The COVID-19 Pandemic as a Critical Incident and its Impact on Depression

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Abbreviations

AIC	Akaike Information Criterion
AUC	Area Under the Curve
BIC	Bayesian Information Criterion
CART	Classification and Regression Tree
CFI	Comparative Fit Index
CI	Confidence Interval
COVID-19	Coronavirus Disease 2019
DSM	Diagnostic and Statistical Manual of Mental Disorders
EMA	Ecological Momentary Assessment
ESM	Experience Sampling Method
FIML	Full Information Maximum Likelihood
HIC	High-Income Countries
IC	Information Criteria
ICD	International Classification of Diseases
LCSM	Latent Change Score Model
LCSMM	Latent Change Score Mixture Model
LMIC	Low- and Middle-Income Countries
MAP-19	The Norwegian COVID-19, Mental Health and Adherence Project
MAR	Missing At Random
ML	Maximum Likelihood
mlVAR	Multi-level (graphical) vector autoregressive model
MSIS	Norwegian Surveillance System for Communicable Diseases
NSD	Norwegian Centre for Research Data
OR	Odds Ratio
PHQ-9	Patient Health Questionnaire
P-BLRT	Parametric Bootstrapped Likelihood Ratio Test
ROC	Receiver Operating Curve
REK	Regional Committee for Medical and Health Research Ethics
RMSEA	Root Mean Square Error of Approximation
SARS-CoV-2	Severe Acute Respiratory Syndrome Coronavirus 2
SDPs	Social Distancing Protocols
SEM	Structural Equation Modelling
SRMR	Standardized Root Mean Square Residual
TLI	Tucker-Lewis Index
TOP	Transparency and Openness Promotion
WHO	World Health Organisation

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Summary

The COVID-19 pandemic is a critical incident that has been accompanied by drastic and sudden changes in individuals' daily lives and societal functioning. Beyond the mental distress tied to the uncertainty and fear of an unknown virus, the pandemic's concomitant social distancing protocols have been suggested to pose a significant burden on individuals. The abrupt changes in individuals' everyday lives resulting from these measures prompted early concerns about mental health and depressive symptoms in the population.

This doctoral thesis examines the impact of the COVID-19 pandemic and its accompanying distancing protocols in connection with depressive symptoms in the general adult population in Norway over a two-year period. The project spans from March 2020, ensuing the initial implementation of social distancing protocols in Norway, to March 2022, where these protocols were discontinued. The thesis encompasses three longitudinal studies that investigate depressive symptomatology during the pandemic across different levels of granularity.

Study 1 followed 4,361 adults (≥ 18 years) over the first 1.5 years of the pandemic across six longitudinal assessment waves, forming 26,166 observations. The participants were measured upon *each* modification of national social distancing protocols, enabling investigation of the association between these protocols and changes in depressive symptomatology over time in the same group of individuals. Societal SARS-CoV-2 infection rates were further measured to investigate how this stressor was linked to depressive symptoms. Employing a non-linear longitudinal model (Latent Change Score Model), Study 1 identified that depressive symptom levels in the adult population were associated with social distancing protocols, but unrelated to infection rates. This contrasted with observed changes in anxious symptomatology, which were more closely related to societal SARS-CoV-2 infection rates. Longer periods of sustained social distancing protocols were related to prolonged periods of

heightened depressive symptoms. Increasing the stringency of social distancing protocols was associated with higher levels of depressive symptoms, while reducing the stringency and discontinuation of these protocols was associated with subsequent reductions in depressive symptomatology. This demonstrated that, on the population level, the observed increases in depressive symptoms were temporary and decreased after the termination of these protocols. When examining depressive symptom change patterns on the individual level however, Study 1 identified a smaller subgroup of adults whose mental health had deteriorated during the pandemic. These findings indicated the presence of heterogeneous responses to the pandemic across adults.

Study 2 investigated whether these individual differences could reveal subgroups of adults displaying distinct and prototypical depressive symptom change patterns during the pandemic. A Latent Change Score Mixture Model was applied to model change over time in 4,361 adults. Through the investigation of depressive symptom levels across nine assessment waves (39,259 observations) from March 2020 to March 2022, five distinct depressive symptom change profiles were identified. The majority of adults displayed either resilience to depressive symptoms (42.5%), or a temporary heightening (i.e. initial shock) in depressive symptomatology during the onset of the pandemic (13.2%). A third subgroup of individuals, predominantly with previous mental health difficulties, reported high levels of depressive symptoms that lasted from the onset throughout the pandemic period (8.5%). A fourth group of adults exhibited mild deterioration in depressive symptom levels during the pandemic (29.0%). A final subgroup of approximately 6.8% of adults displayed strong deterioration and clinically severe levels of gained symptoms occurring during the initial months of the pandemic, which was sustained over the two-year assessment period of this study. The two deteriorating subgroups of individuals did not report any signs of pre-existing psychiatric conditions and reported low levels of depressive symptoms at the beginning of the pandemic.

These individuals reported a high probability of seeking psychiatric treatment by the end of the two-year study period. This indicates the potential emergence of a new subgroup of adults with severe depressive symptoms during the pandemic. Both resilient and adverse types of change patterns in depressive symptoms occurred during the first three months of the pandemic.

The risk factors related to increases in depressive symptoms levels identified across Study 1 and 2 were increased alcohol consumption during the pandemic, lower education, living alone, and belonging to an ethnic minority. The initial shock that was observed in depressive symptoms in a subgroup of adults was predicted by frequent information acquisition about the pandemic, in addition to financial and occupational concerns tied to the pandemic's economic repercussions. An additive dose-response relationship was identified between quarantine exposure and depressive symptoms. Protective factors related to resilient response patterns during the pandemic were being in a relationship, older age, and long-term engagement in physical activity.

Study 3 aimed to extend beyond risk factors to identify psychological mechanisms that were related to increases in specific symptoms of depression during the pandemic. This study followed 1,706 Norwegian adults, each person measured daily over a 40-day period, accumulating into a total of 68,240 observations across adults. A dynamic network model (i.e. multi-level graphical vector autoregressive model) was implemented to examine the relationship between psychological mechanisms and specific symptoms of depression. The study found helplessness to be the key psychological mechanism predicting increases in depressive symptoms over time during the pandemic. Loneliness was identified as a predictor of depressed mood. The study further corroborated how depressive symptoms can amplify each other on an across-day basis during the pandemic. Lethargy and worthlessness were identified as the symptoms with the strongest impact on additional symptoms of depression (i.e.

anhedonia and depressed mood, respectively), highlighting the key role of these symptoms in pushing individuals toward prolonged depressive states during the pandemic.

Overall, this doctoral thesis identified that most adults over time displayed resilience to the abrupt societal changes that accompanied the COVID-19 pandemic. Temporary fluctuations in depressive symptoms on the population level were associated with the pandemic's social distancing protocols. However, a minority subgroup of adults exhibited severe levels of depressive symptoms which emerged during pandemic, without any signs of recovery over a two-year period. Many adults in this subgroup reported seeking psychiatric treatment. Should these trends persist, this underscores a need for careful planning and resource allocation to facilitate preparedness and avoid the potential overburdening of mental healthcare systems. The link between financial concerns and depressive symptoms suggests that the implementation of socioeconomic policies may be warranted during pandemics. Disseminating information about physical activity as a protective factor and frequent information acquisition behaviour as a risk factor could present a useful public health strategy to protect against depressive symptoms during pandemics. The first three months of the pandemic were revealed as a critical period for pandemic adaptation, representing a key time window for implementing preventive measures in future pandemics and similar periods of infectious disease. This thesis further highlights the need for a balanced approach to social distancing, considering their association with depressive symptoms in several subgroups in the population. Such a cautious approach could entail the early implementation of social bubbles and similar interventions, both permitting some degree of social interaction while mitigating infectious spread, thereby having the potential to safeguard psychological as well as physical health.

Norwegian Summary: Norsk Sammendrag

COVID-19 pandemien førte med seg omfattende endringer på samfunns- og individnivå. Utover det mentale stresset knyttet til usikkerheten og frykten for et ukjent virus, ble det foreslått at de sosiale distanseringstiltakene for å begrense smitte og sykdom kunne utgjøre en belastning. Det hurtige skiftet i individers hverdagsmønster som fulgte disse tiltakene førte tidlig til en bekymring for psykisk helse og depressive problemer i befolkningen.

Denne avhandlingen ser på sammenhengen mellom COVID-19 pandemien og depressive symptomer i den voksne norske befolkningen over en to-års periode. Studien strekker seg fra mars 2020, ved den første innføringen av sosiale distanseringstiltak i Norge, til mars 2022, hvor tiltakene ble fjernet. Avhandlingen består av tre longitudinelle studier som utforsker sammenhengen mellom depresjon og pandemien fra ulike vinkler.

I Artikkel 1 følges 4,361 voksne (≥ 18 år) individer gjennom pandemiens første 1.5 år over seks måletidspunkt, og følgelig 26,166 observasjoner. Deltagerne ble målt hver gang det oppsto endringer i nasjonale sosiale distanseringstiltak, slik at endringene i depressive symptomer kunne kartlegges i sammenheng med endringer i tiltakene hos de samme individene. Nivået av SARS-CoV-2 smitte i samfunnet ble i tillegg målt for å se hvordan denne stressoren hang sammen med depressive plager. Ved bruk av en ikke-lineær dynamisk longitudinell modell (Latent Change Score Model), avdekket studien at depressive symptomer i den voksne befolkningen henger sammen med de sosiale distanseringstiltakene, men ikke med nivået av smitte. Dette står i kontrast til funn om endringer i angtsymptomer, som i større grad hang sammen med nivået av SARS-CoV-2 smitte i samfunnet. Lengre perioder med distanseringstiltak hang sammen med lengre perioder med forhøyede depressive symptomer. Innstramminger og strengere distanseringstiltak hang sammen med høyere nivåer av depressive symptomer, mens redusering og eliminering av disse tiltakene hang sammen med påfølgende nedgang i symptomer. Dette impliserer at på befolkningsnivå, altså for de fleste voksne

nordmenn, så var de forhøyede depressive symptomene under pandemien midlertidige og gikk over etter elimineringen av de sosiale distanseringstiltakene. Ved undersøkelse av endringsmønstre på individnivå, oppstod det imidlertid tegn til at en mindre gruppe med voksne nordmenn hadde blitt verre under pandemien. Dette ga indikasjoner på at ulike individer kan ha respondert ulikt på pandemien.

I Artikkel 2 undersøkes det om individer utviser ulike endringsmønstre i deres depressive symptomer under pandemien. En Latent Change Score Mixture Model ble brukt til å modellere endringer hos 4,361 voksne individer. Ved å undersøke endringer i depressive symptomer over ni måletidspunkt (39,259 observasjoner) fra mars 2020 til mars 2022, ble fem ulike typer endringsmønstre avdekket. Majoriteten av voksne utviste motstandsdyktighet mot depressive symptomer (42.5%) eller ikke-vedvarende depressive plager etter en initial økning i symptomer ved starten av pandemien (13.2%). En tredje gruppe individer, hovedsakelig med tidligere mentale plager, rapporterte høye nivåer av depressive symptomer som vedvarte gjennom pandemien (8.5%). En fjerde gruppe voksne viste mindre forverringer i depressive symptomnivåer underveis i pandemien (29.0%). En siste gruppe på omtrent 6.8% av voksne viste drastiske forverringer og klinisk alvorlige nivåer av depressive symptomer som oppsto allerede i pandemiens innledende måneder, hvor disse plagene har vedvart over de to årene deltagerne er blitt målt under pandemiperioden. De to sistnevnte gruppene rapporterte ikke tegn til tidligere psykiske lidelser og hadde lave symptomnivåer ved starten av pandemien. Disse individene rapporterte imidlertid høy sannsynlighet for å oppsøke psykologisk behandling ved slutten av pandemiperioden, noe som samlet sett tyder på at en ny, dog mindre, gruppe med voksne mennesker fikk alvorlige depressive symptomer under pandemien. Både motstandsdyktighet mot og negative endringsmønstre i depressive symptomer oppstod under pandemiens tre første måneder.

Sårbarhetsfaktorer for forhøyede depressive symptomnivåer avdekket av Artikkel 1 og 2 var blant annet økt alkoholinntak under pandemien, lavere utdanning, å bo alene, og etnisk minoritetsbakgrunn. Det initiale sjokket som ble observerte i depressive symptomer hos en subgruppe med voksne ble predikert av hyppig informasjonssøking om pandemien, i tillegg til bekymring for personlig økonomi og frykt for å miste jobben som følge av pandemiens økonomiske konsekvenser. Et additivt dose-respons forhold ble avdekket mellom antall ganger individer ble eksponert for karantene og depressive symptomer. Beskyttelsesfaktorer relatert til motstandsdyktige mønstre under pandemien var å være i et forhold, økt alder, og fysisk aktivitet over lengre tid.

Artikkel 3 hadde som mål å gå forbi sårbarhetsfaktorer for å avdekke psykologiske mekanismer som hang sammen med spesifikke depressive symptomer under pandemien. Denne studien inkluderte 1,706 voksne nordmenn, hver person målt daglig i 40 dager, noe som akkumulerte til 68,240 observasjoner. En dynamisk nettverksmodell (multi-level graphical vector autoregressive model) ble brukt for å undersøke spesifikke sammenhenger mellom sentrale psykologiske mekanismer og depressive symptomer. Resultatene tydet på at hjelpeløshet var den mest sentrale psykologiske mekanismen som predikerte forhøyede depressive symptomer over tid under pandemien. Ensomhet ble identifisert som en viktig prediktor for nedstemthet. Studien viste også hvordan depressive symptomer forsterket hverandre fra dag til dag under pandemien. Redusert energinivå og følelsen av verdiløshet ble avdekket som tidlige forløpere som kan forsterke nedstemthet og anhedoni og følgelig symptomer som spiller en nøkkelrolle i forverringen av depressive tilstander under pandemiske perioder.

Samlet sett fant avhandlingen at de fleste voksne over tid viste motstandsdyktighet til de omfattende samfunnsmessige endringene som fulgte med COVID-19 pandemien. Midlertidige fluktueringer i depressive symptomer på befolkningsnivå hang sammen med sosiale distanseringstiltak. Imidlertid var det en mindre gruppe med voksne individer som viste nyutviklede og alvorlige nivåer av depressive symptomer under pandemien, uten tegn til bedring. Denne gruppen med voksne rapporterte økt behandlingssøkende atferd. Dersom denne trenden vedlikeholder seg over tid, understreker disse funnene et behov for planlegging og fordeling av ressurser for å unngå en potensiell overbelastning av psykisk helsevern i kjølvannet av pandemien. Sammenhengen mellom økonomiske bekymringer og depressive symptomer fremhever at implementeringen av sosioøkonomiske tiltak kan være nødvendige under pandemier. Disseminering om fysisk aktivitet som beskyttelsesfaktor og hyppig informasjonssøking som risikofaktor kan utgjøre et viktig folkehelsetiltak for å skjerme mot depressive symptomer under pandemier. Pandemiens første tre måneder viste seg å være en kritisk periode for tilpasning og et sentralt tidsvindu for innsetting av forebyggende tiltak i fremtidige pandemier og perioder med massespredning av smittsom sykdom. Avhandlingen peker videre på viktigheten av balansert bruk av sosiale distanseringstiltak i fremtidige pandemier gitt deres sammenheng med depressive symptomer i deler av befolkningen. Dette kan eksempelvis oppnås gjennom bruk av sosiale bobler og lignende intervensjoner som både gir rom for sosial kontakt, begrenser smitte, og følgelig ivaretar psykisk i tillegg til somatisk helse.

List of Papers

Study 1

Ebrahimi, O. V., Bauer, D. J., Hoffart, A., & Johnson, S. U. (2022). A critical period for pandemic adaptation: The evolution of depressive symptomatology in a representative sample of adults across a 17-month period during COVID-19. *Journal of Psychopathology and Clinical Science, 131*(8), 881-894. https://doi.org/10.1037/abn0000786

Study 2

Ebrahimi, O. V., Freichel, R., Johnson, S. U., Hoffart, A., Solbakken, O. A., & Bauer, D. J. (2023). Depressive response patterns during the COVID-19 pandemic and its impact on psychiatric treatment seeking: A 24-month representative observational study of the adult population. *Submitted*. Preprint: https://doi.org/10.31234/osf.io/zw6xb

Study 3

Ebrahimi, O. V., Burger, J., Hoffart, A., & Johnson, S. U. (2021). Within and across-day patterns of interplay between depressive symptoms and related psychopathological processes: A dynamic network approach during the COVID-19 pandemic. *BMC Medicine, 19*(317), 1-17. https://doi.org/10.1186/s12916-021-02179-y

1 Introduction

1.1 Depressive Symptoms and Depressive States

Depression is one the most prevalent mental health conditions, affecting more than 280 million individuals worldwide (Torre et al., 2021). The core symptoms characterising depressive states include persistent feelings of sadness, also referred to as depressed mood, and a marked reduction of interest or pleasure in activities once perceived to be enjoyable by the individual, referred to as anhedonia (American Psychiatric Association, 2013; World Health Organization, 1993). Additional depressive symptoms in accordance with the fifth edition of the Diagnostic and Statistical Manual of Mental Disorders (DSM-5; American Psychiatric Association, 2013), such as for instance reduced energy (i.e. lethargy) and feelings of worthlessness, are reported in Table 1, along with the description of each symptom.

When these symptoms impair with the daily functioning of the individual and form into a disorder, major depressive disorder (MDD) ranks as one of the main contributors to the global burden of disease and leading causes of disability (Friedrich, 2017; Kessler & Bromet, 2013; Weye et al., 2021), associated with a range of adverse outcomes, including impairments in quality of life and increased mortality (Kessler & Bromet, 2013).

Beyond functional impairment, for depressive symptom expression to emerge into a full disorder state (i.e. MDD), a total of five of the symptoms in Table 1 need to present, one of which must be depressed mood or anhedonia. Moreover, this collection of symptoms must be present for a minimum of two weeks (American Psychiatric Association, 2013; World Health Organization, 1993). These diagnostic criteria highlight a key interdependency between depressive symptomatology on the one hand, and depression as a diagnostic entity on the other, tied to the number or accumulation of symptoms, in addition to the length that these symptoms are experienced (American Psychiatric Association, 2013; World Health Organization, 1993).

Accordingly, studying how depressive symptoms emerge, change, and maintain themselves over time provides an opportunity to understand the contextual risk factors and mechanistic processes that put individuals at greater risk for developing a depressive condition (e.g., Ebrahimi, Borsboom, et al., 2023; Fried, 2017).

Table 1

The Diagnostic Criteria for MDD According to the DSM-5

Symptom	Description
Depressed mood	Depressed mood most of the day, nearly every day, indicated by either subjective report (e.g., feels sad, empty, hopeless) or observation made by others (e.g., appears tearful).
Anhedonia	Markedly diminished interest or pleasure in all, or almost all, activities most of the day, nearly every day, indicated by either subjective account or observation.
Changes in weight or appetite	Significant weight loss when not dieting or weight gain (e.g., a change of more than 5% of body weight in a month), or decrease or increase in appetite nearly every day.
Sleep disturbance	Insomnia or hypersomnia nearly every day.
Psychomotor changes	Psychomotor agitation or retardation nearly every day.
Lethargy	Fatigue or loss of energy nearly every day.
Worthlessness	Feelings of worthlessness or excessive or inappropriate guilt nearly every day.
Concentration difficulties	Diminished ability to think or concentrate, or indecisiveness, nearly every day.
Suicidal ideation or behaviour	Recurrent thoughts of death, recurrent suicidal ideation without a specific plan, or a suicide attempt or a specific plan for committing suicide.

1.2 Contextual Stressors and Depression

Previous research has shown that major societal challenges that impact a large proportion of the population, such as periods of economic recession or the occurrence of natural disasters, may relate to increases in mental health problems, including the onset and persistence of depressive symptoms (Catalano et al., 2011; Goldmann & Galea, 2014). The key question concerns how such contextual stressors can impact depressive symptomatology? Several psychological theories and perspectives are equipped to investigate how contextual stressors may trigger mental health problems.

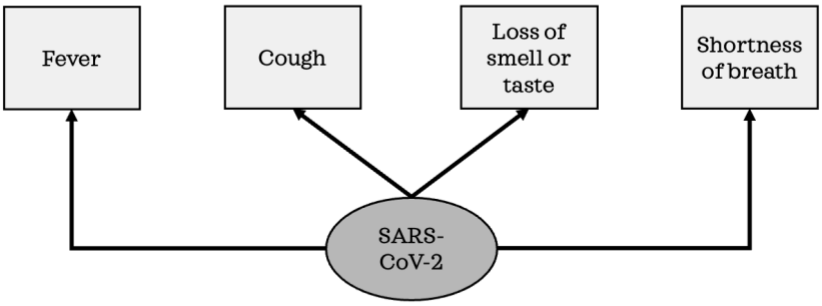
1.2.1 The Network Approach and the Latent Variable Perspective on Mental Health

One of these, the network theory of mental disorders (Borsboom, 2017), has rapidly grown in popularity during the past decade (Robinaugh et al., 2020). This theory provides a central reconceptualization of how mental disorders develop and relate to their external environment through events that can trigger the onset of adverse psychological symptoms (Borsboom, 2017). To elucidate the theory's reconceptualization of mental disorders, it is important to consider the traditional medical model of illness that it critiques.

This illness model, also referred to as the common cause or the latent variable model, has proven to be successful in advancing the understanding of many somatic illnesses (e.g., Borsboom, 2017; Borsboom & Cramer, 2013). The approach postulates that the symptoms of a disease result from an underlying latent (i.e. not directly observable) or common cause, such as the presence of a tumour or virus (e.g., Borsboom, 2017; Borsboom & Cramer, 2013; de Beurs et al., 2021). SARS-CoV-2 (Severe Acute Respiratory Syndrome Coronavirus 2) infection provides an example of the utility of this model, with the observable symptoms of the disease (e.g., fever, cough, and shortness of breath) all arising as a result from infection of the underlying SARS-CoV-2 virus (Ebrahimi, 2023). Put differently, this framework implies that the symptoms of a disease or disorder have no causal impact on one-another, and emerge forth as a result of their common cause (Borsboom, 2017; Borsboom & Cramer, 2013), illustrated in Figure 1.

Figure 1

An Illustration of the Common Cause Model for SARS-CoV-2 and Some of its Symptoms

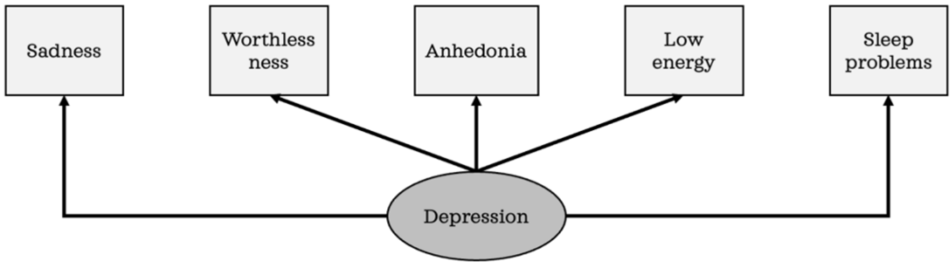


Note. The symptoms of the infection are independent of each other and are directly caused by the presence of the virus. Example adapted from Ebrahimi (2023).

While the common cause model has been pivotal for the success of the medical field, proponents of the network approach have challenged its utility in the context of psychological disorders (e.g., Borsboom, 2017; Borsboom et al., 2021; Borsboom & Cramer, 2013; Bringmann et al., 2013; Cramer et al., 2010; Fried et al., 2017; Roefs et al., 2022; van der Maas et al., 2006). Unlike many medical illnesses, such as SARS-CoV-2 infection illustrated above, the symptoms of mental disorders are not independent of one-another, as would be implied by Figure 2.

Figure 2

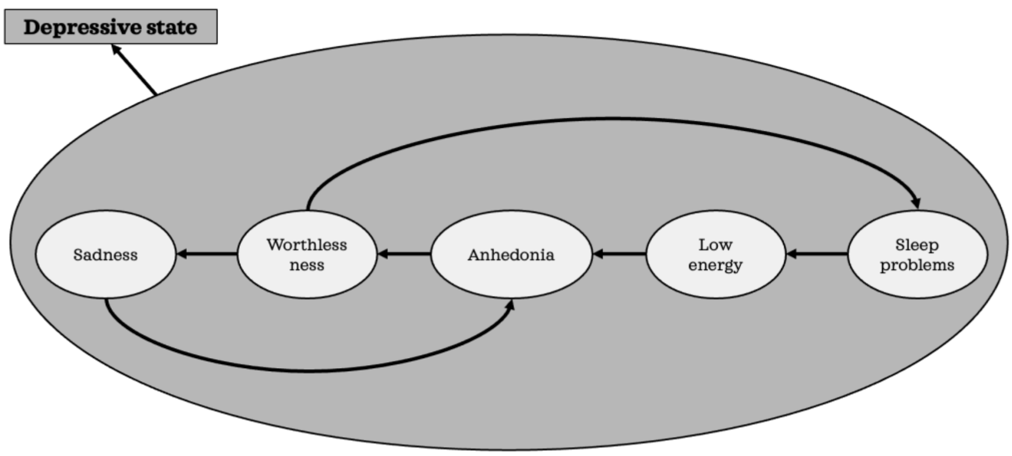
An Illustration of the Common Cause Model for Depression and Some of its Symptoms



Rather, symptoms of mental disorders are postulated to causally impact each other, implying that the onset of one symptom can lead to the emergence of another (Borsboom, 2008, 2017; Cramer et al., 2010; Ebrahimi, Borsboom, et al., 2023). For example, sleep problems over time may result in loss of energy (lethargy), subsequently predicting a loss of interest in activities (anhedonia), and further bringing with it additional symptoms of depression and feedback loops which can accumulate into a depressive state (Figure 3). The network theory of mental disorders postulates that it is through these dynamic interactions between symptoms that mental disorders, such as a depressive episode, arise (Borsboom, 2017).

Figure 3

An Illustration of the Network Theory of Mental Disorders as Proposed by Borsboom (2017)



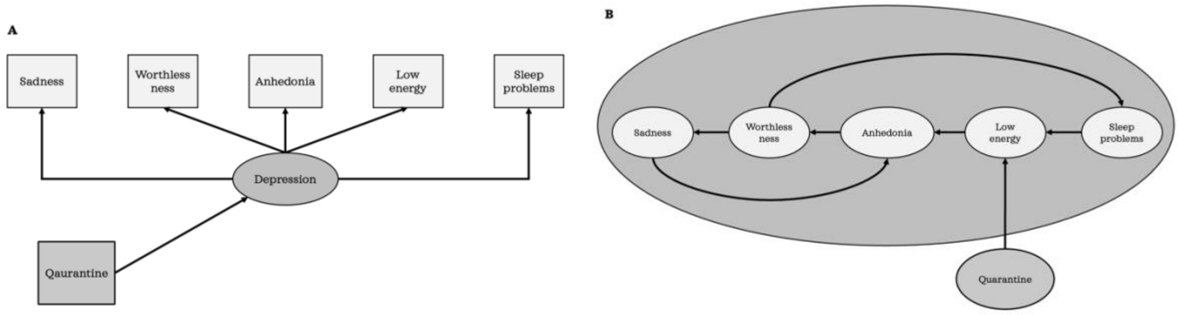
While the network and the latent variable (i.e. common cause) approach may seem theoretically opposing, they can offer complementary perspectives which are of utility when studying the impact of contextual stressors on depression.

First, while the proposed process leading to the constellation of symptoms is different within the two approaches, the sequential symptom dynamics emerging into an ultimate depressive state within the network perspective (Figure 3) may offer another way of viewing the process giving rise to the overall depressive severity level (Guyon et al., 2017), the latter which can be measured through a latent depression factor or sum-score of the overall depressive symptom severity. In other words, a point of integration between the two approaches could embody viewing the symptoms (and their dynamic relationships) as the cause of overall depression (i.e. the emergent depressive state) rather than being caused by it. This facilitates studying changes in overall depressive severity through a composite approach, in addition to symptom-specific relationships through a network approach (Guyon et al., 2017).

Second, both approaches leave room to conceptualise and examine the influence of contextual stressors on depression in a complementary manner, at different levels of specificity. The latent variable perspective enables such an investigation through the modelling of exogenous variables (e.g., Adams & Boscarino, 2011; Schwarzer et al., 2016; Zhang et al., 2023) which impact the overall or latent level of depression (Figure 4A). The network approach facilitates this through the incorporation of contextual factors in the model (e.g., Bjørndal et al., 2023; van der Wal et al., 2021), which can reveal direct and granular relationships with the specific symptoms of depression (Figure 4B).

Figure 4

The Incorporation of Contextual Stressors Within the Latent Variable (Panel A) and Network Framework (Panel B)



Finally and most importantly, the choice of statistical models should be based on the specific research questions at hand (e.g., Carley & Lecky, 2003; Kim et al., 2017). Network models embody significant advantages through enabling the study of how symptoms (and other components relating to depression) impact one-another and are impacted by contextual stressors. However, the current body of covariance-based network models do not lend themselves equally well to investigation of research questions related to mean level changes in overall burden of depressive symptomatology. This limits the investigation of whether changes have occurred in the depressive levels of the population over time during exposure to major societal contextual stressors.

Accordingly, both the latent variable and the network approach enable investigating the impact of contextual stressors on depression at different levels of granularity, with the former allowing the study of change in overall depressive levels over time in relation to contextual stressors, while the latter is equipped to examine the impact of such stressors on specific symptoms within a system of interconnected variables.

1.3 The COVID-19 Pandemic as a Contextual Stressor Aggravating Depressive Symptoms

The COVID-19 pandemic is a recently emerged contextual stressor which has been characterised as a critical incident that can fundamentally alter the mental health landscape (e.g., Holmes et al., 2020; Lokman & Bockting, 2022; Yao et al., 2020). Critical incidents refer to events that impact larger groups of individuals and societal functioning, with secondary repercussions (e.g., for mental health) beyond the direct consequences of the event (e.g., infectious spread; Goldmann & Galea, 2014). But what is it about the COVID-19 pandemic that may function as a perturbator of depressive symptomatology?

Beyond its immediate toll on global somatic health and the spread of infectious disease (e.g., Guan et al., 2020; Huang et al., 2020; Shen et al., 2023), the COVID-19 pandemic has brought with it drastic and sudden changes in the way individuals work, live, and interact with each other (e.g., Long et al., 2022; Tang et al., 2023). These fast-paced changes, which for many involve unprecedented experiences, necessitate adaptation to a new normal and the flexibility to cope with the demands of a new everyday life (Cheng, Wang, et al., 2021; Vowels et al., 2022).

The pandemic has further brought with it a range of novel adverse factors, and widened existing sociodemographic disparities relevant to mental health (e.g., Douglas et al., 2020; Yao et al., 2020; elaborated in the next section). Particularly, two dominant and ubiquitous aspects of the pandemic have been described to be related to depressive symptom expression, namely societal infection rates and the pandemic's accompanying social distancing measures (e.g., Ebrahimi, Hoffart, et al., 2021; Lokman & Bockting, 2022; Santomauro et al., 2021).

First, the pandemic has been followed by widespread fear and uncertainty, particularly during the early stages of the pandemic when less was known about the virus and the risks of infection (Elsharkawy & Abdelaziz, 2021; Mertens et al., 2020). In this light, societal infection rates, as a proxy for fear and worry, have been viewed as a potential source of psychological distress during the pandemic (Fitzpatrick et al., 2020; Lokman & Bockting, 2022). Second, longer periods of social distancing and separation from peers have been described as psychologically challenging for many, reducing, and in periods prohibiting contact with friends, family, peers, and the larger community, to increase a feeling of disconnection which is related to depressive symptomatology (Santini et al., 2020; Wickramaratne et al., 2022).

In summary, the rapid disruption of daily routines, recurrent periods of social isolation, and fear of infection tied to a novel emerging disease, are attributes that have been highlighted as possible key factors relating the COVID-19 pandemic to depressive symptomatology. Several other risk factors are relevant for understanding potential changes in the depressive symptoms of the population during the COVID-19 pandemic, elaborated in the section below.

1.4 Associated Risk Factors of Depression in Pre- and Peri-Pandemic Periods

While contextual stressors have the potential to aggravate depressive symptomatology, exposure to such events are not deterministic in triggering such depressive adversities (e.g., Mazure, 1998; Thoits, 2010). Depressive symptom expression can relate to a combination of exposure to the stressor and individual vulnerabilities, with the latter for instance including different sociodemographic risk factors and the role that psychological mechanisms play in the formation of depressive difficulties (Gotlib & Joormann, 2010; Mazure, 1998).

The impact of several pre-existing risk factors can be amplified during pandemics, and unique aspects of the pandemic can be related to depressive symptom expression. Some previously identified risk factors of depression include lower education levels, the presence of pre-existing psychiatric diagnoses, and biological sex, with the risk of experiencing depressive adversities being higher among females than males (e.g., Herrman et al., 2022). Other pre-existing risk factors, such as for example living alone, fewer social contacts, reduced physical activity, in addition to job-related and financial concerns, are likely relevant during the pandemic, tied to the restrictions in mobility and the economic repercussions that have accompanied the pandemic, respectively (Ettman, Cohen, Abdalla, Trinquart, et al., 2022; Hertz-Palmor et al., 2021; Sommerlad et al., 2022). Similarly, alcohol consumption, a maladaptive coping strategy used by many individuals during periods of stress (Martinez et al., 2022), could be related to depressive symptoms.

Moreover, unique aspects related to the pandemic, such as the need for information acquisition during this period of uncertainty about an emergent and unknown virus, could amplify depressive problems through overexposure to negative and distressing news, further depending on type of platform used to retrieve information and the extent of information seeking behaviour (Amundsen et al., 2021; Holman et al., 2020). Indeed, the pandemic has been accompanied by such a vast volume of distressing news that this has been referred to as an "infodemic" by the World Health Organisation (WHO; Cheng, Ebrahimi, et al., 2021; Depoux et al., 2020; WHO, 2023). Additionally, disruptions in routine due to home confinement could disrupt sleep and other daily habits that may relate to depressive symptoms (Cellini et al., 2020; Kumar & Gupta, 2022; Petrov et al., 2021).

In summary, both pre-existing and novel risk factors accompanying the COVID-19 pandemic are relevant when studying changes in depressive symptoms over time during this stressful period. While all risk factors provide important information about characteristics and conditions that are relevant during the pandemic with respect to vulnerability to depressive symptoms, different risk factors bring with them different possibilities regarding the type of strategies that can be implemented to mitigate depressive adversities.

1.5 Static and Dynamic Risk Factors, and Psychological Mechanisms

A key point is that some of the aforementioned risk factors are considered to be directly modifiable, while others are classified as fixed. This relates to a distinction between what is termed as static versus dynamic risk factors in the epidemiological literature (Douglas &

Skeem, 2005; Heilbrun, 1997; Kraemer et al., 1997). Static risk factors are factors that in themselves cannot be directly modified, either because they are stable and invariant characteristics, or because they include past occurrences (Douglas & Skeem, 2005; Heilbrun, 1997). Examples of these include historical factors, such as familial background or presence of childhood adversities. Demographic variables, such as ethnicity, age (at a specific point in time), and biological sex (assuming this is not medically modified) are other examples that are described as static factors (Douglas & Skeem, 2005).

On the other hand, dynamic risk factors are considered to be concurrently modifiable and thus provide an opportunity for active intervention in the present or at a future time-point (Douglas & Skeem, 2005; Heilbrun, 1997; National Collaborating Centre for Mental Health, United Kingdom, 2015). This does not necessarily imply that one cannot target static risk factors for preventive or interventive purposes. One can for example, identify demographic risk groups (e.g., females or individuals belonging to ethnic minorities) through public health campaigns, and guide them to the right resources before the known high-risk period of a problem onsets (i.e. preventive effort). Similarly, one can direct individuals in risk groups to available services that can aid in mitigating the problem after it has occurred (i.e. interventive effort). Knowledge about static risk factors can also provide useful information about vulnerable subgroups in similar and forthcoming periods of infectious disease, facilitating pandemic preparedness. The distinction between static versus dynamic risk factors therefore more closely concerns the direct modification of the risk factor itself. Examples of dynamic risk factors include information seeking behaviour, physical activity (assuming absence of disability and impairing conditions precluding mobility), and alcohol consumption (Douglas & Skeem, 2005; National Collaborating Centre for Mental Health, United Kingdom, 2015).

A more technical definition of these two types of risk factors describes static risk factors as an interindividual (i.e. between-subject difference) variable that can distinguish between different individuals or subgroups of individuals (e.g., females versus males). A dynamic risk factor varies on the intraindividual (i.e. within-person) level based on the current time-dependent status of the factor, which can fluctuate and change within a single person over time (Douglas & Skeem, 2005).

Dynamic risk factors in the epidemiological literature relate to the concept of psychological mechanisms in the psychological literature, a key notion which has received substantial attention in the field of clinical psychology (e.g., Kazdin, 2007). While definitions somewhat vary and can be more complex (Koch & Cratsley, 2020), one key descriptor of psychological mechanisms is that they vary within a given individual over time (e.g., behaviours or cognitions), thus providing concurrent opportunities for intervention and actionability, similar to dynamic risk factors (e.g., Ebrahimi, Burger, et al., 2021; Hoffart & Johnson, 2020). A possible reason for the use of different terminologies may include that the two terms stem from different literatures (i.e. epidemiology and psychology). Additionally, while related, a nuanced detail is that dynamic risk factors in the epidemiological literature often include a more somatic or lifestyle-based focus (e.g., obesity; physical activity), while psychological mechanisms are often about intrapsychological processes (e.g., rumination) that fluctuate within individuals (e.g., Hoffart & Johnson, 2020). Notably, in the clinical psychology literature, psychological mechanisms are often theorised as the processes which relate to the formation or maintenance of a certain mental health difficulty, such as depressive symptom expression, with different types of psychological interventions developed with the specific aim of modifying these mechanisms and thus alleviating the adverse depressive symptom experience (Hoffart & Johnson, 2020; Kazdin, 2009). Accordingly, studying depressive symptoms together with static and dynamic risk factors, including psychological mechanisms, provides valuable information about vulnerable subgroups in addition to actionable factors that can be manipulated either through public health campaigns or through psychological interventions.

In other words, static risk factors can provide information about the likelihood of experiencing adverse symptoms compared to others in the population, while dynamic risk factors and psychological mechanisms concern processes that can fluctuate within individuals, and thus how within-person increases or decreases in some variable (e.g., behaviour or cognition) relates to depressive symptoms. Statistically, the distinction between these dynamic and static variables, that is, variables displaying intra- versus interindividual variation, relates to the concept of within- versus between-person effects.

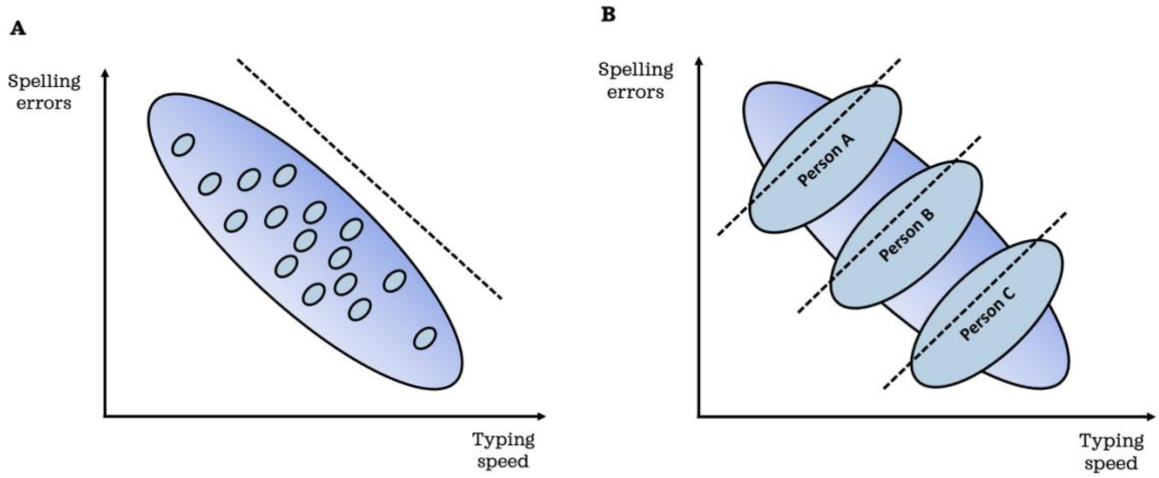
1.6 Within-Person Versus Between-Person Effects

Whether depressive symptom levels fluctuate during the pandemic, for example in relation to different variants of social distancing protocols or across varying rates of COVID-19 infection in society, warrants investigation on a within-person level. This enables examining how depressive symptom levels change in the same individuals across these variations.

The importance of disaggregating within- from between-person effects has been echoed by multiple scholars in the literature (e.g., Bringmann et al., 2022; Curran & Bauer, 2011; Hamaker et al., 2015; Hoffart, 2014; Hoffman & Stawski, 2009). One of the key reasons for these calls relates to the concept of Simpson's paradox (e.g., Kievit et al., 2013; Wagner, 1982). This occurs in scenarios where the investigation of the same relationship, at the within- versus the between-person level, yields different and even opposing results (Kievit et al., 2013). As an illustration, consider the following example concerning the relationship between typing speed and spelling errors, provided by Hamaker (2012), visualised in Figure 5. The research question at hand for this example is whether a person is more or less likely to make spelling errors when they type faster.

Figure 5

The Relationship Between Typing Speed and Spelling Errors



Note. The investigation of the relationship between typing speed (x-axis) and spelling errors (y-axis) at the between-person level (panel A) versus the within-person level (panel B). Each small ellipse in panel A represents an observation from a unique individual in the population, with the larger ellipse in the background highlighting the aggregated between-subject effect based on between-person variability available from the observations of typing speed and spelling errors. In a scenario where multiple observations are available from the same person (i.e. visualised as the medium-sized person-specific ellipses in panel B), a within-person effect can be calculated. Example from Hamaker (2012).

In a cross-sectional design, where only one observation is available for each individual, the only source of variability concerns a comparison between individuals, with studies highlighting that the retrieved effect from such studies involves a conflation of within- and between-person variability captured by the cross-sectional snapshot (e.g., Hamaker, 2012; Hamaker et al., 2015; Hoffman & Stawski, 2009; Schuurman, 2023). Even longitudinal designs that are not equipped with the appropriate statistical analyses are unable to separate within- from between-person effects (e.g., Hamaker et al., 2015). When investigating the relationship of typing speed and spelling errors, the between-person effect (Figure 5A) highlights that faster typing speed is associated with less spelling errors. The question is whether this relationship is representative of the aforementioned research question? Does a person actually make fewer spelling errors as they increase their typing speed?

