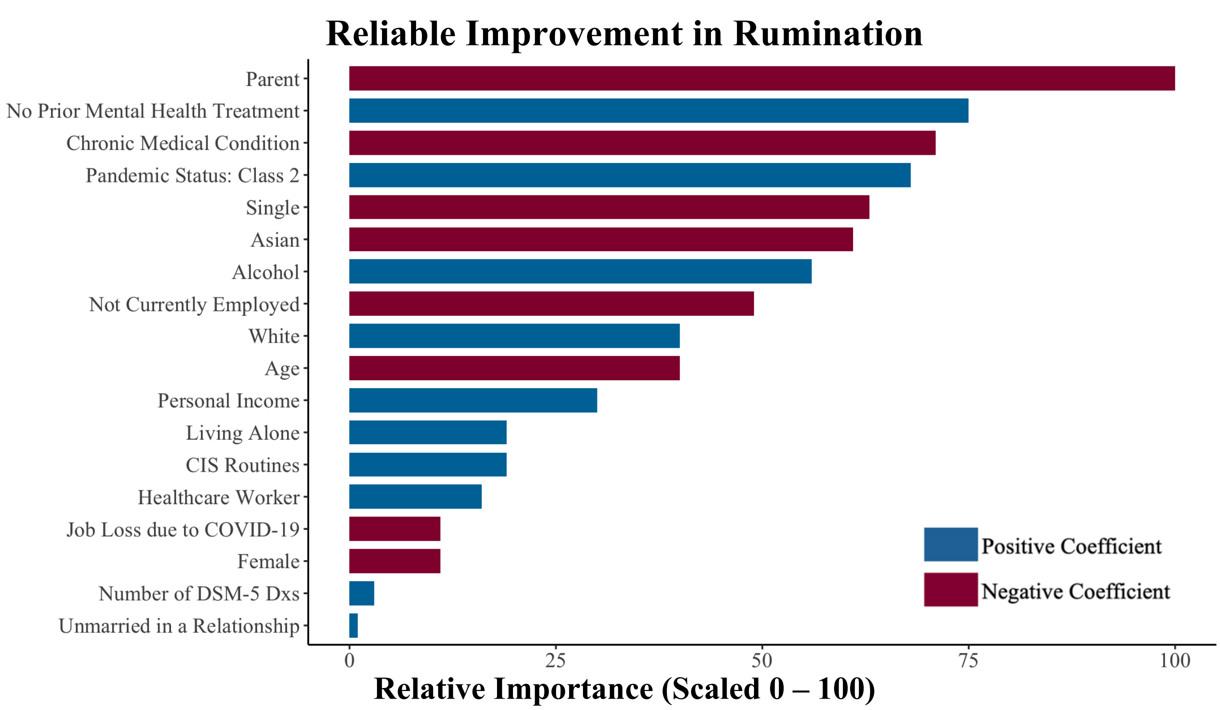
CIS 5: Access to Mental Healthcare	-	-	-0.267
CIS 6: Access to Social Supports	-	-	-
CIS 7: COVID-19 Stress (Severe)	-	-	0.158
CIS 8: Family Stress/Discord	-	-	0.602
CIS 9: Personal COVID-19 Diagnosis	-	-	0.187
CIS 10: Family COVID-19 Diagnosis	-	-	-0.169
CIS 11: Family COVID-19 Death	-	-	-0.162
Job Loss due to COVID-19	-	-0.050	-0.138
"Pandemic Status" Class 1	-	-	-0.208
"Pandemic Status" Class 2	0.089	0.257	0.085
"Pandemic Status" Class 3	-	-	-

[a] Missing data for "Personal Income" were handled with K-nearest neighbor imputation.

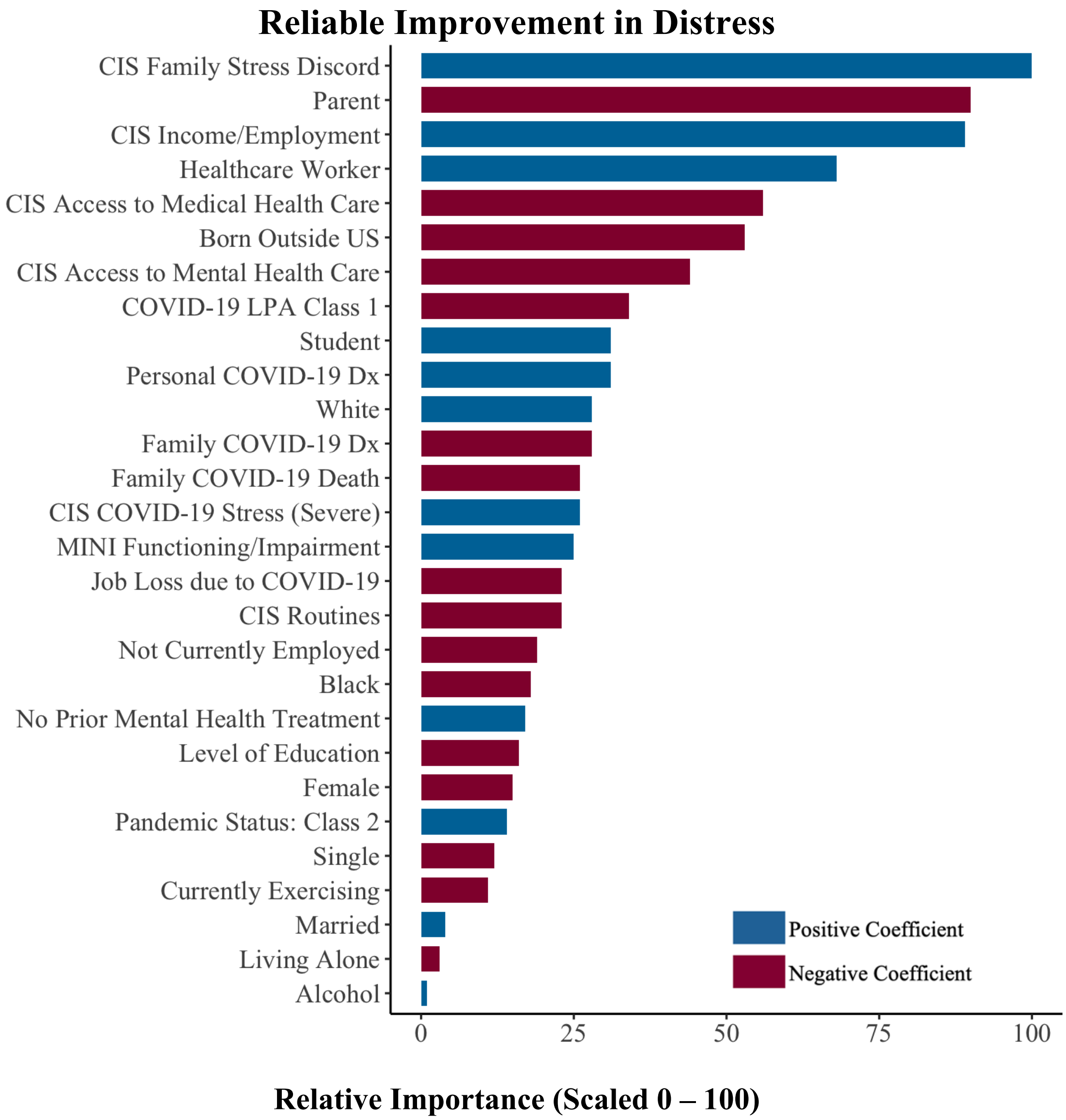
Figure 2: Relative importance of variables in LASSO models predicting reliable improvement in worry, rumination, and distress at posttreatment.



Reliable Improvement in Worry
Single
Parent
Pandemic Status: Class 2
Not Currently Employed
CIS Access to Medical Health Care
Positive Coefficient
Negative Coefficient
0
25
50
75
100
Relative Importance (Scaled 0 – 100)



Reliable Improvement in Rumination
Parent
No Prior Mental Health Treatment
Chronic Medical Condition
Pandemic Status: Class 2
Single
Asian
Alcohol
Not Currently Employed
White
Age
Personal Income
Living Alone
CIS Routines
Healthcare Worker
Job Loss due to COVID-19
Female
Number of DSM-5 Dxs
Unmarried in a Relationship
Positive Coefficient
Negative Coefficient
0
25
50
75
100
Relative Importance (Scaled 0 – 100)



Reliable Improvement in Distress
CIS Family Stress Discord
Parent
CIS Income/Employment
Healthcare Worker
CIS Access to Medical Health Care
Born Outside US
CIS Access to Mental Health Care
COVID-19 LPA Class 1
Student
Personal COVID-19 Dx
White
Family COVID-19 Dx
Family COVID-19 Death
CIS COVID-19 Stress (Severe)
MINI Functioning/Impairment
Job Loss due to COVID-19
CIS Routines
Not Currently Employed
Black
No Prior Mental Health Treatment
Level of Education
Female
Pandemic Status: Class 2
Single
Currently Exercising
Married
Living Alone
Alcohol
Positive Coefficient
Negative Coefficient
0
25
50
75
100
Relative Importance (Scaled 0 – 100)

Table 14: Unregularized binary logistic regressions predicting reliable improvement in worry, rumination, and distress at posttreatment.

Predictor	OR	95% CI	*p*	*d*
Worry				
Single	**0.20**	**[0.09, 0.49]**	**< .001**	**-0.89**
Parent	**0.17**	**[0.06, 0.51]**	**.001**	**-0.98**
Not Currenting Working	0.46	[0.20, 1.08]	.08	-0.43
CIS 4: Medical Healthcare Access	**0.65**	**[0.43, 0.98]**	**.04**	**-0.25**
"Pandemic Status Class 2"	**2.78**	**[1.13, 6.84]**	**.03**	**0.56**
Rumination				
Age	0.96	[0.91, 1.01]	.14	-0.02
Female	0.63	[0.22, 1.81]	.39	-0.26
White	2.32	[0.82, 6.59]	.11	0.46
Asian	0.31	[0.08, 1.27]	.10	-0.65
Single	0.26	[0.05, 1.31]	.10	-0.74
Unmarried in a Relationship	1.07	[0.21, 5.57]	.93	0.04
Parent	**0.18**	**[0.03, 0.99]**	**<.05**	**-0.95**
Healthcare	2.03	[0.50, 8.15]	.32	0.39
Living Alone	2.84	[0.80, 10.18]	.11	0.58
Chronic Medical Condition	**0.36**	**[0.14, 0.94]**	**.04**	**-0.56**
Personal Income [a]	1.24	[0.82, 1.87]	.31	0.12
Not Currently Working	0.65	[0.21, 2.00]	.45	-0.24
Frequency of Alcohol Use	1.39	[0.82, 2.33]	.22	0.18
No Prior Mental Health Treatment	**4.84**	**[1.51, 15.52]**	**<.01**	**0.87**
Number of DSM-5 Diagnoses	1.23	[0.87, 1.74]	.24	0.11
CIS 1: Routines	1.56	[0.50, 4.90]	.45	0.25
Job Loss due to COVID-19	0.42	[0.14, 1.30]	.13	-0.48
"Pandemic Status Class 2"	2.36	[0.87, 6.43]	.09	0.47
Distress				
Female	0.70	[0.24, 2.07]	.52	-0.20
White	2.44	[0.70, 8.47]	.16	0.49
Black	0.51	[0.13, 2.00]	.33	-0.37
Born Outside United States	**0.26**	**[0.08, 0.89]**	**.03**	**-0.74**
Single	0.60	[0.22, 2.41]	.60	-0.28
Married	1.27	[0.23, 7.05]	.78	0.13
Parent	**0.09**	**[0.02, 0.48]**	**<.001**	**-1.33**
Student	2.73	[0.51, 14.60]	.24	0.55
Healthcare	**6.33**	**[1.20, 33.52]**	**.03**	**1.02**
Living Alone	0.69	[0.19, 2.52]	.58	-0.21
Level of Education	0.67	[0.33, 1.36]	.27	-0.22
Currently Exercising	0.64	[0.22, 1.85]	.41	-0.25
Not Currently Working	0.56	[0.16, 1.99]	.37	-0.33
Frequency of Alcohol Use	1.04	[0.60, 1.81]	.90	0.02

Table 14 (continued).