Upon a more detailed inspection of this relationship, it can be revealed that this represents an instance of Simpson's paradox (Kievit et al., 2013). When investigating the relationship between typing speed and spelling errors on the within-person level (Figure 5B), one can see that as a given person (e.g., Person A, B, or C) types faster than they usually do (e.g., when rushed or stressed), this person is likely to make more spelling errors (Hamaker, 2012). This latter within-person effect is a more accurate assessment of the research question at-hand; that is, whether a person's typing speed is related to the amount of spelling errors they make (Hamaker, 2012).

To use a health-related example, when investigating the risk of heart attack, one can see that this risk is lower among physically active people (a between-person effect). However, a given person's risk of having a heart attack is actually higher while they are exercising (a within-person relationship; Hoffart, 2014).

Accordingly, beyond the pivotal importance of mapping research questions correctly to the appropriate level of analysis (Curran & Bauer, 2011; Hamaker et al., 2015; Hoffart, 2014; Hoffman & Stawski, 2009), this example also highlights the importance of appropriately separating these effects to avoid obfuscation of the level of interest.

To summarise, when studying change in depressive symptomatology over the course of the pandemic, the question at hand inherently concerns an investigation of the within-person level. That is, how depressive symptoms change within individuals over time during the course of the pandemic, related to its key accompanying contextual stressors (e.g., distancing protocols; societal infection rates) and other important risk factors and mechanisms. Such investigations necessitate leveraging either longitudinal or intensive longitudinal designs, which involve repeated measurements of individuals and, combined with the appropriate statistical analyses, enable the separation of stable means (i.e. used to estimate the between-person effect) versus changes over time or deviations from one's average (i.e. the within-person effect).

1.7 Longitudinal Research and the Study of Within-Person Change During the COVID-19 Pandemic

Both longitudinal and intensive longitudinal designs enable evaluating change over time in individuals during the pandemic, and thus, when combined with the appropriate statistical techniques (outlined in the Methods section), enable a separation of within- from between-person effects (Curran & Bauer, 2011; Hamaker, 2012; Hoffart, 2014; Hoffman & Stawski, 2009).

Traditional longitudinal investigations often involve what is referred to as panel data (Baumgartner, 2020; Collins, 2006; Walls & Schafer, 2006). In this design, repeated measurements of the same individual are collected over relatively long periods of time (e.g., months). Combined with the retrospective instruments often accompanying them, which also assess longer periods of time (e.g., weeks), these designs are well equipped to address research questions about whether changes have occurred in long-term depressive symptom expression during the period of investigation (Brüderl et al., 2019; Halaby, 2003; Marmar et al., 1999). Longitudinal designs are further well equipped to investigate how risk factors and exposure to contextual stressors over time relate to mental distress and depressive symptoms (e.g., Marmar et al., 1999).

A more frequent assessment schedule has gained increasing popularity during the past decades, broadly referred to as intensive longitudinal designs (e.g., Collins, 2006; Walls & Schafer, 2006). These are study designs involving high-frequent assessments, such as daily measurements (e.g., diary studies; Bolger et al., 2003) or multiple assessments within a single day (e.g., experience sampling or ecological momentary assessment designs; Mestdagh & Dejonckheere, 2021). As intensive longitudinal designs often involve an extensive number of assessments per person (e.g., 20 or 200 assessments), they are exceptionally well-suited to address questions about mechanistic processes that are relevant in aggravating depressive symptoms during the pandemic. This suitability relates to the granular and even denser repeated observations of a variable preceding another, a relationship which for example can be observed 20 or 200 times, rather than for example three or six times as with traditional longitudinal studies. Similar to traditional longitudinal studies, intensive longitudinal designs enable a focus on within-person effects when combined with the appropriate statistical model. Overall, this provides a strong basis for investigating which psychological mechanisms are associated with and precede increases in depressive symptoms during the pandemic.

Despite these strengths, for a long period, the intensive longitudinal literature predominantly involved the study of affective dynamics. That is, how affective states (e.g., irritability, sadness, and happiness) evolve and impact each other over time to predict depression (Hall et al., 2021; Kramer et al., 2014; Myin-Germeys et al., 2001; Wichers et al., 2007; Wichers, Simons, et al., 2011). This relates to a central idea within the affective dynamic literature, namely that moment-to-moment affective patterns form the fundamental and essential building blocks of psychopathology (i.e. Kemp et al., 2023; Wichers, 2014; Wichers et al., 2015), and therefore that mental health difficulties, including depressive states, can be understood by studying these elementary components (e.g., Gross et al., 2019; Kemp et al., 2023; Wichers, 2014; Wichers et al., 2015; Wichers, Hartmann, et al., 2011; Wichers, Simons, et al., 2011).

While the affective dynamics literature has been vital for the advancement of the psychological field and brought with it several significant and innovative developments, most clinicians hold the belief that psychopathology, including depression, is a multifactorial phenomenon which is more complex than fluctuations in affective states (Beck, 1979; Beck & Bredemeier, 2016; Ebrahimi, Borsboom, et al., 2023; Gotlib & Joormann, 2010; Jacobson et al., 2001; Miller & Seligman, 1975; Nolen-Hoeksema et al., 1993). Indeed, most theories of depression link the symptoms of the disorder to a wide-range of factors, such as for instance maladaptive behavioural patterns and cognitions (Miller & Seligman, 1975; Nolen-Hoeksema et al., 1993). This challenges the notion that affective dynamics form the sole elementary building blocks of psychopathology (e.g., Kemp et al., 2023; Wichers, 2014; Wichers et al., 2015). Additionally, the extent to which affective states map onto symptoms has been questioned (e.g., Ebrahimi, Borsboom, et al., 2023).

Accordingly, these clinical psychological theories of depression indicate that a point of strengthening in the intensive longitudinal and affective dynamics literature involves the inclusion of symptoms and mechanistic variables, including cognitions and maladaptive behavioural patterns. The integration of mechanistic variables in such studies can further add to a discussed limitation of the network theory of mental disorders in the literature (e.g., Hoffart & Johnson, 2020), where studying the dynamics between psychological mechanisms (e.g., rumination) and symptoms (e.g., depressed mood), beyond the detrimental impact of symptoms on one-another, has been highlighted as a necessary component related to psychopathological emergence (e.g., Hoffart & Johnson, 2020; Jones et al., 2017).

To address this, the intensive longitudinal and network analytic study in this thesis goes beyond the inclusion of affective states in its dynamic models, incorporating both symptoms of depression, in addition to theorised psychological mechanisms which are proposed to covary with these symptoms (Ebrahimi, Burger, et al., 2021). Moreover, by including other dynamic risk factors in the model, the study seeks to control for contextual factors in identifying unique relationships between psychological mechanisms and depressive symptomatology during the pandemic period.

1.8 The Importance of Timing of Assessments in Longitudinal Studies

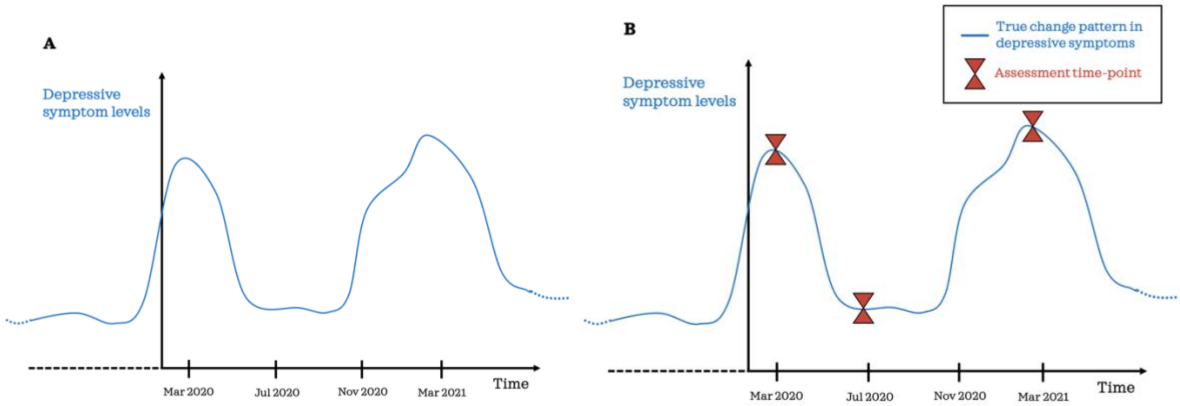
While leveraging longitudinal designs and relevant statistical techniques to map the research question to the appropriate level of analysis (i.e. within-person level) is important (e.g., Curran & Bauer, 2011; Hamaker et al., 2015), another component necessitating vital consideration in longitudinal studies concerns the timing of measurements (i.e. when assessments are conducted; e.g., Collins, 2006; Lerner et al., 2009).

Several scholars have highlighted how the timing of assessments can impact the findings, and that a rationale for the timing of conducted measurements should be provided in studies (Collins, 2006; Collins & Graham, 2002; Lerner et al., 2009). Notably, one limitation of the COVID-19 literature relates to the topic of timing of assessments, with many pandemic studies lacking an a priori justification for when assessments should be carried out and how assessments should be mapped on to the contextual stressors accompanying the pandemic.

To illustrate the importance of this, consider Figure 6A, including a hypothetical 'true change pattern' of depression during a specific window of the pandemic period (March 2020 to March 2021). In this example, the blue line portrays the true change in depressive symptoms in the population during this period.

Figure 6

Hypothetical Example of the True Change Patterns of Depressive Symptoms During the Pandemic Period



Note. The true change patterns of depressive symptoms are illustrated in panel A, while panel B highlights the impact of timing of assessments at various stages of the pandemic on the obtained results.

While population-level changes in depressive symptoms follows the blue line (Figure 6A), the obtained results about occurred changes in these depressive symptom levels during the course of the pandemic can strongly depend on the timing of assessment (Figure 6B). For example, if a study conducts assessments of depressive symptoms in March 2020, a heightening of depressive symptomatology is observed, while studies assessing depressive symptoms during July 2020 find low levels of depressive symptoms in the population.

Several inconsistencies observed in the mental health literature during the early stages of the pandemic can be tied to this concept. For example, studies measuring depression during the early stages of the pandemic (e.g., February to May) found elevations in population-level depressive symptoms, concluding that the pandemic has had a detrimental mental health impact (Aknin et al., 2022; Daly & Robinson, 2021b; Ebrahimi, Hoffart, et al., 2021; Ettman et al., 2020; Huang & Zhao, 2020; McGinty et al., 2020; Nochaiwong et al., 2021; Pierce et al., 2021; Salari et al., 2020; Wang et al., 2020; Wu et al., 2021). However, other studies measuring depression a few months later into the pandemic (e.g., July to October) concluded that the detrimental mental health impact of the pandemic was modest or small (Aknin et al., 2022; Daly & Robinson, 2021a; Robinson et al., 2022). Similarly, studies measuring depressive symptoms during March 2021 reported a heightening in depressive symptomatology (e.g., Ettman, Cohen, Abdalla, Sampson, et al., 2022), and so forth. This shows differences in obtained results about depressive symptom levels in the population related to the time-point of assessment, a pattern which was further identified in studies with multiple assessment waves observing strong fluctuations in depressive symptomatology during the pandemic over time (e.g., Ebrahimi, Hoffart, et al., 2022; Fancourt et al., 2021; Pierce et al., 2021; Riehm et al., 2021).

This highlights a key research gap in the COVID-19 literature: namely a lack of a systematic assessment protocol in many studies investigating depressive symptoms during the course of the pandemic, an issue which has previously been identified as a source of inconsistency and bias (Cohen, 1991; Collins, 2006; Collins & Graham, 2002; Lerner et al., 2009). An unsystematic assessment approach is problematic given the extensive variation in the pandemic's characteristics, driven by various contextual and time-dependent factors. One problem with this is that the pandemic is a highly heterogeneous and multi-staged event, varying both within and across countries (cf. infection rates, variants, in addition to stringency and types of distancing strategies implemented), thus highlighting that that the pandemic cannot be viewed as a monolithic or unitary event (Chen et al., 2022; Chen & Assefa, 2021; Thomas et al., 2020; Vallée, 2022). Accordingly, given this stage-dependent variability during the course of the pandemic, also studies confined to a single country need to incorporate systematic assessment protocols to that enable monitoring of mental health across the different stages of the pandemic. One way to achieve this aim is to map repeated longitudinal assessments to objective and key contextual changes occurring during the pandemic period.

To account for this issue, the two longitudinal studies in the present thesis employed a predefined and systematic rationale for when assessments were to be conducted during the pandemic period. This assessment rationale was mapped to an objective time-varying aspect of the pandemic previously related to depressive symptomatology during previous periods of infectious disease (i.e. social distancing measures), and further to the timescale of the measurement instrument of the outcome (Brooks et al., 2020; Kroenke et al., 2010; detailed in the Methods section).

1.9 Heterogeneity in Depressive Response Patterns During the Pandemic

Beyond the importance of timing of assessments, the observed inconsistencies among several of the studies mentioned above (i.e. with some studies finding heightening and other studies low levels of depressive symptoms) further highlights that there may be heterogeneity present in depressive response patterns during the pandemic (Shevlin et al., 2023).

A limitation with early pandemic studies, including studies stemming from the author of this thesis, concerned an investigation focus surrounding whether the pandemic was (or was not) related to depressive symptomatology overall on the population level (e.g., Aknin et al., 2022; Ebrahimi, Hoffart, et al., 2021; Ettman et al., 2020). This perspective overlooks the extensive heterogeneity that is often present in human response to adversities. Previous studies have shown that contextual stressors impact individuals differently (e.g., Fernandez et al., 2020; Makwana, 2019; Mazure, 1998; Thoits, 2010), with studies identifying such differences in depressive symptom response patterns during the early stages of the COVID-19 pandemic (e.g., Pierce et al., 2021).

Accordingly, a shift away from population-level investigations toward whether there are segments within the population that show resilient or deleterious response patterns during the pandemic was highlighted as necessary (e.g., Shevlin et al., 2023), further enabling the investigation of risk factors and mechanisms associated with such differential change patterns.

2 Aims of the Thesis

At the time of the initiation of this doctoral project (March 2020), several gaps were present in the literature, which the studies of this thesis sought to address. One gap concerned a lack of longitudinal investigations across the different stages of the pandemic, embodying a systematic rationale for assessments mapped to objective contextual aspects of the pandemic.

Study 1 in this thesis sought to address this, investigating changes in the depressive symptom levels of the adult population across *all* variations of national social distancing protocols during the pandemic, while controlling for the impact of societal infection rates and other risk factors of depressive symptomatology.

Second, after identifying large heterogeneity in depressive symptom change patterns in Study 1, Study 2 aimed to investigate whether these individual differences could inform prototypical change patterns in depressive symptoms during the pandemic, indicative of resilient versus deleterious depressive response patterns. Upon identification of these different response patterns, Study 2 sought to identify the risk and protective factors related to resilience versus adverse change, and further how these distinctive depressive response patterns predicted adverse future outcomes beyond depressive symptomatology: namely psychiatric treatment seeking and the presence of a psychiatric diagnosis.

Finally, Study 3 sought to move beyond risk factors to investigate the relationship between psychological mechanisms and specific symptoms of depression during the pandemic. This study aimed to identify the key psychological mechanisms amplifying and maintaining depressive symptoms during the pandemic period, while controlling for other relevant static and dynamic risk factors associated with depressive symptoms.

Following calls for longitudinal within-person investigations during the pandemic (e.g., Skjerdingstad et al., 2021; Wang, Hu, et al., 2020), all three studies focused on the within-person level to mitigate the risk of statistical biases (cf. Simpson's paradox; Kievit et al., 2013) and enable the investigation of how depressive symptoms change and fluctuate within individuals. Through the employment of non-linear models in the longitudinal studies investigating changes in depressive symptoms during the pandemic (Study 1 and 2), the thesis further enabled identification of complex patterns of change arising during the pandemic. Different ubiquitous factors accompanying the pandemic, such as for instance quarantine exposure and obsessive information seeking, were further investigated across the different studies to map out different sets of risk and protective factors associated with depressive symptom expression during the pandemic period.

3 Material and Methods

3.1 The Norwegian COVID-19, Mental Health and Adherence Project

The Norwegian COVID-19, Mental Health, and Adherence Project (MAP-19) was initiated in March 2020 to monitor changes in the mental health of the general adult population during the COVID-19 pandemic (Ebrahimi, Hoffart, et al., 2021). Through its early initiation, already from the onset of the pandemic in Norway, the project has enabled tracking mental health in the Norwegian adult population from the beginning of the pandemic period.

The MAP-19 project received its ethical approval by The Regional Committee for Medical and Health Research Ethics (reference: 125510) and Norwegian Centre for Research Data (reference: 802810).

3.2 Population

The eligibility criteria for the MAP-19 project involved inclusion of I) all adult participants (age ≥ 18 years), who II) provided informed consent to participate in the study, and III) resided in Norway during the study period, thus being exposed to the same set of national social distancing protocols (SDPs). All subjects had a chance to win a pair of Bose headphones as a reward for their participation.

3.3 Study Design

A unique feature of the MAP-19 project has been to adapt a predefined and systematic rationale for its implemented longitudinal assessments, tied to a key objective and relevant contextual stressor that accompanies periods of infectious disease, namely the pandemic's SDPs (Brooks et al., 2020; Venkatesh & Edirappuli, 2020).

Consequently, with the aim of covering the full social distancing-accompanying pandemic period in Norway (i.e. from the onset to termination of SDPs), this longitudinal project lasted for a period of 24 months, conducting nine longitudinal assessments from March 2020 to March 2022. Beginning in March 2020 with the onset of the pandemic and the initial introduction of SDPs in Norway, repeated measurements were conducted across *all* forthcoming modifications in national SDPs. This involved formalising the following five design criteria which are implemented across the longitudinal studies of this thesis (Study 1 and 2; Ebrahimi, Bauer, et al., 2022; Ebrahimi, Freichel, et al., 2023).

The first design criterion involved I) measuring the adult population following *each* alteration in national SDPs. This exposure-oriented design criterion was implemented to provide a comprehensive understanding of the pandemic across modifications of SDPs, a previously identified psychological stressor during periods of infectious disease (Brooks et al., 2020; Venkatesh & Edirappuli, 2020). Criterion I was further applied to embody the fact that the pandemic is a heterogeneous contextual event, enabling investigation of this period across the varying facets of the pandemic, with the aim of mitigating the issues with unsystematic measurements during this period (cf. Introduction section). This design procedure allows for a more systematic investigation of changes in depressive symptoms during the pandemic less prone to temporal and situational confounds that may arise during random assessment occasions. Importantly, the criterion enabled the investigation of within-person changes in depressive symptoms in relation to changes in SDPs, allowing the participants to serve as their own controls, and establishing the basis for an observational design in which depressive symptoms are monitored across SDPs of different stringency levels being implemented, discontinued, reintroduced, and so forth (Ebrahimi, Bauer, et al., 2022).

The second design criterion concerned II) systematically conducting all measurements between two to four weeks after implemented changes in national SDPs. As to be described in the measurement section, outcomes in the MAP-19 study, including the validated instrument measuring depression used in this thesis, concerned assessment of experiences (e.g., depressive symptoms) during the past two to four weeks. Consequently, matching the period of assessment in the study design with the retrospective assessment window of the instruments measuring the outcome variables in the project is critical to ensure that the assessments actually capture the intended period (Ebrahimi, Bauer, et al., 2022). To exemplify the importance of design criterion II, with an instrument of depressive symptomatology enquiring about the past two weeks, if the research question concerns investigating the depressive symptomatology during the presence of a lockdown initiated on March 12, 2020, the appropriate time to measure is first after March 26, 2020. This matches the retrospective assessment window of the instrument (i.e. past two weeks) to the period of the exposure (i.e. the lockdown period starting March 12, 2020).

Following the same line of reasoning of matching the retrospective assessment window of the outcome instruments to the contextual exposure, two other design criteria were incorporated. These criteria ensured that the introduced SDPs were III) present for a minimum of two weeks before any assessments were conducted, and that they IV) remained unchanged (i.e. constant) during each of the assessment periods of the study. Criterion IV was implemented to ensure that the measured period captured an unfluctuating period of SDPs, as modifications in SDP stringency and leniency during an active assessment period obfuscates investigation of association with SDPs and the outcome at a specific time period. Accordingly, criterion IV further ensured that data collection would be terminated immediately if any changes in national SDPs (e.g., introduction of novel SDPs, removal or modification of implemented SDPs) occurred (Ebrahimi, Bauer, et al., 2022). The extent to which the study design successfully managed to capture constant and unmodified stringency levels of SDPs during each of its nine assessment waves was cross-validated against a known measure of SDP stringency (i.e. the Oxford COVID-19 Stringency Index; Hale et al., 2020). This comparison supported the study design criteria's efficiency in achieving this aim by revealing the Oxford Stringency Index (reported in Table 2) to be constant within each assessment period.

The final design criterion was implemented to V) control for expectation effects related to SDPs. This was carried out by incorporating a stopping rule in which data collection would stop immediately if any announcement or novel information was provided about upcoming changes in SDPs during assessment periods. To summarise, these five design criteria allowed the study to incorporate and control for both expectations about changes in pandemic mitigation protocols in addition to actual changes in such SDPs (Ebrahimi, Bauer, et al., 2022; Ebrahimi, Hoffart, et al., 2021).

Table 2

The Oxford Stringency Index During the Assessment Period for Each of the Nine Longitudinal Assessment Waves in the Project

Assessment wave	Assessment period	Oxford Stringency Index	*N*
T1	31 Mar 2020 – 7 Apr 2020	79.63	4361
T2	22 Jun 2020 – 13 Jul 2020	40.74	2151
T3	19 Nov 2020 – 2 Dec 2020	56.02	2239
T4	23 Jan 2021 – 2 Feb 2021	73.13	1963
T5	08 May 2021 – 25 May 2021	63.89	1811
T6	04 Jul 2021 – 01 Aug 2021	47.22	1405
T7	24 Oct 2021 – 12 Nov 2021	20.37	1426
T8	02 Jan 2022 – 14 Jan 2022	51.85	1100
T9	06 Mar 2022 – 27 Mar 2022	13.89	1269

Note. The Oxford Stringency Index remained constant (i.e. had the same value) each day during each assessment period, confirming the SDPs to be unchanged within each period.

3.4 Sampling Strategy

The specific dates for each of the nine assessment periods during the project period (i.e. T1-T9) are provided in Table 2, along with number of respondents per assessment wave among the obtained stratified sample of participants.

Because of disruption to services accompanying the pandemic at its onset, including delays and cancellations in the transportation sector during the first weeks after the national lockdown in March 2020 (Hovi & Pinchasik, 2022), the survey could not be distributed through conventional methods such as postal services (Ebrahimi, Hoffart, et al., 2021). Accordingly, an online survey was conducted.

At study onset (T1), participants were systematically reached out to through disseminating information about the study using two groups of strategies with the aim of achieving a broad coverage across the adult population. This information dissemination involved provision of brief messages about the possibility to participate in a study at the University of Oslo about mental health in the adult population.

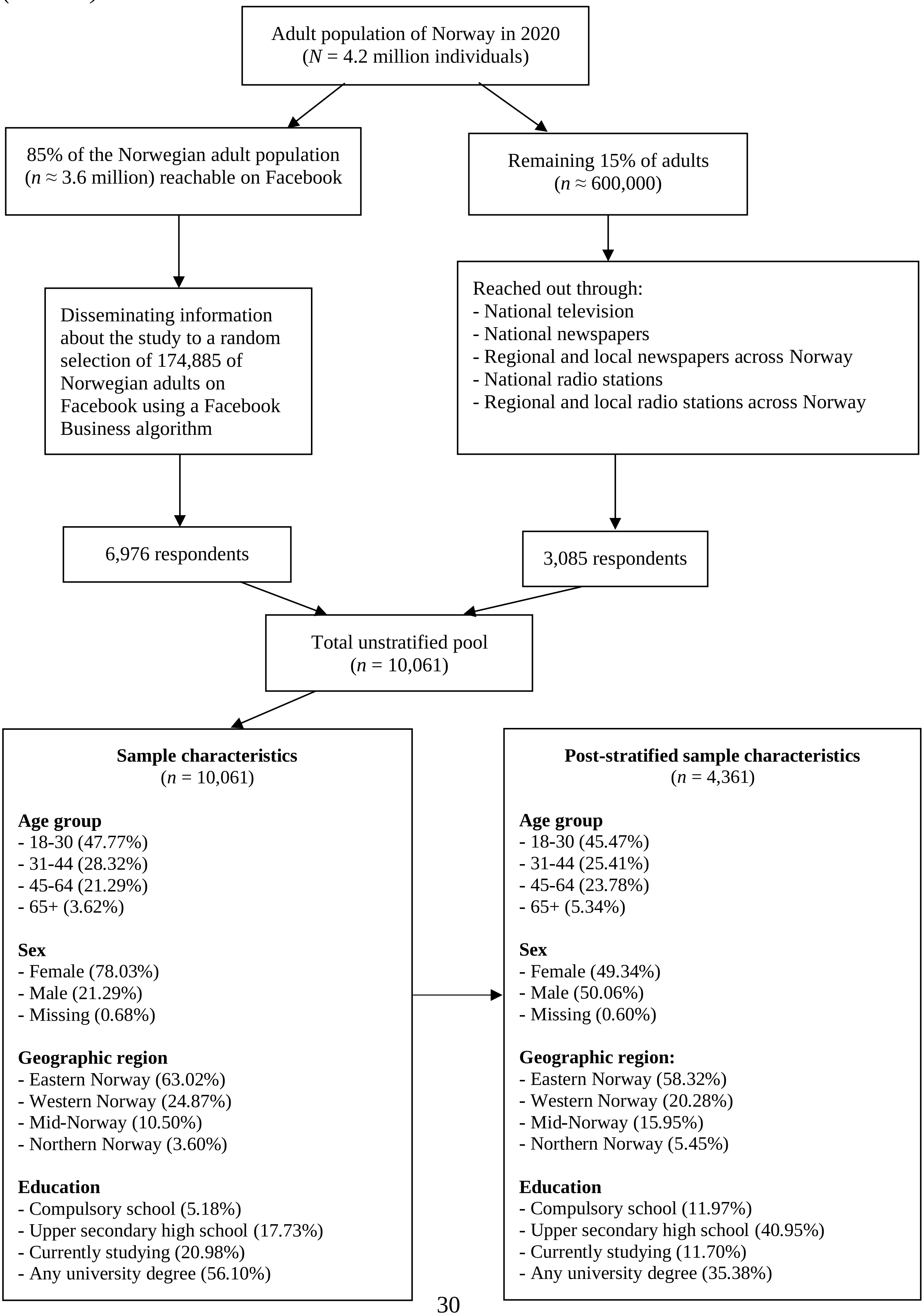
The first strategy involved distributing the survey to a random selection of the pool of Norwegian adults on Facebook using a Facebook Business algorithm relative to the size of the region where the adults resided to provide a geographically representative sample of the country. 85% of the Norwegian adult population (3.6 of 4.2 million) were using Facebook at the time, and the majority of the sample of the MAP-19 study (70%, see Figure 7) were recruited through this strategy (Ebrahimi, Hoffart, et al., 2021).

In attempts to reach the remaining 15% of the adult population not on Facebook, a second group of strategies were systematically employed across a variety of platforms to maximize the opportunity to reach a diverse set of individuals. Specifically, this involved systematically distributing the survey across national, regional, and local information platforms, including television, radio, and newspapers, done by the thesis author together with the other project co-initiators (i.e. Ebrahimi, Hoffart, and Johnson). To provide one example, information about the possibility to participate in the study was broadcasted on the national news channel of Norway (Ebrahimi, Hoffart, et al., 2021).

In sum, 70% of the sample were obtained through a random selection of the adults available on Facebook, while the remaining 30% of the sample were obtained using a wide and systematic dissemination strategy across media platforms. Figure 7 provides the full details of this sampling procedure.

Figure 7

Sampling Procedure of The Norwegian COVID-19, Mental Health and Adherence Project (MAP-19)



After receiving information about the study through the above-mentioned dissemination strategies, the participants formally enrolled in the study by participating in an online survey within the secure Nettskjema-service, with data securely stored in the integrated "Tjenester for Sensitive Data" (TSD; Services for Sensitive Data) hosted by the University of Oslo.

3.5 Stratification of Sample

As with other studies reaching out to a broader population for participation, the survey was susceptible to over- and undersampling of certain demographic subgroups (Cheung et al., 2017). For example, studies have found that females are more likely to participate in health-related research than males (Glass et al., 2015; Ryan et al., 2019). In research focusing on prevalence or estimating the level of symptomatology in a population, such as Study 1 and 2 in this thesis, stratification procedures are critical as they minimize the risk that estimated mean levels are largely driven by certain demographic subgroups which have been oversampled (e.g., females). Ideally, stratification should be done during the sampling procedure, for example by targeting more males than females with a magnitude that is informed by previous literature considering the differences in participation rate between these groups (Arnab, 2017). Such strategies can be implemented with more conventional sampling strategies, such as the obtainment of information from population registries (e.g., addresses and biological sex of individuals) and use of postal services to deploy recruitment letters. However, other sampling strategies (e.g., recruitment through media platforms such as national television) do not enable equal control with respect to targeted recruitment. In such cases, post-stratification strategies are useful to adjust for under- and oversampled characteristics (Glasgow, 2005).

Accordingly, in the longitudinal studies (Study 1 and 2) investigating changes in the mean level of depression, over- and undersampled subgroups were post-stratified to match their respective distributions in the Norwegian population. This was performed by comparing the demographic characteristics of the sample to known occurrences of these characteristics in the Norwegian adult population obtained from The Norwegian Statistics Bureau (The Norwegian Statistics Bureau, 2023a). Characteristics unrepresentative of their occurrence rates in the population (e.g., biological sex) were adjusted through post-stratification, yielding a representative sample for the investigation of mean changes in depression in these studies (Ebrahimi, Bauer, et al., 2022; Ebrahimi, Freichel, et al., 2023).

Study 3 in this thesis did not concern prevalence or means levels of depressive symptomatology, but instead focused on covariances over time. Consequently, the post-stratification procedure was not incorporated in the main analysis of this study. Nonetheless, a sensitivity analysis was conducted on a post-stratified subsample of the participants to investigate the correspondence between the analysis in the main sample and the representative subsample (Ebrahimi, Burger, et al., 2021).

The demographic characteristics of the sample in the three studies of this thesis is presented in Table 3.

Table 3

Demographic Characteristics of the Participants in the Longitudinal Studies (Study 1 and 2) and Intensive Longitudinal Study (Study 3) of This Thesis

Subgroups	**Study 1 & 2: *N* (%)**	**Study 3: *N* (%)**
All	4361 (100%)	1706 (100%)
Sex		
Female	2152 (49.34%)	1336 (78.31%)
Male	2183 (50.06%)	365 (21.40)
Missing	26 (0.60%)	5 (0.29%)
Age, years	(*M* = 37.48, *SD* = 14.81, Range: 18 – 87)	(*M* = 37.30, *SD* = 13.64, Range: 18 – 86)
18-30	1983 (45.47%)	687 (40.28%)
31-44	1108 (25.41%)	554 (32.47%)
45-64	1037 (23.78%)	367 (21.51%)
65+	233 (5.34%)	86 (5.04%)
Missing	0 (0%)	12 (0.70%)
Education level		
Compulsory School	522 (11.97%)	75 (4.39%)
Upper secondary high school	1786 (40.95%)	304 (17.82)
Currently studying	510 (11.70%)	350 (20.52%)
Any university degree	1543 (35.38%)	962 (56.39%)
Missing	0 (0%)	15 (0.88)
Ethnic status		
Non-minority	4136 (94.84%)	1550 (90.86%)
Ethnic minority	225 (5.16%)	156 (9.14%)
Relationship status		
Single or divorced	1765 (40.47%)	876 (51.35%)
In a relationship	2596 (59.53%)	830 (48.65%)
Pre-existing psychiatric diagnosis		
Yes	850 (19.49%)	284 (16.65%)
No	3511 (80.51%)	1422 (83.35%)

3.6 Timeline and Procedures of Longitudinal Studies (Study 1 and 2)

Following the real-time nature of the research to investigate depressive symptomatology during the pandemic and the outlined sampling procedure, the timeline for Study 1 was from March 2020, at the onset of the pandemic, to August 2021, based on data from the first six assessment waves (T1-T6). This period captures the first 17-months of the pandemic and its accompanying SDPs (Ebrahimi, Bauer, et al., 2022).

Study 2 lasted from March 2020 to 2022 and was based on all nine (T1-T9) assessment waves of the MAP-19 project. This 24-month period captures the full social distancing protocol-accompanying period of the pandemic in Norway (Ebrahimi, Freichel, et al., 2023). The assessment period along with number of respondents per assessment wave for both longitudinal studies is provided in Table 2 presented earlier in this text.

Following the design criteria of the project, depressive symptoms and associated risk factors were monitored and measured ensuing all modifications of SDPs in Norway, which on average provided repeated measurements of the participants in the studies every two to four months (average measurement frequency: every 2.88 months).

3.7 Timeline and Procedures of Intensive Longitudinal Study (Study 3)

The longitudinal assessments of long-lasting depressive symptomatology (i.e. experience of symptoms during the past two weeks) over longer timescales (months) in Study 1 and 2 provide the thesis with important information about changes in depressive symptom levels and their associated risk factors over time. To obtain granular insights about the daily experience of symptoms and the day-to-day processes that aggravate these during the pandemic, an intensive longitudinal extension of the MAP-19 project was conducted in Study 3 of this thesis (Ebrahimi, Burger, et al., 2021). At the fourth longitudinal measurement wave of the MAP-19 study (January 2021), the subjects were queried whether they were interested in participating in an intensive longitudinal study about mental health during the pandemic.

Out of the 2,383 subjects expressing interest to participate in the study, a total of 1,706 enrolled in the study.

There are different types of Intensive Longitudinal Designs, such as Ecological Momentary Assessment (EMA), Experience Sampling Method Designs (ESM), and Daily Diary designs (Bolger et al., 2003; Mestdagh & Dejonckheere, 2021; Trull & Ebner-Priemer, 2013). These methods share as a common feature that they involve frequent measuring of participants in their real-life contexts (Mestdagh & Dejonckheere, 2021).

In Study 3, a daily diary study was conducted, where participants were measured with a 24-hour sampling frequency (i.e. once per day; Ebrahimi, Burger, et al., 2021). This daily sampling frequency was selected given its direct relation to the assessment of depressive symptom endorsement in diagnostic manuals, including the DSM-5 (American Psychiatric Association, 2013) and the International Classification of Disorders (ICD-10; World Health Organization, 1993), inquiring about the presence of symptoms during and across days. To exemplify, the symptoms depressed mood and anhedonia (loss of interest or pleasure) are described as needing to be present "most of the day", highlighting the within-day timescale component of these assessments, and "nearly every day", highlighting the across-day (i.e. day-to-day) timescale component of these assessments, which the preregistered design and statistical analyses of Study 3 were matched to (Ebrahimi, Burger, et al., 2021). The study spanned over a 40-day period from February 17 to March 28, 2021, with the 24-hour sampling frequency involving measurements of each participant every evening at 18:30 (06:30 pm).

Intensive longitudinal studies include several important advantages. Frequent measurements in participants' daily lives result in high ecological validity, providing accurate information about behaviours and experiences in day-to-day contexts (Bolger et al., 2003; Trull & Ebner-Priemer, 2013). By assessing shorter intervals of time (e.g., inquiring about experiences over the last day rather than the past month), these designs reduce the impact of recall bias (Bolger et al., 2003; Mestdagh & Dejonckheere, 2021). As outlined in the Statistical Analyses section, together with the multi-level dynamic network models embodied in Study 3, this design allowed for investigation of within- and across-day relationships concerning how symptoms impact each other over time and the extent to which these are aggravated by psychological mechanisms (Ebrahimi, Burger, et al., 2021).

3.8 Quality Control of Data

The data quality was evaluated through the implementation of attention checks (Braitman et al., 2022). This was investigated by adding the following question to the survey, asking participants to “Please provide the response “A little” if you are paying attention to this survey”, with the following response options (1: *Not at all*; 2: *A little*; 3: *Moderately*; 4: *A lot*; 5: *Extremely*). Overall, 97.80% of the participants successfully passed the attention checks. To ensure high data quality, subjects failing the attention checks were omitted from the analysis.

3.9 Measurement

After describing the measurement of sociodemographic factors, the subsequent sections outline the specific measures used in the longitudinal studies and the intensive longitudinal study, respectively.

3.9.1 Sociodemographic Variables

Several sociodemographic variables were provided by the participants at the onset of the project. Age was measured in years. This was subsequently coded into four categories: 0 (18-30 years); 1 (31-44 years); 2 (45-64 years); and 3 (65+ years). Participants provided their biological sex (female; male; other). The ‘other’ category did not include enough respondents to enable investigation of relationships between this variable and the outcomes of interest in the statistical models. Accordingly, data from male and female respondents were used. Educational level was measured through responses to one of the four following categories 0

(Compulsory School); 1 (Upper Secondary High School); 2 (Student); 3 (Any University Degree; Ebrahimi, Bauer, et al., 2022; Ebrahimi, Burger, et al., 2021).

Participants also reported their relationship status, coded into a binary variable with all single respondents across different categories defined as single (coded as 0) and those with a partner categorised as being in a relationship (1). The 'single' category included different variants, such as for example widow(er) and divorced. Similarly, the 'in a relationship' category encompassed several sorts of relationship statuses, such as marriage and domestic partnership. Correspondingly, participants reported their living situation: whether they lived alone (coded as 1) or cohabited with others (0). Subjects further reported their region of residence, which was used to examine the geographic representativeness of the sample, comparing sampled participants from each region to the proportion in the Norwegian population from the specific region (Ebrahimi, Bauer, et al., 2022; Ebrahimi, Burger, et al., 2021; Ebrahimi, Freichel, et al., 2023).

3.9.2 Measurement in Longitudinal Studies (Study 1 and Study 2)

The following measures were used in the longitudinal studies of the present thesis to investigate changes in depressive symptomatology during the two-year pandemic period, their associated risk factors, and adverse future outcomes.

3.9.2.1 Overall Depressive Symptom Severity. Measurement of overall depressive symptom severity was obtained using the Patient Health Questionnaire (PHQ-9; Kroenke et al., 2001). The PHQ-9 is an instrument used for the screening and monitoring of depressive symptomatology. This validated self-report instrument consists of nine items that cover the diagnostic criteria for major depressive disorder as outlined by the DSM-IV (American Psychiatric Association, 1998). The symptoms further match the fifth edition of the DSM (American Psychiatric Association, 2013). The PHQ-9 retrospectively assesses the presence and frequency of depressive symptoms during the last two weeks by inquiring, "Over the last two weeks, how often have you been bothered by any of the following problems?”, before presenting each symptom (Kroenke et al., 2001). Example items include “Feeling down, depressed, or hopeless”, “Little interest or pleasure in doing things”, “Feeling tired or having little energy” and “Feeling bad about yourself – or that you are a failure or have let yourself or your family down”, and “Thoughts that you would be better off dead or of hurting yourself” (Kroenke et al., 2001).

Responses to the specific symptoms are measured on a four-point Likert (0: *Not at all*; 1: *Several days*; 2: *More than half the days*; 3: *Nearly every day*). As per instruction, these scores from the specific symptoms are summed up to provide a total score of depressive severity, ranging from 0 to 27, with higher values denoting greater overall severity.

The PHQ-9 includes validated cut-offs, with scores including and above 10 indicative of a probable depressive state with moderate severity with a sensitivity and specificity of 88% (Kroenke et al., 2001). Consideration of clinically relevant changes in depressive symptomatology was conducted in accordance with the normed guidelines of the scale through changes in the total score in increments of 5 (Kroenke et al., 2001). Starting with scores below 5, considered as negligible or levels of depressive symptoms that are of minimal relevance, changes to scores above 5 indicate moving from insignificant to mild depressive symptoms; with further increments and scores above 10 from mild to the moderate depressive region; and a move from the moderate to severe depressive states with further 5-unit increments and scores above 15 (Kroenke et al., 2001).

Beyond well-established cut-offs for depressive symptom severity and detection of clinically meaningful change, other advantages of the PHQ-9 involve its responsiveness to change for monitoring of symptoms and its validity across different settings such as measurement in the general population, including in Norwegian adults (Dahl et al., 2020; Kroenke et al., 2010; Sun et al., 2020).

In all studies of this thesis, a formally translated version of the PHQ-9 was used, retrieved from The Norwegian Association for Cognitive Therapy, translated by Johnson, Hoffart, Ulvenes, Sexton, and Wampold. The translation of this instrument followed a rigorous translation to back-translation process. In the first step, a Norwegian clinical psychologist and researcher translated the questionnaire from English to Norwegian. In the subsequent step, an independent back-translation was conducted by native English-speaking medical doctor practicing as a psychiatrist in Norway who spoke both languages fluently (Ebrahimi, Bauer, et al., 2022). The psychometric properties of this translated scale have further been demonstrated to correspond to its original English version in Norwegian samples (Wisting et al., 2021).

The internal consistency of the PHQ-9 was excellent across all assessment waves in the studies of this thesis, with Cronbach's α of .88 at T1 and .91 at T2, T3, T4, T5, and T6, .90 at T7, .92 at T8, and .90 at T9.

Importantly, as detailed in the Statistical Analyses section, longitudinal measurement invariance of the PHQ-9 was tested in the sample of participants in this thesis to investigate the instruments appropriateness for the evaluation of mean level changes in depressive symptoms over time during the pandemic (Ebrahimi, Bauer, et al., 2022).

3.9.2.2 Pre-Existing and Concurrent Psychiatric Disorder. At the onset of the pandemic (T1), the presence of a pre-existing psychiatric disorder was measured by asking participants whether they had a formal psychiatric diagnosis as assessed and provided by a healthcare professional. A modified form of the same question, querying about whether participants had received a psychiatric diagnosis as assessed and given by a healthcare professional during the pandemic, was measured at each assessment wave during the project period (i.e. T1-T9). To identify the presence of a novel psychiatric diagnosis arising during the pandemic, participants endorsing this item at T9 (final wave of the study; cf. Study 2 of the thesis; Ebrahimi et al., 2023) who had not reported a pre-existing psychiatric diagnosis were categorised as endorsing the presence of a novel psychiatric condition at T9 (March 2022), two years into the pandemic. This was used to screen for the presence of an arising psychiatric diagnosis in the models predicting forward in time (Study 2).

Such self-reported single-item measurements have previously been used in the literature and further found to be acceptable screeners for assessing mental health disorders (van der Waerden et al., 2015; Veldhuizen et al., 2014).

3.9.2.3 Other Adverse Clinical Outcomes. Beyond assessing depressive symptoms and the presence of a psychiatric diagnosis, psychiatric treatment seeking was measured. This was performed by asking whether participants were seeking treatment for their experienced mental health problems, with the response options allowing specification of the type of mental health difficulty they were seeking treatment for (Ebrahimi, Bauer, et al., 2022; Ebrahimi, Freichel, et al., 2023). These response options included: a) Not seeking any psychiatric treatment; seeking treatment related to b) anxiety difficulties; c) depressive difficulties; d) loss and/or grief; e) loneliness; f) obsessive-compulsive problems; or g) treatment seeking for other psychological problems. This item was measured at the final wave of both Study 1 and 2 (T6 and T9, respectively; Ebrahimi et al., 2022, 2023), with the specific response options further facilitating a specificity analysis (detailed in the Statistical Analyses section) to investigate whether participants experiencing problems with depressive symptoms during the pandemic were more likely of seeking treatment for depressive complaints compared to problems for other internalising (e.g., anxiety) and different disorder domains.

3.9.2.4 Social Distancing Protocols. In Study 1, the association between social distancing protocols and depressive symptomatology was investigated. A detailed list of all SDPs implemented during the study's period (T1-T6) is provided in the study (Ebrahimi, Bauer, et al., 2022). These SDPs were present in Norway during the assessment waves of the study. They are described in this section as they are measured by the study design and part of the systematic measurement protocol that was temporally mapped to modifications of these SDPs. A quantitative measure of SDPs was further measured, reported in the next section (i.e. Oxford Stringency Index). Below, a brief summary of the protocols implemented during the study period is provided.

T1 represented the onset of the pandemic period in Norway (March 2020) and was accompanied by a strict set of SDPs. Examples of T1 SDPs included quarantine for being in contact or suspected contact with individuals infected by SARS-CoV-2, isolation for individuals infected by the virus, closure of day care and educational institutions (e.g., schools, universities), constraints on social contact and gatherings, prohibitions of public activities and events, and restrictions on visitation, international, and domestic travel.

Three months into the pandemic (T2; June 2020), there was a reduction in the severity of the majority of implemented SDPs and discontinuation of several protocols. For instance, domestic travel restrictions were lifted, schools reopened, and public activities and events were re-permitted, enabling a maximum attendance of 200 participants.

Before and throughout the T3 measurement period, representing about eight months into the study period (November 2020), comparable SDPs to those applied at T1 were reintroduced. At T4 (10 months into the study; January 2021), these instated protocols further increased in their severity, with stricter constraints imposed on social contact. In the weeks leading up to the fifth assessment (T5; month 14 in the study; May 2021), the implemented SDPs were reduced in severity. The pandemic mitigation protocols instated during T5 enabled increased opportunities for social contact, visits to restaurants and other public establishments, and alcohol sale. At the last data collection in Study 1 (T6; July-August 2021), approximately 17 months into the pandemic period, many SDPs were discontinued. Examples of the remaining SDPs during this period included limiting the flow of interaction between groups of individuals at restaurants and night clubs by having fixed seating.

During the assessment periods T2 and T6, which correspond to month three and months 16-17 of the study respectively, the reduced severity and discontinuation of many SDPs enabled near-normal social contact (Ebrahimi, Bauer, et al., 2022).

3.9.2.5 The Oxford COVID-19 Stringency Index. Related to the research questions in Study 1 (Ebrahimi, Bauer, et al., 2022), the Oxford COVID-19 Stringency Index was used to obtain a quantitative measure of the strictness level of SDPs implemented in Norway, as provided by the Oxford Coronavirus Government Response Tracker (Hale et al., 2020). This index is based on nine indicators, including 1) school closures, 2) workplace closures, 3) cancellation of public events, 4) closures of public transport, 5) restrictions on public gatherings, 6) stay-at-home requirements, 7) public information campaigns, 8) restrictions on domestic mobility, and 9) international travel restriction. These nine indicators are formed into a composite score with values ranging from 0 (no protocols present) to 100 (strictest response possible). This index thus quantified the stringency of nationally-implemented SDPs over time (Hale et al., 2020).

3.9.2.6 Quarantine Exposure. In Study 1, participants were asked about the number of times they had been in quarantine during the pandemic. Following national guidelines, quarantine exposure was operationalised as being subject to the compulsory stay-at-home orders lasting for a minimum of 10 days due to contact with a SARS-CoV-2 infected person, suspicion of being infected by the SARS-CoV-2 virus, or as pertaining to the rules domestic or international travel (Rotevatn et al., 2022). The frequency of exposure to quarantine was classified into six distinct categories, corresponding to the number of occurrences: 0 (indicating no exposure); 1 (indicating exposure once); 2 (twice); 3 (three times); 4 (four times); and 5 (indicating exposure to quarantine five or more times).

3.9.2.7 COVID-19 Incidence. The weekly incidence rates of SARS-CoV-2 infection in Norway were obtained from the Norwegian Public Health database of infectious disease, also referred to as the Norwegian Surveillance System for Communicable Diseases (MSIS; Norwegian Institute of Public Health, 2023). These incidence rates were subsequently matched with the corresponding response dates of each participant to capture the weekly societal infection rates of COVID-19 during the time-point (i.e. week) the participants responded to the survey at each assessment wave. In Study 1 of this thesis (Ebrahimi, Bauer, et al., 2022), this was used to control for the effect of societal infection rates and included in the model in order to both enable the investigation of the association between SDPs and infection rates with depressive symptoms, each while controlling for the impact of one-another and other variables included in the model.

3.9.2.8 Information Obtainment Preference. Pertaining to Study 1, subjects reported their preferred source for information acquisition, queried to provide their favoured platform in obtaining information about the ongoing COVID-19 pandemic (Ebrahimi, Bauer, et al., 2022). Information platforms were subsequently formed into two categories, with recognised and source-checked national, regional, and local radio, television channels, and newspapers coded as 0 (source-verified information platform preference). Sources not subject to press regulations and source-verification including social media platforms (e.g., Snapchat, TikTok, Instagram), online blogs and forums, and pandemic information preference from family, friends or peers were coded as 1 (unmonitored information platform preference).

3.9.2.9 Frequency of Information Obtainment. After identifying a link between type of platform used to obtain information about the pandemic in Study 1, frequency of information obtainment was measured to investigate whether excessive information seeking behaviour could be related to adverse depressive change profiles during the pandemic in Study 2 (Ebrahimi, Freichel, et al., 2023). This was assessed by asking participants about the extent of information retrieval about the pandemic situation on an 8-point Likert scale (0: *Not at all* to 7: *Multiple times per hour*). Participants reported their frequency of information obtainment across six sources, including news on 1) television, 2) radio, 3) newspapers, 4) social media, 5) forums, blogs and other online sources outside social media, and 6) other sources (Ebrahimi, Freichel, et al., 2023). These categories were based on investigations of commonly reported sources to obtain information about the pandemic (Statista, 2020), with a composite score calculated as an indicator of the overall extent of information obtainment behaviour.

3.9.2.10 Binge Drinking. Change in alcohol consumption patterns during the pandemic was measured by querying about whether and to what extent participants were consuming more or less alcohol compared to before the pandemic period (defined as before March 2020 for the specific Norwegian population). Based on existing studies (e.g., Schmidt et al., 2021), this variable was measured with the following response options: "I do not drink alcohol"; I consume: "much less than compared to before the pandemic"; "less than compared to before the pandemic"; "neither more or less compared to before the pandemic"; "a little more than compared to before the pandemic"; "moderately more than compared to before the pandemic"; and "much more than compared to before the pandemic". This variable was categorised into the binge drinking variable used in Study 2 of this thesis (Ebrahimi, Freichel, et al., 2023), with participants reporting that that they had increased their alcohol intake "much more than compared to before the pandemic" being coded as individuals showing substantial increases in their alcohol consumption patterns during the pandemic.

3.9.2.11 Financial and Occupational Concerns. Inspired by the General Anxiety Disorder-7 instrument (GAD-7; Spitzer et al., 2006), the item "Worrying too much about different things" was modified for increased accuracy to capture specific worries accompanying the pandemic period. These items were enquired in the context of the pandemic situation and included worry about job loss ("I am worried about losing my job") and financial worries ("I am worried about my financial situation"). Both variables were measured using the same response scale as the GAD-7 (Spitzer et al., 2006), measured on a four-point Likert (0:

Not at all; 1: *Several days*; 2: *More than half the days*; 3: *Almost every day*). To capture general concerns about one's finances and occupational situation, a composite score was created from these variables (ranging from 0 to 6; higher scores indicating greater financial and occupational concerns), used as a contextual stressor and predictor of longitudinal depressive change patterns in Study 2 (Ebrahimi, Freichel, et al., 2023).

3.9.2.12 Physical Activity. The frequency of physical activity was measured, with physical activity defined as activities lasting for a minimum of 30 minutes and leading to at least light sweat or increased pulse. This followed the definition of previous single-item measurements of physical activity (Payne et al., 2010; Stults-Kolehmainen & Sinha, 2014). Following this definition, participants reported the number of times they had engaged in physical activity during the past two weeks to provide an indication of longer-term engagement in physical activity.

3.9.3 Measurement in Intensive Longitudinal Study (Study 3)

3.9.3.1 Assessment Challenges in Intensive Longitudinal Studies. Intensive longitudinal studies include several advantages, including high ecological validity and mitigation of recall bias (Bolger et al., 2003; Mestdagh & Dejonckheere, 2021; Trull & Ebner-Priemer, 2013). Nonetheless, there are also several notable measurement issues that accompany such studies (McNeish et al., 2021). Given the frequent nature of assessments in intensive longitudinal studies compared to traditional assessments (e.g., conducting daily measurements instead of measurements every three months), distributed surveys must be brief and fast to respond to in order to minimise the time-burden on respondents (Bolger et al., 2003). The rationale for such brief assessments is further to increase ecological validity and compliance by having respondents to complete as many as possible of the distributed diaries, with lengthy assessments being at risk of creating sample selection bias toward individuals who are able to fit them into their daily lives (e.g., conscientious individuals, those with more spare time;

Bolger et al., 2003; Smyth et al., 2021; Stone et al., 2023). To mitigate these issues, distributed surveys are abbreviated, both in number of items, and in the length of the items (Stone et al., 2023). Specifically, most intensive longitudinal studies often rely on single-item measurements to capture phenomena of interest (Mestdagh & Dejonckheere, 2021). While these practices add to the ecological validity of intensive longitudinal designs, they have also resulted in a literature that is predominantly lacking validated measurements (Degroote et al., 2020; Stone et al., 2023). As such, a frequently raised criticism of intensive longitudinal studies concerns the use of non-validated or self-constructed items, with criticism concerning whether these single item measures align to a satisfactory extent with the constructs of interest (Song et al., 2023).

Study 3 was designed to mitigate these issues. This was done by selecting the majority of items used in the intensive longitudinal study (i.e. to the extent possible, where validated instruments of the constructs of interests existed) from well-known and validated instruments (e.g., Patient Health Questionnaire-9, UCLA Loneliness Scale-8), further identified as reliable measures in their full scale form in the same group of participants measured in other studies from the MAP-19 project (e.g., Ebrahimi, Hoffart, et al., 2021; Hoffart et al., 2020; Solbakken et al., 2023).

This was performed using the following strategy. Given availability of the full validated instruments at previous time-points (i.e. in the longitudinal studies) in the same group of participants that were part of the intensive longitudinal study, the correlation between the items selected for intensive assessment and the respective full scale it was retrieved from was examined in order to ensure a strong overlap between the single-item retrieved and the construct of interest. Specifically, questions selected as single-item indicators of the construct had to reveal a minimum correlation of $r > .70$ to be included in Study 3 (Ebrahimi, Burger, et al., 2021).

3.9.3.2 Item Selection Procedure. Several issues require consideration in designing (dynamic) network studies when selecting which items to measure and include in networks. One issue concerns the topic of topological overlap, where the inclusion of conceptually overlapping items (such as for instance “feeling sad” and “feeling down”) can distort and inflate centrality estimates (McNally, 2021). Items that are near-identical (i.e. overlap too extensively) superficially drive up the centrality of a given node in a network, due the high correlation they reveal with their corresponding overlapping items (McNally, 2021). Accordingly, an important aim in the network analytic literature is to mitigate the potential for topological overlap in the item selection and network construction procedure (de Vos et al., 2021; Levinson et al., 2018). This was done in the following ways in the relevant study (Study 3) of this thesis (Ebrahimi, Burger, et al., 2021).

First, during the design phase (i.e. before data collection), five meetings were held between three clinical scientists with experience in the network analytic field. The meetings were held to discuss which items were most appropriate to capture a) depressive symptoms experienced during pandemics, and b) the psychological mechanisms which may be related to these symptom fluctuations. The suggested mechanistic variables were all derived from specific transdiagnostic and disorder-specific theories of psychopathology, such as the metacognitive model of psychopathology and the learned helplessness model for depression (e.g., Miller & Seligman, 1975; Wells & Matthews, 1996). During this process, all suggested items were evaluated by the team for their potential topological overlap, attempting to maintain unique constructs, while balancing the overall number of variables measured to reduce participant burden in the study. Once the data were collected, this theoretical selection procedure was followed up by investigating the presence of possible topological overlap empirically using three common strategies. First, this was done by inspecting whether the correlation matrix of the items included in the networks was positive definite and that the items were not linear combinations of each other (Bernstein et al., 2019; Blanchard et al., 2021; Skjerdingstad et al., 2021). Following this, the goldbricker algorithm was employed to identify pairings of items that exhibited strong correlations with each other, as well as inspections of whether items demonstrated overlapping patterns to other items within the network (Jones, 2023). Finally, the Hittner method (Hittner et al., 2003) was used to investigate dependent correlations. These analytical techniques detected no overlapping or problematic items in the present study, being in agreement with the theoretical selection of the variables during the design stage of the project (Ebrahimi, Burger, et al., 2021).

3.9.3.3 Depressive Symptoms. Following guidelines of intensive longitudinal research to minimize participant burden by providing brief daily diary surveys (e.g., Degroote et al., 2020), four items were retrieved from the validated PHQ-9 (Kroenke et al., 2010). These four items included the core symptoms of depression in the DSM-5 and ICD-10 (i.e. depressed mood and anhedonia; American Psychiatric Association, 2013; World Health Organization, 1993), in addition to lethargy (low energy) and reduced self-worth which were found to be relevant during the pandemic in previous cross-sectional studies (Skjerdingstad et al., 2021; Zhao et al., 2021). The items were adapted to a daily response format by changing the statement "Over the last 2 weeks" to "Today". As an illustration, the item "Over the last 2 weeks, how often have you been bothered by little interest or pleasure in doing things" was adapted to "Today, I had little interest or pleasure in doing things". Specifically, the following items were retrieved from the PHQ-9, with the correlation of each item with the full instrument at the baseline of the study (T1) in the same group of participants provided in parenthesis. Anhedonia (adapted from PHQ item one) was measured with the item "Today, I had little interest or pleasure in doing things" (correlation with full PHQ-9 scale at T1; $r = .77$). Depressed mood (PHQ item two) was measured with "Today I have been feeling down, depressed or hopeless" ($r = .81$). Lethargy (PHQ item four) was measured with the item "Today I felt tired or that I had little energy” (r = .72), and Worthlessness (PHQ item six) with the item “Today I felt bad about myself or felt like a failure” (r = .76).

Following Fried et al. (2022), we modified the response scales of the validated instruments in the present study to extend them from a range of 0 to 3 (4-point scale) to 1 to 5 (5-point scale), enabling estimation using the multi-level vector autoregressive model (detailed in the Statistical Analyses section). This five-point Likert scale measuring each of the depressive symptoms included the response options 1 (*Not at all*); 2 (*Slightly*); 3 (*Moderately*); 4 (*Very*); and 5 (*Extremely*). Retaining a Likert-scale format was chosen in Study 3 both to be able to compare results to other pandemic intensive longitudinal studies using the same response scale (Fried et al., 2022), in addition to retain the familiarity with the scales for the participants who had provided data at four standard longitudinal waves (T1-T4) with the same type of response options (e.g., Likert cf. PHQ-9) prior to participation in this intensive longitudinal study.

3.9.3.4 Psychological Mechanisms. Helplessness was measured with the item “Today I felt helpless with regard to my problems” from the Therapy Process Questionnaire (TPQ), a validated scale specifically made for high-frequency monitoring of psychological mechanisms (Schiepek et al., 2019). Similarly, emotion regulation difficulty was measured with the item “Today it has been difficult to cope with my emotions”. Rumination was measured by querying “Today I have thought negatively about things that have happened in the past” which was adapted to a daily response format from the Worry and Rumination Questionnaire and the short version of the Ruminative Response Scale (Parola et al., 2017; Roelofs et al., 2006). These items were all measures on a five-point Likert scale (1*: Not at all*; 2: *Slightly*; 3: *Moderately*; 4: *Very*; and 5: *Extremely*).

3.9.3.5 Contextual Factors. Related to the concomitant uncertainties of the pandemic, several contextual variables particularly relevant during pandemics were measured, including perception of receiving sufficient information to cope with the pandemic (Suh et al., 2022), which was measured with the item “Today I find that I have received enough information on how to deal with the pandemic and its associated protocols”.

Additionally, variables that could potentially have been accentuated during pandemic periods (e.g., due to distancing protocols) were measured (Goodwin et al., 2020; Lederman, 2023; Solbakken et al., 2023), including loneliness through the item: “Today I felt lonely”, interpersonal conflict: “Today I argued or had negative discussions with someone”, and relatedness: “Today I have been feeling close to other people”, with the latter measured item adapted from the short version of the Warwick–Edinburgh Mental Well-being Scale (SWEMBS, item six; Tennant et al., 2007). The full SWEMBS was further available at the baseline assessment of the MAP-19 study (T1), with the correlation between the retrieved item to measure relatedness and the full scale being r = .73.

The contextual changes accompanying the pandemic (e.g., working from home) have also been related to disruptions in daily routine and sleep for some individuals (e.g., Xiao et al., 2021). Accordingly, productivity was measured with the item “Today I felt productive or useful” from the SWEMBS (item two; correlation with full scale, r = .76), and sleep through the item “Today I was dissatisfied with my sleep” adapted from Bergen Insomnia Scale (item six; correlation with full scale, r = .86).

All items mentioned so far in this subsection were measured using the same five-point Likert scale (1: *Not at all*; 2: *Slightly*; 3: *Moderately*; 4: *Very*; and 5: *Extremely*) to match the response scale of the other measured constructs in the intensive longitudinal study (Ebrahimi, Burger, et al., 2021).

Related to the disruptions of in-person social activities due to pandemic restrictions and increased online social activity and social media use for many (Cho et al., 2023; Ong et al., 2021), the following items were measured. Offline and online social contact were measured through the items "Today I used … minutes/hours on physical social gatherings (i.e. meeting others face-to-face, offline)" and "Today I used … minutes/hours on digital social gatherings", respectively. Given previous investigations highlighting differences in types of media use, and finding passive usage to be more detrimental than active use (Escobar-Viera et al., 2018), passive social media use was measured using the item "Today I spent … minutes/hours scrolling on social media just to make the time pass". These three time-dependent variables were also measured on a 5-point scale to match the other scales of the study and Fried et al. (2022). The response scale was: 1 (*0 minutes*); 2 (*1-15 minutes*); 3 (*15-60 minutes*); 4 (*1-2 hours*); 5 (*Over 2 hours*).

3.9.3.6 Daily Physical Activity. Following previous studies using single-item measurements of exercise (Payne et al., 2010; Stults-Kolehmainen & Sinha, 2014), daily physical activity was measured with the item "Today I spent … minutes/hours physically exercising to the extent that this led to increased pulse or at least minimal sweating". Continuing to follow the response options used by Fried and colleagues (2022), this item was measured on a 5-point scale with the options: 1 (*0 minutes*); 2 (*10 - 15 minutes*); 3 (*15 - 30 minutes*); 4 (*30 - 60 minutes*); 5 (*Over 1 hour*).

3.10 Statistical Analyses

Study 1 and 2 concerned the evaluation of changes in overall depressive symptom levels, which was investigated using a longitudinal structural equation modelling approach. Study 3 investigated the extent to which fluctuations in specific symptoms of depression could be predicted by previous states of these symptoms and key psychological mechanisms, employing a dynamic network approach. These statistical approaches are outlined below.

3.10.1 Longitudinal Structural Equation Modelling

Structural Equation Modelling (SEM) is a widely used statistical framework in the health and social sciences (e.g., Beran & Violato, 2010; Goldberger, 1972; Jöreskog, 1970).

This framework consists of two main components: a measurement and a structural model. The measurement part involves estimation of latent constructs from observed variables, while the structural part is equipped with the ability to examine the relationship between latent (as well as other observed) variables through regression analysis (Bollen et al., 2010). The incorporation of a measurement model thus presents the SEM with significant benefits over standard regression analyses as this allows accounting for measurement error (Beran & Violato, 2010).

Moreover, SEM is a multivariate analytic technique, allowing for the estimation of all parameters in a model simultaneously. This enables an understanding of the different variables in the model in the context of (i.e. while controlling for) all other variables in the model (Bollen & Noble, 2011). The structural modelling framework further permits an examination of a key issue that arises when assessing constructs (i.e. depression) in a longitudinal setting, namely the issue of measurement invariance over time (e.g., Widaman et al., 2010).

3.10.1.1 Considerations for Longitudinal Research: Measurement Invariance. Measurement invariance is a critical topic in longitudinal research which is often neglected (Liu et al., 2017; Van De Schoot et al., 2015). Put colloquially, in the context of the present thesis investigating changes in depression over time, examining measurement invariance allows an inspection of whether the mean-level changes in the PHQ-9 over time actually reflect changes in depression, and not for example changes in interpretative tendencies (differences in how items are interpreted) over time (Putnick & Bornstein, 2016).

More technically, longitudinal measurement invariance concerns assessment of the psychometric equivalence of the construct measured by a specific instrument across different time-points (Putnick & Bornstein, 2016). To evaluate whether change has occurred in a construct, it is important to know that the instrument used is consistently measuring the same construct over time. Moreover, in using a total score of depression over time, several implicit assumptions are evoked, including equivalence of measurement and equal weighting of items across different time-points (McNeish & Wolf, 2020). Accordingly, the appropriateness of these assumptions and the consistency of the PHQ-9 instrument over time was investigated in Study 1 (Ebrahimi, Bauer, et al., 2022) through the steps outlined below.

First, configural invariance was tested (Putnick & Bornstein, 2016). This is the first and most basic level of invariance which involves investigating the factor structure at each assessment wave, reflecting whether the nine indicator items of the PHQ-9 scale are measuring the same factor (i.e. depression) over time. As an example, if the same items of PHQ-9 measure the latent factor depression at assessment wave 1 and 2, and so forth, then configural variance has been demonstrated. Second, metric invariance examines the extent to which factor loadings are equal over time (Putnick & Bornstein, 2016). This reflects whether the strength of the relationship between the items of the questionnaire and the underlying latent construct is the same across the different assessment waves, indicating that the items are invariant in how representative they are of the underlying latent construct at each time point. This suggests that the items of the scale contribute equally (i.e. invariably) to the measurement of depression over time. Finally, scalar invariance was tested to check invariance in item intercepts across time. This enables a valid comparison of depression scores over time, ensuring that these are not subject to bias by shifting baselines.

In sum, investigating measurement invariance over time provides insight about the appropriateness in interpreting changes in scores on a scale over time (i.e. PHQ-9) as actual changes in the measured construct (i.e. depression). As detailed in Supplementary Document 2 of Study 1, longitudinal measurement invariance for the PHQ-9 was demonstrated to support its appropriateness for the investigation of mean level changes in depression over time in this sample (Ebrahimi, Bauer, et al., 2022).

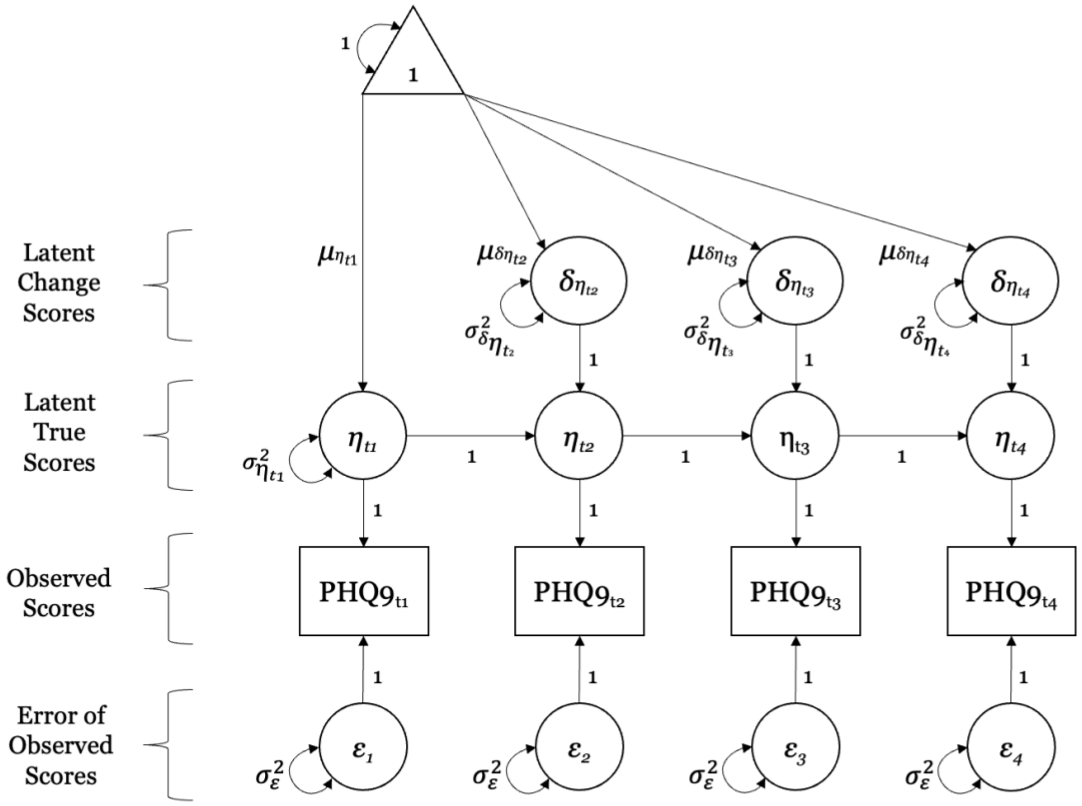
3.10.1.2 Latent Change Score Models. One type of SEM that is particularly suitable for modelling change over time is the Latent Change Score Model (LCSM; Grimm et al., 2016;

Mcardle, 2001; McArdle & Hamagami, 2001). In Study 1 and 2 (i.e. as a step toward constructing a mixture model in Study 2, to be detailed in the next section), the LCSM was employed to investigate changes in depressive symptomatology during the pandemic period (Ebrahimi, Bauer, et al., 2022; Ebrahimi, Freichel, et al., 2023). Given that the LCSM involves the modelling of within-person and time-dependent change (Grimm et al., 2016), this approach integrates strongly with the design of the MAP-19 project, aiming to investigate when critical changes in depressive symptom levels occur during the pandemic at the individual and population level, and to what extent these changes are related to variations in the pandemic's social distancing protocols. As a SEM model, through the estimation of change scores as latent factors, the LCSM accounts for measurement error in observed scores to reduce bias and increase power to detect true effects (Kievit et al., 2018).

To explain the components of the LCSM, an illustrative figure (Figure 8) is provided, highlighting how such a model would look with four assessment waves (instead of six or nine waves, cf. Study 1 and 2, for simplification purposes).

Figure 8

An Illustration of the Unconditional Latent Change Score Model (LCSM) and its Estimated Parameters



Note. Covariances between η_{t1} and the latent change scores $\delta\eta_{t2}$ to $\delta\eta_{t4}$ are omitted from the figure to enhance visualization.

Prior to the introduction of covariates, an unconditional LCSM (Figure 8) is estimated to examine change in the outcome over time and whether this non-linear model presents a suitable functional form of the data. The LCSM examines population-level and individual differences in change over time. As portrayed in Figure 8, the model has four different layers of components: the observed scores at each time-point ($PHQ9_{t1}$ to $PHQ9_{t4}$), the measurement error of these observed scores (ε_1 to ε_4), latent true scores derived from the observed scores (η_{t1} to η_{t4}) which are free of measurement error, and the latent change scores ($\delta\eta_{t2}$ to $\delta\eta_{t4}$).

Note that several paths and factor loadings are fixed to 1 and that the intercepts of the observed scores ($PHQ9_{t1-t4}$) are fixed to 0, simplifying the equations below. The model starts by partitioning the variability in the observed score of depression ($PHQ9_{t1}$) into a latent true score (η_{t1}) and error component (ε_1):

$$PHQ9_{t1} = \eta_{t1} + \varepsilon_1$$

This enables estimation of the mean and variance for the latent variable η_{t1}, the measurement error free initial level of the construct, which in this thesis is depressive symptoms at the onset of the pandemic period (T1). Two parameters are tied to η_{t1}, $\mu\eta_{t1}$ and $\sigma^2\eta_{t1}$. $\mu\eta_{t1}$ provides the average level of depressive symptoms at T1. $\sigma^2\eta_t$ yields the individual differences (i.e. the variance) around this measurement error free latent intercept, revealing to what extent there were individual differences in depressive symptom levels at the onset of the pandemic. Latent levels of depressive symptoms are further present for each time-point (T1-T4), as represented by the η_{t1} to η_{t4} variables. The latent true scores, η_t, are all connected to the observed scores of depression as measured through the validated PHQ-9 instrument, $PHQ9_{t1}$ to $PHQ9_{t4}$, with the observed scores reflecting these latent true scores of depressive symptoms in addition to the error associated with measurement, ε_1 to ε_4.

This lays the foundation for the main purpose of the LCSM, which is to estimate latent levels of *change* over time. This change is obtained through a second layer of latent variables ($\delta\eta_{t2}$ to $\delta\eta_{t4}$). Notably, there is no $\delta\eta_{t1}$, as the $\delta\eta_t$ variable aims to capture change occurring from one time-point to the next, and only one time-point is available at the baseline of the study. As such, starting from $\delta\eta_{t2}$, the model obtains the time-dependent change between all adjacent time-points (i.e. between T1 and T2 with $\delta\eta_{t2}$; between T2 and T3 with $\delta\eta_{t3}$; and between T3 and T4 with $\delta\eta_{t4}$). The change scores $\delta\eta_{t2}$ to $\delta\eta_{t4}$ are latent, thereby also being measurement-error free. The latent change scores are also accompanied by a mean ($\mu\delta\eta_{t2}$ to $\mu\delta\eta_{t4}$) and variance estimate ($\sigma^2\delta\eta_{t2}$ to $\sigma^2\delta\eta_{t4}$), which respectively estimates the degree of change that has occurred at each time-point and the extent to which there were individual differences in such change patterns. Starting from time-point two (T2; once time has elapsed and change is possible to estimate), the measurement-free mean level of the construct (i.e. depression) at each time-point, for instance for T2, is then given by the following formula:

$$\eta_{t2} = \eta_{t1} + \delta_{\eta_{t2}}$$

This highlights the dependency of the latent mean levels of depression at a given time-point (in the above example; T2) being based on the latent levels of depression at the previous time-point (η_{t1}) and the latent change occurring between T1 and T2 ($\delta\eta_{t2}$).

Covariances between initial status (η_{t1}) and all change scores ($\delta\eta_{t2}$ to $\delta\eta_{t4}$) are further incorporated in the model, omitted from Figure 8 to enhance visualisation. As an additional piece, a comprehensive guide to the LCSM and its parameters was provided in Supplementary Document 2 of Study 1 in efforts to mitigate the scientist-practitioner gap and increase the accessibility of the findings and understanding of the model. In general, throughout all studies and analytical techniques of this thesis, either detailed methods sections, supplementary materials describing the methods, or accompanying step-by-step code were added toward this aim.

The fit of LCSMs follow that of other SEMs, using the χ^2 goodness-of-fit index, Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA), and the Standardized Root Mean Squared Residual (SRMR). Following the conventions by Hu & Bentler (1999), good model fit was determined by RMSEA ≤ 0.05, TLI ≥ 0.95, CFI ≥ 0.95, and SRMR ≤ 0.05.

This forms all the core components and evaluation criteria of the LCSM, allowing the investigation of change patterns in depressive symptomatology across the pandemic in Study 1 and 2. In Study 1, this model was expanded into a conditional LCSM, where predictors (e.g., age, sex, as detailed in the Measures section) are brought in to predict the initial levels of depressive symptoms (η_{t1}) in addition to subsequent changes occurring in depressive symptomatology ($\delta\eta_t$) across the pandemic period, while controlling for all other covariates in the model (Ebrahimi, Bauer, et al., 2022).

3.10.1.3 Mixture Models. Building on Study 1, after estimating the overall population-level of change in depressive symptoms and finding support for the presence of individual differences (within-population heterogeneity) in these change patterns, a mixture model was used in Study 2 to extend on the functional form of the described LCSM in order to identify prototypical patterns of change in depressive symptoms (i.e. different depressive response patterns) during the pandemic period. This is done by estimating a Latent Change Score Mixture Model (LCSMM; Ebrahimi et al., 2023).

In longitudinal settings, a mixture model represents a statistical method aimed at identifying subgroups within the population and describe longitudinal change within each of these subgroups (e.g., Bauer, 2011; DeSarbo & Cron, 1988; Muthén & Shedden, 1999; Nagin, 1999). This yields a discrete number of groups with distinctive and unique depressive symptom response patterns during the pandemic. Mixture models are suitable when heterogeneity is expected in the population (or in the context of the present thesis, where heterogeneity was empirically identified in Study 1), but the number of subgroups within the population are not known a priori (Bauer, 2011). The LCSMM model brings with it the advantages of the LCSM, including its ability to capture nonlinear change patterns, in addition to having augmented power to detect true effects through the estimation of latent scores free of measurement error (Grimm et al., 2016; Kievit et al., 2018; McArdle & Hamagami, 2001).

Once the functional form of change over time is identified, which in the present thesis represents non-linear change patterns revealed by the LCSM, the next step involves sequentially estimating a series of mixture models (LCSMMs). This procedure is performed to identify the number of subgroups (i.e. latent classes) displaying differential depressive response patterns in the population over time during the pandemic.

3.10.1.3.1 Class Enumeration. To inform the optimal number of classes, several statistical and substantive class enumeration guidelines were followed. These are elaborated in detail in Study 2 (Ebrahimi, Freichel, et al., 2023). Briefly, model solutions were inspected for their substantive meaningfulness and their correspondence with previous literature (Nylund-Gibson & Choi, 2018). To encourage selection of a parsimonious model balancing between fit and complexity, information criteria (e.g., Bayesian Information Criterion; Akaike Information Criterion) were used (Nylund et al., 2007). To facilitate the recovery of robust and substantively meaningful classes, minimum class size was set to 5%, and only models where the log-likelihood could be replicated across random initiations were considered (Andruff et al., 2009; Nylund-Gibson & Choi, 2018). Moreover, given the aim of bringing in external variables by both predicting latent classes as well as using the latent classes as predictors to better understand their impact on future outcomes, high entropy was favoured in model selection, which yields models with high class separation. This reflects higher distinctiveness of the latent classes and thus less ambiguity in relating the classes to its predictors and distal outcomes (Desarbo et al., 1992; Nylund-Gibson & Choi, 2018).

3.10.1.3.2 Predictors and Distal Outcomes of Latent Classes. A central aim in Study 2 was to understand the risk factors predicting each depressive response pattern. To identify factors predictive of these latent classes, the maximum likelihood-based three-step procedure by Vermunt (2017) was performed. This method employs a multinomial regression of class membership as predicted by the described sociodemographic variables and contextual risk and protective factors.

A second aim of Study 2 concerned investigating how the distinct depressive symptom response patterns (i.e. latent classes) predicted future adverse clinical outcomes, including psychiatric treatment seeking and reported psychiatric diagnosis. This was performed through the three-step procedure of Bolck, Croon & Hagenaars (2004) as extended by Vermunt (2017). Key advantages accompany these three-step approaches, including eliminating the potential for class distortion when external variables are introduced, while simultaneously accounting for uncertainty present for class membership to mitigate bias from classification error.

In other words, these approaches to modelling external variables result from state-of-the-art guidelines in the field following discussions about when it is optimal to include external variables in the model, with simulation studies highlighting it appropriate to include external variables in a separate step (Nylund-Gibson & Masyn, 2016) as outlined in the procedures above.

3.10.1.4 Missing Data. All SEM models (including the mixture extension in Study 2) involved Full Information Maximum Likelihood (FIML) estimation. Maximum likelihood estimation is regarded as the state-of-the-art approach in cases of missing data (Baraldi & Enders, 2010). This approach permits the inclusion of all available data in the analysis, including records with partial missing data, and is shown to effectively reduce bias and increase statistical power in comparison to complete-case analysis (Baraldi & Enders, 2010).

3.10.2 Multi-Level Dynamic Network Modelling

In Study 3, a multi-level dynamic network model was estimated to investigate the within-person relationships between symptoms and psychological mechanisms within- and across days over a 40-day period. These dynamic networks were derived from the lag-1 multi-level (graphical) vector autoregressive model (mlVAR; Bringmann et al., 2013; Epskamp et al., 2023; Epskamp, Waldorp, et al., 2018). The term multi-level highlights the model's ability to separate within-person and between-person effects. The mlVAR model outputs three networks, a temporal, contemporaneous, and a between-subject network (Epskamp, Waldorp, et al., 2018). Each of these networks includes a set of nodes (i.e. variables; portrayed as circles) and edges (lines) which reveal the statistical relationships between these nodes. Positive statistical relationships are often, and in this thesis, visualised as blue edges, while negative relationships are represented by red edges (Epskamp, Waldorp, et al., 2018). Two of the three mentioned networks (the temporal and contemporaneous) model within-person effects (Borsboom et al., 2021), with the associations among symptoms and between symptoms and psychological mechanisms in these networks being the primary focus of Study 3 in this thesis.

The three networks resulting from the mlVAR model are obtained through a two-step estimation approach (Epskamp, Waldorp, et al., 2018). To exemplify the components in each of these networks, an illustrative formula (Burger et al., 2022) is provided with three example variables, $DM_{t,p}$, $H_{t,p}$, and $WL_{t,p}$, representing depressed mood, helplessness, and worthlessness at timepoint t for a person p, respectively. In this example, depressed mood ($DM_{t,p}$) is used as the node which is to be estimated as a function of itself and the other variables ($H_{t,p}$ and $WL_{t,p}$), with the calculation following the same procedure for each node in the dynamic network model. Before estimation begins, all variables are standardised to *z*-scores (Burger et al., 2022). Variables are lagged to distinguish between the variables at the current time-point (t) with the value of these variables at the previous time-point ($t-1$; i.e. the lagged variables). For the separation of between and within-person variances, the lagged variables used as predictors (i.e. the variables at the previous time-point, $t-1$) are within-person centered (Hamaker & Grasman, 2015):

$$\widetilde{DM}_{t-1,p} = DM_{t-1,p} - \overline{DM}_p$$

Within-person centering is performed by subtracting person p's average score (across time) on depressed mood ($\overline{DM}_p$) from their score on depressed mood at a specific time-point. Here, $\widetilde{DM}$ denotes the within-person centered variable, while $\overline{DM}$ denotes the person-specific mean of depressed mood. Once the variables have been within-person centered, the first step of the mlVAR algorithm computes a (within-person) temporal network and a between-subject network through node-wise multi-level regression derived by the following formula per node, using the depressed mood node ($DM_{t,p}$) as an example:

$$DM_{t,p} = \beta_{0p} + \beta_{11p}^{(T)} \cdot \widetilde{DM}_{t-1,p} + \beta_{12p}^{(T)} \cdot \widetilde{H}_{t-1,p} + \beta_{13p}^{(T)} \cdot \widetilde{WL}_{t-1,p}$$
$$+ \beta_{12}^{(B)} \cdot \overline{H}_p + \beta_{13}^{(B)} \cdot \overline{WL}_p + \varepsilon_{tp}^{(DM)}$$

Here, $DM_{t,p}$ represents depressed mood at timepoint t for person p, with the within-person centered lagged variables $\widetilde{DM}_{t-1,p}$, $\widetilde{H}_{t-1,p}$ and $\widetilde{WL}_{t-1,p}$, and the person-specific means $\overline{H}_p$ and $\overline{WL}_p$ serving as the predictors. The temporal network is constructed based on the $\beta^{(\mathrm{T})}$ parameters, while the $\beta^{(\mathrm{B})}$ parameters are used to create the between-subject network (Epskamp, Waldorp, et al., 2018).

In the second step of the estimation, within-person contemporaneous effects are calculated by conducting multi-level node-wise regressions on the residuals resulting from step one (Epskamp, Waldorp, et al., 2018):

$$\hat{\varepsilon}_{tp}^{(\mathrm{DM})} = \beta_{12p}^{(\mathrm{C})} \cdot \hat{\varepsilon}_{tp}^{(\mathrm{H})} + \beta_{13p}^{(\mathrm{C})} \cdot \hat{\varepsilon}_{tp}^{(\mathrm{WL})} + \zeta_{tp}^{(\mathrm{DM})}$$

Here, $\hat{\varepsilon}_{t,p}$ represents residual term for each variable, and the $\beta^{(\mathrm{C})}$ parameters are used to construct the contemporaneous network.

The fixed-effect temporal network reveals directed statistical relationships, visualised through one-headed directed arrows, specifically embodying the average within-person (i.e. average intraindividual) autoregressive and cross-lagged parameters (Epskamp, Waldorp, et al., 2018). The autoregressive parameter refers to a node's (at time-point $t-1$) predictive effect on itself at the consecutive time-point (t), while the cross-lagged parameters reflect a node's (at time $t-1$) predictive effect on other nodes at the next time-point (t), respectively. The edges in the temporal network are regression coefficients. These directed edges represent Granger-causal relationship, a term highlighting satisfaction of the temporal criterion of causality (Granger, 1969). The time-lag of the temporal edges depend on the design of the study and its measurement frequency. In the context of Study 3, these temporal edges capture the across-day (i.e. from one day to the next) temporal interactions between depressive symptoms, and the measured contextual variables and psychological mechanisms (Ebrahimi, Burger, et al., 2021).

While the temporal network provides information about whether and to what extent a symptom predicts average within-person increases or decreases in another at the next day, the fixed-effect contemporaneous network can provide information about dynamics that are potentially faster than those captured in the lag-1 model (Epskamp, van Borkulo, et al., 2018). In the context of the time-lag used in Study 3, this represents average within-person associations between nodes that occur within a daily time window (i.e. within the same day; Ebrahimi, Burger, et al., 2021). The edges in the contemporaneous network are partial correlation coefficients (Epskamp, Waldorp, et al., 2018).