No Prior Mental Health Tx	1.47	[0.40, 5.42]	.56	0.21
Impairment/Functioning (MINI)	1.02	[0.99, 1.05]	.14	0.01
CIS 1: Routines	0.39	[0.10, 1.46]	.16	-0.52
CIS 2: Income/Employment	**3.07**	**[1.47, 6.41]**	**<.001**	**0.62**
CIS 4: Medical Healthcare Access	**0.54**	**[0.31, 0.94]**	**.03**	**-0.34**
CIS 5: Mental Healthcare Access	0.67	[0.41, 1.08]	.10	-0.22
CIS 7: COVID-19 Stress (Severe)	1.61	[0.58, 4.43]	.36	0.26
CIS 8: Family Stress and Discord	**2.65**	**[1.34, 5.22]**	**.01**	**0.54**
CIS 9: Personal COVID-19 Dx	1.81	[0.59, 5.56]	.30	0.33
CIS 10: Family COVID-19 Dx	0.55	[0.17, 1.73]	.31	-0.33
CIS 11: Family COVID-19 Death	0.57	[0.14, 2.29]	.43	-0.31
Job Loss due to COVID-19	0.49	[0.13, 1.94]	.31	-0.39
"Pandemic Status Class 1"	0.31	[0.08, 1.22]	.09	0.65
"Pandemic Status Class 2"	1.34	[0.37, 4.82]	.65	0.16

Note. OR = odds ratio, 95% CI = 95% confidence interval [lower limit, upper limit], *d* = Cohen's *d* effect size. Only the predictors with non-zero coefficients in the full LASSO models predicting reliable improvement were retained for unregularized binary logistic regression. Significant effects ($p < .05$) are in bold.

[a] Missing data for "Personal Income" were handled with K-nearest neighbor imputation.

Chapter 4: Discussion

The primary objective of the current study was to evaluate the efficacy of Emotion Regulation Therapy-Pandemic (ERT-P), a blended telehealth intervention, in alleviating distress among adults residing in the United States' first COVID-19 epicenter. ERT-P integrates synchronous telehealth therapy sessions with internet- and mobile-delivered components (i.e., video modules, mindful regulation skill practices, between-session exercises). This hybrid model allows for personalized treatment, tailored to each patient's pandemic experience, while providing IMI tools to enhance engagement with treatment both during and after the nine-session intervention.

Throughout the pandemic, individuals faced unprecedented uncertainty and a multitude of stressors, prompting a reevaluation of the ways in which they manage distress—especially as previously relied upon coping methods were inaccessible or proved ineffective in the face of crisis. Worry and rumination, often conceptualized as counterproductive cognitive efforts at self-regulation, have consistently been shown to exacerbate and perpetuate distress (Mansueto et al., 2022; Mennin et al., 2013; Watkins & Roberts, 2020). This link was underscored during the pandemic, as perseverative negative thinking (PNT) was strongly associated with heightened emotional distress and decreased overall well-being (Adamis et al., 2024; Hoffart et al., 2022; O'Connor et al., 2023). Thus, the explicit targeting of PNT, through improving attentional and metacognitive regulatory capacities within the ERT approach, was tested to relieve distress amidst the COVID-19 crisis.

I first hypothesized that ERT-P patients would exhibit statistically significant improvement in primary (i.e., worry, rumination, distress), secondary (i.e., anxiety, depression), and tertiary (i.e., functional impairment, life satisfaction, meaning and purpose) during the acute treatment phase and through follow-up. A second aim was to investigate whether the status and severity of the pandemic at each patient's baseline predicted treatment response. I hypothesized that distinct patient cohorts, differentiated by COVID-19 severity at the time of enrollment and identified through latent profile analysis of regional COVID-19 data (i.e., cases, hospitalizations, deaths; availability of vaccines; days since first COVID-19 case), would exhibit varying responses to ERT-P. Lastly, as an exploratory aim, I sought to examine sociodemographic, clinical, and contextual patient characteristics as predictors of differential treatment response

Together, these objectives constitute a comprehensive evaluation of ERT-P's efficacy within the unique context of the COVID-19 pandemic, over a span of two years. This final chapter will provide a summary and interpretation of findings relevant to each aim, discuss the study's strengths and limitations, and propose potential avenues for future research.

4.1 Aim 1

Supporting my Aim 1 hypotheses, ERT-P patients exhibited statistically significant improvement in all outcomes of interest during the acute treatment phase and through follow-up. From pre- to posttreatment, within-group effect sizes were substantial, ranging from $d = 1.53$ to $d = 2.74$, indicating marked improvements across all measured outcomes. Notably, these effect sizes exceed those reported in pre-pandemic studies of telehealth psychotherapy (*d*s 0.99 – 1.29; Fernandez et al., 2021), online MBIs (*d*s 0.26 – 0.44; Sommers-Spijkerman et al., 2021), and iCBT (*d*s 0.42 – 1.78; Etzelmueller et al., 2020) . Moreover, the magnitude of improvements following ERT-P, a briefer and more intensive blended telehealth intervention, matched or exceeded within-group effect sizes reported in F2F trials of ERT in 20-session format (*d*s 0.76 – 1.79; Mennin et al., 2015), 16-session format (*d*s 1.45 – 2.97; Renna et al., 2018), and in 8-

session format for informal caregiver of cancer patients (Hedges' *g*s 0.36 – 0.66; Applebaum et al., 2018).

A literature search yielded only a small number of self-described blended interventions that were tested during the COVID-19 pandemic. In a large-scale ($N = 6{,}738$), "real world" study of blended care CBT (BC-CBT), treatment consisted of telehealth therapy sessions integrated with digital lessons and exercises from a range of contemporary CBTs (i.e., Unified Protocol, Dialectical Behavior Therapy, and Acceptance and Commitment Therapy; Owusu et al., 2022). Enrolled between Fall 2019 and Summer 2021, patients received six therapy sessions over the course of about eight weeks and demonstrated substantial reductions in depression ($g = -1.89$) and anxiety ($g = -1.82$), as indicated by paired-sample *t*-tests. In a smaller study ($N = 67$) conducted in Germany between Fall 2021 and Spring 2022, two blended CBT (bCBT) interventions were tested among university students experiencing anxiety and depression (Atik et al., 2023). Students who completed the anxiety- or depression-specific bCBTs, which consisted of six 25-minute telehealth therapy sessions and internet-based exercises (e.g., behavioral activation plan, progressive muscle relaxation, cognitive restructuring), demonstrated large magnitude improvements in anxiety ($d = -0.86$) and depression ($d = -0.90$).

Through the follow-up period of the current study, improvements remained statistically significant and robust, evidenced by large-magnitude, within-group improvements in worry ($d = -1.33$) and rumination ($d = -1.32$), distress ($d = -1.08$), depression ($d = -0.94$), and functional impairment ($d = -1.14$). Gains in life satisfaction ($d = -0.76$) and meaning and purpose ($d = -0.75$) were medium-to-large magnitude, while improvements in anxiety ($d = 0.45$) were small-to-medium magnitude when including the follow-up period. These sustained improvements were comparable to or larger than those reported in pre-pandemic studies of telehealth psychotherapy (*d*s 0.80 – 1.24; Berryhill et al., 2019), online MBIs (*d*s 0.23 – 0.25; Sommers-Spijkerman et al., 2021), and iCBT (standard mean difference [SMD] 0.69 – 0.90; Sztein et al., 2018). Regarding the comparatively lesser sustained improvements in anxiety, a similar trend was observed in Ye and colleagues' (2022) meta-analyses of guided and unguided online interventions during COVID-19. Overall, these interventions led to large magnitude reductions in anxiety (SMD = -0.78; 95 % CI [-1.13, -0.44]) and depression (SMD = -0.80; 95 % CI [-1.18, -0.41]) from pre- to posttreatment. However, through follow-up, effects were observed only for depression (SMD = -0.21; 95 % CI = -0.35, -0.06) and not anxiety (SMD = -0.14; 95 % CI = -0.29, 0.12).

One possible explanation for this anxiety-specific finding lies in the evolving nature of the pandemic, with the emergence of new COVID-19 strains and waves of illness and death, potentially contributing to increasing or persistent anxiety. Supporting this notion, a 2022 Italian study found that regional mortality rates were significantly associated with more severe anxiety over time, though not depression or stress (Carrà et al., 2022). Additionally, as restrictions eased (i.e., social distancing, quarantine, travel) and life returned to a semblance of normalcy, individuals faced new challenges, including heightened risk of COVID-19 exposure and difficulties readjusting to social life, potentially exacerbating anxiety (Lim et al., 2022; Wolfe et al., 2021). Furthermore, it's worth noting that average pretreatment anxiety levels (M = 18.81, SD = 6.13), as measured by the AA subscale of the MASQ-D30 (range = 10 – 50), were relatively low, especially compared to depression (M = 39.96, SD = 6.63). This may be related to the AA subscale itself, which primarily captures fear- and panic-related physiological symptoms (i.e., "Was trembling and shaking," "Felt dizzy or light-headed"). Indeed, findings from prior studies of the MASQ-D30 suggest that the predictive value of AA may be restricted to panic disorder

(Wardenaar et al., 2012), for which only four patients (3.0%) in the current study met DSM-5 criteria.

Symptoms of depression, anxiety, and stress were the primary outcomes most consistently reported in telehealth and IMI studies conducted during COVID-19, making comparisons somewhat difficult. Nonetheless, a handful of studies reported results pertaining to PNT and indicators of functioning and quality of life. For instance, in one RCT testing a 10-day unguided iCBT, researchers found that the pandemic-adapted intervention significantly reduced worry (d = 0.43) and improved well-being (d = 0.40) and resilience (d = 0.22) compared to a waitlist control condition (Heckendorf et al., 2022). Additionally, student participants in Atik and colleagues' (2023) anxiety- and depression-specific bCBT interventions exhibited significant improvements in quality of life (ds 0.45 - 0.82), but improvements in functional impairment were only observed within the depression-specific treatment group (d = -0.49). Further, in their individually tailored iCBT for COVID-19 distress, Aminoff and colleagues (2023) observed that the eight-week, therapist-guided intervention led to improvements in depression symptoms but not quality of life, anxiety, or stress. These findings underscore the importance of assessing transdiagnostic mechanisms of emotional distress, functioning, and quality of life and highlight the robustness of improvements observed within these domains among ERT-P patients.

With regard to acceptability, the majority of patients expressed high satisfaction with the intervention, as well as with the quality and amount of services they received. Additionally, patients perceived the ERT-P IMI platform to be usable and of high quality, with SUS scores earning an "A-" rating (i.e., 85-89th percentile) based on established benchmarks (Lewis, 2018). Only 14 out of 134 enrolled patients (10.45%) discontinued treatment prematurely, a notably lower attrition rate compared to meta-analyses of F2F CBT ((26.2%; Fernandez et al., 2015) and therapist-guided iCBT (25%; Karyotaki et al., 2021). Patients who identified as SGM accounted for a higher proportion of treatment drops. Prior research has noted lower satisfaction with healthcare services among the SGM population (Blosnich, 2017; Ferrucci et al., 2021), potentially influencing their decision to discontinue mental health treatment. While digitally-delivered, SGM-affirming interventions targeting minority stress have demonstrated robust effects (Gilbey et al., 2020), ongoing research is needed to more effectively reach, support, and optimize treatment for this vulnerable population (Pachankis, 2018).

In addition, individuals who dropped out of ERT-P reported significantly more pandemic-attributed disruptions in access to food (i.e., mild to moderate changes, "Enough food but difficulty getting to stores and/or finding needed items" to "Occasionally without enough food and/or good quality foods"). During COVID-19, food insecurity was found to predict poor mental health outcomes in the general population (Nagata, Ganson, Whittle, et al., 2021) and increase the risk of anxiety and depression by over 250% (Fang et al., 2021). In future studies, it may be of benefit for therapists to explicitly screen for food insecurity, as recommended by Nagata and colleagues (2021). This proactive approach would better support patients in accessing essential resources, reducing their burden and facilitating continued participation in psychosocial treatment. Lastly, patients who dropped out of treatment reported significantly greater pandemic-attributed disruptions to medical healthcare access (i.e., moderate to severe changes, "Delays or cancellations in appointments and/or delays in getting prescriptions; changes have minimal impact on health" to "Unable to access needed care resulting in moderate to severe impact on health"). Highlighting the impact of medical care on psychological distress during crisis, Raker and colleagues (2020) observed that uncertain access to medications and medical healthcare was associated with significantly increased odds of psychological distress and posttraumatic stress symptoms years after Hurricane Katrina. Explicit assessment of barriers to medical healthcare and providing patients updated information on healthcare programs and policies may reduce stress and promote continued engagement with mental health treatment.

While the absence of a control group limits definitive causal inferences, the observed outcomes suggest preliminary efficacy of ERT-P in alleviating distress and enhancing quality of life during the pandemic, with sustained improvement beyond the treatment period. Furthermore, results affirm the feasibility and acceptability of ERT-P in blended format, evidenced by high ratings of patient satisfaction, perceived usability of the IMI platform, and low attrition rate.

4.2 Aim 2

To examine whether the status and severity of the pandemic was associated with treatment response, I first conducted LPA using regional COVID-19 data from government sources corresponding to each patient's baseline date (i.e., daily averages of cases, hospitalizations, deaths over the previous seven days; availability of vaccinations; and days since the first confirmed COVID-19 case in the region). The LPA revealed three distinct subgroups of the latent variable, termed "Pandemic Status." Patients in the "Earliest, No Vaccines Available" (45.5%) had the earliest enrollments in the overall sample, initiating treatment before COVID-19 vaccinations were accessible. The "Most Severe" class (29.1%) comprised patients who began ERT-P during the highest peak of COVID-19 cases, hospitalizations, and deaths while the study was active. Patients in the "Latest, Vaccines Available" class (25.4%) began treatment latest in the overall sample, when vaccines were publicly available and hospitalizations and deaths were lowest.

For subsequent analyses examining group differences, the "Most Severe" class served as the reference group based on the heightened pandemic conditions at treatment initiation compared to the other two classes. Additionally, the other two classes differed in terms of enrollment timing (i.e., earliest and latest) and vaccine availability (i.e., pre- and post-vaccine availability to the public). Results, as described below, partially supported my Aim 2 hypothesis, that “Pandemic Status” would differentially predict treatment response.

During the acute treatment phase, significant differences in treatment response emerged concerning PNT but not for distress. Specifically, patients in the “Latest, Vaccines Available” class (d = -1.11) exhibited significantly lesser reductions in worry compared to those in the “Most Severe” class (d = -2.00), a significant small-to-medium magnitude difference (d = -0.40, p =.04). Regarding rumination, both the “Earliest, No Vaccines Available” (d = -1.41) and “Latest, Vaccines Available” (d = -0.86) classes demonstrated significantly lesser reduction in rumination, compared to the “Most Severe” class (d = -2.26). Again, the effect sizes of these differences were significant and small-to-medium for the “Earliest, No Vaccines Available” (d = -0.41, p = .02) and “Latest, Vaccines Available” (d = -0.44, p = .01) classes. It is crucial to acknowledge that the interpretation of these PNT findings can be approached in two ways: 1) patients in the “Earliest, No Vaccines Available” and “Latest, Vaccines Available” classes made comparatively lesser improvement, or 2) patients in the “Most Severe” class demonstrated significantly greater improvement compared to the other classes.

Taking a closer look at the “Most Severe” class, patients in this group had a mean enrollment date of April 6, 2021 (M = 400.62 days since March 1, 2020, the date of the first identified case in the region), with a wide standard deviation of 125.71 days. Notably, the “Most Severe” class also included five patients who started treatment during the subsequent wave of COVID-19 in Winter 2022. Given that patients in the “Most Severe” class enrolled during peaks of COVID-19, it is possible that reductions in PNT followed improvements in the status and severity of the pandemic at the time. Interestingly, despite enrolling during different phases of the pandemic, there were no significant differences in baseline measures of worry or rumination across the "Pandemic Status" classes (*p*s > .27). This suggests that the more robust improvements in PNT observed in the “Most Severe” class were not attributable to higher severity at the start of treatment.

Researchers examining seasonal trends of COVID-19 in the United States have documented “spikes” in cases, hospitalizations, and deaths occurring between November and April in both 2021 and 2022 (Wiemken et al., 2023). During the first year of the pandemic, Burdett and colleagues (2021) observed steadily decreasing mental health symptoms among UK adults between April and July, coinciding with the easing of lockdown restrictions heading into Spring 2020. A similar pattern was observed among adolescents in New York, where symptoms of distress decreased at a rapid rate after peaking in April 2020 (Burdett et al., 2021). Although prior research has not established a definitive link between seasonal variation and mental health (Øverland et al., 2020), it is plausible that improvements observed within the “Most Severe” class were related to seasonal changes and subsequent recession of COVID-19, which in-turn reduced distress. Another factor to consider is increased time spent outdoors, which is often associated with warmer weather. Stock and colleagues (Stock et al., 2022) found that, during the pandemic, increased time outdoors predicted declines in anxiety and depression, as well as increases in life satisfaction. Taken together, these studies highlight the complexities of investigating the longitudinal impacts of a chronic and evolving stressor such as COVID-19 on mental health.

Results of longitudinal analyses indicated that trajectories of improvement were not significantly different across “Pandemic Status” classes for any of the primary outcomes. Despite slight variations in the shapes of trajectories during the follow-up period, the evolving context of the pandemic at patients' baselines did not have a substantial impact on longer-term outcomes of worry, rumination, or distress. This suggests that the gains achieved during treatment were relatively stable over time, irrespective of when patients began ERT-P during the two-year enrollment period.

While Aim 2 focused on examining the impact of the COVID-19 context at each patient's baseline, future investigations might incorporate objective COVID-19 data as time-varying covariates in analyses. This approach would help identify the most influential pandemic-related factors impacting treatment response at the individual level and better isolate the effect of treatment from the dynamic, temporal changes of the pandemic.

4.3 Aim 3

The final aim of the current study was to examine sociodemographic, clinical, and contextual patient characteristics as predictors of reliable improvement in primary outcomes. At posttreatment, the majority of patients exhibited "Reliable Improvement" (RI; Wise, 2004) in each of the primary outcomes: worry (56.7%), rumination (56.0%), and distress (49.3%). Rates of RI often vary by therapeutic approach, modality, population, and diagnosis but are estimated to range from 44.5 - 51.1% for anxiety (Loerinc et al., 2015)and from 59.0 - 68.0% for depression (Cuijpers et al., 2021). The most recent meta-analytic evidence of iCBT for depression estimates RI rates of 56.2% (Karyotaki et al., 2018). While there are no meta-analyses examining rates of RI within iCBT for anxiety, a 2019 systematic review suggests considerable variability in response, with rates of RI ranging from 27.3 to 79.2% (Andersson, Carlbring, & Rozental, 2019). In terms of non-response, characterized as "Indeterminate Change" in the current trial, Rozental and colleagues' (2019) meta-analysis of iCBT interventions found the highest rates among studies testing iCBT for comorbid anxiety and depression, ranging from 48.5% to 58.8%. Conversely, the current study observed substantially lower rates of "Indeterminate Change" for worry (30.6%), rumination (30.6%), and distress (38.8%), in a sample of patients with considerable psychiatric comorbidity (i.e., mean number of DSM-5 diagnoses was 2.29). Moreover, "Reliable Deterioration" rates were markedly lower in ERT-P (i.e., worry = 1.5%, rumination = 2.2%, and distress = 0.8%) compared to iCBT (5.8%; Rozental et al., 2017) and F2F psychotherapy (estimated to range from 5 – 10%; Lambert, 2007). Taken together, the posttreatment responses observed in worry, rumination, and distress within ERT-P are on par with those reported for F2F psychotherapy and internet-delivered interventions.

Regarding LASSO prediction models, the small sample size precluded the ability to train and validate the model through more traditional data-splitting methods. Instead, three repetitions of 10-fold cross-validation were employed, which introduces risks for overfitting and biased estimates (Cawley & Talbot, 2010). LASSO models exhibited "poor" discrimination (AUCs .63 - .64) and accuracy (Sensitivity .41 - .62). This may be attributed to a range of factors including small sample size, large number of dichotomous predictor variables, exclusion of other more predictive and/or clinically relevant variables (e.g., baseline severity), and poor distinction of the dichotomous outcome of RI (i.e., just above/below RCI cutoff). In their study exploring the prediction of psychotherapy outcomes from intake data extracted from electronic medical records, Coley and colleagues (2021) encountered similar issues with LASSO model performance. Echoing the sentiments of these researchers, as well as underscoring the need for and challenges with prediction modeling in mental health treatment, the LASSO findings discussed here should be interpreted with both "enthusiasm and skepticism." In the current study, LASSO was employed for feature selection, identifying variables for inclusion in unregularized, multivariable logistic regression models, as summarized below.