Finally, the between-subject network is estimated based on the person-specific means. The subjects in Study 3 provided data over a 40-day period on each measured variable (Ebrahimi, Burger, et al., 2021). The person-specific means, that is, the mean of each measured variable for each person, is obtained by taking the average value of the variable over this 40-day period. This person-specific average represents the stable levels of this variable for the person over the study period. The edge weights in the between-subject networks consist of partial correlations (Epskamp, Waldorp, et al., 2018).

Following recommendations for large networks (i.e. consisting of more than six nodes), the temporal and contemporaneous networks used orthogonal estimation (Epskamp et al., 2023; Epskamp, Waldorp, et al., 2018). The mlVAR model was further estimated ensuing common pre-processing steps to adhere to a key assumption in the VAR model, the stationarity assumption (Epskamp, Waldorp, et al., 2018), where the presence of any linear and nonlinear trends (i.e. through the inspection of weekday versus weekend effects) were investigated and detrended before model estimation (Ebrahimi, Burger, et al., 2021). The study design, measuring participants at the same time every day during the 40-day study, further adhered to the equidistant measurement assumption of VAR models.

3.10.2.1 Interpretation of the Networks. Importantly, all three mentioned networks provide estimations of the associations between nodes while controlling for all other nodes in the network, with the contemporaneous network additionally controlling the for temporal effects present in the temporal network (Epskamp, Waldorp, et al., 2018).

When it comes to interpretation, both the within-person networks (i.e. temporal and contemporaneous network) represent average within-person effects (across days and within days, respectively), reflecting how displaying higher scores on a node compared to one's own average is associated with within-person level deviations from one's own average in another variable (Ebrahimi, Burger, et al., 2021). These within-person type of relationships accounting for individuals' stable means are potent in identifying mechanistic relationships, as they reflect how greater-than-usual engagement in certain process (e.g., rumination) or a certain symptom is related to greater-than-usual increases or decreases in another. The interpretation of the between-subject networks involves a comparison between subjects rather than within-person effects, thus revealing how higher average levels on a variable compared to peers is associated to mean levels in another variable compared to others in the population (Ebrahimi, Burger, et al., 2021; Epskamp, Waldorp, et al., 2018).

3.10.2.2 Centrality Estimates. Each of the above-mentioned networks are accompanied by their respective centrality metrics. Centrality metrics are statistical entities in the network literature that describe the role each node plays in the overall flow of information in networks (Opsahl et al., 2010). The use of betweenness and closeness centrality has been criticised in the psychometric network literature, as it is unclear what they represent in psychological networks compared to social network analysis where these estimates originate from (Bringmann et al., 2019). Accordingly, strength centrality was estimated, which provides information about how strongly a node is conditionally (i.e. controlling for all other nodes in the network) and directly connected to other nodes in the network (Borsboom et al., 2021; Opsahl et al., 2010). Depending on whether the network is directed or undirected, strength centrality can include subcomponents providing information about the direction of impact.

As the temporal network includes directed edges, it enables the calculation of outstrength and instrength centrality. These two metrics represent the sum of all outgoing and ingoing absolute edge weights (excluding the autoregressive effect) from and to a node, respectively. Instrength centrality provides information about how strongly a node is impacted by other nodes in the system, while outstrength centrality provides information about how strongly a node influences other nodes in the network over time.

Both the contemporaneous and the between-subject networks are undirected, enabling the estimation of strength centrality. This metric calculates the sum of all absolute edge weights connected to a node, thereby providing information about the node's overall weighted connectivity in the network, or how strongly it relates to other variables in the system (Borsboom et al., 2021; Opsahl et al., 2010). Study 3 further adhered to reporting guidelines for network analytic studies, recommending the use of raw centrality scores instead of standardised estimates, as the latter can inflate differences between centrality indices (Burger et al., 2023).

3.10.3 Sensitivity and Specificity Analyses

Several sensitivity and specificity analyses were employed in the studies of this thesis. Briefly summarised, this involved inspections of a) whether there were any systematic patterns of attrition over time through the employment of a tree-based machine learning approach; b) sensitivity analyses to inspect differences in parameters between the overall sample versus a representative post-stratified subsample in Study 3; and c) specificity analysis to examine to the extent to which the identified findings pertained to depressive symptoms above other (internalising) disorder domains (e.g., anxious symptomatology). These analyses are each detailed in the respective articles and their supplementary documents.

3.10.4 Statistical Software

The statistical models employed in this thesis were performed in R (unconditional and conditional LCSMs in Study 1 using the ‘lavaan’ package; dynamic network models in Study 3 using the ‘mlVAR’ package) and Mplus Version 8.3 (LCSMM in Study 2).

4 Summary of Findings

4.1 Study 1: Population and Individual-Level Depressive Symptom Change Patterns and Their Association With Social Distancing Protocols

Study 1 (Ebrahimi, Bauer, et al., 2022) investigated population-level changes in the depressive symptom levels of adults during the COVID-19 pandemic in Norway and its relationship with variations in national social distancing protocols and societal SARS-CoV-2 infection rates over time. Moreover, the study examined whether individual differences were present within the adult population in these depressive symptom change patterns during the pandemic period.

Overall, changes in the depressive symptom levels of the adult population covaried strongly with the presence and stringency of social distancing protocols. In contrast to observed changes in anxious symptomatology in adults, changes in depressive symptoms were unrelated to societal infection rates. Longer continuous periods with stringent social distancing protocols were associated with prolonged periods of depressive symptom experience after the reduced severity and discontinuation of these distancing protocols. Moreover, a dose-response relationship was identified between depressive symptomatology and quarantine exposure, a widely used social distancing protocol during the pandemic, revealing number of times exposed to quarantine during the course of the pandemic to be incrementally related to higher levels of depressive symptoms.

The strong relationship between depressive symptomatology and distancing protocols highlights that, fortunately, for the majority of adults that displayed heightened symptomatology during the periods of embodying strict distancing protocols, depressive symptoms decrease after reductions in the severity and discontinuation of these protocols. This finding reveals that, for most adults, the observed heightening in depressive symptom levels during the pandemic was temporary.

However, moving beyond the population-level, large individual differences were identified in depressive symptom change patterns. These individual-level analyses indicated the presence of at least one vulnerable subgroup of adults, providing indication of major increase occurring in depressive symptom levels during the first three months of the pandemic, lasting until August 2021 (the final measurement wave of Study 1). Up to this period, this detrimental pattern was revealed by approximately 10% of Norwegian adults.

Following these results, a naturally ensuing question concerned whether the highly heterogeneous depressive symptom response patterns (i.e. individual differences) observed during the pandemic could reveal subgroups of adults displaying characteristic and distinct profiles of depressive symptom change.

4.2 Study 2: Prototypical Depressive Symptom Response Profiles During the COVID-19 Pandemic and Their Relationship With Future Adverse Outcomes

Study 2 (Ebrahimi, Freichel, et al., 2023) investigated the presence of differential and prototypical profiles of change in depressive symptoms among adults over two years during the COVID-19 pandemic. Adding to the granularity of Study 1 which examined the population-level, Study 2 further sought to identify risk and protective factors associated with different prototypical depressive change profiles. Another key question concerned whether the different depressive change profiles displayed by different subgroups of adults could predict future adverse outcomes beyond symptomatology, including psychiatric treatment seeking and diagnosis.

Five distinct profiles of depressive symptom change were identified. Two subgroups of adults displayed resilient response patterns, encompassing the majority of adults in the population. The largest subgroup among the two resilient groups, and in the population overall, consisted of adults who displayed a consistently resilient pattern (Consistently Resilient group; 42.52%), showing no or negligible (below the minimal clinical relevance cut-off on the PHQ-

9) levels of depressive symptoms throughout the pandemic period. The second subgroup (Shock to Resilience; 13.17%) displayed a predominantly resilient pattern which differentiated itself from the consistently resilient group by revealing an initial shock (i.e. substantially high levels) in depressive symptoms during the onset of the pandemic, prior to a quick recovery and reduction in depressive symptoms during the initial months of the pandemic. Corresponding to the known prevalence rate of depression in the Norwegian population (Norwegian Institute of Public Health, 2023b), a third subgroup of adults revealed consistently high depressive symptom levels throughout the pandemic period (Consistently High group; 8.50%). A fourth depressive symptom response profile was identified, revealing small increases in depressive symptoms levels during the pandemic period (Mild Deterioration group; 29.04%). The fifth and final subgroup of adults displayed substantial and clinically severe levels of gained symptoms over time during the pandemic (Strong Deterioration group; 6.77%).

Overall, Study 2 highlighted that most adults displayed resilience to development of adverse depressive symptoms during the pandemic, and that initially heightened symptom levels declined for most adults in the population. However, 6.77% of adults showed no sign of recovery from adverse changes in depressive symptom expression occurring during the first three months of the pandemic. These adverse patterns which manifested during the initial months of the pandemic predicted a high probability of the presence of a psychiatric diagnosis (probability: .84) and treatment seeking behaviour (probability: .82) at the end of the pandemic period, nearly two years after the adverse depressive changes had occurred.

Importantly, all five prototypical depressive response patterns that were identified predominantly emerged during the first three months of the pandemic. Combined with the findings of Study 1, this identifies the first three months of the pandemic as a window of sensitivity for the development of long-lasting depressive states versus patterns of resilience and recovery.

4.3 Risk Factors Identified in Study 1 and Study 2

Across Study 1 and 2, static and dynamic risk factors predicting adverse change patterns on the population-level in addition to the subgroup level were investigated. In general, risk factors predicting early adverse change in population-level depressive symptoms in Study 1 (i.e. younger age, pre-existing psychiatric diagnosis, and lower education) also predicted adverse depressive change profiles in Study 2. Study 1 further identified associations between information acquisition from unmonitored platforms (i.e. mediums not subject to systematic press regulations) and such unfavourable depressive change patterns.

In taking a more granular look at the subgroup level, Study 2 corroborated the role of living alone in predicting general adverse depressive patterns (i.e. across all unfavourable profiles). Study 2 further identified patterns uniquely or most strongly related to specific depressive response patterns during the pandemic, identifying a strong relationship between frequency of information seeking behaviour and financial and occupational concerns at the onset of the pandemic with the subgroup of adults showing initial shocks in depressive symptoms prior to recovery during the early stages of the pandemic. Belonging to an ethnic minority and binge drinking were influential predictors of the strongly deteriorating group of adults. Resilience and recovery patterns were predicted by long-term engagement in physical activity, older age, and being in a relationship.

These results highlighted key sociodemographic and contextual risk factors related to detrimental depressive change patterns during the pandemic. A remaining question thus concerned which psychological mechanisms were related to increases in depressive symptoms during the pandemic period, which was investigated in Study 3 of this thesis.

4.4 Study 3: Psychological Mechanisms Predicting Depressive Symptomatology During the Pandemic

Monitoring 1706 Norwegian adults, each every day for 40 consecutive days during the pandemic, Study 3 (Ebrahimi, Burger, et al., 2021) sought to move beyond risk factors to identify psychological mechanisms that predicted fluctuations in depressive symptoms during the pandemic. Moreover, the study aimed to identify whether specific symptoms of depression behaved differently in their role of amplifying other symptoms of depression over time. This was studied while controlling for important contextual risk factors previously identified to aggravate depressive symptomatology before and during the pandemic period.

The findings of this study revealed that depressive symptoms were not interchangeable in which additional symptoms they impact. Different depressive symptoms displayed unique across-day impact on other specific symptoms of depression over time. Notably, the key symptoms pushing individuals toward prolonged depressive states during the pandemic period were worthlessness and lethargy, with the former related to amplification in depressed mood, while the latter predicted greater anhedonia.

The main psychological mechanism predicting increases in adverse depressive symptomatology during the pandemic was helplessness. Particularly, helplessness predicted across-day increases in depressed mood and worthlessness. No predictive across-day effect was identified from rumination and emotion regulation difficulties to any depressive symptoms in the general adult population during the pandemic period. On a within-day time window, both rumination and emotion dysregulation were associated with greater depressed mood and worthlessness. The undirected nature of these contemporaneous associations, however, left it unclear whether rumination and emotional dysregulation were predicting or predominantly being predicted by the other components in the network, with findings from the temporal network predominantly indicating the latter pattern, particularly for rumination. Notably, none of the psychological mechanisms, neither on a within-day or across-day time window, were associated with anhedonia or lethargy, revealing gaps in the literature concerning the identification of psychological mechanisms related to these two specific depressive symptoms on the within-person level during the pandemic period.

Among the contextual factors amplified during the pandemic, greater loneliness predicted increases in depressed mood over time, highlighting the important relationship between loneliness and depressed mood during the COVID-19 pandemic.

In sum, helplessness served as the key psychological mechanisms amplifying adverse experience of depressive symptoms over time during the pandemic, further aggravating other psychological mechanisms including rumination. Among the symptoms of depression, lethargy and worthlessness revealed the strongest impact on other symptoms over time, highlighting the initiating role that these symptoms may play in pushing individuals toward prolonged depressive states during the pandemic period.

5 Discussion

In the sections below, I discuss the main findings of the present thesis in light of central theoretical perspectives, outline several ethical and methodological considerations of relevance to the studies, highlight future directions for pandemic and critical incidents research, and finally the implications stemming from the findings of this thesis.

5.1 Social Distancing Protocols and Depressive Symptomatology

One of the main findings of this thesis concerns the identification of an association between social distancing protocols and elevations in depressive symptoms during the COVID-19 pandemic, even when controlling for societal infection rates and relevant sociodemographic and contextual risk factors. Several concepts may provide an explanation of how social distancing protocols could be related to depressive symptomatology, elaborated below.

5.1.1 Solitude Inertia

One possible explanation relates to the concept of solitude inertia. Solitude has been described as social isolation, or being alone, in daily life (Elmer et al., 2020). Solitude inertia refers to an individual's tendency to remain in seclusion, engaging less in social interactions over time (Elmer et al., 2020). Elmer and colleagues (2020) have identified that as opposed to shorter periods of being alone, prolonged states of solitude can be detrimental and predict increases in depressive symptomatology.

During the COVID-19 pandemic, many individuals have been mandated to stay at home due to SDPs restricting social contact and access to public activities to mitigate viral transmission. Accordingly, many individuals, particularly those who live alone (e.g., single-person households), may have been put in a state of solitude inertia, being socially isolated for longer periods of time and maintaining this state. This could provide an explanation of the link between SDPs and depressive symptomatology in periods embodying strict distancing protocols and isolation during the pandemic.

5.1.2 Immobility

Another possible explanation for the link between SDPs and increases in depressive symptoms during the pandemic may be related to the increases in immobility over time (Lokman & Bockting, 2022). Such immobility (restrictions to move around due to lockdown measures, including limited physical activity) has been associated with depression during the COVID-19 pandemic (Santomauro et al., 2021).

Several studies have identified a link between depressive symptomatology and reduced mobility in strict distancing-mandated periods during the COVID-19 pandemic (Devaraj & Patel, 2021; Perlis et al., 2023), providing support for the notion that immobility and reduced physical activity may be among the processes linking SDPs to depression during the pandemic (Lokman & Bockting, 2022). This is further in line with Study 2 of this thesis, where longer-term engagement in physical activity was identified as a protective factor against adverse depressive symptom expression (Ebrahimi, Freichel, et al., 2023).

5.1.3 Loneliness

The link between SDPs and depressive symptomatology could also be related to loneliness. The implemented distancing protocols have been followed by reports of increases in loneliness worldwide (e.g., Steen et al., 2022), with loneliness being highlighted as a key risk factor for depression during the COVID-19 pandemic (Killgore et al., 2020; Steen et al., 2022). This link has further been observed in other studies from the doctoral candidate and colleagues based on the sample of participants included in the present thesis, highlighting an association between loneliness and depressive symptomatology in the Norwegian population during the pandemic (Hoffart et al., 2022).

Finally, in Study 3 (Ebrahimi, Burger, et al., 2021), loneliness was related to depression by predicting increases in depressed mood over time, identifying the specific link through which loneliness is associated with depressive symptoms during the pandemic. In this study, loneliness preceded depressed mood, highlighting the role that loneliness plays in the aggravation of depression, consistent with previous findings in the literature (Erzen & Çikrikci, 2018).

Overall, the link between social distancing protocols and depressive symptomatology is unlikely to be sufficiently explained by a single, monocausal process. Accordingly, this complex relationship could be governed by multiple factors, including those mentioned above. That is, SDPs may have been related to depressive symptomatology during the pandemic through their impact on immobility, tendency to remain in solitude, in addition to increases in loneliness, all of which concern states of social disconnection and reduced physical activity, which have been identified as risk factors for depressive symptoms (e.g., Pearce et al., 2022; Wickramaratne et al., 2022).

5.2 Resilience Versus Adverse Change in Depressive Symptoms

A second key finding of this thesis concerned the identification of heterogeneity in depressive symptom response patterns during the pandemic. While many adults showed resilient responses to depressive symptoms, others displayed deterioration involving development of severe depressive symptomatology during this period (Ebrahimi, Bauer, et al., 2022; Ebrahimi, Freichel, et al., 2023). The diathesis-stress model, also referred to as the vulnerability-stress model, may function as a useful theory in understanding the individual differences observed in depressive symptom expression during the pandemic.

This theory suggests that exposure to stressors, such as for instance prolonged periods of isolation accompanying the pandemic or being infected by the SARS-CoV-2 virus (e.g., Elmer et al., 2020; Magnúsdóttir et al., 2022), may activate a pre-existing diathesis (vulnerability), with this predisposition increasing the chance of the stressor resulting in an adverse psychopathological state (e.g., depressive symptoms; Ingram & Luxton, 2005; Monroe & Simons, 1991). Different individuals possess different types and degrees of vulnerabilities, with the onset of psychological adversities ensuing exposure to a stressor depending on the extent to which the individual is vulnerable (Broerman, 2020).

In addition to sociodemographic risk factors, examples of such individual vulnerabilities can for example include genetic susceptibilities, with studies finding polygenetic risk scores to increase the risk of depression after the exposure to stressful incidents (e.g., Colodro-Conde et al., 2018). Accordingly, the heterogeneity in depressive symptom expression identified during the pandemic may be related to differences in pre-existing vulnerabilities, putting some individuals at greater risk of displaying adverse change in depressive symptoms after the exposure to the stressors accompanying the pandemic, while others without such vulnerabilities display resilience to these stressors.

Among the risk factors investigated in this thesis, several factors (e.g., living alone and being an ethnic minority; see Summary of findings section for an overview) were identified to be related to experience of depressive symptoms, highlighting the role these pre-existing sociodemographic vulnerabilities played in amplifying depressive symptom experience during the pandemic period.

5.3 Maintenance of Depressive Symptoms After Diminishment of Key Contextual Stressors

The COVID-19 pandemic has involved a range of stressors (e.g., economic decline, social distancing protocols), many of which (e.g., social distancing protocols) have diminished or were discontinued at the end of this longitudinal doctoral project. Among the challenges accompanying the pandemic investigated in this thesis, the SDPs were identified as a key contextual stressor associated with depressive symptoms during this period. However, if SDPs or other diminished aspects of the pandemic function as stressors associated with increased depressive symptoms, what explains that a small subgroup of individuals did not recover from adverse depressive symptoms gained during the pandemic period, even after the removal of these protocols? One possible explanation of this is related to the concept of hysteresis (Borsboom, 2017).

The aetiology of mental disorders, as understood from the network theory of mental disorders, encompasses four phases. The symptoms are first dormant in a stable state (phase one), where this dormant symptom network can be activated by events in the external field (phase two). From activation of a few symptoms, the activation can spread throughout the network to other symptoms (phase three). This can lead to an emergent psychopathological state, such as a depressive condition. Once this state has emerged, it can maintain itself even when the contextual stressor or triggering event has diminished, due to the mutually reinforcing activity between symptoms (phase four; Borsboom, 2017).

The concept of hysteresis describes how adverse depressive states can be maintained even after the triggering stressor no longer is present, and how some individuals are more susceptible to remaining in a depressive state due to a stronger connectivity between their depressive symptoms, increasing the symptoms' ability to maintain themselves over time (Borsboom, 2017).

Through this lens, the contextual stressors accompanying the COVID-19 pandemic (e.g., SDPs) can be understood as adverse events triggering the onset of specific depressive symptoms, with certain individuals being stuck in this novel heightened depressive state even after the triggering event has diminished, due to their individual vulnerability as a result of increased connectivity between their symptoms compared to other individuals. In this regard, the stronger connectivity between symptoms in some individuals compared to others can further be understood as a diathesis (vulnerability), linking the network theory of mental disorders to the diathesis-stress model.

5.4 Alternative Explanations for Increases in and Maintenance of Depressive Symptoms in Subgroups of the Population

It is important to note that while SDPs were strongly associated with fluctuations in depressive symptomatology throughout the pandemic period, this relationship is not deterministic, nor is the only factor related to experience of depressive symptoms during this period.

To include a few examples, studies have found that being infected with the coronavirus is associated with an increased risk for long-term depressive symptomatology (e.g., Magnúsdóttir et al., 2022). However, the majority of participants showing adverse changes in depressive symptoms displayed this pattern as early as during the first months of the pandemic, a time period where only 0.51% of the individuals in this sample reported to have been infected by the SARS-CoV-2 virus, and 0.83% to 1.02% of the Norwegian population were estimated to be infected (Norwegian Institute of Public Health, 2023c). Although it cannot be ruled out that some participants were infected by the virus without awareness, the general low societal infection rates in Norway during these initial months of the pandemic renders this alternative as less plausible for the subgroup of patients showing early deterioration identified in this thesis.

Among other explanations, studies have found long-term depressive symptoms among individuals losing their significant others (e.g., parents or partners) during the pandemic (e.g., Lovik et al., 2023). The pandemic has also brought with it significant economic and occupational repercussions for certain individuals (Blomqvist et al., 2023; Wörn et al., 2023). For example, many adults reported significant loss of income and changes in their financial situation, while others reported losing their job as a result of lockdowns or the broader economic challenges accompanying the pandemic (e.g., Blomqvist et al., 2023; Dragano et al., 2022; Wörn et al., 2023). Accordingly, although discontinuation of SDPs and a return to everyday life were associated with reductions in depressive symptoms and could function as a candidate explanatory process for those whose depressive states were related to factors such as immobility, reduced social contact and social disconnection, other factors (e.g., job loss and continued financial strain) could also be related to the observed increases in depressive symptomatology and further explain the sustained heightened symptomatology in some individuals, even after the removal of SDPs. In support of this interpretation, a study on Norwegian adults identified that adults exposed to job loss during the pandemic experienced stronger increases in depressive symptomatology compared to employed individuals (Wörn et al., 2023).

5.5 Methodological Considerations

The findings of this thesis must be considered in light of its methodological strengths and limitations, with several of these outlined below.

5.5.1 Measurement-Related Considerations

Measuring psychological constructs is a challenging task and serves as the foundation upon which conclusions are drawn (e.g., Flake & Fried, 2020). Beyond the complexity of the phenomena under investigation in psychological science, this partially relates to the fact that the type of measurement approach used (e.g., self-report) can introduce unique challenges and biases.

5.5.1.1 Self-Reported Assessments of Depressive Symptoms. The use of self-report measures brings with it several noteworthy limitations. The first limitation is that certain symptoms are not easily identifiable by the participants themselves during self-report assessments (e.g., cognitive impairment) and thus less reliably assessed compared to clinician-rated instruments. In the context of the measure of depression used in the present thesis, this issue can pertain to symptoms such as psychomotor agitation or slowing down. Beyond the differential utility in the ability to capture specific symptoms, self-report assessments are subject to specific biases that may have impacted the results of the present thesis.

One limitation with self-reported instruments concerns that individuals can over- or underestimate the presence and severity of their psychological symptoms, related to different types of response biases (Althubaiti, 2016; Coughlin, 1990). One example includes social desirability bias.

While there are no right or wrong answers to survey questions, responses provided by participants in self-report assessments may be impacted by social norms and societal expectations. This can for example relate to dominant viewpoints of socially acceptable behaviours or to stigma around responding to personal questions about one's mental health. In these settings, if respondents conform to what they feel is most appropriate to respond to, this is referred to as social desirability bias, resulting in over- or underreporting of certain phenomena (Althubaiti, 2016; Coughlin, 1990).

Social desirability bias may have impacted the findings of the present study, for example through the participants reporting greater compliance to distancing measures (e.g., quarantine) given the strong and ubiquitous social expectations tied to this behaviour during the pandemic, in addition to for example underreporting certain symptoms (e.g., suicidal ideation, worthlessness) due to the associated stigma with such symptoms in some individuals and subgroups of the population.

However, several studies show that privacy can be an effective way to reduce social desirability bias (e.g., Althubaiti, 2016). Accordingly, the greater privacy accompanying online surveys and self-report assessments, including the ability to respond to the survey in a desirable setting for the individual (e.g. in one's room alone, at a desirable time) rather than for example in an open office space, may have protected against social desirability bias. Previous studies have found that the use of online surveys, as employed in this thesis, reduce the risk of social desirability bias compared to other methods (Joinson, 1999; Kreuter et al., 2008). Another approach to reduce social desirability bias involves ensuring confidentiality and providing thorough descriptions of the de-identification processes implemented in studies (Ried et al., 2022), both of which were undertaken in the studies of this thesis.

The use of self-reported instruments also has several advantages. This includes their scalability and usability in large population studies, with these instruments further able to surpass several barriers in the context of the COVID-19 pandemic where distancing and isolation practices (e.g., quarantine) are widespread and ability to adapt clinician-rated instruments are impaired and unrealistic in cost (“Keep Mental Health in Mind” 2020).

5.5.1.2 Recall Bias and Retrospective Reporting. Other biases than social desirability are also relevant in the context of subjective inquiry-based methods. Study 1 and 2 relied on retrospective assessment of the constructs investigated (e.g., depression). Retrospective assessments entail instances where individuals are asked to report on past mental states (e.g., symptoms) and experiences over a certain time window. While commonly employed across the psychological and social sciences, the use of instruments involving retrospective assessments may have impacted the data collected. This is related to the use of specific cognitive shortcuts that can impact the memory of individuals’ during the assessment procedure (Shiffman et al., 2008). One key cognitive bias is recall bias, referring to instances where individuals inaccurately remember past events or states (Althubaiti, 2016). Previous studies have shown that this bias may materialise through individuals more easily remembering past information in light of their current mental and emotional states and most recent experiences (e.g., Fredrickson, 2000; Horwitz et al., 2023). In a recent study, Horwitz and colleagues (2023) demonstrated that there is evidence for a modest peak-end recall bias for depressive symptoms assessed with the PHQ-9, highlighting that both the peak (i.e. highest) levels of depressive symptoms and the most recent level of depressive symptoms at the end of the retrospective assessment period has some influence on the overall PHQ-9 score. As such, the retrospective assessments in Study 1 and 2 may have impacted the accuracy of obtained scores through overrepresentation of salient or recent experiences in the retrospective summary (Althubaiti, 2016). However, studies have also found reduced presence and impact of recall bias in given individuals (e.g., Leertouwer et al., 2022), and further identified individual differences in recall accuracy, identifying that neurotic adults tend overreport negative mental states, while extraverted individuals tend to overreport positive states (Barrett, 1997). Accordingly, while the presence of recall bias may influence findings in a more unidirectional manner in homogenous clinical samples (e.g., possible overreporting of negative states in a sample of depressive patients), the impact of such biases could potentially be somewhat more evenly spread (in both positive and negative directions) in a general population sample where both mental ill-health and mental well-being are more variably distributed.

One way to mitigate impact of recall bias includes incorporating assessment schedules involving shorter recall periods (e.g., Althubaiti, 2016; Horwitz et al., 2023; Shiffman et al., 2008). In Study 3, the intensive longitudinal nature of assessments was leveraged to reduce the recall period from two weeks (cf. PHQ-9) to one day, serving as a strength in mitigating recall bias in this study.

5.5.1.3 The Patient Health Questionnaire. Beyond the aforementioned biases, measuring depression specifically has proven to be a challenging task, particularly given the heterogeneous symptom expressions of the disorder. This has been echoed by the wide variety of scales developed to measure this construct (Fried, 2017b). Accordingly, the choice of the instrument used to measure depression is relevant for the findings of the study, as different instruments bring with them unique strengths and weaknesses, and further, depending on their items, highlight different aspects of depression (Fried, 2017b).

In Study 1 and 2, the Patient Health Questionnaire (PHQ-9) was used to measure depressive symptoms, with items from this instrument further adapted to a daily timescale for Study 3. The PHQ-9 is a widely accepted instrument in research settings. This brief instrument is quick and easy to administer, rendering it particularly suitable for the evaluation of depressive symptoms in population-based research studies where diagnostic interviews are infeasible to conduct (Martin et al., 2006). The scale is further revealed to be accurate and sensitive to detecting change (Kroenke et al., 2010), with the specific use of PHQ-9 recommended in evaluating changes in depressive symptoms during the course of the pandemic ("Keep Mental Health in Mind" 2020). Another strength of the PHQ-9 includes that the symptomatology it measures is precisely mapped to the symptoms in diagnostic manuals, specifically based on the DSM (American Psychiatric Association, 1998). This makes the PHQ-9 well-suited to measure more typical forms of depression closely aligning with the diagnostic symptom criteria.

However, depressive states may also involve irritability (Pine, 2019) and other symptoms (e.g., pessimism about the future), which are left uncaptured by the PHQ-9. This serves as a limitation with the PHQ-9 and thus the present thesis, precluding it from providing insight about changes in depressive states involving symptoms such as irritability during the pandemic. Moreover, while a strength of the PHQ-9 includes the presence of validated cut-offs shown to be indicative of a depressive disorder (i.e. with high sensitivity and specificity; Levis et al., 2019), such indicators of clinically significant symptomatology are not sufficient to identify a depressive diagnosis. Furthermore, as mentioned in the section above, the questionnaire is susceptible to recall bias, given that the participants are required to retrospectively assess the presence of symptoms experienced during the preceding two weeks (Horwitz et al., 2023).

In summary, the use of PHQ-9 to study depressive symptomatology in this thesis may have impacted the results by a) precluding information on unmeasured symptoms that may accompany depressive states (e.g., irritability), b) providing less accurate assessments of the extent and severity of depressive symptoms in Study 1 and 2 related to possible recall bias due to the lengthy retrospective time window, in addition to c) as with other self-reported instruments, being insufficient with respect to provision of information about changes in diagnostic rates of depression during the pandemic.

5.5.1.4 Measurement Error and use of Validated Instruments. The longitudinal studies in this thesis (i.e. Study 1 and 2) account for measurement error through the implementation of a structural equation modelling approach. This serves as a major strength of these studies, as addressing measurement error in observed scores reduces bias and increases statistical power in the detection of true effects (e.g., Grimm et al., 2016). Study 1 and 2 further had the possibility to use an established validated instrument in the assessment of depression (Kroenke et al., 2001).

Study 3, on the other hand, involved an intensive longitudinal design and implemented a dynamic network approach. Given the high measurement frequency in such studies (e.g., measuring participants once per day), the measurement procedure in intensive longitudinal studies predominantly involves the use of single items in the assessments of constructs, in order to provide brief and efficient assessments that reduce participant burden (e.g., Eisele & Kuppens, 2021). Such brief assessment procedures further facilitate ecological validity by reducing the amount of interference in the participants daily life (Bolger et al., 2003). Another advantage of the approach in Study 3 includes the provision of an additional layer of granularity in identifying factors aggravating specific depressive symptoms rather than depression as an overall construct. Nonetheless, the approach used in Study 3 did not account for measurement error, which for instance may have impacted the findings by either over- or underestimating the identified relationships between variables (Groenwold & Dekkers, 2020; Schmidt & Hunter, 1996).

Beyond measurement error, there is a general lack of psychometrically validated instruments developed for use in intensive longitudinal studies (e.g., Myin-Germeys et al., 2018; Stone et al., 2023), with no broad consensus present among researchers concerning how constructs should be measured in such studies (Eisele & Kuppens, 2021). The absence of validated measures may impair the ability to know for certain whether items accurately represent the constructs they set to measure, which can lead to uncertainties about the identified relationships between variables. A notable strength of Study 3, as detailed in the Methods section, included attempts to address this issue by pre-selecting the utilised single items from established instrument, in addition to basing these selections on the items' overall correlation with their corresponding full version validated instrument available in the same subgroup of participants. This identified the selected items to be representative indicators of the constructs of interest (Ebrahimi, Burger, et al., 2021). While this strategy serves as an intermediate step in inspecting the correspondence between single-item measures with constructs of interest, the lack of validated assessment of psychopathology and its associated mechanisms has resulted in calls for their development to improve the measurement-related issues in intensive longitudinal studies (Myin-Germeys et al., 2018). These calls have resulted in recent innovative efforts moving the intensive longitudinal literature closer to the construction of such validated measures of psychopathological symptoms and mechanisms (Martínez et al., 2023).

In summary, two of the three studies in this thesis involved the predominant use of validated instruments and accounted for measurement error. These issues were however more challenging to address in Study 3 given its intensive longitudinal design, which may have impacted the findings through less precise estimation of certain relationships and greater uncertainty around the construct validity of some of the measured variables.

5.5.2 Attrition

Attrition is a common concern in longitudinal studies. This refers to the loss of participants over the course of the study and occurs when individuals who initially agreed to participate in the study discontinue prior to the completion of the data collection. The attrition rates in the studies of this thesis were comparable to other online longitudinal studies during the pandemic (e.g., Pierce et al., 2021). Nonetheless, attrition can be problematic and may introduce bias in estimates and generalisability of findings if certain groups of participants drop out systematically over time (Gustavson et al., 2012). An example of systematic attrition concerns a scenario where more females than males drop out over time, or vice versa. In the case of such a systematic attrition pattern, this can for example impact mean-level estimates of depression over time, if the group disproportionately dropping out (e.g., females) is a known subgroup with higher or lower mean levels of depression in general (Gustavson et al., 2012).

A major strength of this thesis included the incorporation of several procedures to investigate attrition over time. Specifically, a tree-based machine learning classification approach was used to inspect whether any demographic characteristics could predict drop-out at each specific assessment wave above chance (Ebrahimi, Bauer, et al., 2022). Moreover, differences in initial levels of depression were investigated between completers and non-completers at each wave of the study, finding no significant differences in mean levels of depression between completers and those dropping out at any assessment wave. These extensive analyses (elaborated in detail in the Supplementary Document 2 of Study 1) revealed no systematic patterns of attrition, including that none of the investigated subgroups in the study disproportionately dropped out over time, strengthening the confidence in the presented results with respect to adverse impacts from attrition (Ebrahimi, Bauer, et al., 2022).

5.5.3 Accuracy and Stability of Network Models

Study 3 in this thesis used a dynamic network analytic approach. Concerns have been raised in the literature about the accuracy and stability of network models (e.g., Forbes et al., 2017). Since the emergence of these criticisms, specific methods have been developed to investigate the robustness of network models, aimed at estimating the accuracy of edge weights and stability of centrality estimates (e.g., Epskamp, Borsboom, et al., 2018). Statistical software packages for the implementation of these robustness analyses are currently only available for cross-sectional network models (Epskamp, Borsboom, et al., 2018). Nonetheless, strategies to investigate the stability and accuracy of longitudinal network models have been presented in the literature (e.g., Funkhouser et al., 2021). A strength of this thesis concerns the implementation of such robustness tests for the dynamic network model in Study 3, which revealed the estimated networks to be robust by identifying the estimated edge weights to be accurate and the obtained centrality estimates to be stable (Ebrahimi, Burger, et al., 2021).

5.6 Generalisability of the Findings

The extent to which the findings from the present thesis are generalisable across different populations is noteworthy of attention. Several factors are relevant when considering generalisability, including the obtained sample and similarity between the studies of the thesis to the context the findings are compared to (Degtiar & Rose, 2023).

In comparison to the target Norwegian population, several strategies (i.e. dissemination of survey across a variety of platforms; post-stratification) were implemented to attempt to reach the broader general adult population and obtain a representative sample of Norwegian adults. While this procedure facilitated for a representative sample based on key demographic variables and geographic representativeness across all regions of Norway, the online nature of this study may have resulted in selection bias of computer savvy adults with greater familiarity with online surveys.

With respect to other Western countries, the findings may be generalisable to comparable populations in countries where similar pandemic mitigation strategies (i.e. social distancing protocols) have been implemented. This is further supported by findings from other European countries and the United States, identifying similar depressive response patterns and associations with SDPs during the pandemic (e.g., Daly & Robinson, 2021b; Ettman, Cohen, Abdalla, Sampson, et al., 2022; Pedersen et al., 2022; Pierce et al., 2021).

Nonetheless, the extent to which the findings are generalisable to other populations beyond Western samples warrants investigation. Norwegian samples can be categorised as what is termed a W.E.I.R.D. population, referring to Western, Educated, Industrialised, Rich and Democratic (Henrich et al., 2010). It has previously been noted that W.E.I.R.D. populations should not be taken as representative for other, including non-Western, samples.

Accordingly, while a considerable amount of research has been done on the COVID-19 pandemic, it has been noted that the preponderance of the current pandemic mental health literature is based on Western and high-income countries (HIC; Kola et al., 2021) consisting of such W.E.I.R.D. samples, with limited longitudinal data available particularly from South America and African nations (Cénat et al., 2022; Penninx et al., 2022). This has resulted in scholars calling for increased research efforts on the pandemic and mental health in low- and middle-income (LMIC) countries, where 83% of the world's population resides (Kola et al., 2021). In extending investigations LMIC countries, it is important to be cognisant of the diversity that resides within a label encompassing 83% of the world's population, with scholars warning about homogenisation of non-Western samples into unitary categories (Ghai, 2021).

5.7 Ethical Considerations

Several ethical considerations are of relevance for the present body of work. First, the online nature of the studies warrants attention. While 98% of the Norwegian population have access to the internet (The Norwegian Statistics Bureau, 2023b), the online data collection procedure excludes 2% of the Norwegian adult population from participation. This relates to the concept of the digital divide, referring to the existing and amplification of differences between individuals with and without internet access (Lythreatis et al., 2022). As participants in the target population should have an equal opportunity to participate in the study, the exclusion of specific subgroups of the population raises ethical concerns about equity and fairness in research through the exclusion of marginalised groups. Beyond these ethical concerns, excluding individuals without internet access can impact the representativeness of the studies in this thesis, as this subgroup of individuals are often from lower socioeconomic backgrounds, which may introduce selection bias (Toscos et al., 2019). While the present project could not reach the 2% of Norwegians without internet access, efforts were taken to reduce the selection bias tied to the use of digital tools. This was done by using standard rather than specialised online methods (i.e. communication through e-mail, available on both phones and computers) including a simple text and a direct link to a secure survey, instead of the relying on specialised apps which could have increased the technological barrier through the requirement of additional installation steps.

A second ethical issue pertaining to this thesis concerns its longitudinal nature, spanning over a two-year period. Longitudinal studies mapped on to contextual events can change over time, for example through necessitating measurement of additional variables that are identified to be of relevance during a dynamically evolving pandemic. In such instances, it is important to continuously ensure that participants have a clear understanding of the study's aims and procedures, and an active informed choice on whether they wish to continue to partake in the study. In the studies of the present thesis, informed consent was obtained from all participants at each assessment wave, providing clear information about the study's objectives, even in instances when the study had not undergone any changes, as a reminder of these aims and the ability to withdraw from the study at any moment in time without consequences.

A third issue relates to the intensive longitudinal study of this thesis. One topic that has received attention in this literature is whether taking part in such studies, due to their frequent measurement procedures, may have an adverse impact on participants (Roth et al., 2017). This concern was for example raised in the context of substance use disorder, where repeated inquiries about substance use could potentially function as a triggering cue or reminder. While some heterogeneity and individual differences in perceived benefit is present, empirical investigations show limited signs of iatrogenic effects related to intensive longitudinal measurement (e.g., Coppersmith et al., 2022; Roth et al., 2017), with some studies further identifying beneficial effects associated with intensive measurement (Walz et al., 2014; Yang et al., 2019). In a study from the thesis author and colleagues conducted on the sample of participants in Study 3, the majority of adults reported that the intensive measurement protocol was beneficial, particularly by providing them with insight into patterns relevant in maintaining their experienced problems (Du et al., 2023). However, as a smaller proportion of participants also reported some negative impact of the measurement procedure, this presents an important ethical obligation in identifying subgroups of individuals that are more or less likely to benefit from ambulatory assessment (Du et al., 2023).

Finally, the COVID-19 pandemic has been a topic of interest for the broader press, with several of the findings from the studies of this thesis being disseminated in the media. Several ethical considerations were of relevance for the dissemination of the findings of this thesis. The challenges related to the pandemic have been multifaceted, impacting several large domains in society simultaneously, including somatic health, mental health, and the economy. A major challenge has been that these different perspectives have, during periods of the pandemic, required distinct strategies in order to protect against the adverse impact of the pandemic in their respective areas. This highlights how the implementation of a strategy protecting one perspective can be in conflict with the mitigation efforts of another. For example, while a medical perspective has warranted the use of isolation and social distancing measures to protect physical health and reduce transmission, this strategy has come at the cost of an economic perspective (e.g., bankruptcy of certain businesses and decline in overall economy) and been associated with a negative impact on mental health. Awareness of these imperative and partially colliding perspectives was an important ethical consideration in sharing the findings from the present thesis with the broader public. In these instances (i.e. particularly with respect to Study 1), beyond practicing caution and avoidance of causal claims, the project group had preparation meetings to ensure balanced communication, highlighting the importance of SDPs in mitigating transmission, and further highlighting how adverse associations with SDPs were temporary in nature for most individuals, while acknowledging that these measures are associated with negative outcomes for certain groups of individuals in the population. Beyond this, to address the need of real-time knowledge about preventive health measures and facilitate adherence to SDPs, studies from the MAP-19 project by the thesis author and the project group (Ebrahimi, Hoffart, et al., 2023; Ebrahimi, Johnson, et al., 2021) were communicated in the media and shared with colleagues in the Norwegian Directorate of Health to assist transmission mitigation aims during the pandemic. In summary, these strategies were implemented to provide a balanced perspective when disseminating the findings of this thesis and in engaging in research communication about the pandemic.