In examining predictors of RI, a key finding emerged: parenthood was consistently associated with reduced likelihood of achieving RI across all primary outcomes (ORs 0.09 – 0.18, *d*s -0.95 – -1.33). Beyond managing their own COVID-related distress and work-life balance, parents faced additional stressors stemming from dramatic shifts in their children's routines, the complexities of online schooling, and threats to their children's physical and mental well-being (Adams et al., 2021). This burden was especially pronounced during the earliest phase of the pandemic, when schools and workplaces were operating remotely, and essential support services were less accessible. Previous research investigating the dynamics of parental stress, familial conflict, and parent-child interactions during times of crisis has highlighted parent's heightened vulnerability to emotional distress and compromised mental health (Achterberg et al., 2021; Johnson et al., 2021).

A longitudinal analysis of more than 3,000 U.S. parents during the early stages of the pandemic revealed that 72% endorsed persistently low distress, possibly indicating resilience. Conversely, approximately 26% of parents reported increasing or persistently high distress, linked to factors such as loss of child care, job loss or employment instability, financial strain, and increased family conflict (Zalewski et al., 2023). Amidst the increased stress experienced by parents during the COVID-19 pandemic, psychologists warned of a heightened risk of family conflict and violence (Pereda & Díaz-Faes, 2020). In response, several parent-specific, internet-delivered interventions emerged, aiming to mitigate chronic stress and enhance parental emotion regulation (MacKinnon et al., 2022). Preuss et al. (2021) tested two brief, self-directed online interventions (i.e., cognitive reappraisal vs. self-compassion) for parental distress in the context of COVID-19. Both significantly reduced individual stress compared to the waitlist control, with cognitive reappraisal ($d = 0.87$) outperforming self-compassion ($d = 0.51$), but neither intervention reduced parenting-specific stress. Notably, reductions in individual stress within the cognitive reappraisal group were found to meditate improvements in parenting stress, highlighting the potential benefit of treatments focused on intrinsic emotion regulation to alleviate parental distress. Still, despite the theoretical suitability of ERT-P, parents in the current study were less likely to exhibit RI across all primary outcomes. Further analysis is needed to assess the extent to which parents benefitted from ERT-P and to explore potential underlying mechanisms of suboptimal response in this population.

Additionally, reporting greater reductions in access to medical healthcare was linked to decreased likelihood of exhibiting RI in worry (OR = 0.65, $d = -0.25$) and distress (OR = 0.54, $d = -0.34$). In the Fall of 2021, 36% of adults deferred or forwent necessary medical care due to worry about exposure to COVID-19 and limited access to services (Gonzalez et al., 2021). Prior studies have linked disruptions in medical care during the pandemic to an increased risk of psychological distress (Breslau et al., 2023). Giannouchos and colleagues (2022) found that the association between medical care delays and distress persisted across three waves of data collection in 2020 despite respondents reporting fewer healthcare access disruptions over time. Additionally, while the current study did not collect data on patients' insurance statuses, prior research has demonstrated that uninsured and underinsured patients were at increased risk of heightened emotional distress during the pandemic (Coley et al., 2022). It is possible that disrupted access to medical care may have heightened patients' worry, due to concerns about worsening physical health due to delays or facing the threat of COVID-19 infection when seeking medical services (Papautsky et al., 2021).

Three other patient characteristics were associated with lesser likelihood of achieving RI in primary outcomes: identifying as single (worry: OR = 0.20, d = -0.89), being born outside of the U.S. (distress: OR = 0.26, d = -0.74), and reporting a chronic medical condition (rumination: OR = 0.36, d = -0.56). Regarding relationship status, a meta-analysis of guided, internet-delivered depression treatments found higher odds of RI among adults in relationships compared those who were single (Karyotaki et al., 2018). Prior research shows that single individuals reported significantly greater anxiety, depression, and stress compared to those in relationships during COVID-19 (Kowal et al., 2020; Nkire et al., 2022). Isolation and quarantine measures, alongside disruption of social norms and surge of remote work and virtual interaction, contributed to decreased social engagement. In this context, single patients may have continued to rely on worry to cope with social disconnection, uncertainty of future relationships, or increased risks of contamination or illness in pursuit of relationships.

Similar to the current study, Karyotaki and colleagues' (2018) meta-analysis of guided internet interventions showed an increased likelihood of RI among "native-born" participants compared to ethnic minorities (OR = 1.66, 95% 1.07–2.59; p = .02). Prior research suggests that immigrants are disproportionately impacted by national disasters (Purtle, 2012). Among adults in the United States, foreign-born adults reported significantly higher levels of distress, specifically fear and worry, during COVID-19 (Fitzpatrick et al., 2020). Travel bans and restrictions, especially early in the pandemic, were shown to negatively impact the mental health of immigrants (Ormiston et al., 2023; Serafini et al., 2021), as well as individuals living in the U.S. with family abroad. International college students who remained in the U.S. or U.K. reported significantly higher COVID-19-related stress compared to students who returned to their home country (Lai et al., 2020). Separation from central social support networks, vulnerability to discrimination, and increased likelihood of being an essential worker, with greater exposure to COVID-19, are all contextual factors linked to chronic distress among immigrants, potentially explaining lesser clinical improvement (Behbahani et al., 2020; Maleku et al., 2022; Zhou et al., 2021).

In the current sample, almost half of patients (48.5%) self-reported having a chronic medical condition, aligning closely with prevalence estimates among adults in the U.S. population (51.8%; Boersma et al., 2020). Prior research conducted before and after COVID-19 has indicated that individuals with chronic conditions face increased risk of emotional distress, perhaps due to limited social interactions related to their health status and dysfunctional metacognitive beliefs (Audrey, 1988; Lenzo et al., 2020). In their study exploring the impacts of COVID-19 on individuals with chronic conditions, Umucu and Lee (2020) found that self-blame, a facet of "brooding" rumination, was negatively associated with well-being. Messaging from the CDC consistently emphasized the heightened risk of severe COVID-19 illness and mortality among individuals with certain chronic conditions (CDC, 2022c). This emphasis likely contributed to heightened self-awareness among patients in this population, potentially exacerbating self-reference and distress and complicating efforts at self-regulation.

Five patient characteristics were associated with greater likelihood of achieving RI in primary outcomes: being a healthcare worker (distress: OR = 6.33, d = 1.02), being naïve to mental health treatment (rumination: OR = 4.84, d = 0.87), increased COVID-related financial strain (distress: OR = 3.07, d = 0.62), greater familial discord (distress: OR = 2.65, d = 0.54), and initiating treatment during the peak severity of COVID-19 (worry: OR = 2.78, d = 0.56). Despite healthcare workers representing a small subset of the current sample (n = 17, 12.7%), this is an encouraging finding, especially in the context of documented pandemic-related psychological distress within this population (Mediavilla et al., 2022; Umbetkulova et al., 2024). During the pandemic, Nomeikaite and colleagues (2023) tested a six-week, internet-delivered stress reduction intervention for healthcare workers and showed that participants in both study arms (i.e., therapist support vs. optional therapist support) demonstrated significant improvement in distress and dimensions of stress recovery (e.g., psychological detachment, relaxation) three months after treatment. Given the chronic occupational stress and barriers to accessing mental healthcare (e.g., time, stigma, societal expectation; Moll, 2014), there is a need for further development and evaluation of tailored, lower-intensity mental health interventions for healthcare workers (see Søvold et al., 2021).

With regard to mental health treatment naivety, in a study of depressed adults receiving technology-mediated therapy via TalkSpace, patients new to therapy showed significantly faster improvement in depression symptoms over the 16-week assessment period compared to those with prior therapy experience (Darnell et al., 2022). This effect persisted even after controlling for baseline depression severity, leading the authors to speculate that individuals with prior therapy experience may have more chronic symptoms. In their study testing an internet-delivered, cognitive enhancement therapy intervention targeting residual cognitive symptoms of depression, Myklebost and colleagues (2022) found that individuals with shorter durations of depression exhibited greater improvement compared to those with longer-duration depression, possibly supporting the argument for chronicity.

Somewhat paradoxically, increased COVID-related financial strain and greater familial discord were associated with higher odds of achieving RI in distress. Regrettably, the current study did not re-administer the Coronavirus Impact Scale at posttreatment, preventing the evaluation of whether changes in contextual factors influenced improvements in distress. It is possible that patients experienced positive changes in these domains (e.g., stimulus checks, employment, lifting of COVID-19 restrictions, less time in the home), leading to subsequent reductions in distress. It is also conceivable that improved emotional regulation capacities and greater flexibility in behavioral responding altered individuals' experiences of and responses to these contextual difficulties (e.g., reduced PNT, greater emotional awareness and self-compassion, proactive problem-solving, and approach-oriented actions).

Mirroring results from Aim 2, patients who began treatment during the peak severity of COVID-19 (i.e., "Most Severe" class) were more likely to demonstrate RI in worry. This outcome isn't entirely unsurprising, given the large reductions in worry (b = -16.81, SE = 1.60) which exceeding the RCI threshold (i.e., -8.55 PSWQ points). On the mean date of enrollment within the "Most Severe" Class" (April 6, 2021), seven-day averages showed 3,458 cases, 250 hospitalizations, and 53 deaths due to COVID-19. This second wave of COVID-19 eventually abated in Summer 2021. Findings from longitudinal studies examining the temporal covariation of COVID-19 severity and emotional distress during this period have been mixed. For instance, a study in Italy between March 2020 and March 2021 found elevated and sustained levels of worry during this time, despite observing decreases in symptoms of traumatic stress (Gori & Topino, 2021). Similarly, a study in the United Kingdom observed deterioration of mental health symptoms during this same span of time (Patel et al., 2022). Conversely, a multi-wave study conducted in Austria between March 2020 and March 2022, found that subjective well-being within at the population level fluctuated in accordance with COVID-19 cases and deaths (Oberndorfer et al., 2022). These findings stress the importance of continued longitudinal research examining the time-varying relationship between metrics of COVID-19 severity and psychological distress, as well as the pandemic's impact on response to mental health treatment.

In summary, these findings highlight the importance of examining patient characteristics as predictors of treatment response to tailor interventions and optimize outcomes. The current study examined the impact of sociodemographic, clinical, and pandemic-related factors, aligning with the social determinants of health framework (e.g., economic strain, social support, and access to resources; Kirkbride et al., 2024). However, both in and beyond the COVID-19 context, further research on social determinants of mental health and their impact on psychosocial treatment outcomes is needed for a more comprehensive understanding of how societal factors shape mental health.

4.4 Strengths and Limitations

Before discussing limitations, a few of the study's strengths should be highlighted. First, this trial offers a comprehensive evaluation of ERT-P for distress adults living in the initial U.S. epicenter of the COVID-19 pandemic, explicitly examining the impact of pandemic-related factors on treatment response. Furthermore, patients were continuously enrolled over a span of two years, setting it apart from other intervention studies conducted during discrete periods of the COVID-19 pandemic (e.g., Aminoff et al., 2023; Lv et al., 2022) . Continuous enrollment coincided with multiple waves of illness, rapid creation and widespread distribution of vaccinations and boosters, and the gradual return to "in-person" life. While these events challenge the internal validity of this and other clinical trials, they also provide opportunities to explore how the evolving pandemic landscape impacts mental health and intervention response.