5.8 Future Directions

Beyond the methodological considerations mentioned above, the studies of the present thesis include several limitations which outline paths for future research. First, the causal relationship between SDPs and depressive symptoms remains unclear and cannot be informed by the findings of this thesis. As previously noted, other stressors accompanying the pandemic, such as financial and occupational stressors, have also been associated with depressive symptoms. Accordingly, there is a need for causal insights about the relationship between SDPs and depressive symptomatology. The gold standard for causal inference involves the use of randomised controlled trials (e.g., Rubin, 2007). Nonetheless, implementation of causal experimental designs involving viral spread in the population is both unethical and unrealistic to conduct (Rubin, 2007). However, this does not imply that gaining causal insight about the relationship between SDPs and depressive symptomatology will be entirely impossible. Novel methodological advances in the field, including the use of Target Trial Emulation, which include methods that apply the principles of randomised trials to observational studies (e.g., Hernán et al., 2022; Matthews et al., 2022), are key future steps in moving closer to gaining causal knowledge about the association between SDPs and depressive symptomatology. Moreover, advanced applications of these designs, including exposure mixture models (Keil et al., 2020) can enable the estimation of the specific SDPs with the least and greatest mental health burden, serving as imperative information for future pandemics in identifying strategies that are effective in mitigating viral spread while having the lowest possible psychological burden. Future efforts should further expand investigations of mental health in relation to SDPs occurring at the local and regional level, as the preponderance of studies in the literature, including the present body of work, focus on national social distancing protocols, which serves as a limitation of this thesis.

Second, while providing a comprehensive overview of depressive symptom change across the different facets of the COVID-19 pandemic, a key limitation of this thesis concerns the lack of pre-pandemic data. Results from studies with comparable Western samples including pre-pandemic data (e.g., Pierce et al., 2021) are consistent with the findings of this study, identifying similar response patterns in the population, including deteriorating patterns pertaining to smaller subgroups of adults, and predominantly resilient patterns in the majority of adults in the population. The lack of pre-pandemic data on Norwegian adults in the present thesis, however, precludes comparisons with symptom levels in the population before the emergence of the pandemic, and highlights a need for future prospective pandemic studies in the Norwegian population. In line with this, the team behind the MAP-19 study (Ebrahimi, Hoffart, and Johnson) together with Helmich have designed and launched a new study (Critical Incidents and Psychological Adaptation; The CIPA Study), aiming to prospectively investigate the Norwegian adult population before, during, and across forthcoming critical incidents (e.g., including pandemics and other periods of infectious disease, economic recession, and natural and industrial disasters) over the next 15 years.

Third, as previously mentioned, there is a need for more studies investigating the pandemic and mental health in non-Western and LMIC countries (Cénat et al., 2022; Kola et al., 2021; Penninx et al., 2022). Beyond enhancing the understanding of the pandemic period across the globe, added studies from LMIC countries can provide increased insights about the impact of specific SDPs on depression and mental health. This relates to different countries' differential implementations of SDPs in their pandemic mitigation efforts, increasing the overall variability and availability of different types of implemented SDPs, which can benefit the investigation of specific distancing protocols.

Finally, as a critical incident with large-scale impacts on the population and societal functioning, the extent to which the pandemic shares similarities with other critical incidents is an important topic of future research, with scholars pointing that different critical incidents may share common components (Goldmann & Galea, 2014). Accordingly, an important avenue for future research involves studying and identifying similar components across critical incidents, which has the potential to provide imperative insights about novel and unprecedented critical incidents, especially in cases where they share similar components with previous ones.

5.9 Contributions of This Thesis and its Implications

The present thesis identified population-level depressive symptoms to covary with the presence and stringency of SDPs, which, in contrast to anxious symptomatology, was found to be unrelated to societal SARS-CoV-2 infection rates. Considerable individual differences were detected in depressive symptom change patterns during the pandemic. These individual differences revealed five prototypical profiles of depressive symptom change. Most adults displayed resilience to the pandemic as a contextual stressor over time, including to its SDPs. About 7% of adults developed clinically severe levels of depressive symptoms during the pandemic, which was maintained over time. These adverse depressive change patterns predicted future psychiatric treatment seeking and the presence of a psychiatric diagnosis nearly two years after their emergence. Both resilient and deteriorating change patterns in depressive symptoms occurred during the first three months of the pandemic. Beyond demographic risk (e.g., lower education levels, ethnic minority status, living alone) and protective factors (e.g., being in a relationship, older age), several factors that are subject to modification by individuals were identified to be related to depressive symptom experience, such as frequency of information acquisition. The main psychological mechanism predicting depressive symptomatology was helplessness. Loneliness was related to depression by predicting increases in depressed mood over time. Moreover, the key symptoms pushing individuals toward prolonged depressive states during the pandemic period were identified to be worthlessness and lethargy.

These findings have several notable implications for public health and policymakers. First, the identified association between depressive symptoms and SDPs, including longer periods with stringent protocols being related to prolonged sustenance of heightened symptomatology, suggests that careful consideration is warranted concerning the implementation length of distancing protocols. Second, to mitigate the psychological strain of SDPs, the use of social bubbles, which have been shown to effectively reduce transmission rates while allowing some degree of social contact (Leng et al., 2021; Tupper et al., 2020), may be a useful strategy to implement early during pandemic periods to reduce societal infection rates while limiting the mental health burden of these protocols. Third, the findings of this thesis highlight that an optimal period for the insertion of such preventive strategies includes the first three months of pandemics, a period which was identified as a window of sensitivity for development of adverse symptoms versus resilient response patterns.

Fourth, the identified adverse links between financial concerns and depressive symptoms in this thesis and other studies in the literature (e.g., Ettman, Cohen, Abdalla, Trinquart, et al., 2022), suggests that socioeconomic policies may be of importance to mitigate depressive adversities for certain subgroups of adults in future pandemics. Fifth, the associated mental health benefits of physical activity during periods of infectious disease, in addition to the adverse associations tied to the use of unmonitored information sources and information over-engagement, highlight two modifiable strategies on the individual level which may be of utility to disseminate in future preventive public health campaigns during periods of infectious disease.

Finally, consistent with ongoing national (Ose & Kaspersen, 2021) and global reports (Santomauro et al., 2021), the findings of this thesis highlight that mental health services may observe an increase in referrals in the aftermath of the pandemic. Should these trends maintain themselves ahead, this finding calls for careful planning and strategic distribution of resources by health and governmental agencies in order to facilitate preparedness to avoid overburdening of the healthcare system.

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Papers

Study 1

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Supplementary Document 1: Social Distancing Protocols Across the 17-Month Study Period: T1 to T6

(Article 1)

Supplementary Document 1: Social Distancing Protocols Across the 17-Month Study Period: T1 to T6

Supplementary Table S1

All nationally implemented social distancing protocols (SDPs) actively in place in Norway during the first wave of data collection (T1; between March 31 to April 7, 2020). No new information was given about modifications of SDPs during the measurement period, controlling for expectation effects. All SDPs were stable and unchanged for the weeks prior to and during data collection

Protocol
1. Individuals who have been in contact with an infected person are quarantined for 14 days following initial contact with the infected person.
2. Anyone suspecting having coronavirus symptoms or is confirmed to have the virus must be in isolation.
3. Social and physical distancing: individuals are disallowed from being in groups with more than five peers and must maintain at least two meters distance from others.
4. Closing of schools, kindergartens, and universities.
5. Closing of all businesses in the catering, food, and beverage industry. The exception of the rule involves eateries that may facilitate visitors to have at least a one-meter distance from each other.
6. Closure of all additional businesses with increased risk of infectious spread. This includes any business involving human contact, with the exception of essential stores (e.g., grocery stores, pharmacies).
7. Individuals returning to Norway receive an automatic quarantine duration of 14 days.
8. Cancellation of cultural events (e.g., concerts), closing of gyms and physical work-out centers.
9. Health personnel disallowed from leaving the country.
10. All hospitals and health institutions must introduce access control and stop regular visitation routines.
11. Ban on traveling to and staying overnight at one’s leisure property outside the individuals residing municipality.
12. Border control: The borders are closed with regards to visitors from other countries.

Supplementary Table S2

All nationally implemented social distancing protocols (SDPs) actively in place in Norway during the second wave of data collection (T2; between June 22 to July 13, 2020). No new information was given about modifications of SDPs during the measurement period, controlling for expectation effects. As with T1, all SDPs were stable and unchanged for the weeks prior to and during data collection

Protocol
1. Individuals who have been in contact with an infected person are quarantined for 10 days following initial contact with the infected person.
2. Anyone suspecting having coronavirus symptoms or is confirmed to have the virus must be in isolation.
3. Social and physical distancing: individuals are disallowed from being in groups with more than twenty peers and must maintain at least a one-meter distance from others.
4. Universities and colleges are closed (Elementary and high school have re-opened)
5. Individuals visiting or returning to Norway receive an automatic quarantine duration of 10 days.
6. Public events must not exceed more than 200 individuals. In this case, they may be allowed if events can maintain the one-meter distance rule and meet the requirement of infection control protocols.
7. Re-opening of direct contact health service providers (e.g., psychologists and physiotherapists) provided they meet the requirement of infection control protocols.
8. Re-opening of one-to-one contact services (e.g., hair salons), gyms, and the catering and beverage industry may provided they meet the requirement of infection control protocols (as well as the maintenance of a one-meter distance for gyms and the catering and beverage industry).
9. All hospitals and health institutions must introduce access control and stop regular visitation routines.

Supplementary Table S3

All nationally implemented social distancing protocols (SDPs) actively in place in Norway during the third wave of data collection (T3; November 19 to December 2, 2020). No new information was given about modifications of SDPs during the measurement period, controlling for expectation effects. All SDPs were stable and unchanged for the weeks prior to and during data collection

Protocol
1. Individuals who have been in contact with an infected person are quarantined for 10 days following initial contact with the infected person.
2. Anyone suspecting having coronavirus symptoms or is confirmed to have the virus must be in isolation
3. Social and physical distancing: Recommended to avoid social contact. Individuals are disallowed from being in groups with more than five peers and must maintain at least 1 meter distance from others.
4. Masks are mandatory indoors, in public transportation areas, crowded places, and anywhere where it is not possible to maintain at least a one-meter distance.
5. Mandatory home-office wherever possible and particularly in areas with high transmission rates.
6. All universities, schools, and colleges must employ digital teaching where possible, reducing teaching and other activities that contribute to increased mobility, including pressure on public transport.
7. Individuals visiting or returning to Norway receive an automatic quarantine duration of 10 days. Extended restrictions for quarantine and travel to Norway, including but not limited to mandatory quarantine duty and presentation of a certificate of a negative COVID-19 test. Individuals, including tourists and visitors, who do not have their own residence or employer in Norway must stay in a quarantine hotel and get tested during the quarantine period.
8. Public events must not exceed more than 50 individuals.
9. National prohibition on serving alcohol after midnight. Restaurants with a license to sell alcohol disallowed from admitting new guests after 22:00
10. Avoid non-essential domestic travel. It is allowed to travel to leisure properties if one can travel without contact with other people.
11. All hospitals and health institutions must introduce access control and stop regular visitation routines.

Supplementary Table S4

All nationally implemented social distancing protocols (SDPs) actively in place in Norway during the fourth wave of data collection (T4; January 23 to February 2, 2021). No new information was given about modifications of SDPs during the measurement period, controlling for expectation effects. All SDPs were stable and unchanged for the weeks prior to and during data collection

Protocol
1. Temporary full stop of social contact: Avoid hosting guests in your home. Wait at least 14 days to make private visits.
2. Ensuing the 14 days, everyone should limit social contact to the greatest extent possible. It is recommended that meetings with other individuals, if any, take place outdoors, for individuals to avoid visits including more than five peers.
3. All organized leisure activities, sporting activities, cultural events and indoor faith community gatherings are to be halted and postponed.
4. Children in day-care facilities and primary schools must be organized in cohorts and can only receive visits from members of their own cohort.
5. Avoid all non-essential travel domestically and abroad. Stays in cabins with individuals from the same household continue to be permitted provided they take place in accordance with all applicable local and national rules and guidelines.
6. Re-recommendation of working from home.
7. Reclosing of universities, colleges and several types of schools: All teaching and planned events at universities, university colleges and vocational training schools must take place digitally.
8. All shopping centers and stores must introduce limits on the number of customers permitted inside to enable distancing and to control access to the premises.
9. The elite tiers of sports are recommended to postpone all league matches for a minimum period of two weeks.
10. Cultural events such as performances, courses, conferences, religious and life stance ceremonies shall be postponed if they gather attendees from multiple municipalities.
11. A maximum of ten individuals may attend private gatherings outside their own home, such as a birthday celebration in a rented premises with implemented transmission control. If the private gathering is taking place outdoors, the limit is 20 attendees.
12. There is a limit of ten individuals for indoor sporting events, cultural events, seminars, life stance community gatherings, ceremonies, etc., in addition to a limit of 200 individuals where everyone in the audience is seated in fixed seating. Up to 50 individuals are

permitted to attend funerals, even if the seating is not fixed.

13. A maximum of 200 people may attend outdoor events, while the limit is 600 people for events at which all members of the audience are seated in fixed seating.

14. Prohibitions on serving alcohol in the food, beverage, and catering industry.

Supplementary Table S5

All nationally implemented social distancing protocols (SDPs) actively in place in Norway during the fifth wave of data collection (T5; May 8 to May 25, 2021). No new information was given about modifications of SDPs during the measurement period, controlling for expectation effects. All SDPs were stable and unchanged for the weeks prior to and during data collection

Protocol
1. Individuals who have been in contact with an infected person are quarantined for 10 days following initial contact with the infected person.
2. Anyone suspecting having coronavirus symptoms or is confirmed to have the virus must be in isolation.
3. Social and physical distancing: A maximum of 10 individuals for inside events. A maximum of 20 individuals if the event is outside. Recommended to maintain a one-meter distance from others and maintain good hand hygiene.
4. Re-opening of schools, workplaces and universities: Students and employees are allowed to be on campus, in reading halls, and the library. Large-scale physical lectures are not recommended.
5. Children and young adults under 20 can engage in physical and in leisure activities. Adults can participate in organized physical activities in groups of 10 or smaller if possible to maintain a one-meter distance. Physical activities outside are allowed up to 20 adults.
6. Public events allowed up to 100 individuals with fixed seating, 200 individuals if event is outside, and 600 individuals when divided in cohorts of 200 with fixed seating.
7. Domestic travel allowed, but events gathering individuals from different municipalities recommended to be delayed.
8. Re-opening of alcohol sale: Allowed to serve alcohol but only accompanied with food. Serving alcohol is prohibited after 10 pm. Entrance prohibition after 10 pm.

Supplementary Table S6

All nationally implemented social distancing protocols (SDPs) during the COVID-19 pandemic in Norway actively in place during the sixth wave of data collection (T6; July 4 to August 1, 2021). No new information was given about modifications of SDPs during the measurement period, controlling for expectation effects. All SDPs were stable and unchanged for the weeks prior to and during data collection

Protocol
1. Social gathering in one's own home is allowed with up to (unvaccinated) 20 peers. Vaccinated peers do not count in the peer limit. Thus, private social gatherings may surpass the 20-person limit if guests are vaccinated.
2. No longer a one-meter rule for vaccinated individuals. The one-meter distance rule now only applies for unvaccinated individuals. Vaccinated individuals are exempt from the one-meter rule when having social contact with other vaccinated peers.
3. Discontinuation of quarantine upon contact with or share of housing with an infected individual.
4. Full opening of all schools, universities, kindergartens, and workplaces without restrictions. Universities no longer need to have digital solutions and may also include large-scale physical lectures.
5. No more travel domestic travel restrictions: Domestic travel allowed within and across all municipalities.
6. No more international travel restrictions: There is no longer a quarantine requirement for individuals returning or visiting Norway upon documenting vaccination, previous infection, or negative test.
7. Individuals allowed to travel internationally outside the country. Vacations outside of Norway are allowed, while not necessarily recommended.
8. No restrictions for children with respect to physical and in leisure activities. Adults can participate in organized physical activities up to groups of 40 individuals. There is no longer a requirement to maintain a one-meter distance.
9. Public events allowed up to 1000 individuals if the event is inside with fixed seating and 400 without fixed seating, 2000 individuals if event is outside with fixed seating, 800 individuals outside without fixed seating.
10. Night clubs reopened on top of all other services in the catering and beverage industry. Alcohol sale is no longer only limited to food servings and serving time is no longer restricted.
11. All professional sports activities can be conducted as normal again both indoors and outdoors.

Supplementary Document 2: Additional Analyses

(Article 1)

Supplementary Document 2: Additional Analyses

Diagnostic Analyses of Missing Data Patterns

Missing data patterns in the present study were investigated through two series of systematic analyses. The first set of analyses focused on whether the missing values on the outcome itself (i.e., depression) at each specific assessment wave where missing data was present (i.e., T2-T6) was related to the participants' initial values of the outcome. This series of independent samples t-tests (Table S7) revealed no differences in initial depressive levels between completers and non-completers at any assessment wave of the study.

Table S7

Differences in Initial Levels of Depression Between Completers and Non-Completers at Each Wave of the Study

Assessment wave	***M (SD)***	***t***	***p***
T2		-1.08	.283
Completers	7.54 (6.02)		
Non-completers	7.73 (6.06)		
T3		1.12	.264
Completers	7.73 (6.14)		
Non-completers	7.53 (5.94)		
T4		-0.19	.849
Completers	7.62 (6.06)		
Non-completers	7.65 (6.02)		
T5		-1.32	.186
Completers	7.49 (5.94)		
Non-completers	7.74 (6.11)		
T6		-1.13	.261
Completers	7.49 (6.06)		
Non-completers	7.71 (6.03)		

Additionally, another series of analysis was conducted to thoroughly investigate overall patterns of attrition at each assessment wave as related to the wide range of demographic variables available in the data set through the employment of decision tree-based machine learning classification approach, referred to as Classification and Regression Trees (CART). This involved inspection of variables such as age, biological sex, education, psychiatric illness, ethnicity, employment status, relationship status, living situation, region of residency, urban versus rural residency, in addition previous depressive levels and potentially relevant cognitive-affective such as worry about losing one's job.

In this series of analyses, attrition at each wave was used as the target (i.e., criterion or outcome) variable, while the aforementioned variables were used as features (i.e., predictors). This machine learning technique examines whether and the degree to which the mentioned features can meaningfully predict patterns of missingness above and beyond chance (i.e., always guessing "Yes" on whether data is missing or not) at each assessment wave. The results from these machine learning models in predicting attrition at each assessment wave can be found in Supplementary Document 3, with the left panel of the figures portraying classification performance as per the Receiver Operating Curve (ROC), and the right panel revealing the extent to which features, if any, improved model performance. Note that the CART model is likely to identify predictors that to any degree can predict attrition, while the extent to whether this is meaningful depends on the models' predictive ability and performance (i.e., AUC and predictive ability above chance).

The CART models revealed no discriminative ability in predicting completers versus non-completers across any assessment wave, with Area Under the ROC Curve (AUC) ranging from 0.50 to 0.55 (mean AUC: 0.52). Additionally, these models did not for any of the assessment waves (i.e., T2-T6) predict attrition meaningfully better than chance, with mean improvements in Accuracy above chance across waves being 1.41% (range: [0.00, 4.40]).

Overall, while it is not possible to verify whether data are Missing at Random (MAR) or Missing Not At Random (MNAR; Enders, 2010, p. 6 and p. 8), this extensive series of analyses strengthen the case that no influential pattern of missingness exist in the present study among its measured variables and as dependent on previous values of the outcome, increasing the plausibility that the assumption of MAR underlying the studies FIML-based analyses are reasonable.

Formal Translation of the Patient Health Questionnaire-9

A formal translation of the PHQ-9 available from The Norwegian Association for Cognitive Therapy was used, detailed in Supplementary Document 2. This instrument was translated through a translation-backtranslation procedure, first from English to Norwegian by a Norwegian clinical psychologist and researcher, prior to independent backtranslation by a native English-speaking MD practicing as a psychiatrist in Norway who spoke Norwegian fluently. The psychometric properties of this translated instrument were found to correspond to its English version in Norwegian samples (e.g., Wisting et al., 2021).

Post-Stratification of Sample

The demographic characteristics of the subjects were compared to their occurrence rates in the Norwegian adult population. In cases where assessments must be conducted within a specific time-period that cannot be flexibly extended to ensure proportionate participants in each stratum, poststratification of participants can be conducted to match the ratio of subgroups to that of the target population. Such procedures are relevant in public health studies in minimizing the risk of prevalence estimates being disproportionately driven by certain demographic groups (e.g., females) above others. As such, characteristics unrepresentative of the Norwegian adult population were poststratified to be proportional to their known rate to yield a representative sample of the Norwegian adult population.

Specificity of Findings for Depression

Three series of analyses were conducted to assess the specificity of the findings for depressive symptomatology. First, symptom-level patterns of change were investigated to assess the specificity of the results for the core symptoms of depression. Second, supplementary analyses on anxious change profiles were conducted using a validated

Norwegian translation of the GAD-7 instrument (Johnson et al., 2019) to compare depressive change profiles and its predictors to anxious change profiles. Finally, we tested whether the identified subgroup of individuals revealing detrimental depressive symptom profiles (i.e., 10% of adults in the sample; cf. Results section) could specifically and more dominantly be tied to outcomes related to depression above other psychopathological domains (e.g., anxiety, obsessive-compulsive problems). This was done through investigating psychiatric treatment seeking at the last wave of the study. Psychiatric treatment seeking at the last wave of the study was measured with a categorical question querying participants about whether they were seeking treatment at the final wave of the study and the specific psychological problem domain they were seeking treatment for. The response options on this item included the following categories: 0: Not seeking any psychological treatment; 1: Treatment related to anxiety; 2: Treatment related to depressive symptoms; 3: Treatment related to loneliness; 4: Treatment related to stress and trauma-related problems; 5: Treatment for loss and/or grief; 6: Treatment for obsessive-compulsive problems; and 7: Treatment for other psychological problems.

Symptom-Level Analyses and Patterns of Change

First, nine additional analyses were conducted to investigate the patterns of change for each specific symptom of depression. Model fit for each of these nine symptom-specific Latent Change Score Models can be found in Table S8, with the population-level and individual-level changes in each symptom over the study period provided in Supplementary Figure S3. The two symptoms that were identical (i.e., displayed significant and identical change patterns with the same direction at the exact same time-points; $\delta\eta_{t2}$, $\delta\eta_{t3}$, $\delta\eta_{t5}$ and $\delta\eta_{t6}$) to the overall depressive change patterns were its main identifiers (i.e., core symptoms; American Psychiatric Association, 2013), namely anhedonia and depressed mood.

Ensuing these key identifiers, lethargy was the symptom that partially assimilated the overall change patterns of depression, with significant change occurring at 3 of 5 time-points for this symptom, but not all change occurring in the same direction. Of particular note, while anhedonia and depressed mood increased during the intensive social distancing period after the Christmas holidays and early new year period at T4, lethargy decreased. Significant change in worthlessness occurred only 2 of 5 time-points, depicting a divergent pattern of change than depression and its two key identifiers, through worthlessness first revealing significant elevations well into the second wave of the pandemic (around November-December 2020).

Overall, no significant change patterns occurred for suicidal ideation, except for a slight decrease in the prevalence of such thoughts occurring upon predominant termination of the social distancing protocols at T6. Change patterns of psychomotor impairment/agitation were also different than the overall depressive change patterns, predominantly decreasing across the study period. Finally, significant change in appetite, sleep, and concentration problems solely occurred 3 of 5 time-points. In sum, only the two main identifiers (i.e., core criteria; American Psychiatric Association, 2013) of depression revealed identical and significant change patterns as the main analysis on the depression construct, highlighting the specificity of the results for key depressive symptoms including anhedonia and depressed mood.

Table S8

Model fit for the Each of the Nine Symptom-Specific Latent Change Score Models (LCSM)

Item number (Symptom)	χ^2 **(df),** ***p***	***RMSEA*** **[90% CI]**	***CFI***	***TLI***	***SRMR***
PHQ-1 (Anhedonia)	39.09 (9), $p < .001$	0.028 [0.019, 0.037]	0.990	0.984	0.026
PHQ-2 (Depressed Mood)	46.58 (9), $p < .001$	0.031 [0.023, 0.040]	0.989	0.982	0.028
PHQ-3 (Sleep disruption)	29.74 (9), $p < .001$	0.023 [0.014, 0.032]	0.994	0.991	0.020
PHQ-4 (Lethargy)	21.23 (9), $p = .012$	0.018 [0.008, 0.028]	0.996	0.994	0.016
PHQ-5 (Appetite change)	18.79 (9), $p = .027$	0.016 [0.005, 0.026]	0.997	0.995	0.015
PHQ-6 (Worthlessness)	22.06 (9), $p = .009$	0.018 [0.009, 0.028]	0.997	0.995	0.018
PHQ-7 (Concentration diff.)	19.43 (9), $p = .022$	0.016 [0.006, 0.026]	0.997	0.996	0.018
PHQ-8 (Psychomotor change)	58.19 (9), $p < .001$	0.035 [0.027, 0.044]	0.982	0.971	0.027
PHQ-9 (Suicidal ideation)	34.07 (9), $p < .001$	0.025 [0.017, 0.035]	0.995	0.992	0.024

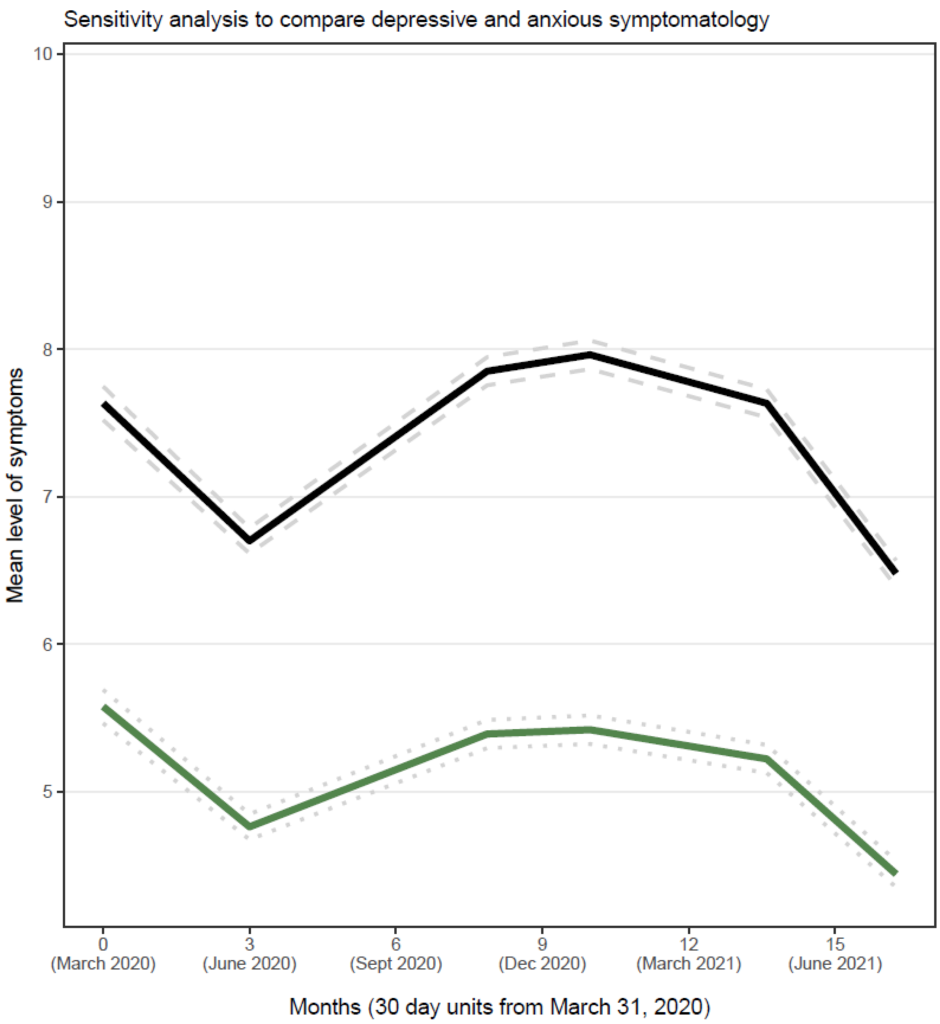
Contrasting Depressive and Anxious Change Profiles

Anxious change profiles were estimated to compare depressive change profiles and its predictors to anxiety. The correlation between depression (PHQ-9) and anxiety (GAD-7) across all six time-points is provided in Table S9 below. The analyses on anxiety followed the same procedures as described for depression (cf. Statistical analyses section). The fit metrics for the anxiety models were χ^2 (10) = 58.31 ($p < .001$), *RMSEA* = 0.033 (90% CI: [0.025, 0.042]), *CFI* = 0.992, *TLI* = 0.988, *SRMR* = 0.029 for the unconditional LCSM), and χ^2 (96) = 396.54 ($p < .001$), *RMSEA* = 0.027 (90% CI: [0.024, 0.030]), *CFI* = 0.961, *TLI* = 0.942, and *SRMR* = 0.045 for the conditional LCSM.

Supplementary Figures S4 and S5 (below) depicts the change profiles of anxious symptomatology across the study period along with depressive symptomatology, stringency of social distancing protocols (SDPs) and weekly infection rates (cf. COVID-19 incidence section; Methods section). Key differences were identified between evolution of anxious versus depressive symptomatology and their predictors. In contrast with depression, ensuing an initial heightening in symptoms occurring for both symptom domains, anxiety both fluctuated less and revealed several notable differences in fluctuation patterns than depression. Specifically, the standardized estimates of change were -0.42 vs. -0.35 (at $\delta\eta_{t2}$), 0.86 vs. 0.46 ($\delta\eta_{t3}$), 0.20 vs. -0.00 ($\delta\eta_{t4}$), -0.35 vs. -0.16 ($\delta\eta_{t5}$), and -0.64 vs. -2.29 ($\delta\eta_{t6}$) for depression versus anxiety, respectively. In contrast with depression, no significant decrease in anxious symptomatology was observed at T5 during the reduction of SDPs (p = .425). Anxious symptoms levels were further highest during the first stringent SDP period (T1), while depression was highest during the re-introduction of strict distancing measures and further increase in their stringency at T3 and T4. Importantly, while infection rates did not significantly predict depressive symptomatology at any time-point during the study period, higher infection rates predicted heightened anxiety at both T1 and T4 (ps < .05). One possible explanation relates to concerns about viral spread, which has been tied increase in anxiousness during the present pandemic (e.g., Wheaton et al., 2021). Depression on the other hand has been more strongly tied to loneliness during the present pandemic and previously mechanistically demonstrated to be predicted by the prolonged states of social isolation (Elmer et al., 2020), corresponding to the findings of the present study in identifying fluctuations in depressive symptoms more strongly being tied to the changes in SDPs than anxiety. Finally, while quarantine manifested itself as an early (i.e., T3) predictor of deleterious depressive symptom profiles, this was not significantly tied to anxiety (p = .13). In summary, depressive symptom profiles were more strongly tied to fluctuations in SDP stringency, the socially isolating incidence of quarantine, and further unrelated to infection rates, while anxiety symptoms in contrast was related to infection rates and revealed lesser fluctuations to SDPs. Accordingly, while the pandemic and its accompanying SDPs also were tied to fluctuations in anxious symptoms, these were less tied (and at times, i.e., T5, disconnected) to the changes in SDPs relative to depression, with anxious symptoms further uniquely being predicted by infection rates in contrast to depression.

Figure S4

Sensitivity Analysis Comparing Depressive and Anxious Symptomatology Across Three Waves of the COVID-19 Pandemic From March 31, 2020, to August 1, 2021



N*ote*. The green line represents anxiety symptoms, while the black line represents depressive symptoms, with the dotted and dashed lines representing the 95% confidence intervals, respectively.

Table S9

Correlation Between Depression (PHQ-9) and Anxiety (GAD-7) at Each of the six Assessment Waves of the Study

T1	T2	T3	T4	T5	T6
0.784	0.795	0.831	0.817	0.832	0.809

Specificity of Findings in Relation to Treatment Seeking Behavior

As a third and final step in investigating the specificity of findings for depression compared to anxiety and other psychiatric problem domains, we investigated self-reported treatment seeking-behavior at the last assessment of the study (T6) among the individuals revealing deleterious depressive symptom change profiles during the study (i.e., 438 individuals; 10.04% of the sample; cf. Results section). Being in treatment for depressive problems specifically was compared and contrasted with being treatment related to all other available measured psychiatric problem domains. Overall, the individuals identified to have deleterious depressive symptom profiles through the pandemic period were in treatment for depression between 1.65 to 14.30 more frequently compared to any other problem domain. Particularly, treatment seeking for depression (i.e., 24.16%) was 2.15 times more frequent than for anxiety (11.24%), 14.30 times higher for depression than for obsessive-compulsive problems (1.69%), 14.30 times higher than for loneliness (1.69%), 1.65 times higher than stress and trauma-related problems (14.61%), 10.74 times higher for loss and/or grief (2.25%), and 3.31 times higher than ‘other’ reasons for treatment seeking (7.30%). Accordingly, the individuals revealing deleterious depressive change patterns were approximately 2 to 14 times more frequently in treatment for depression than any other internalizing problem domains, in addition to between 3 to 10 more often in treatment for other problem domains.

Additional Inspection of the Link Between Social Distancing Protocols and Depressive Symptomatology

The investigation of social distancing protocol (SDP) modifications in relation to depressive symptomatology is a key feature built into the study design (cf. study design criterion a to e; cf., Methods section). Nonetheless, additional analyses using information from complimentary sources were conducted to augment the study design in further examining the link between SDPs and depressive symptomatology. In addition to conducted statistical examination of the connection between one of the most frequently used and ubiquitous SDPs (i.e., quarantine exposure; cf. Results section) in the main analysis of the study, further inspections were conducted on overall SDP stringency levels at each assessment.

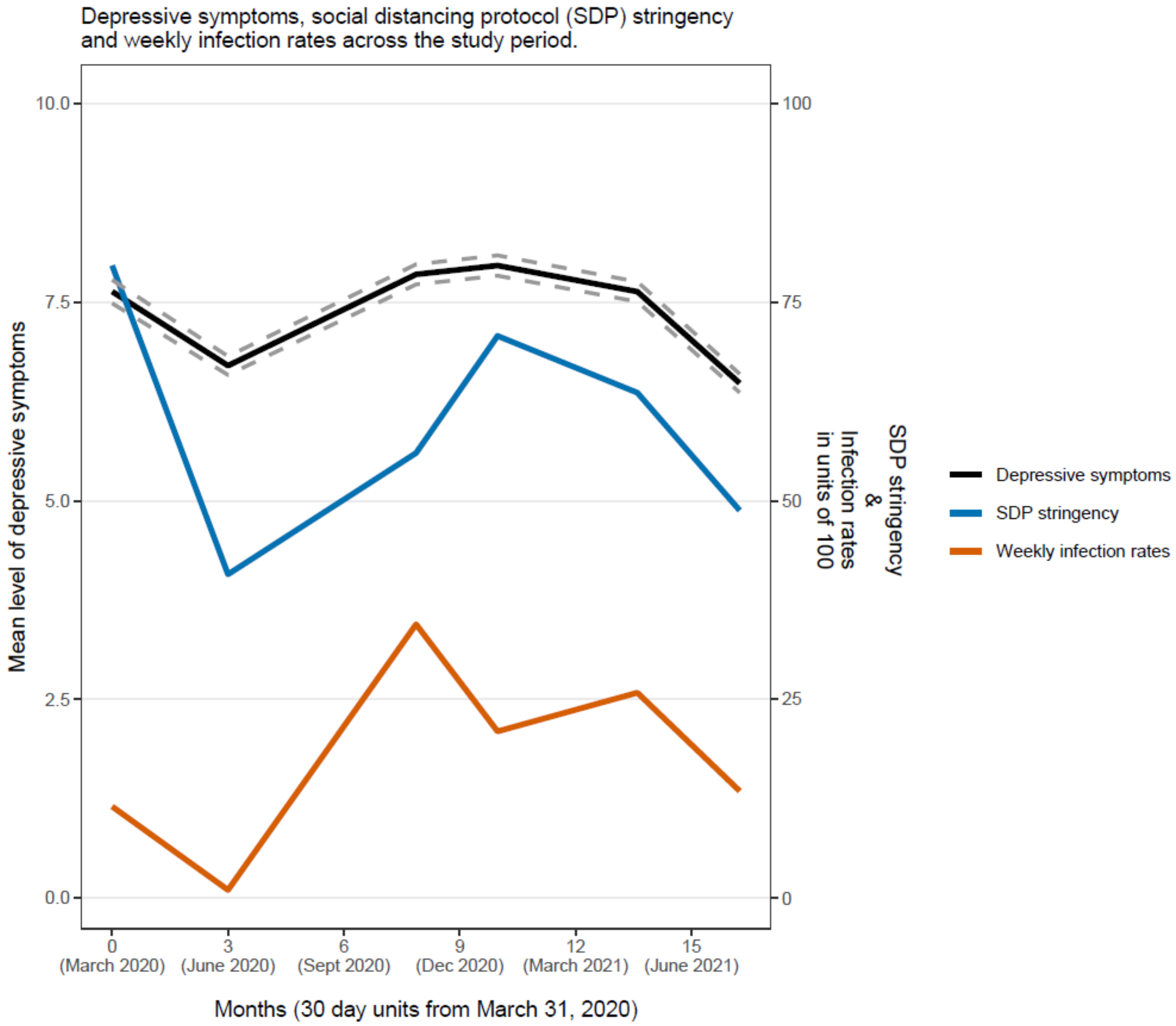
First, depressive symptom evolution was plotted along with an internationally validated stringency index of social distancing protocols (i.e., extracting the country-specific SDP stringency for Norway at the six assessment waves of the study) and weekly infection rates across the study period. This is illustrated in Supplementary Figure S5 below. Second, additional statistical examinations were conducted, inspecting the correlation between the extracted stringency of SDPs and the mean level of depressive symptoms at each wave of the study. This was done through using the Oxford COVID-19 Stringency Index (Hale et al., 2020), which was used as an additional and complimentary objective measure of overall strictness of SDPs. The Oxford COVID-19 Stringency Index is based on nine metrics, yielding a final stringency score ranging from 0 (no protocols present) to 100 (strictest response possible). The nine metrics utilized by the Stringency Index in calculating and providing SDP strictness estimates include: 1) workplace closures; 2) school closures; 3) cancellation of public events; 4) closures of public transport; 5) stay-at-home requirements; 6) restrictions on public gatherings; 7) public information campaigns; 8) restrictions on internal movements; and 9) international travel controls. In contrast with the national protocols which the present study implemented in its design and investigated over time, this internationally adaptable index does not account for the length implemented protocols into stringency severity. Overall, the stringency scores calculated for Norway at each wave of the present study by the Oxford COVID-19 Stringency Index were 79.63 (T1), 40.74 (T2), 56.02 (T3), 70.76 (T4), 63.61 (T5), 48.79 (T6). The index matched well with the national SDPs which the present study was designed to incorporate, revealing a near-identical profile in increase and decrease of SDP strictness.

The results incorporating this additional stringency index revealed a strong correlation ($r = .74$) between SDP stringency levels and mean level of symptoms across the study period. Notably, infection rates and SDP stringency were not strongly tied together ($r = .29$). This is further depicted in Supplementary Figure 5 below, with infection rates and SDP stringency revealing opposite patterns over longer periods during the pandemic, specifically at T3 to T4, and T4 to T5, where depressive symptom expression mimicked the SDP stringency trajectories as opposed to infection rates. These results are further in line with main statistical analyses revealing no relationship between infection rates and depressive symptoms as demonstrated in Table 1 and elaborated in the Results section of this study.

In sum, strong correlations were revealed between the complimentary and statistical measures of global SDP stringency and depressive symptoms, with depressive symptom expression further revealed to be statistically unrelated to infection rates as opposed to for anxious symptomatology where infection rates were deemed relevant.

Figure S5

Depressive Symptomatology Along With SDP Stringency and Weekly Infection Rates During the Study Period



Note. The left Y-axis reveals the mean level of depressive symptoms, while the right Y-axis portrays SDP stringency levels (0-100) and weekly infection rates in units of 100 at each wave of the study.

Expanded Explanation of the Latent Change Score Models

The latent change score model (LCSM) assesses and analyses individual differences in change over time, represented as latent *change scores* between adjacent occasions of measurement. First, an *unconditional* LCSM is fit to the data. This refers to as a model without any predictors which investigates whether and the extent to which any meaningful change exists in the outcome of interest (i.e., here change in depressive symptoms over time). In this model, first the initial latent (i.e., measurement error free) level of depressive symptoms is estimated at the onset of the study (T1). This is denoted as η_{t1}, yielding the latent initial levels of depressive symptoms at T1 in the sample. The average initial level is represented by the term in $\mu\eta_{t1}$ (cf. denoted in Figures 1 and 2, through regression on the constant **1**). The individual differences (i.e., variance) around this latent intercept are estimated by $\sigma^2\eta_{t1}$, providing information about the extent to which individuals differed from the sample intercept on initial levels of depressive symptoms at T1. The latent true score (i.e., η_{t1}; latent intercept in this context) is a measurement error free representation of the level of depressive symptoms at T1 as reflected by the observed score (i.e., y_{t1}), with the error term for the score denoted as ε_1.

Just as the latent measurement-error free level of depressive symptom at T1 is denoted η_{t1}, latent levels of depressive symptoms at each consecutive time-point (i.e., T2 to T6) are denoted as η_{t2} to η_{t6}. The observed scores (i.e., y_{t2} to y_{t6}) reflect these latent variables plus error (i.e., ε_2 to ε_6). Note that separating the true and error variance in the observed scores to obtain measurement error-free latent levels of depression requires a sufficient number of time points and appropriate constraints on the error variance (equality over time).

The primary focus in LCSM is on how latent levels of the construct change over time, as represented by a second layer of latent variables representing *time-dependent changes*, which are denoted as $\boldsymbol{\delta\eta_{t2}}$, $\boldsymbol{\delta\eta_{t3}}$, $\boldsymbol{\delta\eta_{t4}}$, $\boldsymbol{\delta\eta_{t5}}$, and $\boldsymbol{\delta\eta_{t6}}$, representing the change at time-points T2 to T6, respectively. Because these represent change in the latent variables (i.e., $\boldsymbol{\eta_{t1}}$ to $\boldsymbol{\eta_{t6}}$), these *latent change scores* are likewise free of free of measurement error. As depicted in Figures 1 and 2, these latent *change* scores capture change between each pair of adjacent assessments (i.e., T1 to T2; T2 to T3; T3 to T4; T4 to T5; and T5 to T6) and are denoted as $\boldsymbol{\delta\eta_{t2}}$, $\boldsymbol{\delta\eta_{t3}}$, $\boldsymbol{\delta\eta_{t4}}$, $\boldsymbol{\delta\eta_{t5}}$, and $\boldsymbol{\delta\eta_{t6}}$, respectively. Just as $\boldsymbol{\mu\eta_{t1}}$ and $\boldsymbol{\sigma^2\eta_{t1}}$ represent the mean and variance of the initial level of the construct (i.e., $\boldsymbol{\eta_{t1}}$), $\boldsymbol{\mu\delta\eta_{t2}}$ to $\boldsymbol{\mu\delta\eta_{t6}}$ and $\boldsymbol{\sigma^2\delta\eta_{t2}}$ to $\boldsymbol{\sigma^2\delta\eta_{t6}}$ capture the means and variances of the latent change scores. Note that covariances between initial status and latent changes are typically also included in an unconditional LCSM. Sometimes a third layer of latent variables is added to an LCSM to impose a parametric growth function on the latent change scores; however, in this application the pattern of change did not follow a simple function and interest focused on the specific time adjacent changes that were observed as pandemic protocols shifted.