The implementation of block stratification methods during screening not only improved treatment accessibility for racial and ethnic minority groups, who were disproportionally affected by COVID-19, but also yielded a sample that reflects the region's demographic composition. A 2024 systematic review of iCBT RCTs conducted in the U.S. found that individuals identifying as White were overrepresented in studies that reported race, accounting for 76.6% of those treated (De Jesús-Romero et al., 2024). Moreover, of the studies that reported ethnicity, only 11.3% identified as ethnically Hispanic or Latino. In contrast, patients identifying as Hispanic or Latino ethnicity comprised 34.3% of the ERT-P sample, with nearly 70% identifying as a race other than White. Disappointingly, meta-analyses of IMIs conducted during COVID-19 failed to report or examine efficacy differences by race and ethnicity (e.g., Komariah et al., 2022; Yet et al., 2023; Chi et al., 2022). Given evidence showing poorer response to therapist-guided internet-delivered interventions among racial and ethnic minorities (Karyotaki et al., 2018), it is imperative that clinical trials include and meta-analyses examine these historically underrepresented groups. This will improve the generalizability of findings and ultimately inform whether and how interventions are culturally adapted.

The findings of the current study should be considered in light of its limitations. Firstly, the open trial design precludes the ability to make causal claims about ERT-P's efficacy. Launched in early May 2020, shortly after the first confirmed COVID-19 case and subsequent lockdown in New York City, the initial aim was to rapidly extend access to evidence-based mental health services. While the inclusion of a waitlist control condition was considered, this would have inevitably resulted in significant treatment delays for individuals in urgent need. Nonetheless, prior ERT trials have demonstrated efficacy compared to control conditions (Mennin et al., 2018; O'Toole et al., 2020) and that improvements following this shorter, 8-session version are comparable to longer formats (Renna et al., 2023). The results of the current study suggest that ERT is feasible, acceptable, and preliminarily efficacious as a brief, blended intervention. Future RCTs could further explore the impact of therapist involvement by comparing blended ERT against unguided or minimally guided formats and a control condition.

Second, stringent eligibility criteria resulted in 65.1% of treatment-seeking individuals being excluded at the prescreening stage. Further, while block stratification greatly improved diversity and representativeness, 52.1% of individuals eligible for a screening interview were referred to other mental health resources for this reason. Ultimately, only 7.4% of those who completed a pre-screening application received treatment. Therefore, caution is advised when generalizing these findings to all treatment-seeking adults during the COVID-19 crisis.

Next, despite over 40 years of widespread use in clinical research, the RCI is not without its criticisms and limitations (McAleavey, 2024). Chief among these criticisms is the RCI's categorization of a continuous outcome, resulting in a loss of important within-person information and nuance. Since clinical cut-offs were not available for two of the three primary outcomes, clinical significance was not assessed (Jacobson & Traux, 1991). Consequently, individuals with higher baseline severity might have had a greater potential for achieving RI but continued to experience elevated symptoms after treatment, even with the RI designation. Despite its limitations and the proposed alternatives, the RCI remains a simplistic statistical test of treatment-related change (Blampied, 2022).

Regarding predictors of treatment response, several variables in the LASSO models, showed no significant association with treatment response, most notably race and ethnicity. These null findings offer some encouragement, suggesting potential benefits of ERT-P across racial and ethnic groups. While LASSO is commonly criticized for its arbitrary selection of features in the presence of strong pairwise correlations (Zou & Hastie, 2005), an examination of correlations among baseline variables suggests that racial and ethnic differences were not masked by other variables. Owusu and colleagues' (2022) large-scale trial of BCT during the pandemic showed that the blended intervention was equally effective across racial and ethnic groups in a large (*N* = 6,492), diverse sample (i.e., Asian or Pacific Islander, 27.5%; Black or African American, 5.4%; Hispanic or Latino, 9.3%, White, 47.2%). In their study, therapists received training in culturally responsive care, underscoring a key advantage of blended interventions over unguided or minimally guided IMI: the therapist's capacity to tailor treatment to individuals' sociocultural context, identity-related needs, and clinical presentation.

Relatedly, during exploration of baseline predictors of treatment response, interactions among predictors were not examined. Future investigations may employ subgroup analysis to investigate the number and severity of hardships, especially among racial and ethnic groups, and their impact on treatment outcome. Given well-documented disparities in mental health outcomes among minority groups during the COVID-19 pandemic, a more targeted investigation exploring sociodemographic moderators of both acute and long-term ERT-P response is warranted.

4.5 Future Directions

Research suggests that clinical improvement in ERT is driven by enhanced and/or restored regulatory capacities (i.e., attention regulation, metacognitive regulation), consistent with its theoretical model. Indeed, findings from previous studies have shown significant indirect effects of these mechanisms on treatment outcomes (Mennin et al., 2018; O'Toole et al., 2021; Spaeth et al., 2024) and that clinical improvements are temporally preceded by changes in mechanisms across time (O'Toole et al., 2019; O'Toole et al., 2021). Thus, a logical next step is utilizing session-to-session data to examine these mechanism-outcome relationships during ERT-P and within the COVID-19 context. Additionally, a more nuanced investigation of change processes occurring during treatment is warranted, as patterns of early symptom change have been found to predict treatment response (Saunders et al., 2019) and long-term outcomes (Andrews et al., 2020).

Relatedly, 2-year posttreatment follow-up assessments will be completed in Summer 2024, marking the conclusion of data collection for the ERT-P trial. A 2017 systematic review of therapist-supported iCBT suggests that this intervention format can produce sustained clinical improvements for years after treatment (Andersson et al., 2018). Conducting a standalone study or incorporating these 2-year follow-up data into current trajectory analyses would greatly enrich the existing literature on long-term outcomes of ERT and brief interventions that integrate technology.

Given ERT-P's brief duration, the IMI component may have enhanced clinical outcomes by facilitating engagement with materials outside of sessions, especially compared to traditional paper-and-pencil methods (i.e., workbooks, meditation logs). In a previous ERT study, higher self-rated homework compliance was associated with larger reductions in psychological distress among informal caregivers of cancer patients (O'Toole et al., 2021). Similarly, completing digital lessons (i.e., videos reviewing concepts and skills) and digital exercises (i.e., between-session practice of skills) in blended CBT has been linked to greater clinical progress (Lungu et al., 2022; Owusu et al., 2022; Sapkota et al., 2023). In addition, between-session mindfulness practice has been shown to enhance clinical improvement (Parsons et al., 2017; Zhu et al., 2021). Prior research suggests that psychotherapy skills practice can indirectly boost treatment outcomes and prevent relapse, mediated through gains in treatment-related mechanisms (Segal et al., 2019). In light of these findings, an important future direction will be to examine engagement with ERT-related material and activities via the IMI platform. The use of IMI technology allows for the collection of "paradata" (e.g., number of activities completed, minutes of mindfulness practice completed), providing a more objective measure of engagement compared to patient reports. Future studies should aim to determine whether IMI engagement: 1) is associated with clinical improvement and regulatory mechanism gains during treatment, 2) leads to clinical improvement through regulatory mechanism gains, and 3) plays a role in the maintenance of clinical improvement after treatment.

Conclusion

The findings of the current study demonstrate the preliminary efficacy of ERT-P, a brief blended telehealth intervention, in alleviating distress and enhancing quality of life, with sustained improvements observed beyond the treatment period. Moreover, findings affirm that ERT-P was feasible and acceptable, evidenced by high patient satisfaction ratings, perceived usability of the internet and mobile intervention platform, and low attrition rates. In addition, the study sought to investigate the impact of COVID-19 severity on treatment response. Patients who enrolled in treatment when the pandemic was most severe demonstrated greater improvement in PNT at posttreatment compared to those who enrolled earlier and later, irrespective of vaccine availability. Trajectories of treatment response, including the follow-up period, did not appear to be impacted by pandemic severity and time of enrollment. A final aim of the current study sought to identify subgroups and predictors of treatment response. At posttreatment, a majority of patients exhibited reliable improvement in worry, rumination, and distress, comparable to rates observed in face-to-face and internet-delivered interventions. Exploring predictors of treatment response, a mix of sociodemographic, clinical, and contextual characteristics were associated with acute treatment response. Notably, parenthood was consistently associated with a decreased likelihood of reliable improvement in all three primary outcomes at posttreatment. Although the study's open trial design precludes causal attributions of clinical improvement to ERT-P, it succeeded in its clinical objective: to rapidly mobilize and extend access to evidence-based mental health services to a diverse group of distressed adults amidst the evolving landscape of the COVID-19 pandemic.

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Appendix A

A.1 Data Handling for LASSO

For LASSO analyses, the following predictors were derived: 1) "Gender, " was dichotomized as "Female," comparing female patients to patients identifying as male or non-binary; 2) "Race" was recoded into three dichotomous variables, comparing "White," "Black," and "Asian" patients to all other patients; 3) patients identifying as "Non-Binary" ("Gender") and/or "Gay or Lesbian, "Bisexual," "Pansexual," or "Asexual" ("Sexual Orientation") were pooled to form a dichotomous variable, "Sexual/Gender Minority" (n = 30); 4) "Relationship Status" was recoded into three dichotomous variables, comparing "Single," "Unmarried in a Relationship," and "Married," patients to all other patients; 5) "Level of Education" was recoded into a three-level ordinal variable (i.e., "0" = < 4 year college, no degree; "1" = 4 year college, degree; "2" = graduate school); 6) "CIS 7: COVID-19 Stress" was dichotomized, as all patients endorsed either "Moderate" or "Severe" stress due to the pandemic; 6) patients reporting immediate and/or extended family diagnosis = Family COVID-19 Diagnosis; 7) patients reporting immediate and/or extended family death = Family COVID-19 Death. As previously stated, twenty-one patients (15.67%) did not provide personal income information, accounting for 0.36% of missing data for all LASSO predictors. These missing data were imputed using K-nearest neighbor (KNN) imputation. The frequency of substance use was excluded due to the low base rate. "Pandemic Status" classes were added as predictors, comparing each class to all other classes. A total of 42 predictors were included in LASSO models.

A.2 Longitudinal Trajectories of Primary Outcomes

As an exploratory aim, longitudinal trajectories of response (i.e., acute treatment phase and follow-up period) were examined using latent growth class analysis (LCGA) and following guidelines by Jung and Wickrama (2008). LCGA is form of growth mixture modeling in which within-class variance is fixed to zero, assuming within-class homogeneity. LCGA, which is less computationally complex compared to latent growth mixture modeling, is recommended for smaller sample sizes and to ease model convergence issues (Berlin et al., 2014). Unconditional piecewise LCGA models were tested for the three primary outcomes. Linear growth was specified for the first growth phase (i.e., pre- to posttreatment, "Time" coded 0-1-1-1) and second growth phase (i.e., posttreatment through 9-month follow-up, "Time" coded 0-0-1-2).