The above-mentioned details form the core elements of the model which investigates *patterns of change* in depressive symptoms across the studies 17-month period and 6 assessment waves. With the change model in-place, *predictors* of change patterns can be brought in, expanding the model into a *conditional* LCSM (cf. Figure 2). These predictors each respectively predict the latent initial level of depressive symptoms (i.e., $\boldsymbol{\eta_{t1}}$) in addition to the latent change occurring at each time-point (i.e., $\boldsymbol{\delta\eta_{t2}}$, $\boldsymbol{\delta\eta_{t3}}$, $\boldsymbol{\delta\eta_{t4}}$, $\boldsymbol{\delta\eta_{t5}}$, and $\boldsymbol{\delta\eta_{t6}}$). The conditional LCSM model thus informs about *whether* and *the extent* to which each predictor can explain differences in initial levels (i.e., $\boldsymbol{\eta_{t1}}$) of depressive symptoms and the subsequent change patterns (i.e., $\boldsymbol{\delta\eta_{t2}}$, $\boldsymbol{\delta\eta_{t3}}$, $\boldsymbol{\delta\eta_{t4}}$, $\boldsymbol{\delta\eta_{t5}}$, and $\boldsymbol{\delta\eta_{t6}}$), *while controlling for* all other variables in the model.

For readers interested in more detailed mathematical overviews of LCSMs and its variants, McArdle (2001) and Grimm et al. (2016) may serve as suitable starting points, further encompassed with additional useful references.

Rank-Order Stability Analysis

The full correlation matrix showing the rank-order stability across all assessments (i.e., T1-T6) of the present study can be found in Table S10 below.

Table S10

Correlation Matrix Between the Latent Status Factors at Each of the six Assessment Waves of the Study

	η_{t1}	η_{t2}	η_{t3}	η_{t4}	η_{t5}	η_{t6}
η_{t1}	1.000					
η_{t2}	0.195	1.000				
η_{t3}	0.196	0.993	1.000			
η_{t4}	0.195	0.990	0.999	1.000		
η_{t5}	0.161	0.978	0.992	0.995	1.000	
η_{t6}	0.089	0.966	0.981	0.985	0.996	1.000

Longitudinal Measurement Invariance Inspection of the PHQ-9

The present investigation uses the sum-score of the PHQ-9 as its unit of analysis in modelling latent change given its well-established cut-off criteria validated in the general population which the study uses to identify subgroups of individuals revealing *clinically significant* increases in depressive symptomatology (i.e., Kroenke et al., 2001). As sum-scores implicitly make the assumption of equivalent measurement over time, in addition to the assumption of equal weighting of the items, longitudinal measurement invariance tests were conducted to examine the appropriateness of these assumptions and the use of sum-scores for the present study.

Measurement invariance test are highly sensitive large sample sizes, with high-powered studies prone to over-rejection of models due to trivial differences particularly related to item intercepts (i.e., scalar invariance testing). As such, next to conventional evaluations of model fit (i.e., Hu & Bentler, 1999), the use of ΔCFI has been advocated as a criterion for model comparisons in cases with large sample sizes (Cheung & Rensvold, 2002). Accordingly, model comparisons were conducted using Cheung & Rensvold's (2002) criteria where a ΔCFI of -.01 or more suggests that the less parsimonious model (i.e., model with fewer constraints) should be preferred, while smaller changes suggests that the more parsimonious model (i.e., model with more constraints) should be chosen. We further used ΔBIC to complement the above-mentioned criteria.

First, a configural invariance model was conducted to assess appropriateness of the construct in relation to its nine indicators and that the same factor structure applies across assessment waves. This model yielded good fit to the data, with χ^2 (1227) = 3616.33 (p < .001), RMSEA = 0.023 (90% CI: [0.022, 0.024]), CFI = 0.965, TLI = 0.960, SRMR = 0.042, and BIC = 235038.080.

Ensuingly, a metric invariance model was conducted to test whether the items were invariant in how representative they are of the construct across assessment waves. This model also portrayed good fit to the data, with χ^2 (1267) = 3703.19 (p < .001), RMSEA = 0.023 (90% CI: [0.022, 0.024]), CFI = 0.965, TLI = 0.960, SRMR = 0.041, and BIC = 234813.699. ΔCFI (Metric – Configural) was 0.000, revealing that metric (i.e., weak invariance) holds and thus that items do not vary in how representative they are of the construct (i.e., the factor) across different time-points. In other words, the different indicators do not become more or less representative of depression at different occasions. ΔBIC (Metric - Configural) was equal to -224 and supported this conclusion.

Finally, a scalar invariance model was conducted, testing whether the mean levels of the underlying items vary across time-points. This model revealed excellent fit to the data, with χ^2 (1307) = 4148.88 (p < .001), RMSEA = 0.024 (90% CI: [0.024, 0.025]), CFI = 0.959, TLI = 0.955, SRMR = 0.045, and BIC = 234989.204. Model evaluation through ΔCFI supported that full scalar invariance holds, with ΔCFI (Scalar – Metric) = -0.006. ΔBIC (Scalar - Metric) was equal to 175 and thus not in agreement with ΔCFI. Accordingly, as a sensitivity analysis, modification indices were utilized to inspect whether a partial invariance model would be deemed more acceptable by all evaluation metrics. These indices highlighted the intercept constraints on item one (i.e., anhedonia), which were subsequently freed estimate a partial scalar invariance model. This model demonstrated better fit to the data, χ^2 (1302) = 4003.09 (p < .001), RMSEA = 0.024 (90% CI: [0.023, 0.025]), CFI = 0.961, TLI = 0.957, SRMR = 0.044, and BIC = 234860.001. As with the full scalar invariance model, ΔCFI supported that partial scalar invariance holds, with ΔCFI ($\text{Scalar}_{partial}$ – Metric) = -0.004. ΔBIC (Scalar - Metric) also approached zero, being equal to 46, a negligible difference given the scale. Accordingly, item intercepts were inspected to check whether the differences captured by the BIC were meaningful. Inspection of item intercepts indicated that the intercept differences for item one across assessment waves may be trivial (i.e., largest differences was 0.17 on a 4-point scale, between T1 and T6). Accordingly, to test whether these intercept differences were actually meaningful, the factor scores from the partial scalar invariance model at each assessment wave were correlated with a) the corresponding the factor scores yielded from the full scalar invariance model above (i.e., with explicit invariance assumptions) and b) the sum-scores means (i.e., with implicit invariance assumptions). Correlations between the full scalar invariance factor scores with the sum-scores are also provided, with all mentioned correlations reported in Table S11 below.

Table S11

Correlation Between Factor Scores From the Partial Scalar Invariance model, the Full Scalar Invariance Model, and Sum-Scores

Time-point	Partial scalar invariance and full scalar invariance factor scores	Partial scalar invariance factor scores and sum-scores	Full scalar invariance factor scores and sum-scores
T1	.9999	.9941	.9941
T2	.9999	.9911	.9911
T3	.9999	. 9901	.9900
T4	.9999	.9918	.9916
T5	.9999	.9908	.9907
T6	.9999	.9906	.9907

Finally, the correlation between the means of the factor scores from the partial scalar invariance model and corresponding sum-scores means were investigated *across time* to demonstrate the stability in mean trends between the sum-scores and partial invariance scores, yielding a correlation of r = .9890). This same analysis comparing the correlation of the factor scores from the full scalar invariance model and sum-score means across time yielded a correlation of r = .9957.

All correlations were close to unity (i.e., between .9890 to .9999), revealing no meaningful differences between the factor scores from either invariance model (i.e., full scalar invariance or partial scalar invariance) and the sum-scores, providing support that the assumption of equivalent measurement holds and that sum-scores may appropriately be used to evaluate mean level changes in the present study.

In sum, all invariance models fit well to the data, with ΔCFI supporting a full scalar invariance model, while ΔBIC indicated possible differences in intercepts of item one. Inspections of these intercepts and correlations between score estimates indicated these differences were trivial in magnitude and supported the use of sum scores in the LCSMs.

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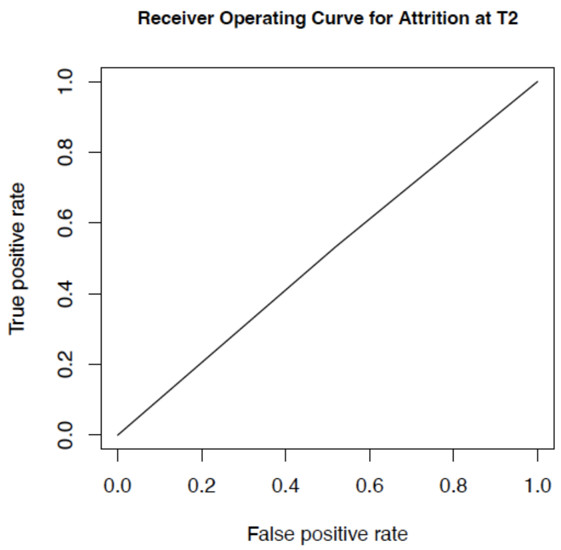
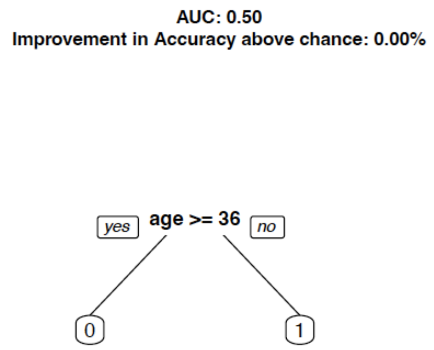
Supplementary Document 3: Classification and Regression Trees (CART) to Inspect Attrition

(Article 1)

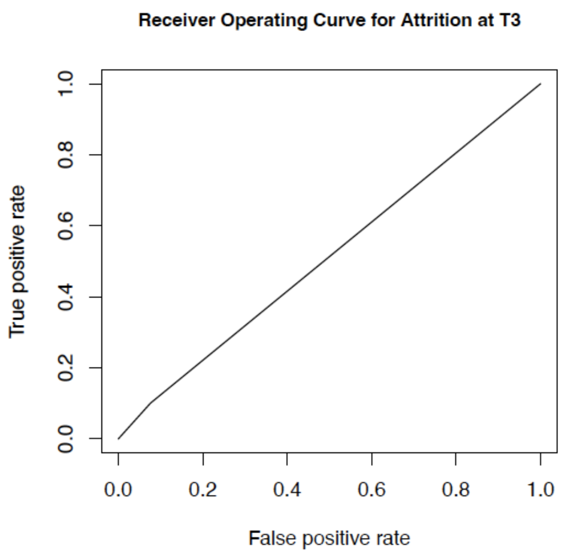
Supplementary Document 3: Classification and Regression Trees (CART) to Inspect Attrition

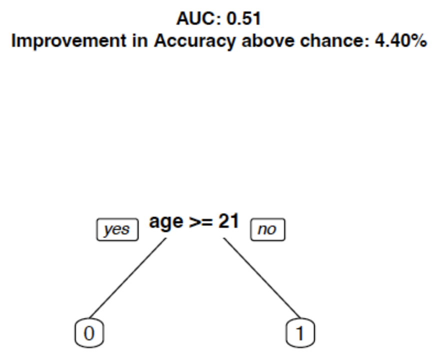
T2



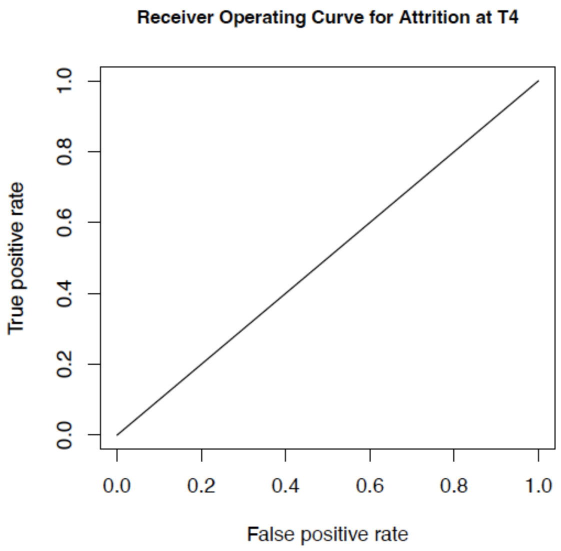


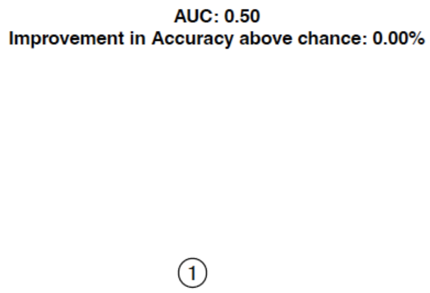
T3



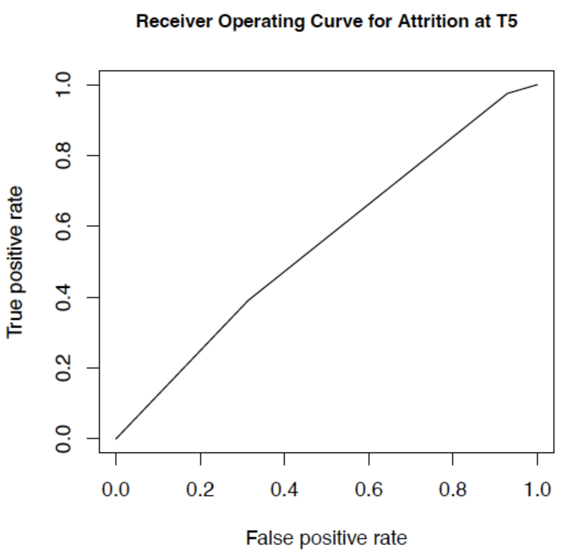


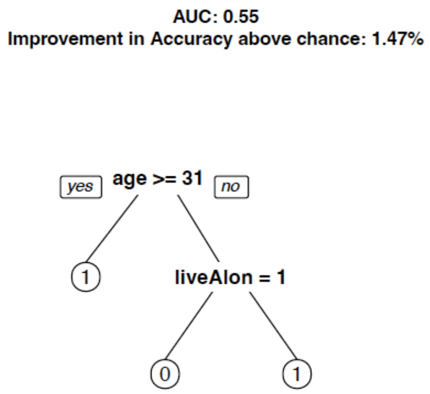
T4


Receiver Operating Curve for Attrition at T4
True positive rate
0.0
0.2
0.4
0.6
0.8
1.0
False positive rate

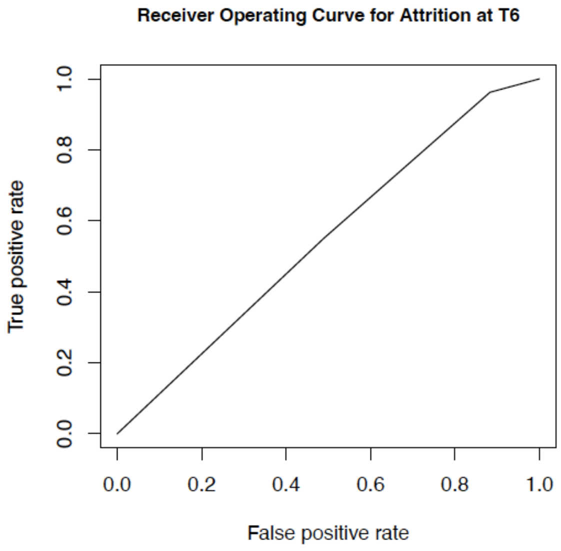

AUC: 0.50
Improvement in Accuracy above chance: 0.00%
1

T5

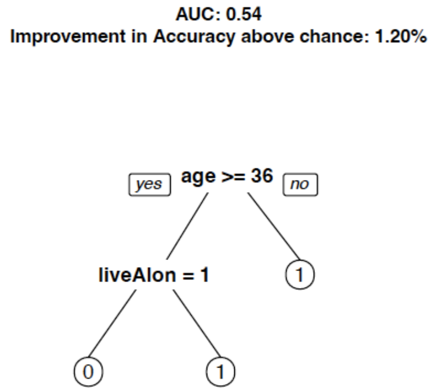

Receiver Operating Curve for Attrition at T5
True positive rate
0.0
0.2
0.4
0.6
0.8
1.0
False positive rate


AUC: 0.55
Improvement in Accuracy above chance: 1.47%
yes
age >= 31
no
1
liveAlon = 1
0
1

T6



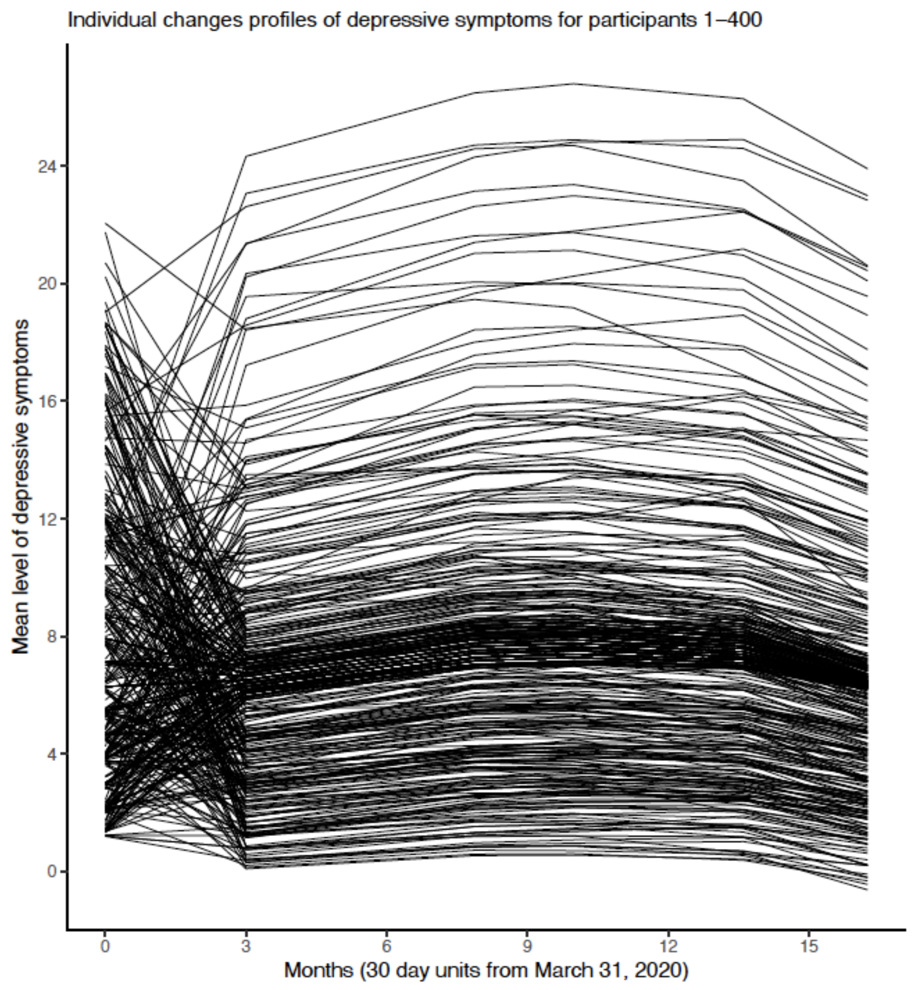
Receiver Operating Curve for Attrition at T6
True positive rate
0.0
0.2
0.4
0.6
0.8
1.0
False positive rate

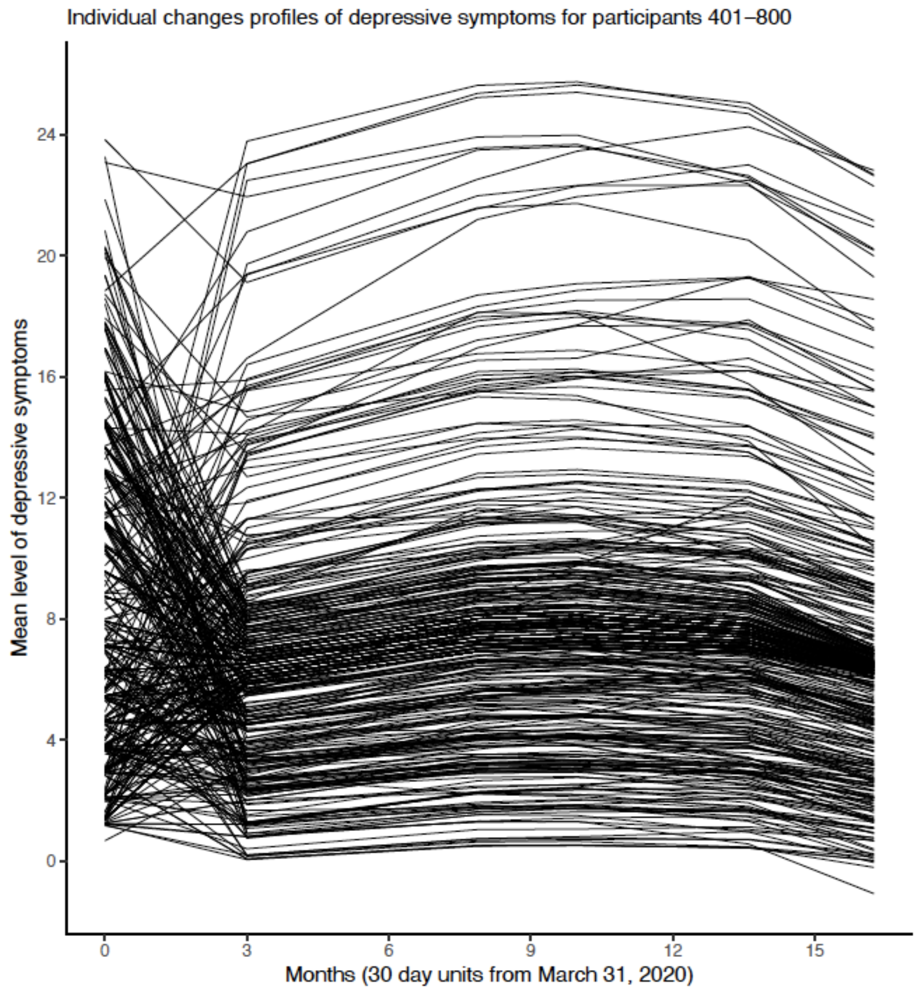


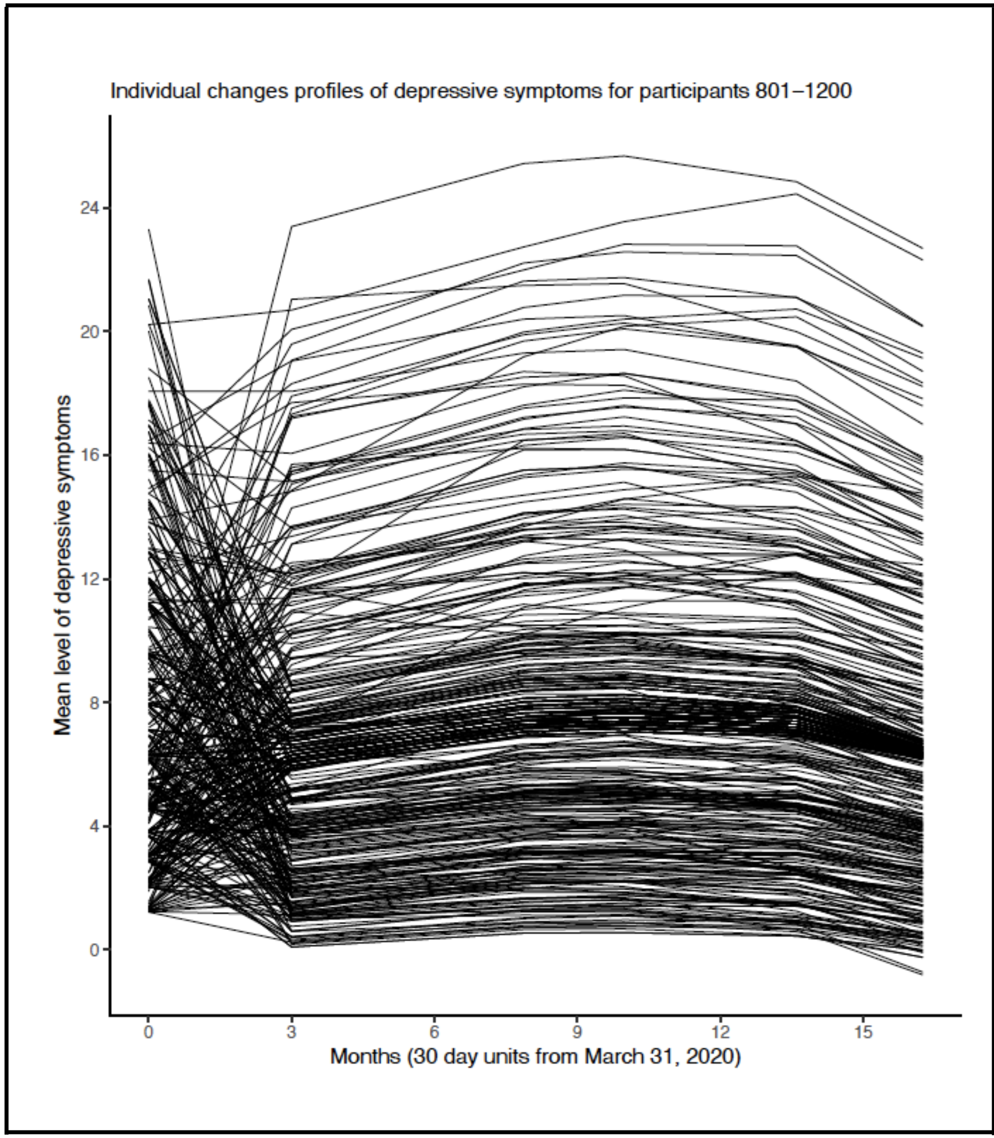
AUC: 0.54
Improvement in Accuracy above chance: 1.20%
yes
age >= 36
no
liveAlon = 1
1
0
1

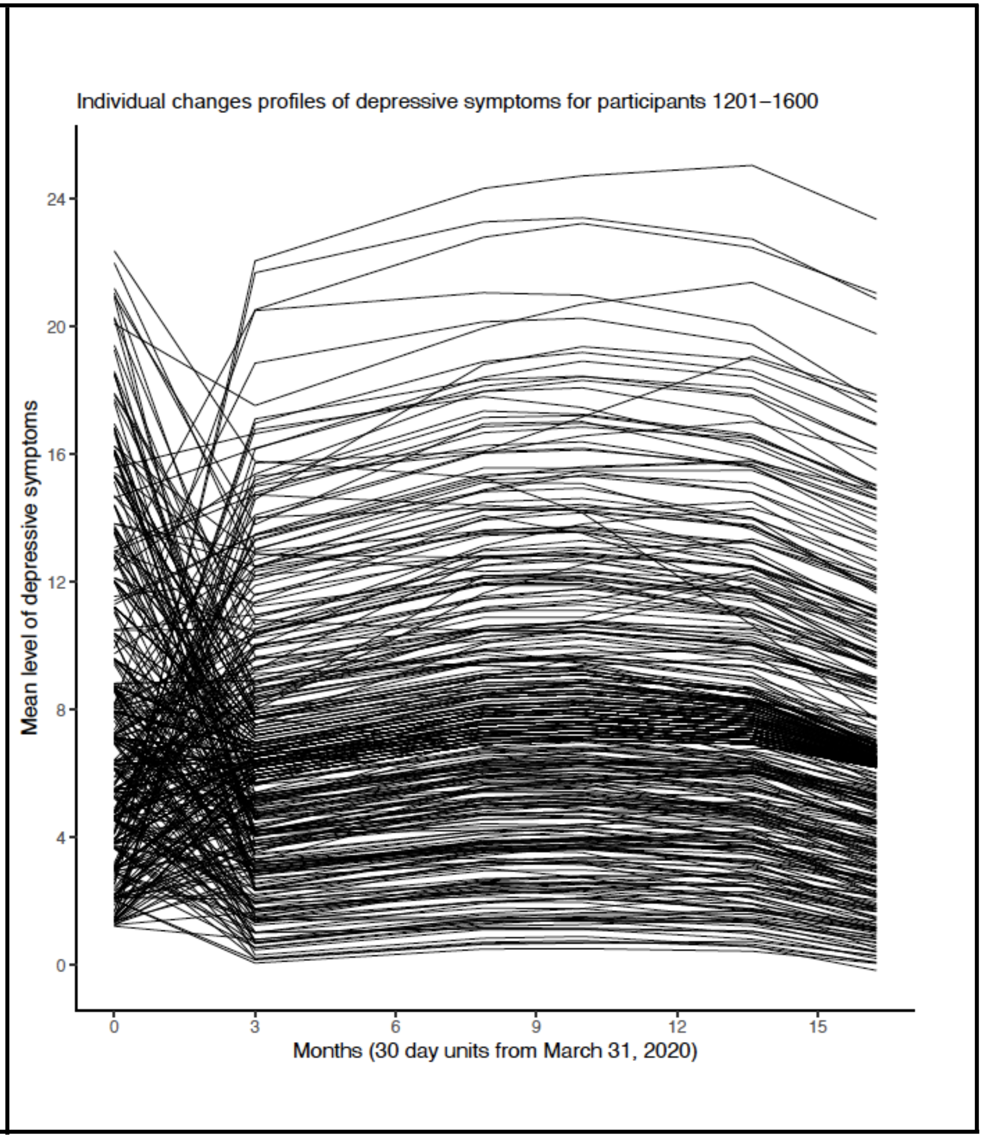
Supplementary Figures S1: Individual Change Profiles of all Participants in the Sample

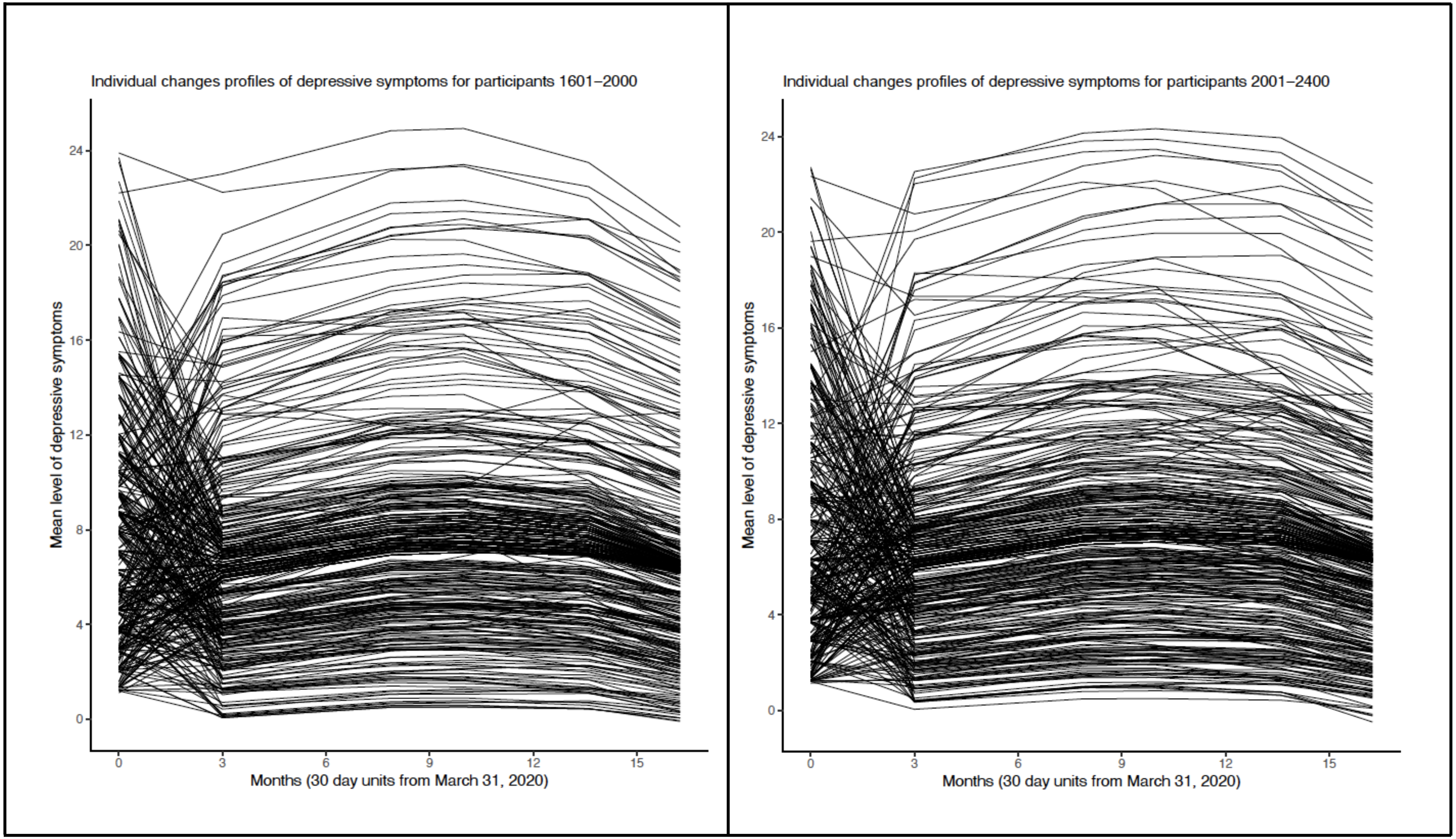
(Article 1)


Individual changes profiles of depressive symptoms for participants 1–400
Mean level of depressive symptoms
0
4
8
12
16
20
24
0
3
6
9
12
15
Months (30 day units from March 31, 2020)

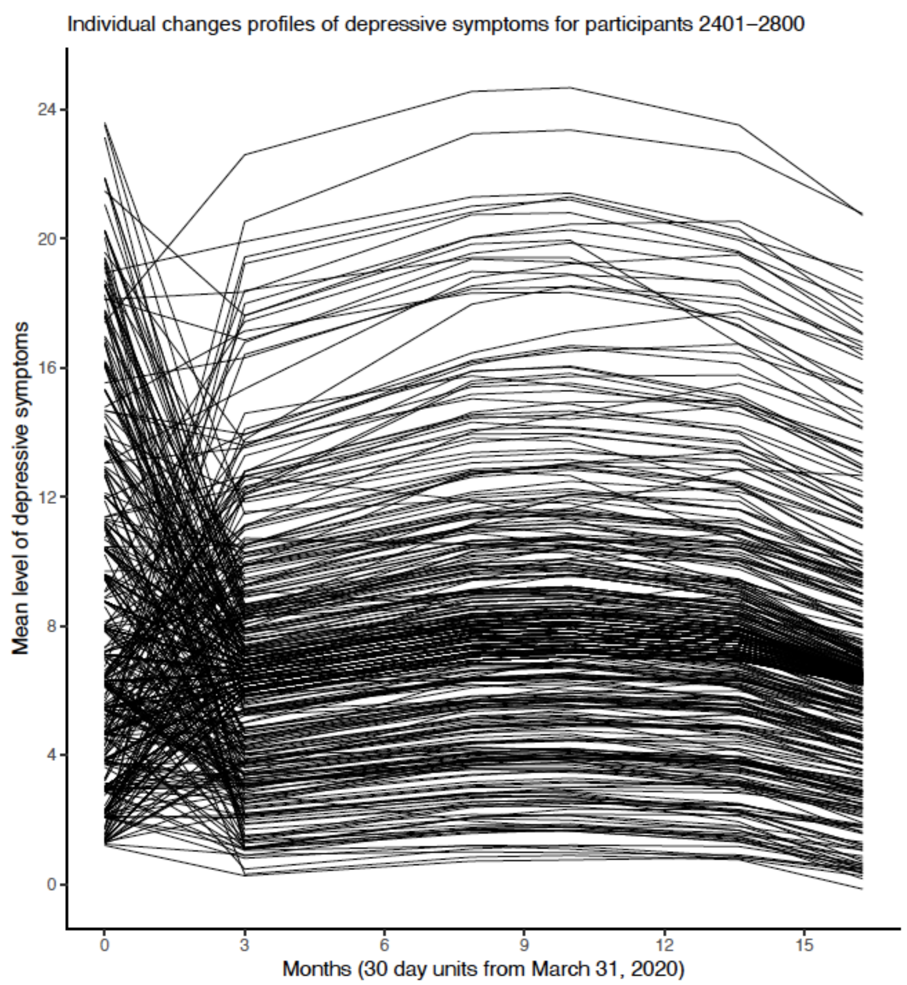

Individual changes profiles of depressive symptoms for participants 401–800
Mean level of depressive symptoms
0
4
8
12
16
20
24
0
3
6
9
12
15
Months (30 day units from March 31, 2020)

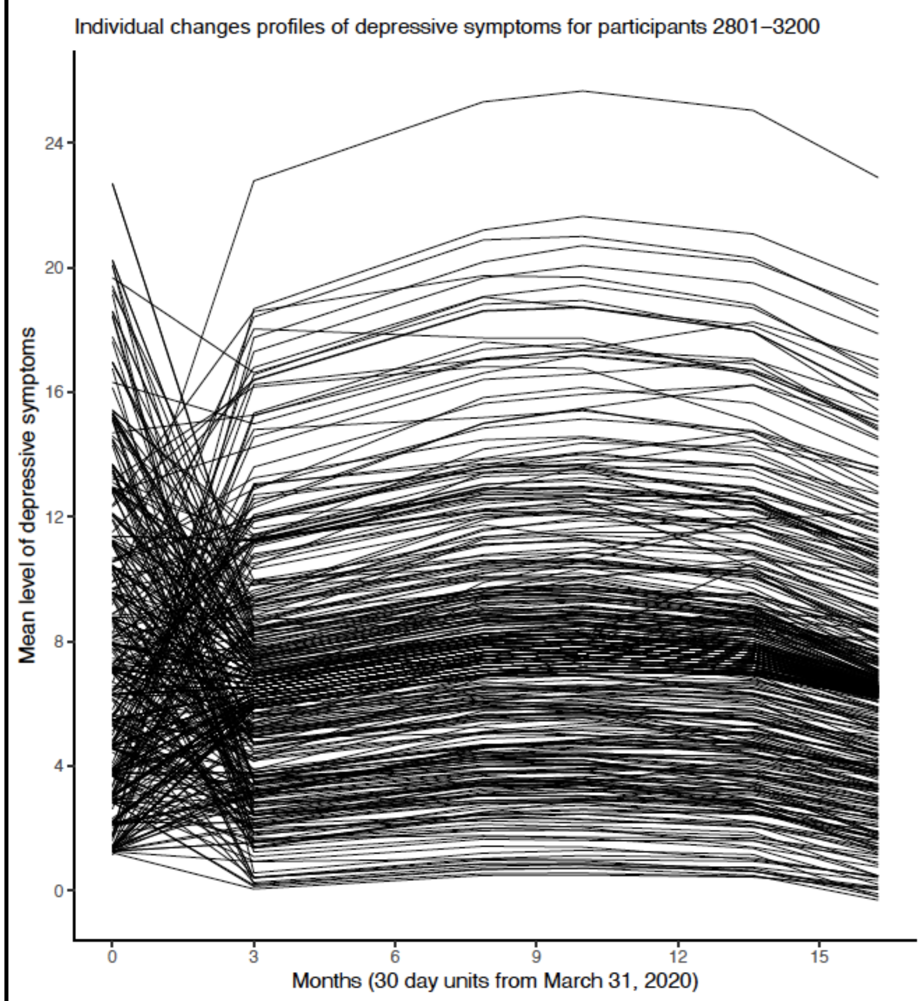

Individual changes profiles of depressive symptoms for participants 801–1200
Mean level of depressive symptoms
0
4
8
12
16
20
24
0
3
6
9
12
15
Months (30 day units from March 31, 2020)

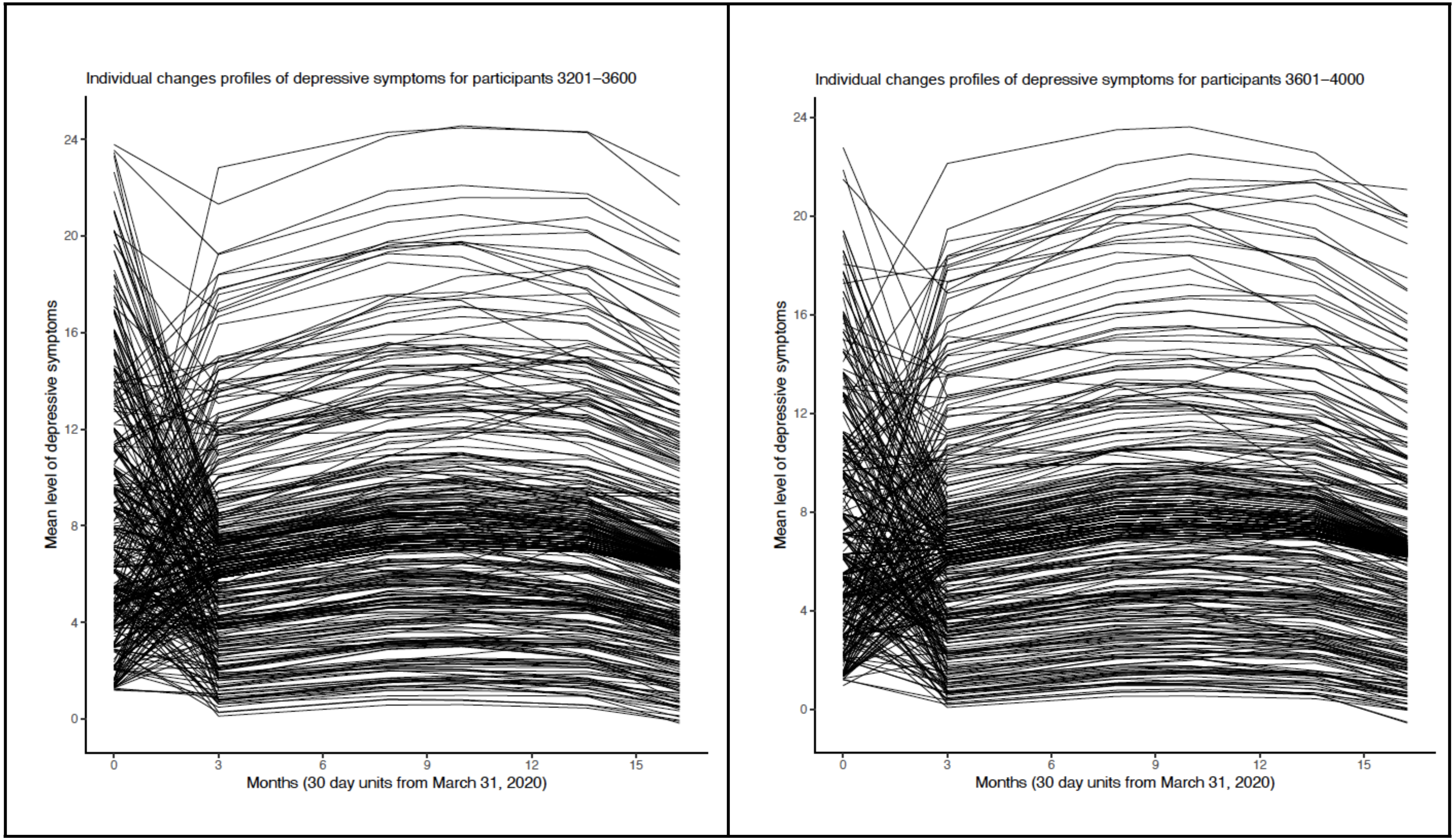

Individual changes profiles of depressive symptoms for participants 1201–1600
Mean level of depressive symptoms
0
4
8
12
16
20
24
0
3
6
9
12
15
Months (30 day units from March 31, 2020)