To identify the optimal number of patient classes exhibiting similar response trajectories, I started with a 1-class model and incrementally increased the number of classes. Each model (*k*) was then compared to a model with one fewer classes (*k*-1). Model fit was assessed using Akaike's Information Criterion (AIC), sample size-adjusted Bayesian Information Criterion (ssaBIC), entropy value, and the Lo-Mendell-Rubin likelihood ratio test (LMR-LRT) and bootstrapped LRT (BLRT). The BLRT uses bootstrapped samples to compare the *k* class and *k*-1 class models and tests the statistical significance of improvement to model fit (Nylund et al., 2007). The best-fitting model is characterized by the lowest AIC and ssaBIC values, highest entropy values (Celeux & Soromenho, 1996), and a statistically significant improvement over a *k*-1 class model, as evidenced by LMR-LRT and BLRT values ($p < .05$; Jung & Wickrama, 2008). In addition to these fit indices, class size and interpretability of class membership were also considered model selection. Missing data were handled using full information maximum likelihood. The LCGA analyses were conducted in MPlus version 8.

A.3 Latent Class Growth Analyses of Primary Outcomes

Single-group, piecewise LCGA models revealed significant reductions in worry ($b = -13.44$, $p < .001$), rumination ($b = -9.83$, $p < .001$), and distress ($b = -10.61$, $p < .001$), during the acute treatment phase. During follow-up, improvements in worry and rumination were maintained, as indicated by non-significant slopes of the second growth phase (worry: $b = -0.20$, $p = .66$; rumination: $b = -0.33$, $p = .37$). However, in the single-group LCGA model of distress, a slight but significant rebound in distress symptoms ($b = 0.77$, $p = .03$) was observed. Table A1 displays fit indices for LCGA models of primary outcomes. Refer to Table A2 for latent growth model parameter estimates and Figure A1 for plots of LCGA trajectories.

Worry. Although the 4-class solution for worry had the highest entropy value (.80) and the BLRT and LMR-LRT values were statistically significant ($p < .01$), the smallest identified class was < 5.0%. The LMR-LRT value for the 3-class model was not significant ($p = .17$). As such, the 2-class model of worry was selected. Class 1's proportion was 52.2% ($n = 70$) and Class 2's proportions was 47.8% ($n = 64$). Posterior probabilities were .916 and .932 for Class 1 and Class 2, respectively. Class 1 evidenced higher pretreatment worry (Intercept = 67.62, SE = 1.06, $p <.001$) than Class 2 (Intercept = 61.12, SE = 1.63, $p <.001$). Both groups demonstrated large-magnitude, statistically significant reductions in worry during the acute phase of treatment (ps < .001) and maintained gains during follow-up (ps > .43). Effects sizes of slopes during the acute phase of treatment were larger in Class 2 ($d = 1.89$) than Class 1 ($d = 1.38$). For this reason, Class 1 was labeled "Higher Baseline Worry, Lesser Gains" and Class 2 was labeled "Lower Baseline Worry, Greater Gains."

Rumination. The 3-class solution for rumination had the highest entropy value (.74); however, the LMR-LRT value was not statistically significant ($p = .25$). Consequently, the 2-class model of rumination was selected, wherein Class 1's proportion was 50.8% ($n = 68$) and Class 2's proportion was 49.3% ($n = 66$). Posterior probabilities were .910 and .924 for Class 1 and Class 2, respectively. Class 1 demonstrated higher pretreatment rumination (Intercept =

48.73, SE = 0.85, p <.001) than Class 2 (Intercept = 43.91, SE = 1.21, p <.001). Both groups demonstrated large-magnitude, statistically significant reductions in rumination during the acute phase of treatment (ps < .001) and maintained gains during follow-up (ps > .27). Effects sizes of slopes during the acute phase of treatment were larger in Class 2 (d = 2.03) than Class 1 (d = 1.12). For this reason, Class 1 was labeled "Higher Baseline Rumination, Lesser Gains" and Class 2 was labeled "Lower Baseline Rumination, Greater Gains."

Distress. For distress, the 3-class solution was selected, wherein Class 1's proportion was 9.0% (n = 12), Class 2's proportion was 58.2% (n = 78), and Class 3's proportion was 32.8% (n = 44). Posterior probabilities were .972, .931, and .827 for Class 1, Class 2, and Class 3, respectively. Class 1 had the highest pretreatment distress scores among the classes (Intercept = 37.11, SE = 1.53, p <.001) and demonstrated a pattern of non-response, as evidenced by non-significant slopes during acute (b = -1.88, SE = 2.02, p = .35) and follow-up (b = -0.56, SE = 0.97, p = .56) periods. As such, Class 1 was labeled distress "Non-Responder." Pretreatment distress scores were lower in Class 2 (Intercept = 28.69, SE = 1.25, p <.001) than Class 3 (Intercept = 35.14, SE = 0.94, p <.001). Class 2 demonstrated statistically significant improvement during the acute phase of treatment (b = -12.04, SE = 1.01, p < .001) but returned some of those gains during follow-up, as evidenced by positive and significant slope (b = 1.14, SE = 0.44, p = .01). Class 3 also demonstrated statistically significant improvement during the acute phase of treatment (b = -10.79, SE = 1.55, p < .001) but gains were maintained during follow-up, as evidenced by the non-significant slope (b = 0.52, SE = 0.83, p = .53). Class 2 was labeled "Higher Baseline Distress, Lesser Gains," and Class 3 was labeled "Lower Baseline Distress, Greater Gains."

A.3 Predicting LCGA Classes

Similar to procedures used to examine predictors of posttreatment response, LASSO models were employed for feature selection. LASSO models were built to predict the "Higher Baseline, Lesser Gains" LCGA trajectories of worry and rumination and the distress "Non-Responder" trajectory against all other trajectory classes. Features selected by LASSO models were then entered in unregularized multivariable logistic regressions to obtain odds ratios for predictors of longitudinal trajectories of the primary outcomes.

Lasso Model Performance and Variable Importance

LASSO models for worry (AUC = .62, 95% CI [.56, .68]) and rumination (AUC = .66, 95% CI [.61, .71]) demonstrated "poor" predictive accuracy. The LASSO models for distress demonstrated "good" predictive accuracy (AUC = .81, 95% CI [0.75, 0.85]). Model performance metrics are displayed in Table A3.

The "Higher Baseline Worry, Lesser Gains" LASSO model retained nine of the 42 predictors. Identifying as female was the most important feature and positively associated with membership to this class. In the "Higher Baseline Rumination, Lesser Gains" LASSO model, just two of the 42 variables were retained. Severity of functional impairment, as assessed by the MINI, was identified as the most important feature and positively associated with membership to this class. Four of the 42 variables were retained in the LASSO model predicting membership to the distress "Non-Responder" class. Primary or coprimary clinical severity was identified as the most important feature and positively associated with distress "Non-Responder" class membership.

LASSO coefficients of variables predicting these longitudinal trajectories are displayed in Table A4. Refer to Figure A2 for plots of predictors in descending order of importance.

Unregularized Logistic Regressions (Longitudinal)

Table A5 displays the results of unregularized binary logistic regressions with features selected by LASSO models.

Worry. The unregularized, binary logistic regression model for worry was statistically significant, χ^2 (9) = 35.82, $p < .001$, Nagelkerke $R^2 = 0.31$, correctly identifying 75% of cases. Three of the 9 retained predictors were statistically significant and positively associated with "High Baseline Worry, Lesser gains" class membership: identifying as female, (OR = 3.45 [1.39, 8.57], $p < .01$, $d = 0.68$), not currently working (OR = 3.68 [1.42, 9.53], $p < .01$, $d = 0.72$) and reporting greater impairment in functioning ($b = 0.02$, SE = 0.01, OR = 1.02 [1.00, 1.04], $p = .02$, $d = 0.01$).

Rumination. The unregularized, binary logistic regression model for rumination was statistically significant, χ^2 (2) = 19.80, $p < .001$, Nagelkerke $R^2 = 0.18$, correctly identifying 65% of cases. Both retained predictors were statistically significant in unregularized the model and predicting membership to the "Higher Baseline Rumination, Lesser Gains" class: being female (OR = 2.76 [1.23, 6.27], $p = .01$, $d = 0.56$) and reporting greater impairment in functioning (b = 0.03, SE = 0.63, OR = 1.03 [1.01, 1.04], $p < .01$, $d = 0.02$).

Distress. The unregularized, binary logistic regression model was statistically significant, χ^2 (1) = 29.19, $p < .001$, Nagelkerke $R^2 = 0.43$, and correctly identified 90% of cases. Three of the four predictors were statistically significant in the unregularized logistic regression and all predicted increased odds of membership to the distress "Non-Responder" Class: higher clinical severity ratings ($b = 1.17$, SE = 0.49, OR = 3.23 [1.32, 8.46], $p = .02$, $d = 0.65$), reporting more severe changes to family income and employment ($b = 1.15$, SE = 0.55, OR = 3.15 [1.07, 9.30], $p = .04$, $d = 0.63$), and reporting greater impairment in functioning ($b = 0.04$, SE = 0.02, OR =

1.04 [1.00, 1.08], $p = .04$, $d = 0.02$). In unregularized logistic regression, without up-sampling, no patients identified as SGM in the distress “Non-Responder” class.

A.4 Discussion of LCGA Trajectories of and Predictors of Longitudinal Response

Examining longitudinal trajectories of primary outcomes, piecewise LCGA revealed differential patterns of treatment response over time. Two classes of longitudinal response for both worry and rumination were identified: one class exhibited higher baseline severity and lesser gains during treatment (e.g., “Higher Baseline Worry, Lesser Gains”), while the other class showed comparatively lower baseline severity but greater gains (e.g., “Lower Baseline Rumination, Greater Gains”). In both cases, slopes during the acute treatment phase were statistically significant and of large magnitude (ds 1.12 – 2.03) and were followed by non-significant slopes during the follow-up period of less-than-small magnitude (ds < 0.19). LCGA identified three treatment trajectories of distress, the most distinct of which was a small group of patients exhibiting persistently elevated distress symptoms during treatment and follow-up (“Non-Responder,” 9.0%). The remaining two classes (“Higher Baseline, Lesser Gains,” 58.2%; “Lower Baseline, Greater Gains,” 32.8%) both showed treatment response but diverged in baseline severity and magnitude of treatment gains. Additionally, slight disparities in the maintenance of treatment gains were observed.

Concerning distress, Cumpanasiou and colleagues (Cumpanasoiu et al., 2023) identified a small subgroup of non-responders with persistently elevated distress symptoms (i.e., “stable high” depression 7.2%; “stable high” anxiety 4.5%) after an 8-module, guided iCBT. LCGA revealed five distinct classes of treatment response, with roughly 70% of their sample ($N = 256$) demonstrating improvement, varying by baseline symptoms severity, rate of change, and posttreatment scores. Identifying individuals or groups that do not respond to psychological intervention is integral for treatment optimization, particularly in the domain of internet-delivered interventions for psychological distress. In ERT-P, this small subset of “Non-Responders” may have benefitted from additional efforts to promote IMI adherence, further personalization of treatment, and/or additional F2F therapy sessions.

Examining predictors of distress “Non-Response,” patients’ self-reported level of impairment and disability due to psychiatric symptoms emerged as a significant predictor of this “Non-Responder” class. For each unit increase in the MINI Assessment of Impairment of Functioning/Disability score, there was a 4% increase in odds of membership to this chronic distress trajectory. In addition, patients who reported increased economic strain (i.e., CIS Item 2) were significantly more likely to be a “Distress Non-Responder” (OR = 3.15, $d = 0.63$). Interestingly, the CIS 2 item assessing financial strain emerged as a positive predictor of RI in distress but a negative predictor in longitudinal analysis, suggesting more chronic mental health impacts of economic insecurity. Findings from longitudinal studies suggest that financial strain, unemployment, disruption of employment, and loss of work hours were all associated with unremitting distress trajectories during the pandemic (Breslau et al., 2023; J. O. Lee et al., 2021; Yao & Wu, 2022). Specifically related to CIS Item 2, which directly probes difficulties paying bills, Pierce and colleagues (2021) identified worsening trajectories of distress during the first year of COVID-19 among individuals reporting this particular economic hardship.

Lastly, clinician-rated diagnostic severity emerged as a significant predictor of the distress “Non-Responder” trajectory. With each one-unit increase in clinical severity rating, there was a 223% increase in odds of belonging to the distress “Non-Response” class. Baseline symptom severity is often included as a predictor of treatment outcomes, although its association with non-response has varied across studies. Meta-analyses of online and internet-delivered interventions suggest that higher baseline symptom severity is associated with increased odds of non-response to treatment (Rozental et al., 2019; Andersson et al., 2019). Conversely, however, increased diagnostic severity and baseline distress symptoms have been associated with more substantial treatment improvement in previous iCBT trials (Cumpanasoiu et al., 2023; Edmonds et al., 2018).

The trajectory classes observed for worry and rumination align with those identified in a study testing a self-guided, six-module iCBT for anxiety and depression. Utilizing LGMM, Sunderland and colleagues (2012) identified two latent classes within the anxiety and depression intervention groups: "Responders" and "Low Responders." Like the current study, "Low Responders" were characterized by higher baseline symptom severity. These results are encouraging, as they indicate that, on average, patients in both classes exhibited improvement in PNT during the acute phase of ERT-P and that this progress was sustained through the 9-month follow-up period. While speculative, it's plausible that this sustained improvement is linked to enhanced regulatory capacities, enabling patients to respond to stressors and emotions more effectively without relapse and reliance on PNT.

Similar to predictors of the distress "Non-Responder" class, patients' self-reported level of impairment and disability due to psychiatric symptoms emerged as a significant predictor of the "Higher Baseline, Lesser Gains" trajectory classes for worry and rumination. For each unit increase in the MINI Assessment of Impairment of Functioning/Disability score, there was a 2% and 3% increase in odds of membership to the "Higher Baseline, Lesser Gains" trajectories of worry and rumination, respectively.

Identifying as female was a significant predictor of membership to the "Higher Baseline, Lesser Gains" trajectory classes for both worry (OR = 3.45, d = 0.68) and rumination (OR =

2.76, *d* = 0.56), suggesting that females were more likely to endorse higher baseline PNT and be somewhat less responsive to treatment compared to other genders (i.e., male, non-binary). This finding aligns with prior studies showing that females reported higher levels of worry (Laufer & Shechory Bitton, 2021) and rumination (Knauft et al., 2024) during the pandemic. Moreover, longitudinal studies examining mental health during COVID have found more persistently severe or increasing distress over time among women (Novotný et al., 2023; Patel et al., 2022). Drawing links to Carol Gilligan's "ethics of care" theory (1993), Laufer & Bitton-Schechory posit that these findings are attributable to societal expectations placed upon women to be caretakers. Prior meta-analyses have also identified gender differences in worry, rumination, and self-blame, suggesting that women may be more prone to internalizing distress in comparison to men (Johnson & Whisman, 2013; Olatunji et al., 2010). A meta-analysis of online psychosocial interventions during COVID-19 found significant gender differences in treatment-related improvement in anxiety, which varied by intervention type (He et al., 2023). Specifically, results indicated that females responded better to MBI than to CBT and exercise-based interventions. Further research is needed to better understand the mechanisms underlying vulnerability to distress and suboptimal response to psychosocial treatment among females, especially in the context of the pandemic (Almeida et al., 2020).

Individuals who reported being unemployed at the start of treatment had significantly higher odds of belonging to the worry "Higher Baseline, Lesser Gain" class (OR = 3.68, *d* = 0.72). Prior studies examining the relationship between employment- and finance-related stressors and treatment response have shown that unemployment is associated with an increased likelihood of iCBT noncompletion (Mathiasen et al., 2018) and a reduced likelihood of recovery following psychotherapy (Lorenzo-Luaces et al., 2017). Addressing the mental health needs of those out of work or experiencing financial strain is of particular importance, given evidence showing that unemployment-related distress negatively impacts the path to reemployment (Stolove et al., 2017) and increases the risk for suicide (Blakely et al., 2003), the latter of which was also documented during COVID-19 (Kim, 2022). Encouragingly, government financial assistance during COVID-19 may have mitigated some of the pandemic's negative mental health impacts. Berkowitz and Basu (2021a) found that receipt of unemployment benefits was associated with reduced risk for psychological distress.

Table A1: Fit indices for piecewise latent class growth analyses examining longitudinal trajectories of distress.

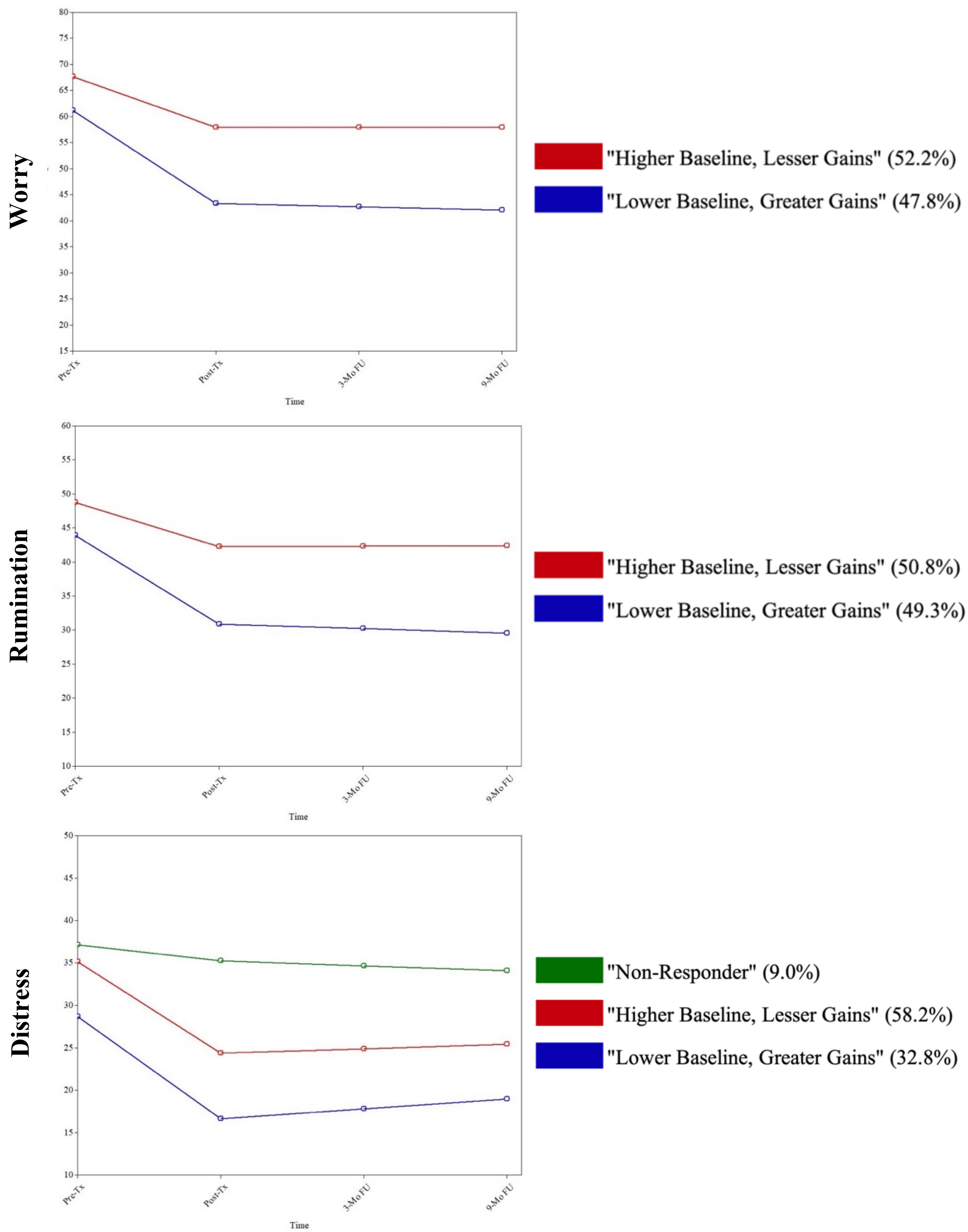
Class Number	LL	AIC	ssaBIC	Entropy	LMR-LRT (*p*)	BLRT (*p*)	Smallest (%)
Worry							
1	-1785.70	3585.40	3583.54				
2	**-1720.92**	**3463.85**	**3460.93**	**.76**	**<.001**	**<.001**	**47.8%**
3	-1707.99	3445.98	3442.00	.76	.19	<.001	8.2%
4	-1698.21	3434.41	3429.37	.80	<.01	.01	3.7%
Rumination							
1	-1657.42	3328.84	3326.98				
2	**-1598.02**	**3218.05**	**3215.13**	**.72**	**<.001**	**<.001**	**49.3%**
3	-1578.43	3186.85	3182.87	.74	.25	<.001	10.4%
4	-1569.88	3177.76	3172.72	.69	.12	.01	10.4%
Distress							
1	-1628.53	3271.06	3269.20				
2	-1563.90	3149.81	3146.89	.82	<.001	<.001	23.9%
3	**-1546.15**	**3122.30**	**3118.32**	**.78**	**.03**	**<.001**	**9.0%**
4	-1539.72	3117.44	3112.40	.71	.28	.13	9.0%

Note. $N = 134$. LL = log likelihood value, LAIC = Aikaike information criterion; BIC = Bayesian information criterion; ssaBIC = sample-size adjusted Bayesian information criterion; LMR-LRT = Lo–Mendell–Rubin likelihood ratio test; BLRT = bootstrap likelihood ratio test.

Table A2: Slopes for classes identified by piecewise latent class growth models.