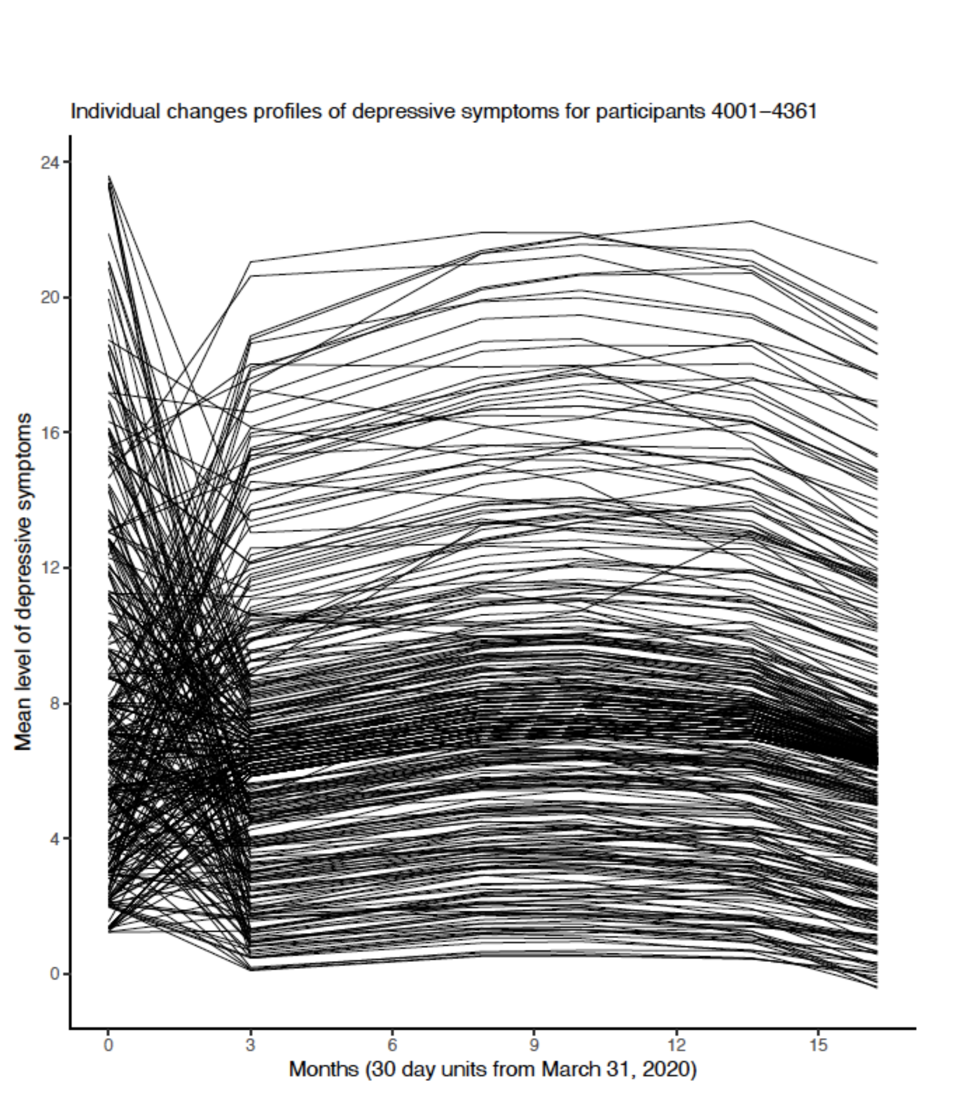


Individual changes profiles of depressive symptoms for participants 1601–2000
Mean level of depressive symptoms
Months (30 day units from March 31, 2020)
Individual changes profiles of depressive symptoms for participants 2001–2400
Mean level of depressive symptoms
Months (30 day units from March 31, 2020)


Individual changes profiles of depressive symptoms for participants 2401–2800
Mean level of depressive symptoms
0
4
8
12
16
20
24
0
3
6
9
12
15
Months (30 day units from March 31, 2020)


Individual changes profiles of depressive symptoms for participants 2801–3200
Mean level of depressive symptoms
0
4
8
12
16
20
24
0
3
6
9
12
15
Months (30 day units from March 31, 2020)

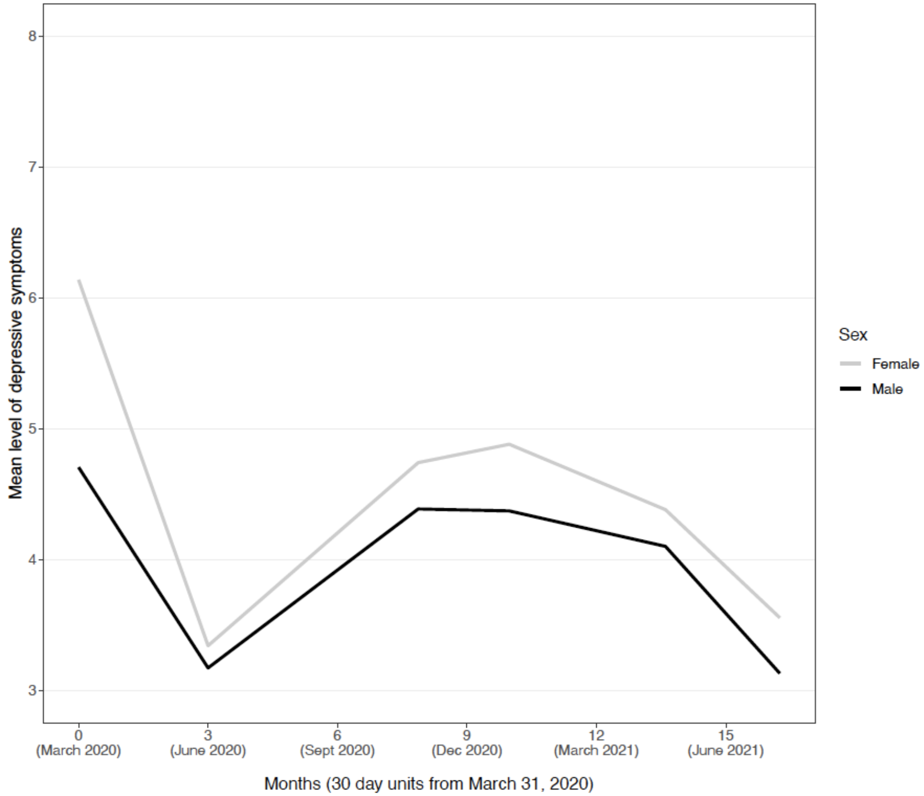

Individual changes profiles of depressive symptoms for participants 3201–3600
Mean level of depressive symptoms
24
20
16
12
8
4
0
0
3
6
9
12
15
Months (30 day units from March 31, 2020)
Individual changes profiles of depressive symptoms for participants 3601–4000
Mean level of depressive symptoms
24
20
16
12
8
4
0
0
3
6
9
12
15
Months (30 day units from March 31, 2020)


Individual changes profiles of depressive symptoms for participants 4001–4361
Mean level of depressive symptoms
24
20
16
12
8
4
0
0
3
6
9
12
15
Months (30 day units from March 31, 2020)

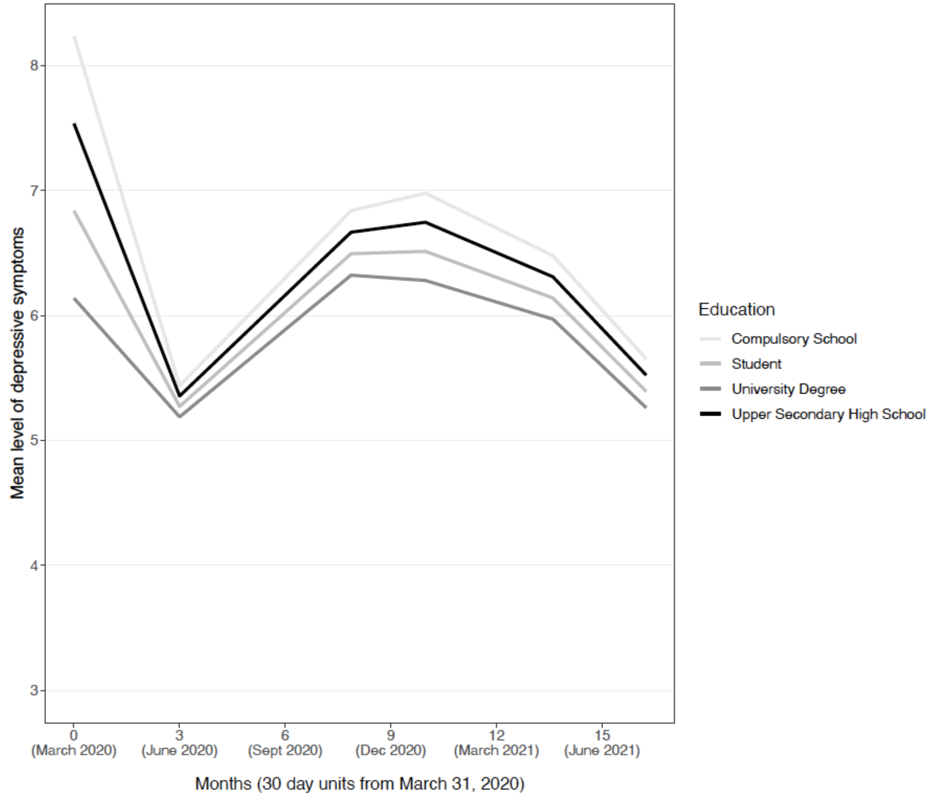
Supplementary Figure S2: Change Patterns of Depressive Symptoms as Predicted by Biological Sex and Education Level

(Article 1)

Change patterns of depressive symptoms as predicted by Biological Sex

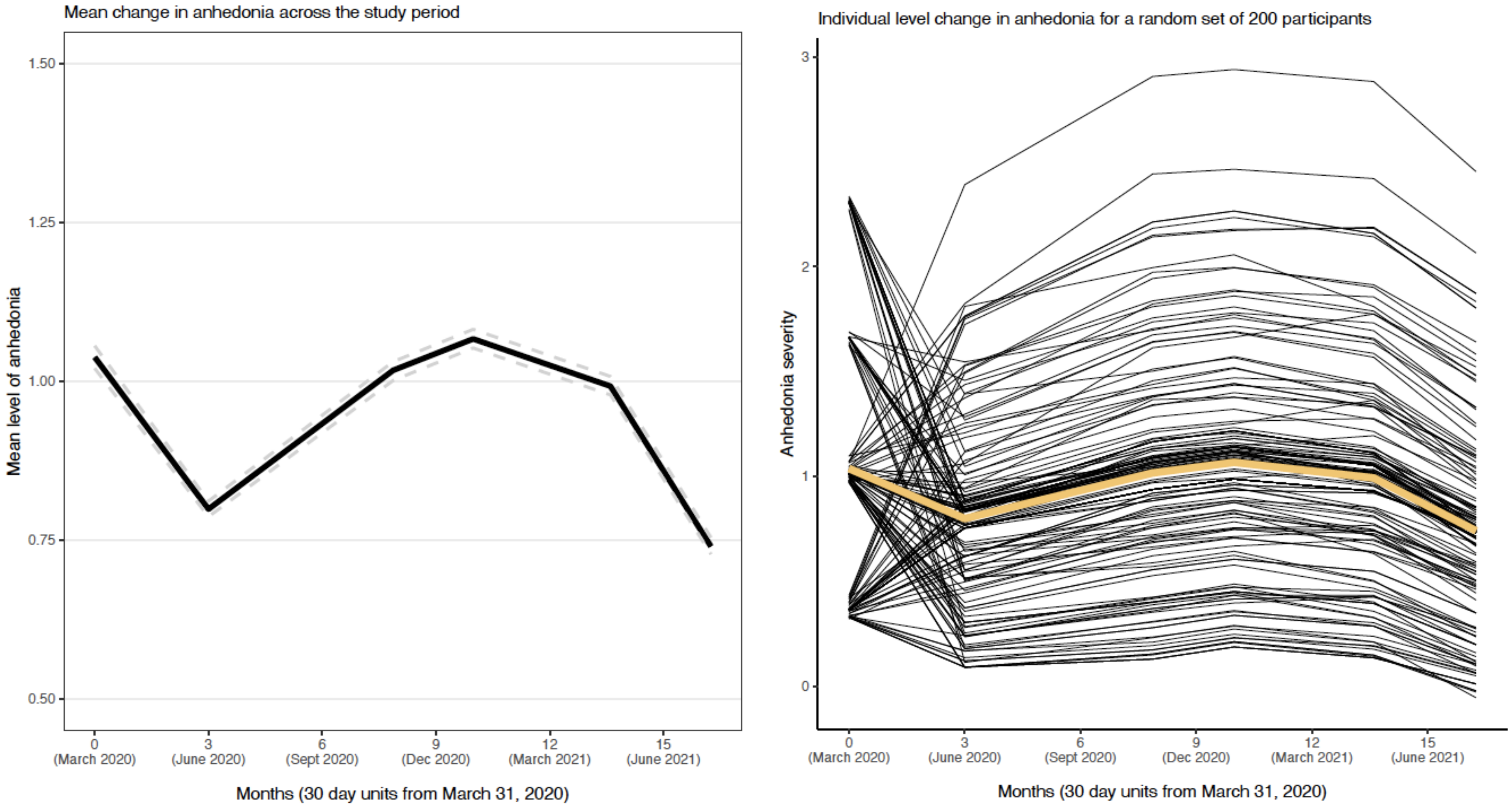


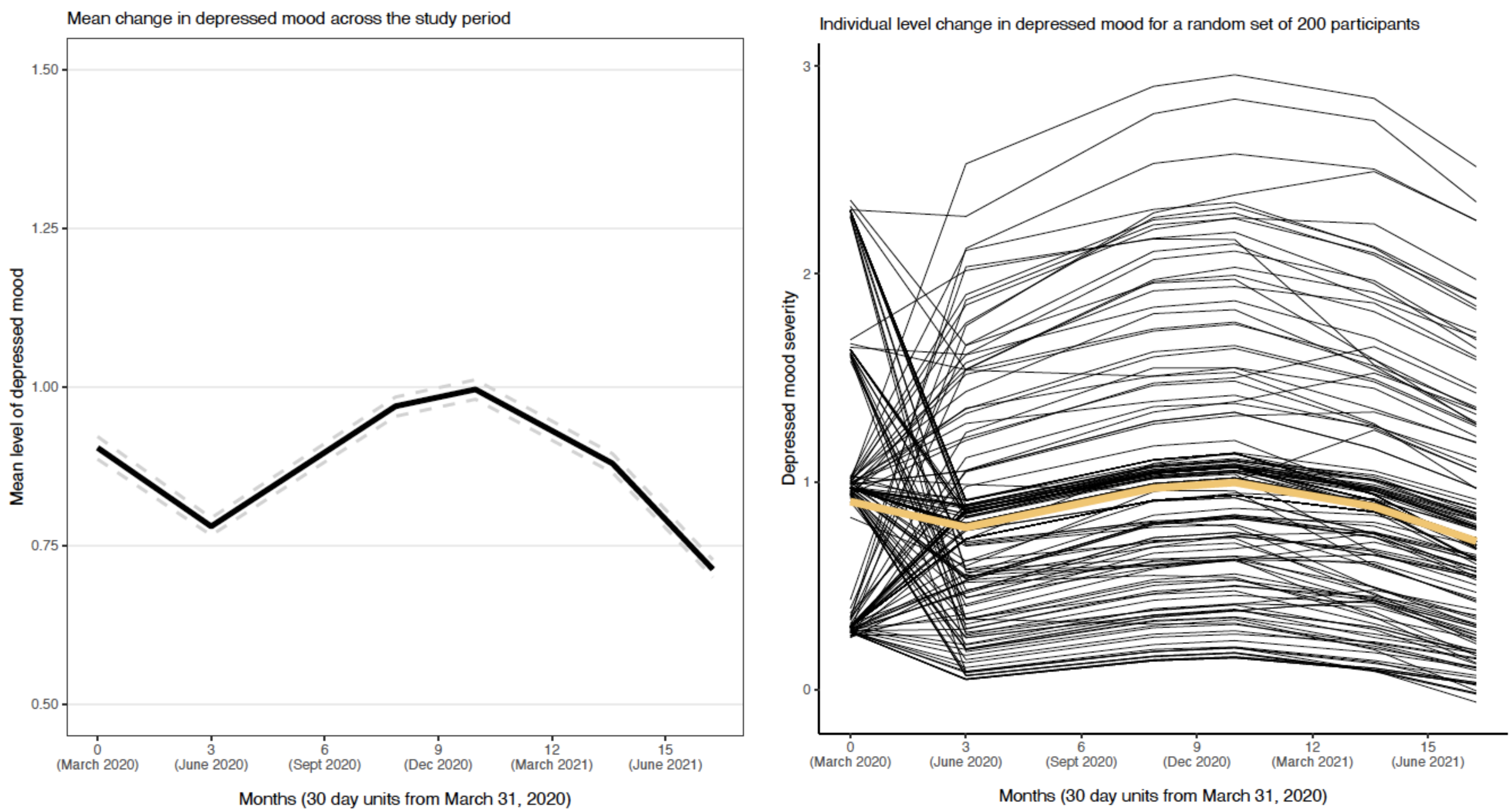
Change patterns of depressive symptoms as predicted by Education Level

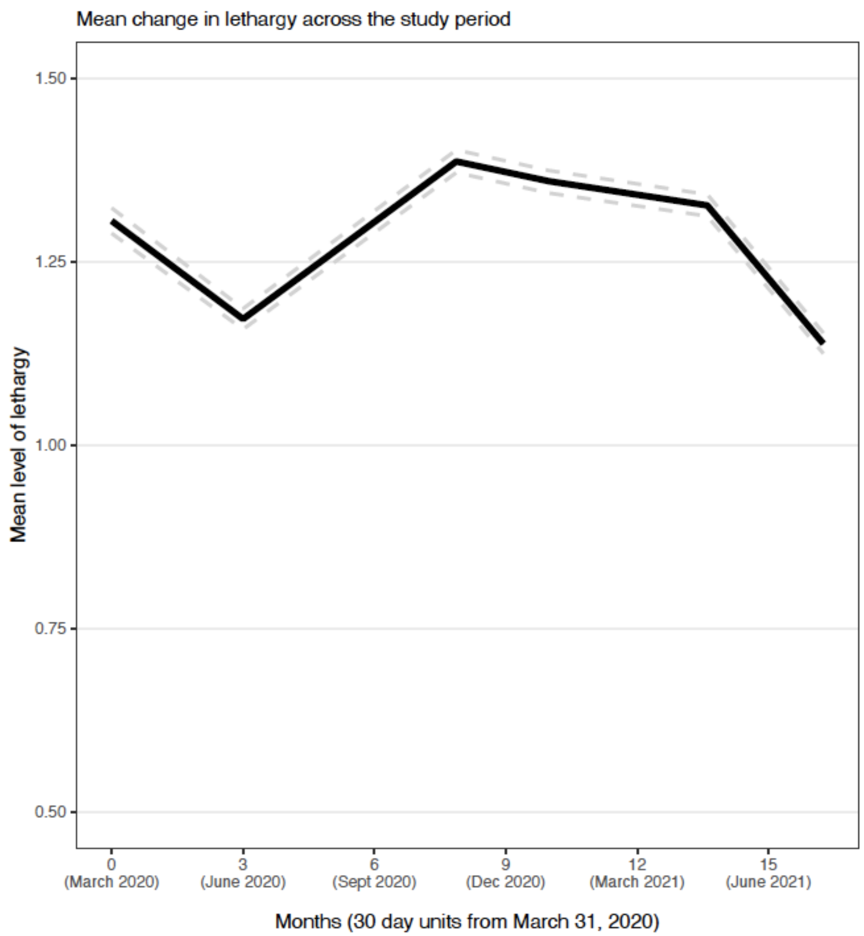


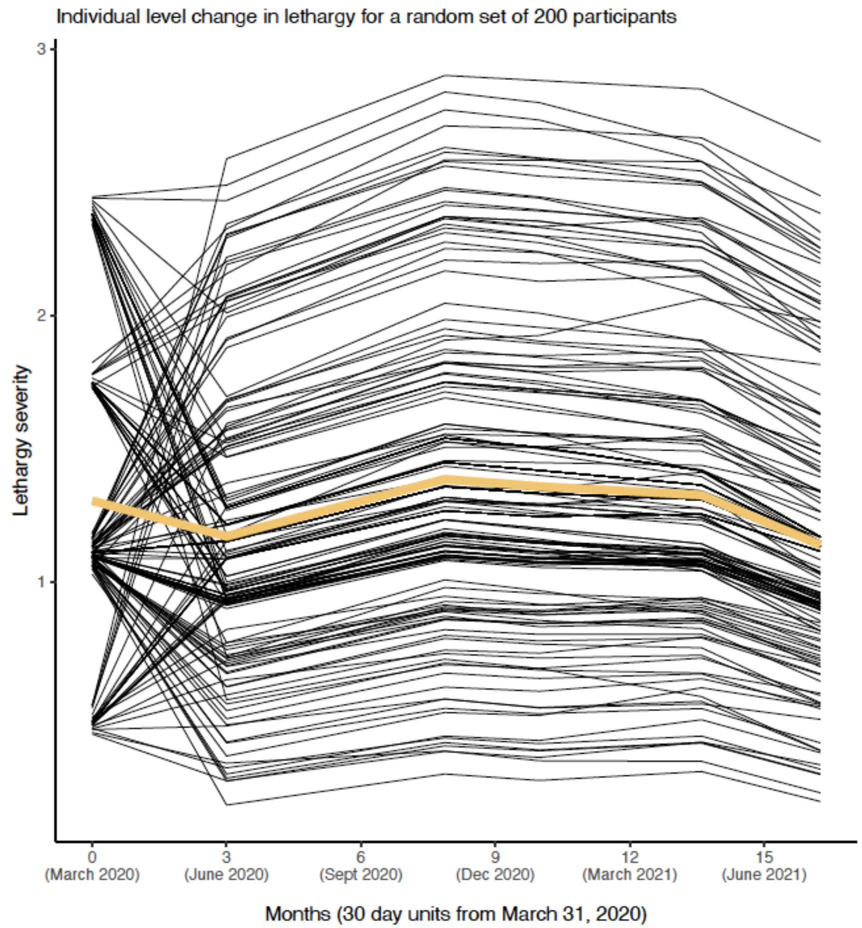
Supplementary Figures S3: Symptom-Specific Patterns of Change

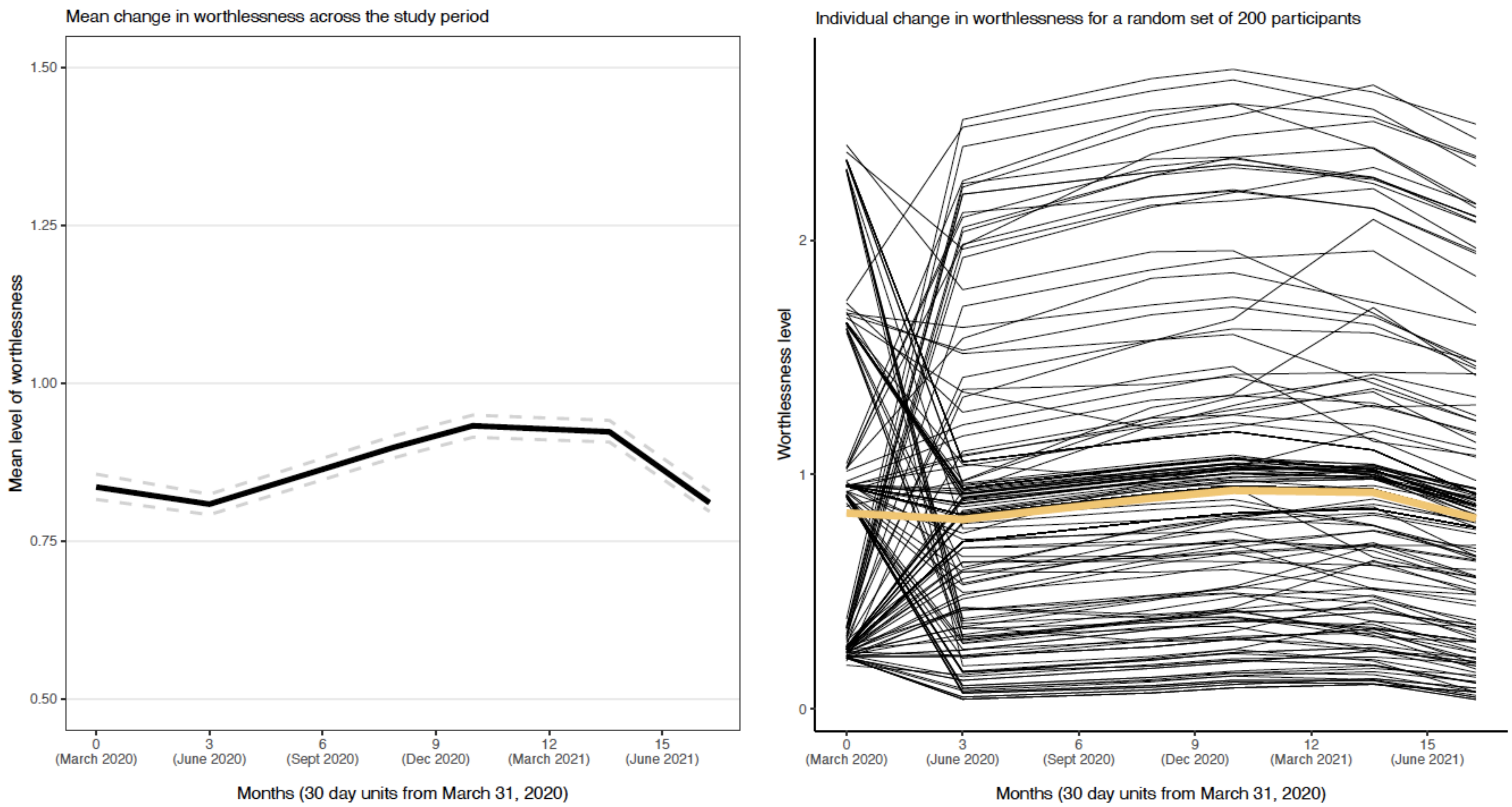
(Article 1)


Mean change in anhedonia across the study period
Mean level of anhedonia
1.50
1.25
1.00
0.75
0.50
0
(March 2020)
3
(June 2020)
6
(Sept 2020)
9
(Dec 2020)
12
(March 2021)
15
(June 2021)
Months (30 day units from March 31, 2020)
Individual level change in anhedonia for a random set of 200 participants
Anhedonia severity
3
2
1
0
0
(March 2020)
3
(June 2020)
6
(Sept 2020)
9
(Dec 2020)
12
(March 2021)
15
(June 2021)
Months (30 day units from March 31, 2020)

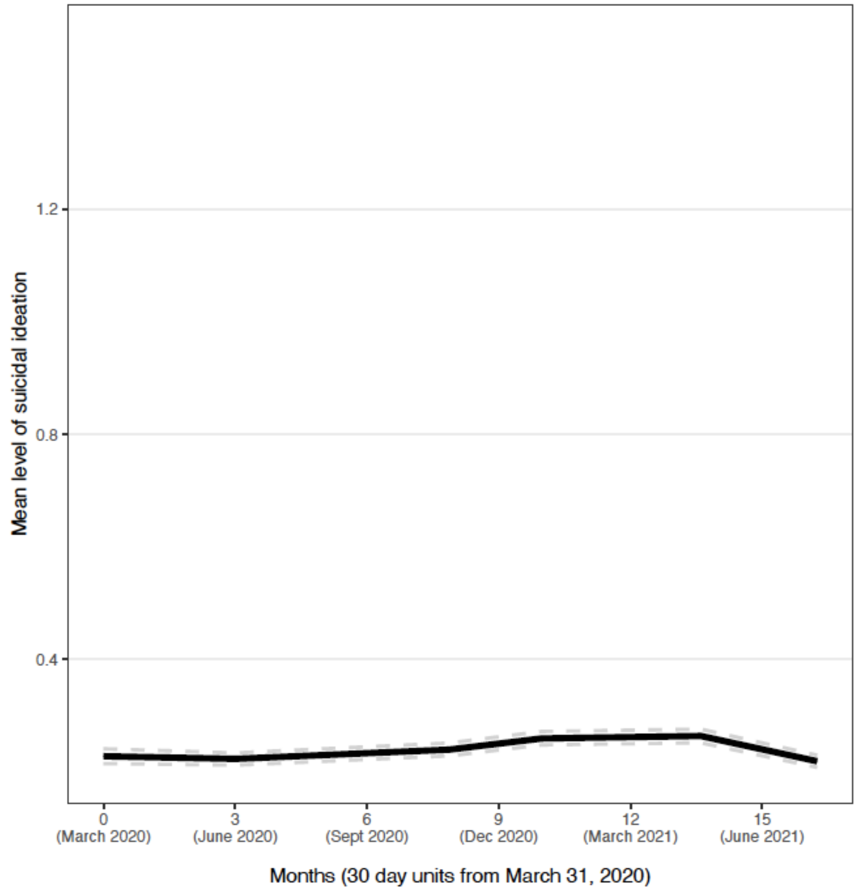

Mean change in depressed mood across the study period
Mean level of depressed mood
1.50
1.25
1.00
0.75
0.50
0
(March 2020)
3
(June 2020)
6
(Sept 2020)
9
(Dec 2020)
12
(March 2021)
15
(June 2021)
Months (30 day units from March 31, 2020)
Individual level change in depressed mood for a random set of 200 participants
Depressed mood severity
3
2
1
0
0
(March 2020)
3
(June 2020)
6
(Sept 2020)
9
(Dec 2020)
12
(March 2021)
15
(June 2021)
Months (30 day units from March 31, 2020)


Mean change in lethargy across the study period
Mean level of lethargy
1.50
1.25
1.00
0.75
0.50
0
(March 2020)
3
(June 2020)
6
(Sept 2020)
9
(Dec 2020)
12
(March 2021)
15
(June 2021)
Months (30 day units from March 31, 2020)

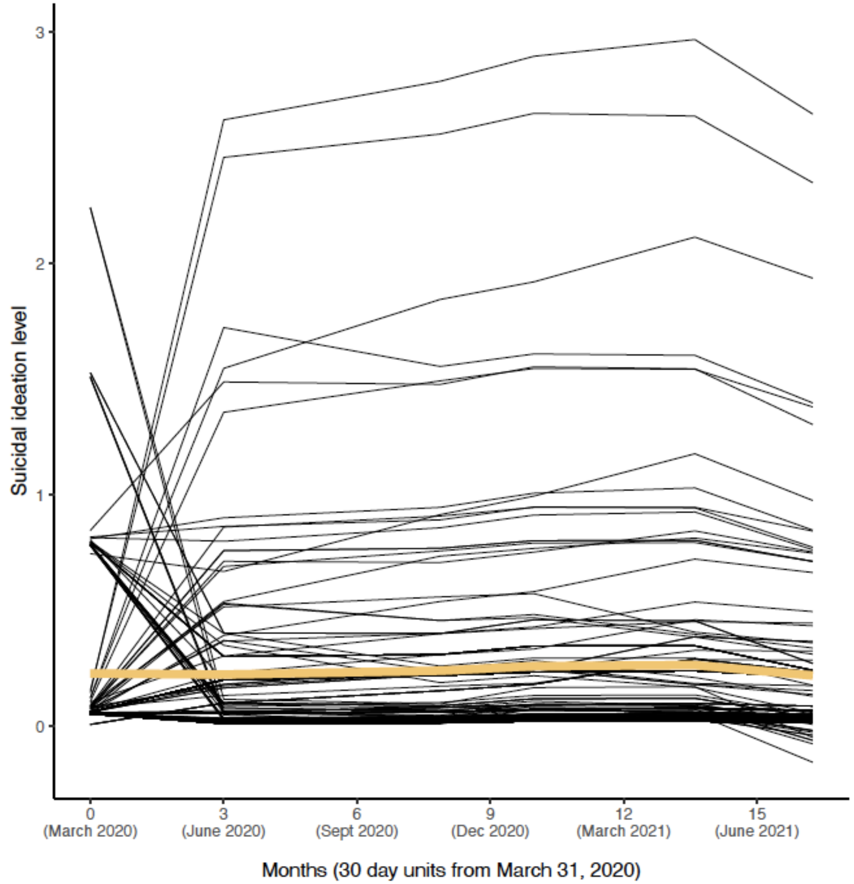

Individual level change in lethargy for a random set of 200 participants
Lethargy severity
3
2
1
0
(March 2020)
3
(June 2020)
6
(Sept 2020)
9
(Dec 2020)
12
(March 2021)
15
(June 2021)
Months (30 day units from March 31, 2020)

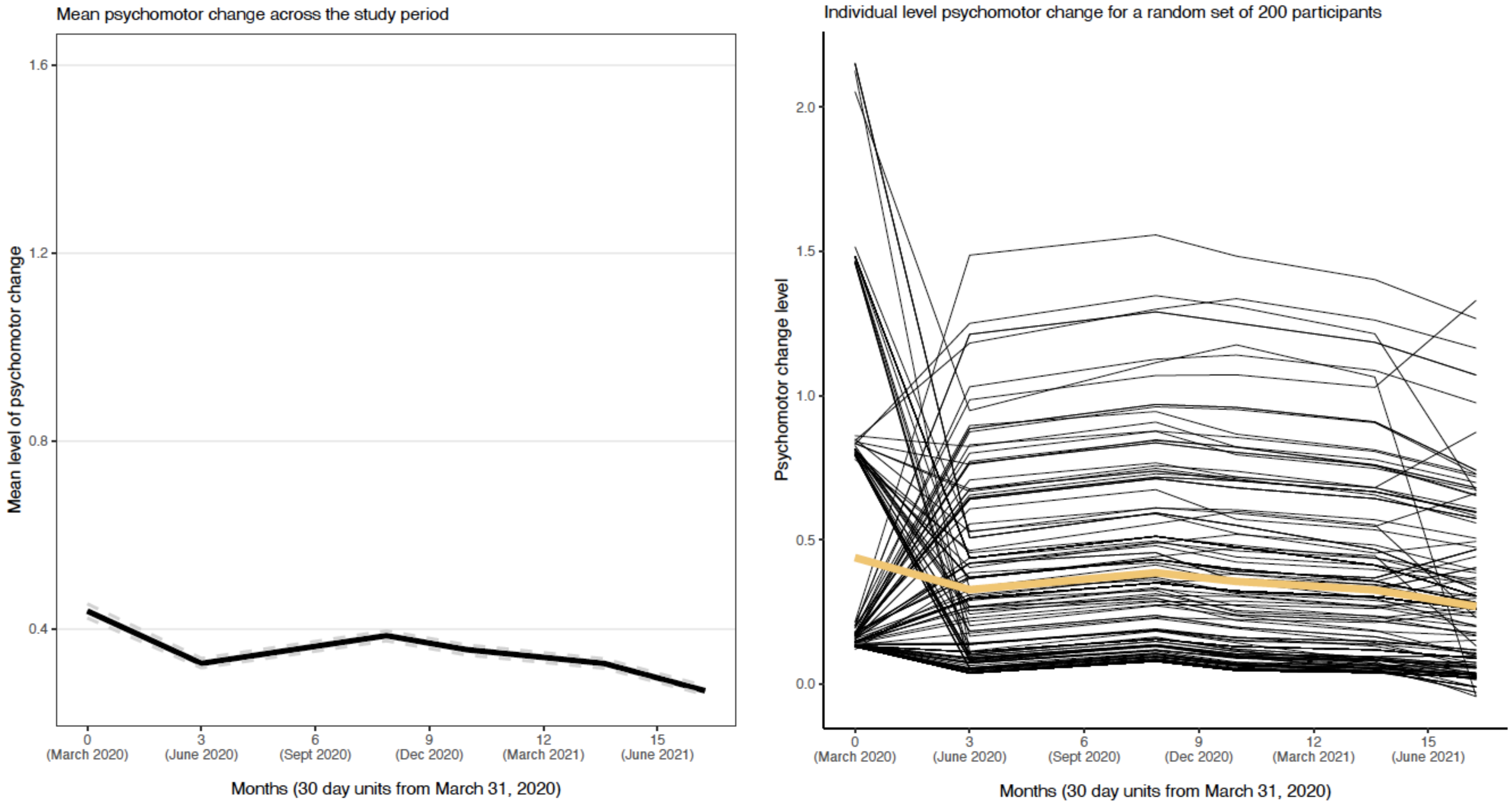

Mean change in worthlessness across the study period
Mean level of worthlessness
1.50
1.25
1.00
0.75
0.50
0
(March 2020)
3
(June 2020)
6
(Sept 2020)
9
(Dec 2020)
12
(March 2021)
15
(June 2021)
Months (30 day units from March 31, 2020)
Individual change in worthlessness for a random set of 200 participants
Worthlessness level
2
1
0
0
(March 2020)
3
(June 2020)
6
(Sept 2020)
9
(Dec 2020)
12
(March 2021)
15
(June 2021)
Months (30 day units from March 31, 2020)

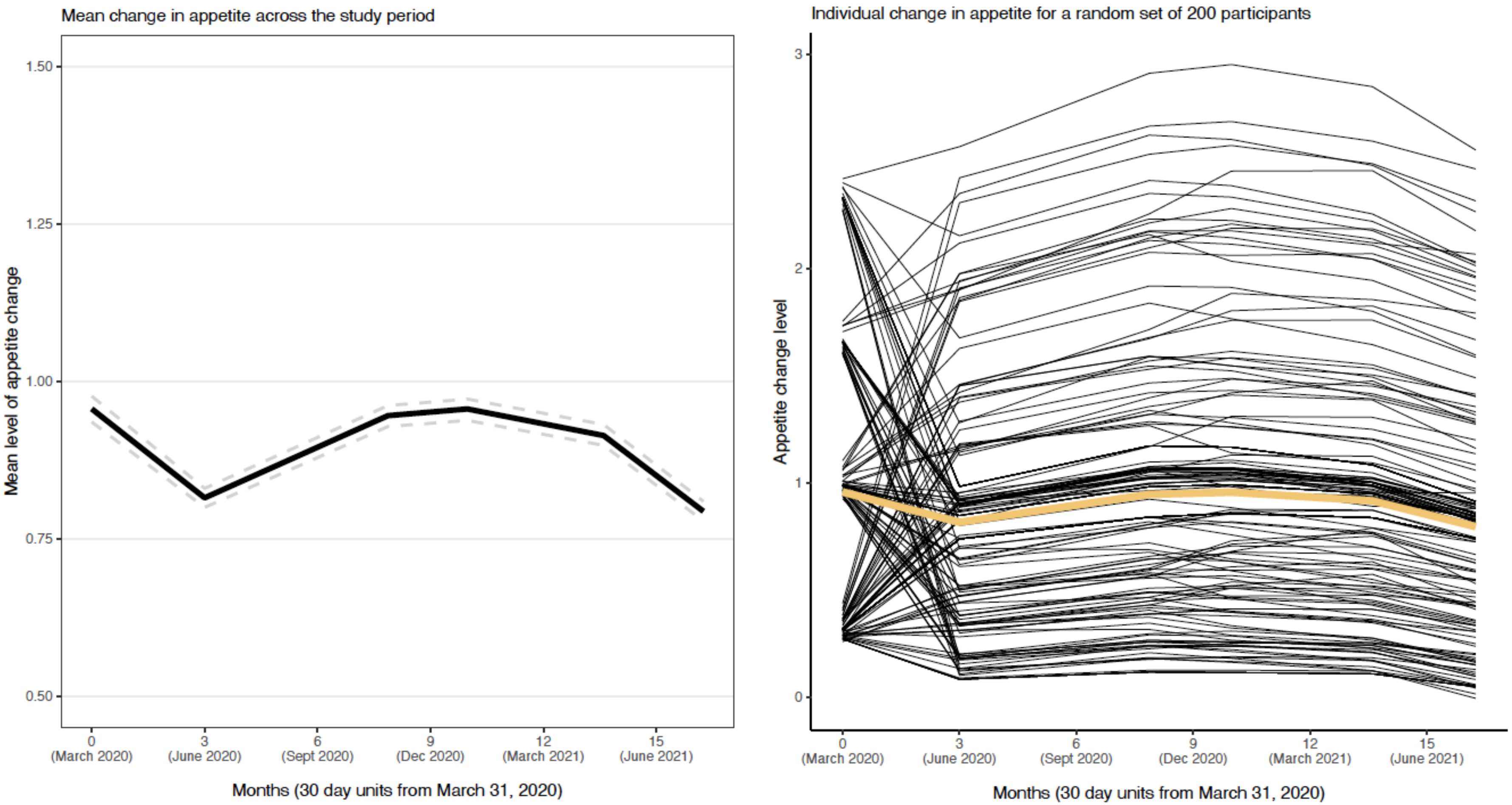
Mean change in suicidal ideation across the study period