	Estimate	SE	*p*	*d*
Worry				
"Higher Baseline Worry, Lesser Gains"				
Intercept	67.62	1.06	<.001	
Time 1: Acute Tx	-9.71	1.22	<.001	-1.38
Time 2: Follow-up	0.01	0.48	.99	<0.01
"Lower Baseline Worry, Greater Gains"				
Intercept	61.12	1.38	<.001	
Time 1: Acute Tx	-17.85	1.63	<.001	-1.89
Time 2: Follow-up	-0.60	0.77	.43	-0.14
Rumination				
"Higher Baseline Rumination, Lesser Gains"				
Intercept	48.73	0.85	<.001	
Time 1: Acute Tx	-6.44	0.99	<.001	-1.12
Time 2: Follow-up	0.06	0.44	.89	0.02
"Lower Baseline Rumination, Greater Gains"				
Intercept	43.91	0.85	<.001	
Time 1: Acute Tx	-13.04	1.21	<.001	-2.03
Time 2: Follow-up	-0.66	0.59	.27	-0.19
Distress				
"Non-Responder"				
Intercept	37.11	1.53	<.001	
Time 1: Acute Tx	-1.88	2.02	.35	-0.28
Time 2: Follow-up	-0.56	0.97	.56	-0.18
"Higher Baseline Distress, Lesser Gains"				
Intercept	35.14	0.94	<.001	
Time 1: Acute Tx	-10.79	1.55	<.001	-1.28
Time 2: Follow-up	0.52	0.83	.53	0.12
"Lower Baseline Distress, Greater Gains"				
Intercept	28.69	1.25	<.001	
Time 1: Acute Tx	-12.04	1.01	<.001	-2.09
Time 2: Follow-up	1.14	0.44	<.01	0.45

Note. SE = standard error, *p* = significance value, *d* = Cohen's *d* effect size, Tx = treatment, PSWQ = Penn State Worry Questionnaire, RRQ = Rumination Reflection Questionnaire, General Distress = Mood and Anxiety Symptom Questionnaire-D30, general distress subscale.



Note. TX = Treatment, FU = follow-up, Worry = Penn State Worry Questionnaire, Rumination = Rumination-Reflection Questionnaire. Distress = Mood and Anxiety Symptoms Questionnaire-30 item, general distress subscale.

Figure A1: Piecewise LCGA trajectories of worry, rumination, and distress.

Table A3: Model performance of LASSO logistic regression models predicting LCGA trajectories of worry, rumination, and distress.

Outcome	AUC [CI]	Sensitivity [CI]	Specificity [CI]	λ
“Higher Baseline, Lesser Gains” vs. “Lower Baseline, Greater Gains”				
Worry	.63 [.59, .68]	.54 [.48, .60]	.64 [.58, .70]	.046
Rumination	.66 [.61, .71]	.53 [.47, .58]	.68 [.63, .73]	.096
“Non-Responder” vs. Other Classes				
Distress	.81 [.75, .85]	.74 [.68, .79]	.68 [.48, .82]	.099

Note. Note. AUC = area under curve, λ = lambda tuning parameter, CI = 95% confidence interval [lower limit, upper limit].

Table A4: LASSO coefficients predicting "Higher Baseline Worry, Lesser Gains," "Higher Baseline Rumination, Lesser Gains," and distress "Non-Responder" LCGA trajectories.

Predictors	Worry	Rumination	Distress
Age	-		-
Female	0.279	0.043	-
White	-	-	-
Black	-	-	-
Asian	0.179	-	-
Hispanic/Latino Ethnicity	-	-	-
Sexual or Gender Minority	-	-	-0.355
Born Outside the US	-	-	-
Single	-	-	-
Unmarried in a Relationship	-	-	-
Married	-	-	-
Parent	-	-	-
Student	-	-	-
Healthcare	-	-	-
Living Alone	-	-	-
Level of Education	0.003	-	-
Chronic Medical Condition	-	-	-
Personal Income	-	-	-
Currently Exercising	-	-	-
Not Currently Working	0.197	-	-
Frequency of Alcohol Use	-	-	-
Frequency of Marijuana Use	-0.166	-	-
No Prior Mental Health Treatment	-	-	-
Taking Psychiatric Medication	-	-	-
Number of DSM-5 Diagnoses	-	-	-
Primary or Coprimary Clinical Severity	-	-	0.460
MINI Functioning/Impairment	0.179	0.234	0.246
CIS 1: Routines	0.029	-	-
CIS 2: Income/Employment	-	-	0.297
CIS 3: Food Access	-0.098	-	-
CIS 4: Access to Medical Healthcare	-	-	-
CIS 5: Access to Mental Healthcare	-	-	-
CIS 6: Access to Social Supports	-0.069	-	-
CIS 7: COVID-19 Stress (Severe)	-	-	-
CIS 8: Family Stress/Discord	-	-	-
CIS 9: Personal COVID-19 Diagnosis	-	-	-
CIS 10: Family COVID-19 Diagnosis	-	-	-
CIS 11: Family COVID-19 Death	-	-	-
Job Loss due to COVID-19	-	-	-
COVID-19 LPA Class 1	-	-	-
COVID-19 LPA Class 2	-	-	-
COVID-19 LPA Class 3	-	-	-

Note. [a] Missing data for "Personal Income" were handled with K-nearest neighbor imputation.

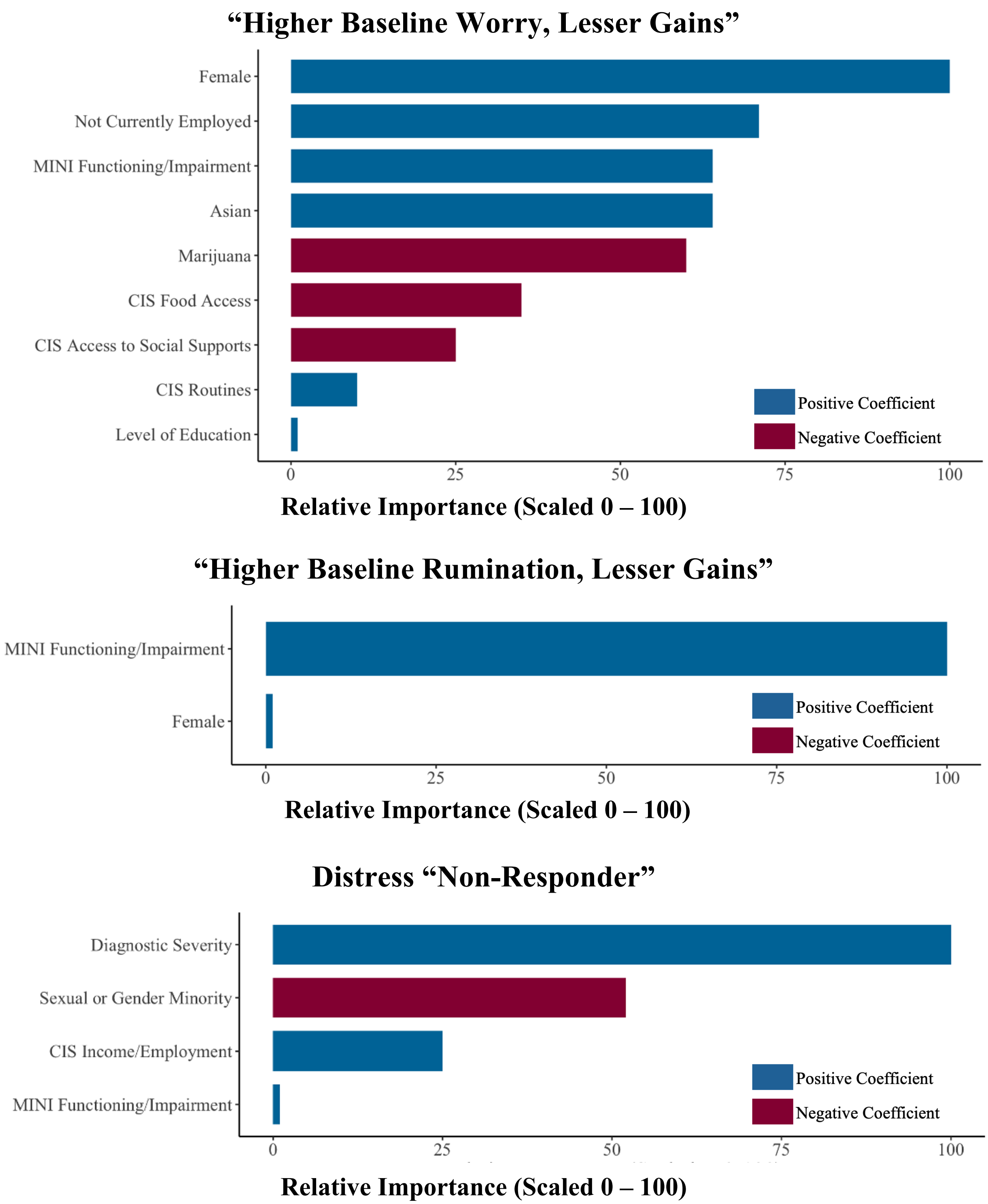


Figure A2: Relative importance of variables in LASSO models predicting LCGA trajectories of worry, rumination, and distress.

Table A5: Unregularized binary logistic regressions predicting LCGA trajectories of worry rumination, and distress.

Predictor	OR	95% CI	*p*	*d*
"Higher Baseline Worry, Lesser Gains"				
Female	**3.45**	**[1.39, 8.57]**	**<.01**	**0.68**
Asian	2.60	[0.75, 8.99]	.13	0.53
Not Currently Working	**3.68**	**[1.42, 9.53]**	**<.01**	**0.72**
Level of Education	1.42	[0.79, 2.54]	.24	0.19
Frequency of Marijuana Use	0.76	[0.52, 1.09]	.13	-0.15
MINI Functioning/Impairment	**1.02**	**[1.00, 1.04]**	**.02**	**0.01**
CIS 1: Routines	2.16	[0.82, 5.58]	.12	0.43
CIS 3: Food Access	0.63	[0.38, 1.07]	.09	-0.26
CIS 6: Access to Social Supports	0.64	[0.35, 1.16]	.14	-0.25
"Higher Baseline Rumination, Lesser Gains"				
Female	**2.76**	**[1.24, 6.16]**	**.01**	**0.56**
MINI Functioning/Impairment	**1.03**	**[1.01, 1.06)**	**<.001**	**0.02**
Distress "Non Responder"				
Sexual or Gender Minority [a]	0.00	(0.00, 0.00)	1.00	0.00
Clinical Severity	**3.23**	**(1.23, 8.46)**	**.02**	**0.65**
MINI Functioning/Impairment	**1.04**	**[1.00, 1.08)**	**.04**	**0.02**
CIS 2: Income/Employment	**3.15**	**(1.07, 9.30)**	**.04**	**0.63**

Note. OR = odds ratio, 95% CI [LL, UL] = 95% Confidence Interval (Lower Limit, Upper Limit), *d* = Cohen's *d* effect size. Significant effects ($p < .05$) are in bold.
[a] Zero SGM patients in unregularized logistic regression (without up-sampling from LASSO models).