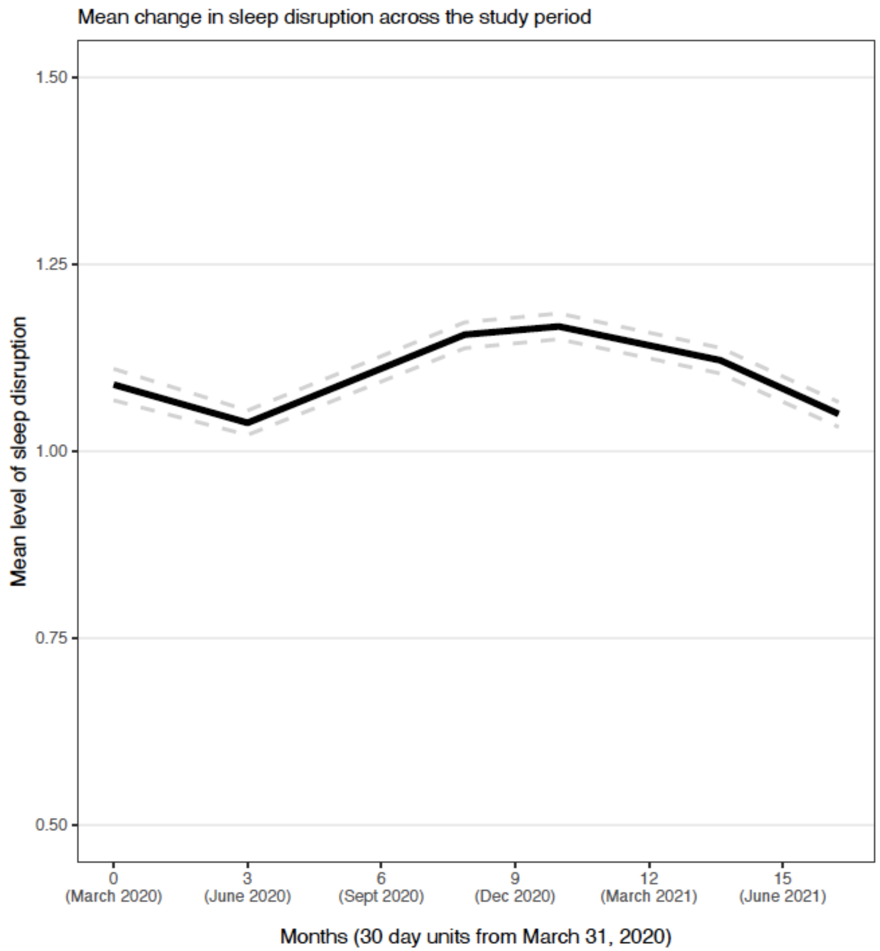


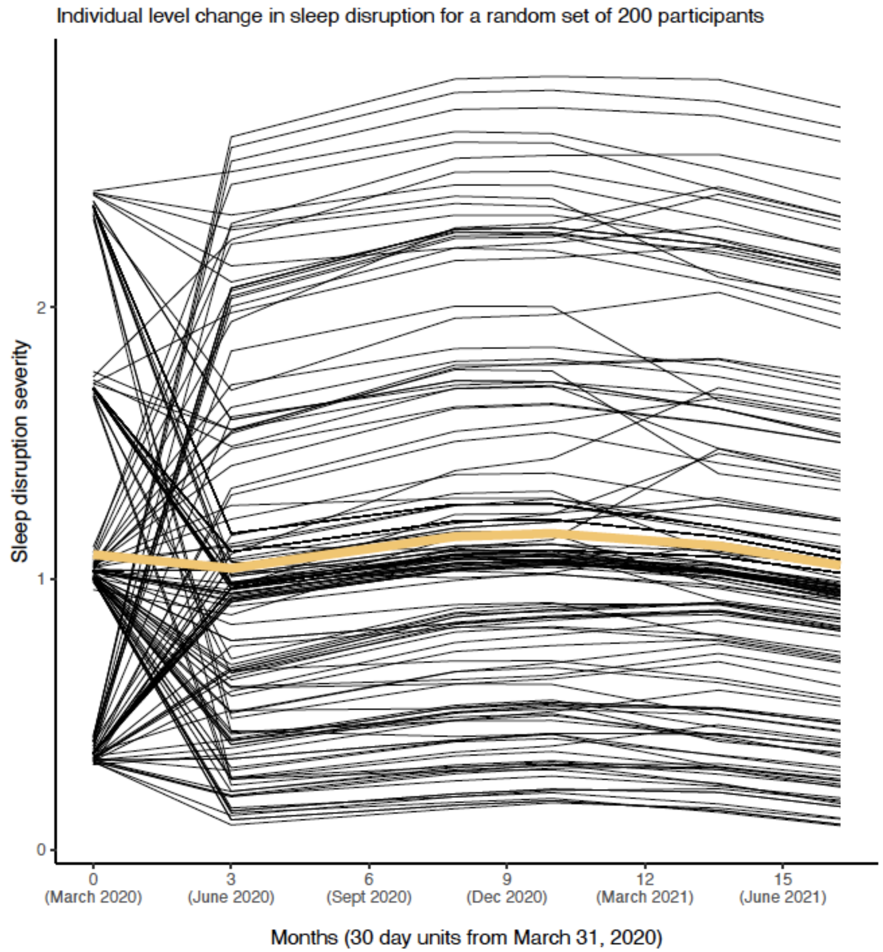
Individual level change in suicidal ideation for a random set of 200 participants



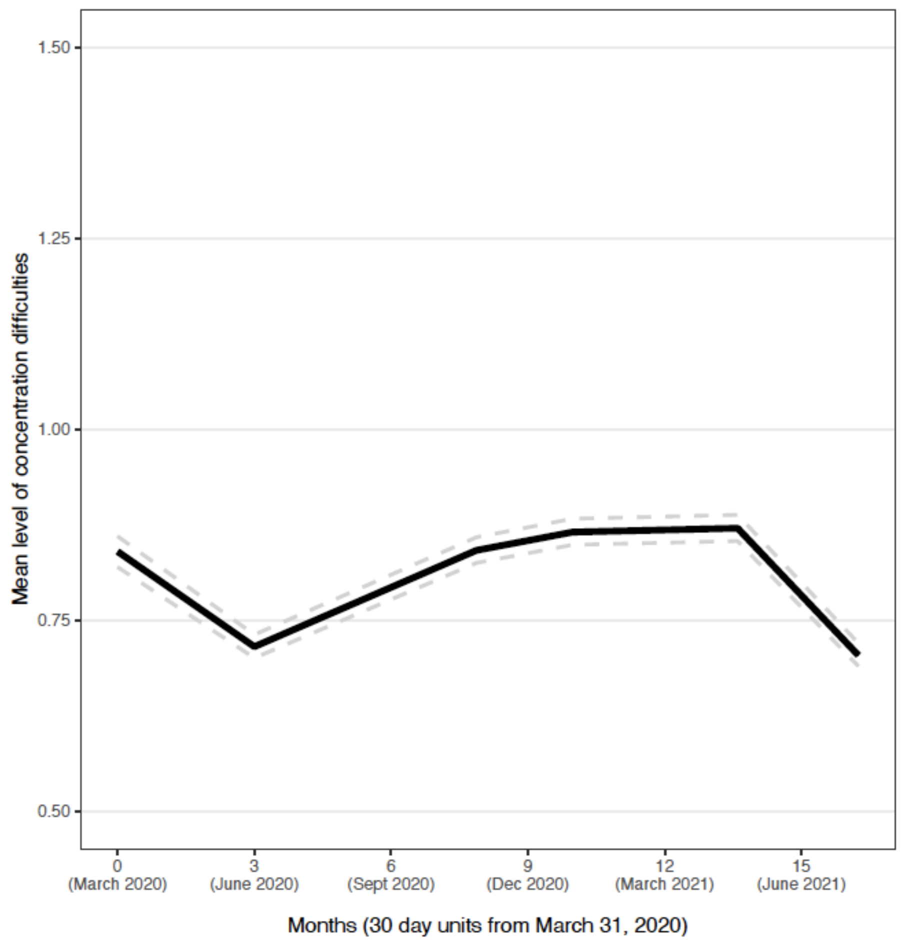

Mean psychomotor change across the study period
Mean level of psychomotor change
1.6
1.2
0.8
0.4
0
(March 2020)
3
(June 2020)
6
(Sept 2020)
9
(Dec 2020)
12
(March 2021)
15
(June 2021)
Months (30 day units from March 31, 2020)
Individual level psychomotor change for a random set of 200 participants
Psychomotor change level
2.0
1.5
1.0
0.5
0.0
0
(March 2020)
3
(June 2020)
6
(Sept 2020)
9
(Dec 2020)
12
(March 2021)
15
(June 2021)
Months (30 day units from March 31, 2020)


Mean change in appetite across the study period
Mean level of appetite change
1.50
1.25
1.00
0.75
0.50
0
(March 2020)
3
(June 2020)
6
(Sept 2020)
9
(Dec 2020)
12
(March 2021)
15
(June 2021)
Months (30 day units from March 31, 2020)
Individual change in appetite for a random set of 200 participants
Appetite change level
3
2
1
0
0
(March 2020)
3
(June 2020)
6
(Sept 2020)
9
(Dec 2020)
12
(March 2021)
15
(June 2021)
Months (30 day units from March 31, 2020)

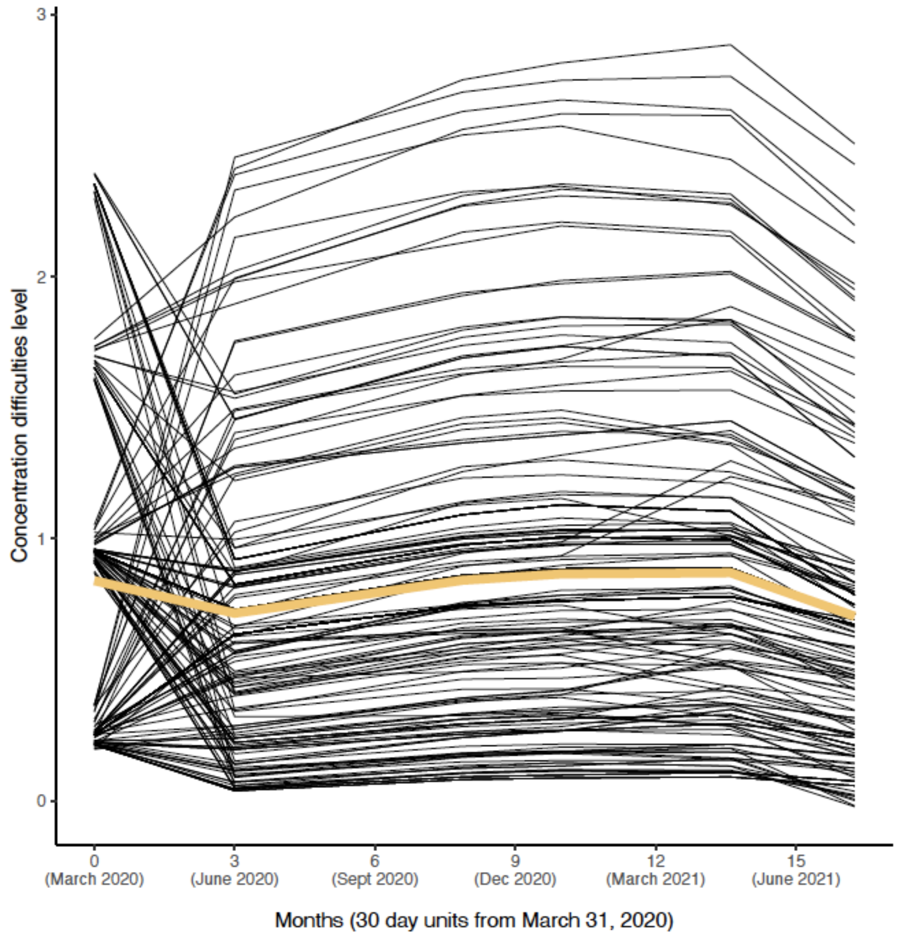

Mean change in sleep disruption across the study period
Mean level of sleep disruption
1.50
1.25
1.00
0.75
0.50
0
(March 2020)
3
(June 2020)
6
(Sept 2020)
9
(Dec 2020)
12
(March 2021)
15
(June 2021)
Months (30 day units from March 31, 2020)


Individual level change in sleep disruption for a random set of 200 participants
Sleep disruption severity
2
1
0
0
(March 2020)
3
(June 2020)
6
(Sept 2020)
9
(Dec 2020)
12
(March 2021)
15
(June 2021)
Months (30 day units from March 31, 2020)

Mean change in concentration difficulties across the study period



Individual change in concentration difficulties for a random set of 200 participants



Study 2

Ebrahimi, O. V., Freichel, R., Johnson, S. U., Hoffart, A., Solbakken, O. A., & Bauer, D. J. (2023). Depressive response patterns during the COVID-19 pandemic and its impact on psychiatric treatment seeking: A 24-month representative observational study of the adult population. *Submitted*. Preprint: https://doi.org/10.31234/osf.io/zw6xb

Depressive Response Patterns During the COVID-19 Pandemic and its Impact on Psychiatric Treatment seeking: A 24-Month Representative Observational Study of the Adult Population

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Abstract

Despite the presence of individual differences in the depressive response of adults during the COVID-19 pandemic, most studies have investigated population-level changes in depression during the first year of the pandemic. This longitudinal repeated-measurement study obtained 39,259 observations from 4,361 adults assessed nine times over a 24-month period in Norway (March 2020 to March 2022). Using a Latent Change Score Mixture Model to investigate differential change patterns in depressive symptoms, five profiles were identified. Most adults revealed a consistently resilient (42.52%) or predominantly resilient pattern differentiated by an initial shock in symptomatology (13.17%). Another group exhibited consistently high depressive adversities (8.5%). One group showed mild deterioration with small increases in depressive symptomatology compared to onset levels (29.04%), and a second strong deterioration group exhibited clinically severe levels of gained symptoms over time (6.77%). Both deteriorating depressive response patterns predicted the presence of a psychiatric diagnosis and treatment-seeking at the end of the study period. Together, the absence of a preexisting psychiatric diagnosis at the onset of the pandemic, severe symptom increases during, combined with reports of psychiatric treatment-seeking and diagnosis at the end of the study period, indicated that the strongly deteriorating subgroup represents an additional group of adults struggling with depressive problems. Factors related to general adverse change (lower education levels, lone residence), initial shocks prior to recovery (frequent information seeking, financial and occupational concerns), and resilience and recovery (older age, being in a relationship, physical activity) were identified. Binge drinking and belonging to an ethnic minority were influential predictors of the strongly deteriorating group. All major changes in response patterns occurred during the first three months of the pandemic, suggesting this period represents a window of sensitivity for the development long-lasting depressive states versus patterns of recovery and resilience. These findings call for increased vigilance of psychiatric symptoms during the initial phases of infectious disease outbreaks and highlight a specific target period for the implementation of preventive measures.

Keywords: Depressive response patterns, Resilience, Treatment seeking, Adult population, Individual differences, Growth mixture modeling, COVID-19 pandemic, Longitudinal study

Word count: 5253

Figures: 3. Tables: 3. Supplementary Files: 2

Depressive Response Patterns During the COVID-19 Pandemic and its Impact on Psychiatric Treatment seeking: A 24-Month Representative Observational Study of the Adult Population

The global pandemic caused by the coronavirus disease (COVID-19) strained essential domains in society, including the economy, health, and healthcare systems, with changes in average population-level mental health being reported (Daly et al., 2020; Ettman et al., 2021). Among the psychiatric symptom domains most strongly tied to the pandemic stands depression. While there is evidence for heterogeneity in the depressive response patterns of adults, most studies have investigated overall population-level changes in depressive symptoms (Ebrahimi et al., 2022a; Salanti et al., 2022). Such investigations lack the ability to disaggregate differential responses to the pandemic (Pierce et al., 2021).

Results from the early pandemic stages indicate that certain groups in society were disproportionately affected by the COVID-19 health crisis (Parsons et al., 2022; Pierce et al., 2020; Riehm et al., 2021). Alongside resilient response patterns, initial evidence suggests that a group of individuals showed an early worsening in mental health that was sustained through the first year of the pandemic (Joshi et al., 2021; McPherson et al., 2021; Pierce et al., 2021; Shevlin et al., 2023). These early findings add to the evidence that different depressive response patterns may be present in the adult population (Salanti et al., 2022).

To date, however, little research has been conducted to evaluate population heterogeneity in depressive response patterns beyond the first year of the pandemic (McPherson et al., 2021; Shevlin et al., 2023), with more research needed on the risk factors predicting long-term differences in response (Ebrahimi et al., 2022a; Landi et al. 2022; Rosa et al., 2022). Alongside demographic descriptors, risk factors on the population-level which could be related to differences in depressive response types include: increases in alcohol intake, as a potential coping mechanism (Martinez et al., 2021); news consumption, related to the mass dissemination of pandemic-related information and individual differences with news engagement (Holman et al., 2021); ethnicity, to investigate impact of the pandemic in minority groups (Li et al., 2023); job and financial concerns related to the pandemics' economic repercussions (Hertz-Palmor et al., 2021); and physical activity as a potential protective factor against symptom development (Harvey et al., 2018).

Notably, a key gap in the literature concerns a need to understand future adverse outcomes related to differential depressive response patterns during the pandemic (Daly et al., 2020; Ebrahimi et al., 2022a). That is, it is unclear whether different depressive response patterns during the pandemic period relate to adverse future clinical outcomes beyond symptomatology, including treatment seeking and diagnosis (Daly et al., 2020; Ebrahimi et al., 2022a).

Leveraging nine longitudinal assessment waves, the present study seeks to address these gaps by investigating differential depressive response patterns in adults over a 24-month period. Factors tied to resilient and adverse depressive response patterns in periods of infectious disease will be investigated. Finally, the extent to which depressive change profiles can predict adverse future outcomes is examined by investigating whether different symptom change profiles occurring during the first two years of the pandemic can predict psychiatric diagnosis and treatment-seeking behavior at the end of this period. This extends the literature by moving beyond the experience of symptoms and investigating the impact of symptom change patterns on future adverse clinical outcomes.

Methods

Study Design and Participants

This study is part of The Norwegian COVID-19, Mental Health and Adherence Project (MAP-19), ethically approved by The Regional Committee for Medical and Health Research Ethics (reference: 125510). MAP-19 is a large-scale longitudinal study designed to investigate depressive symptomatology in the general adult population across the pandemic period. The duration of the study was 24 months, covering the full containment-accompanying (i.e., mitigation protocol implemented) pandemic period, from the onset of these protocols to their termination in Norway (i.e. March 2020 to March 2022). Eligible participants were all adults (i.e., over 18 years old) who resided in Norway across the assessment period, providing informed consent to partake in the study.

Procedures

The sampling procedure was designed to recruit a proportionate number of subjects from each region of the country with respect to the regions size. Upon recruitment in March 2020 (T1), subjects responded to an online survey disseminated to a random selection of Norwegian adults using a Facebook algorithm, in addition to systematic dissemination of the survey via national, regional, and local information platforms (i.e., television, radio, and newspapers). This procedure is elaborated in detail elsewhere (Ebrahimi et al., 2022a; Magnúsdóttir et al., 2022). The final assessment of the study was conducted in March 2022, resulting in nine overall repeated measures of the adult population.

Stratification of Sample and Quality Control of Data

The demographic features of the sampled subjects were contrasted with their known occurrence rates in the population. Attributes not fully representative of the adult population were post-stratified to be proportional to their known rate, harmonizing parameters in the sample to the population parameter to render a representative sample of the target adult population. The final stratified and representative sample included 4,361 adults (T1: Assessment period: March to April, 2020), with the coverage at each wave including 2,151 (T2: June to July, 2020), 2,239 (T3: November to December, 2020), 1,963 (T4: January to February, 2021), 1,811 (T5: May 2021), 1,405 (T6: July to August 2021), 1,426 (T7: October to November, 2021), 1,110 (T8: January 2022), and 1,269 (T9: March to April 2022) participants. Attrition levels were consistent with other longitudinal studies during the pandemic (Pierce et al., 2022). A tree-based machine learning classification approach was used to inspect attrition in the study, with no systematic patterns of attrition found in the data (Ebrahimi et al., 2022a). The quality of the data was further assessed using attention checks, with 97.80% of the participants passing the attention check and subjects failing the attention check excluded to assure high data quality.

Measurement

Sociodemographic Characteristics

Respondents provided demographic information including their age (18-30 years; 31-44 years; 45-64 years; and 65 years and above), biological sex, relationship status (single; in a relationship), education level (compulsory school; upper secondary high school; student; any university degree), living status (lives with others; lives alone), history of psychiatric disorders (no; yes), and ethnic minority status (no; yes). Additionally, contextual risk and protective factors including physical activity frequency, binge drinking (no; yes), frequency of information seeking about the pandemic (0: Not at all to 7: Multiple times per hour), and financial and occupational concerns were reported (0: Not at all to 6: Almost every day).

Depressive Symptomatology

Depressive symptoms were assessed with the Patient Health Questionnaire (PHQ-9; Kroenke et al., 2001), consisting of nine items covering the DSM symptom criteria of depression (American Psychiatric Association, 2013) measured on a four-point Likert-scale (0–3; 0 = Not at all, 3 = Nearly every day). Sum scores range from 0 to 27 with higher scores indicating greater depression severity. Scores greater than 10 have been found to be indicative of depressive diagnosis with moderate severity with a sensitivity and specificity of 88% (Kroenke et al., 2001). Scores below 5 reveal no sign of depression and no clinical relevance. The questionnaire was formally translated and found to have sound psychometric properties (Wisting et al, 2021), and shown to be appropriate for longitudinal investigation (cf. measurement invariance) of depression in the Norwegian population and the present sample (Ebrahimi et al., 2022a). The scale further revealed excellent internal consistency across the full study period (Cronbach's α of .88 at T1 and ranging from .90 to .92 at T2 to T9).

Statistical Analyses

All statistical analyses were performed using Mplus (Version 8.3) and R (Version 4.3.1). Change profiles in depressive symptomatology were captured via a Latent Change Score Model (LCSM; McArdle, 2001), enabling the estimation of nonlinear response patterns to the pandemic. Model fit for the LCSM was determined by Root Mean Square Error of Approximation (RMSEA) ≤ 0.05, Comparative Fit Index (CFI) ≥ 0.95, Tucker-Lewis Index (TLI) ≥ 0.95, and Standardized Root Mean Squared Residual (SRMR) ≤ 0.05 (Hu & Bentler, 1999). After computing the average profile of change in symptomatology across the two-year period for the overall population, the presence of distinctive depressive response patterns across subgroups (i.e., latent classes) were investigated by extending the model into a Latent Change Score Mixture Model (LCSMM). Whereas the standard LCSM assumes graded, continuous differences in latent change parameters across individuals in the population, the LCSMM instead semi-parametrically captures individual differences via discrete latent classes that reflect prototypical change profiles. Unique advantages of the LCSMM for this investigation include that (1) it inherits from the standard LCSM the ability to capture nonlinear profiles of true change and to recover these with less bias and greater power than the analysis of observed difference scores contaminated by measurement error (Grimm et al., 2016); and (2) it allows for the estimation of distinct patterns of change over time, characterizing differential responses during the pandemic. A path diagram detailing the specification of the LCSMM is provided in Figure 1. Each of these models was estimated by maximum likelihood (ML) using the full dataset, including records with partial missing data. The treatment of missing data by ML is considered state-of-the-art, decreasing bias and increasing statistical power relative to complete-case analysis (Baraldi & Enders, 2010).

Following best practice for latent class models, class enumeration was based on consideration of multiple statistical and substantive criteria (Andruff et al., 2009; DeSarbo et al., 1992; McLachlan, 1987; Nylund-Gibson & Choi, 2018; Nylund et al., 2007). First, to ensure recovery of robust and meaningful classes, a minimum class size of 5% was set, and only models for which the solution and log-likelihood could be replicated across random initializations were considered (Andruff et al., 2009; Nylund-Gibson & Choi, 2018). Second, information criteria (IC) values were compared, which seek to balance model fit versus complexity, between models with different numbers of classes (Nylund et al., 2007). In practice, with very large samples like the one analyzed here, ICs often continue to decrease, sometimes trivially, as more classes are added to the model. Accordingly, scree plots were used to identify when drops in IC values gave way to small improvements, that is, the point of diminishing returns, such that the selected number of classes would capture the principal patterns present in the data without becoming trained on less important fine detail ("splitting hairs") or chance sampling variation (Nylund-Gibson & Choi, 2018). Third, models with high class separation (measured by entropy) were favored (DeSarbo et al., 1992; Nylund-Gibson & Choi, 2018), indicating higher distinctiveness of the latent classes and less ambiguity in identifying covariates related to class membership and predicting adverse future outcomes by class membership. Last, these statistical criteria were cross-checked with substantive considerations (Nylund-Gibson & Choi, 2018), inspecting model solutions to ensure that new classes captured clinically meaningful differences in level and/or change, and favoring class solutions consistent with previous findings in the literature. Full details of the class enumeration procedure are outlined in the supplementary appendix.

Following class enumeration, classes were further characterized by considering their relations to external variables, including both class predictors and distal outcomes. To identify factors predictive of differential depressive response patterns, the ML-based 3-step procedure of Vermunt was implemented (2010), providing a multinomial regression of class membership on each of the aforementioned demographic characteristics and contextual risk and protective factors. Additionally, the predictive utility of the latent classes for adverse outcomes at the final wave of the study (T9) were examined, including psychiatric treatment-seeking and reported psychiatric diagnosis, using the 3-step procedure of Bolck, Croon & Hagenaars (2004) as extended by Vermunt (2010). These 3-step approaches (Asparouhov & Muthén, 2014) obviate the potential for class distortion (redefinition of the classes) with the introduction of external variables while accounting for uncertainty of class membership to mitigate bias due to classification error.

Results

Participant Characteristics

The demographic characteristics of the participants are presented in Table 1. The prevalence of preexisting mental health conditions in this sample was 19.49%, representative of the known rate of psychiatric disorders in the Norwegian adult population between 16.66% and 25.00% (Norwegian Institute of Public Health, 2016). The quota of adults sampled from each region of the country was further proportional to the respective region size, providing a geographically representative sample of Norway.

Model fit and Class Selection

The LCSM estimated population-level change and yielded excellent fit to the data, with χ^2 (29) = 110.53 ($p < .001$), RMSEA = .025 (90% CI: [.020, .030]), CFI = .992, TLI = .991, and SRMR = .033. Supplementary Figure S1 shows the aggregated population-level change patterns in depressive symptoms across the study period. This overall pattern masked within-population heterogeneity, with comparison of LCSMMs ranging from one to eight classes leading to the selection of the five-class model as an optimal of the different depressive response patterns (appendix pp 1-2). Models with more classes consistently produced lower IC values, however, diminishing returns were observed after five classes. Additionally, the five-class model produced a stable solution, with replication of the highest log-likelihood across multiple random initializations, whereas models with more classes evidenced instability (i.e., the highest log-likelihood could not be replicated across initializations). The five-class model also yielded the highest entropy (.71), with these classes exceeding 5% of the population and class profiles capturing the principal patterns of change within the data. Five classes were further is consistent with previous results during the early phase of the pandemic (Pierce et al., 2021; Shevlin et al., 2023). Accordingly, the five-class model was selected to provide a stable and substantively meaningful representation of the data that optimally balanced parsimony and fit.

Profiles of Change Across the Pandemic Period

Five distinctive change patterns in depressive symptom expression were identified across the two-year pandemic period. Table 2 presents the estimated initial levels and latent changes over time of the five change patterns in depressive symptoms. Figure 2 shows the longitudinal profiles captured by these estimates, with Supplementary Figure S2 further revealing the individual depressive symptom change patterns for a random subset of 100 individuals per profile.

Two profiles were characterized by resilience. A large subgroup representing 42.52% of adults displayed consistently low depressive symptoms throughout the pandemic (i.e., Consistent Resilience class), following a slight elevation at the start of the pandemic that resolved to consistent low levels throughout the remainder of the study period. Another class, encompassing of 13.17% of the adult population, exhibited an initial shock in symptomatology at the onset of the pandemic, but likewise recovered swiftly and displayed stably low levels of depressive symptom from the third month of the pandemic and forward (Shock to Resilience Class).

Two subgroups of adults revealed deteriorating change patterns in depressive symptoms occurring during the first three months of the pandemic. One subgroup (Mild Deterioration class) consisting of 29.04% of the adult population, exhibited modest increases in symptom levels across the first year of the pandemic, with the largest increase occurring during the first three months of the pandemic, followed by slight decreases in symptom levels during the second year. This group showed a mean increase of 2.77 in depressive symptoms at the end of the study period (March, 2022; mean depression scores: 8.76) compared to at the onset of the pandemic period (March, 2020; 5.99). The other subgroup consisting of 6.77% of the adult population (Strong Deterioration class) revealed a pronounced pattern of major deterioration in depressive symptom expression, exhibiting critical change in depressive symptomatology in moving from a predominantly asymptomatic level to symptom levels indicative of a moderate to severe depressive state during the first three months of the pandemic ($\delta\eta_{t2}$; Table 2). This strong deterioration group showed a mean increase of 12.14 in depressive symptoms by the end of the two-year study period (mean: 17.36) compared to the onset of the pandemic period (mean: 5.22).

Finally, a last class emerged, encompassing about 8.50% of adults who revealed consistently high levels of depressive symptoms during the pandemic period (Consistently High class).

Predictors of Class Membership

Several key predictors of class membership were identified. In all analyses, the largest class, Consistent Resilience, was used as the reference category for comparison. Table 3 displays the increase or decrease in odds associated with being in each of the other classes relative to the Consistent Resilience class (i.e., the odds ratios).

Compared to Consistent Resilience, the odds of Strong Deterioration were significantly higher for those living alone (OR 2.98 [95% CI: 1.65-5.40]), those who started binge drinking during the pandemic (OR 16.78 [2.86-98.52]), and those identifying as an ethnic minority (OR 3.66 [1.36-9.81]). Higher education levels were associated with lower odds of Strong Deterioration relative to Consistent Resilience (OR 0.78 [0.60-0.99]).

The odds of Mild Deterioration relative to Consistent Resilience were higher among individuals residing alone (OR 2.36 [1.46-3.81]), binge drinkers (OR 6.84 [1.17-39.88]), and those engaging in more frequent information seeking (OR 1.22 [1.01-1.47]). Higher age (OR 0.69 [0.56-0.84]) and increases in physical activity (OR 0.84 [0.73-0.97]) served as protective factors that reduced the odds of Mild Deterioration versus Consistent Resilience.

The odds of Consistently High symptom levels relative to the Consistent Resilience were higher for those having a preexisting psychiatric diagnosis prior to the pandemic period (OR 12.21 [6.02-24.76]), binge drinking (OR 13.99 [2.26-85.92]), living alone (OR 3.13 [1.52-6.43]), and displaying higher financial and occupational concerns (OR 1.51 [1.26-1.80] per unit increase). Greater physical activity (OR 0.59 [0.46-0.77]), being in a relationship (OR 0.51 [0.27-0.97]) and older age (OR 0.43 [0.29-0.65]) reduced the odds of being in the Consistently High class compared to Consistent Resilience.

Finally, the odds of Shock to Resilience relative to Consistent Resilience was higher among those who engaged in information seeking about the pandemic more intensively (OR 1.30 [1.06-1.56]), resided alone (OR 2.03 [1.14-3.59]), had a preexisting diagnosis (OR 11.35 [6.57-19.61]), and financial and occupational worries (OR 1.53 [1.35-1.74]); and lower among older adults (OR 0.45 [0.34-0.60]), those in a relationship (OR 0.52 [0.32-0.83]), with higher education levels (OR 0.73 [0.58-0.92]), and higher levels of physical activity (OR 0.67 [0.57-0.79]).

Class Membership and Adverse Future Outcomes

The identified depressive response patterns were used to predict two important clinical outcomes at the final assessment of the study, psychiatric treatment-seeking and reported psychiatric diagnosis, two years after the commencement of the identified change patterns. Figure 3, displaying the probability of revealing these two adverse outcomes, shows that the two resilient classes, Consistent Resilience and Shock to Resilience, had comparably low likelihoods for both treatment seeking and psychiatric diagnosis at the end of the study period. The highest likelihoods of both clinical outcomes were observed for the Strong Deterioration class, followed by the Mild Deterioration class who also had notable likelihood of reporting a psychiatric diagnosis and treatment seeking at the end of the two-year study period. The Consistently High class showed intermediate rates of treatment seeking and psychiatric diagnosis. These patterns comport with the substantive interpretation of these classes as clinically meaningful and distinct change profiles for depressive symptoms during the pandemic.

Discussion

This empirical investigation demonstrated how an overall view of symptom levels in the adult population masks key differences in depressive symptom change patterns during the pandemic. A Latent Change Score Mixture Model was implemented to approximate individual differences in depressive symptoms over time and found support for five different depressive response patterns across a 24-month period during the pandemic. Consistent with previous literature from the first year of the pandemic (Parsons et al., 2023; Pierce et al., 2021; Shevlin et al., 2023), this study identified two subgroups that predominantly displayed resilience to adverse depressive symptomatology. One of these constituted nearly half the population, displaying consistently low levels of symptoms throughout the study period following a minor heightening in symptom levels during the first three months of the pandemic. The second subgroup of adults experienced an initial shock characterized by high levels of depressive symptoms at the onset of the pandemic, before displaying adaptation and resilience within three months which remained throughout the two-year study period. Adults in the former consistent resilience group were more likely to have higher education, belong to the ethnic majority, live with others, and not have increased alcohol intake during the pandemic. Some of these characteristics (higher education, not living alone) were also protective factors of the shock to resilience group. The initial shock in depressive symptom levels distinguishing this second group from the consistently resilient group was related to increased financial and occupational worries at the onset of the pandemic, and older age, with improvement in symptomatology related to more frequent engagement in physical activity. This is in line with previous findings identifying that financial assets protect against persistent depressive symptomatology during the present pandemic (Ettman et al., 2022; Witteveen & Velthorst, 2020). The initial shock displayed by older aged individuals may have been related to greater infection fears, previously related to depressive symptomatology (Sakib et al., 2021) and possibly explained by the greater risk of severe illness and mortality in these adults (Ho et al., 2020; Semenzato et al., 2021). These findings are also consistent with previous studies showing a positive association between physical activity and symptom reduction (Ebrahimi et al., 2022b; Puccinelli et al., 2021), which highlights that this may be a useful strategy in mitigating adverse symptomatology in periods of lockdown and distancing.

Notably, the adults in the shock to resilience subgroup who displayed substantially heightened levels of depressive symptoms prior to recovery, reported highly frequent information seeking about the pandemic during its initial stages, consistent with previous findings linking greater pandemic news consumption to depressive symptomatology

(Amundsen et al., 2021; Feng et al., 2022). This may be explained by a heightened stress response that can accompany exposure to negative and distressing news about a novel threat (Garfin et al., 2020). These individuals were also in a relationship, which may have been related to their recovery over time given the identified associations between loneliness and depressive symptomatology during the earlier stages of the pandemic (Hoffart et al., 2022; Odenthal et al., 2023). Interestingly, having a preexisting psychiatric diagnosis was also related to this initial elevation and a reduction in depressive symptomatology during the first three months of the pandemic. This indicates that some individuals with preexisting mental health problems may have somewhat benefitted from the major contextual change and lockdown period occurring at the start of the pandemic. This interpretation is consistent with findings from another study, identifying that the increased time for self-care activities and the perception of lower external pressures following lockdown restrictions was by some individuals perceived as beneficial in processing mental health problems (Gillard et al., 2021). Together, the two predominantly resilient subgroups encompassed of approximately 55% of the population. Both groups were unlikely to report adverse future outcomes, including treatment-seeking and reporting of a psychiatric diagnosis. This strengthens the message that the majority of the population displayed resilient response patterns to the pandemic (Pierce et al., 2021).

Corresponding to the known prevalence of depression in Norway (Norwegian Institute of Public Health, 2016), a subgroup encompassing of approximately 9% of adults was identified, displaying consistently high depressive symptomatology during the pandemic period. Unsurprisingly, having a preexisting psychiatric diagnosis was among the most predictive variables of this subgroup. Preexisting mental health problems have also been associated with stronger increases in distress in response to the pandemic (Asmundson et al., 2020; Vissink et al., 2021), which may be sustained for particularly vulnerable groups.

Individuals younger of age, single, living alone, binge drinking, and having financial and occupation concerns were also at greater risk of belonging to this consistently high group, which correspond to risk factors of sustained depressive states during pre-pandemic periods (Herrman et al., 2022). Greater engagement in physical activity protected against this depressive response pattern, once again pointing at the possible mitigating utility of this ubiquitously available intervention during periods of infectious disease. The likelihood of this group reporting a future psychiatric diagnosis and seeking treatment was intermediate, which is meaningful as many of these individuals reported already having a psychiatric diagnosis at the onset of study.

The two final subgroups of adults displayed deteriorating depressive response patterns during the pandemic period, although to varying degrees and with large differences compared to their onset symptom levels. Combined, these groups encompassed of approximately 35% of the adult population. Both subgroups displayed depressive symptomatology of minimal clinical relevance at the onset of the pandemic (Kroenke et al., 2001). Key differences distinguished these two subgroups of adults from and following the third month of the pandemic. While one group displayed a slight increase in depressive symptom expression, the other group exhibited substantially higher deterioration during this period, an increase which was more than five-fold higher than the former group. Moreover, the strongly deteriorating group showed an increase in symptom severity of 12.1 points by the end of the two-year period compared to its beginning, equivalent to a moderate to severe increase in depressive symptomatology (Kroenke et al., 2001). These results indicate that the strongly deteriorating adults to have been pushed toward a new and severe state of depression already occurring during the first three months of the pandemic which has been retained over time. This is consistent with patterns of deterioration in mental health observed in the UK during the early stages of the pandemic, where adverse gains in symptomatology accumulated during the first months of the pandemic (Pierce et al., 2021; Shevlin et al., 2023). Both deleterious depressive symptom profiles were found to be detrimental beyond the adverse momentary experience of the symptoms in and of themselves, as these subgroups of adults displayed a high probability of reporting a psychiatric diagnosis and psychiatric treatment-seeking by the end of the two-year study period. Of note, both deteriorating subgroups of adults were identified above and beyond the consistently high subgroup displaying high depressive symptomatology from the onset of the pandemic. These findings are consistent with the novel global burden of disease study (Santomauro et al., 2021) which identified 53.2 million additional cases of major depressive disorder (i.e., an increase of 27.6%) during the pandemic. The strongly deteriorating subgroup had a higher probability to seek treatment at the end of the study period compared to the mildly deteriorating group of adults, which may be explained by the large differences in gained symptomatology between the groups across the pandemic period.

Several risk and protective factors relating to deterioration patterns were identified. Binge drinking and living alone at onset of the pandemic were found to be strong predictors of both classes exhibiting deleterious depressive symptom change patterns. Extensive alcohol intake has been found to increase the risk of depression related to adverse neurophysiological and metabolic changes, in addition to disruptions in interpersonal functioning (Boden & Ferguson, 2011). Living alone may further reduce the accessibility of social support, which has been found to be protective against depressive symptoms (Choi et al., 2023). Older age and increased physical activity were protective features of the mildly deteriorating subgroup, with intensive information seeking during the onset of the pandemic further predictive of the response pattern identified within this subgroup. The protective link between physical activity and depression has been attributed to reduced inflammatory response and improved resilience to psychological stress (Kandola et al., 2019; Pearce et al., 2022). The adults in the strong deterioration subgroup were more likely to have lower education levels, and belonging to an ethnic minority was the only unique predictor of this subgroup. Both minority status and binge drinking substantially increased the odds of exhibiting this strongly deteriorating depressive response pattern during the pandemic, where these adults shared alcohol consumption increase and lone residency as the most predictive characteristics of their group membership together with the consistently depressed individuals.

Importantly, having a preexisting psychiatric diagnosis was not predictive of the strongly deteriorating subgroup, which together with the substantial gains in symptomatology during the pandemic, and the finding of these adults reporting high probability of treatment-seeking and obtainment of a psychiatric diagnosis at the end of the two-year study period, indicates these adults may have transitioned from a predominantly asymptomatic to a disorder state during the pandemic (Santomauro et al., 2021). These findings are consistent with reports of added burden on the national healthcare system by the Norwegian Health Department, reporting additional increases in psychiatric treatment-seeking among adults during the pandemic (Ose & Kaspersen, 2021). Unlike for all other subgroups, no actionable protective factors (e.g., physical activity) were identified for the strongly deteriorating subgroup of adults among the investigated variables, highlighting the need for future studies to identify routes to alleviate the adverse symptomatology of this newly emerged subgroup during the pandemic.

Future Directions

Several areas warrant further investigation that would be beneficial for the literature. In this study, large within-nation variability was found in depressive response patterns during the pandemic. Future research investigating cross-national variability in mental health change profiles is needed, particularly in low- and middle-income countries, where the majority of world population resides (Kola et al., 2021). Leveraging the additional variability across nations with respect to different policy implementations and other contextual variables relevant during the pandemic, such internationally comparative investigations can provide additional opportunities for understanding the mechanistic processes underlying resilience and adverse patterns of change in mental health. Moreover, studying variability across different types of critical events is a key area for future preventive efforts. The extent to which processes and risk factors aggravating mental health identified during the present pandemic operate in a similar or different manner across other types of critical incidents (e.g., economic recessions, natural, and industrial disasters) is an important area for future preparedness, highlighting a need for prospective multiple incident studies in the literature.

Strengths and Limitations

The present study has several noteworthy strengths such as its large representative sample, nine repeated measurements over a two-year period, adaptation of a modeling framework incorporating measurement error and enabling investigation of complex non-linear change patterns during the pandemic, and the use of validated measures with well-established clinical cutoffs. Importantly, the study extends the literature by mapping out the future adverse outcomes related to deleterious depressive symptom change patterns during the COVID-19 pandemic. This study also includes noteworthy limitations. While adults were randomly obtained and stratified to accurately represent population characteristics, the online procedure may have favored particularly subgroups above others, such as older adults with more frequent computer usage. Efforts were taken to reduce such biases through additional recruitment on platforms more accessible through the elderly population, in addition to employment of stratification procedures. Finally, the use of self-report measures is another limitation which precludes more objective assessment of depressive symptomology.

Concluding Remarks

To conclude, the present findings have implications for mental health service planners and policy makers. The identified window of sensitivity for depressive adversities calls for increased vigilance of psychiatric symptoms during the first three months of pandemic periods and a target point for insertion of preventive measures, after which symptom transitions stabilize and are less subjectable to change throughout the pandemic period. As periods of infectious disease may follow similar behavioral mitigation strategies and be subject to similar psychological mechanisms (i.e., need for information obtainment), it is likely that these findings can help inform future pandemic preparedness. Among modifiable possibilities, dissemination about the adverse associations tied to intensive information seeking behavior and the beneficial impact of physical activity during periods of reduced mobility and isolation may be a fruitful strategy. This study further highlights the role of financial and occupational worries in aggravating depressive symptoms, suggesting that socioeconomic policies may be of importance in post-pandemic recovery programs and as preventive measures in future pandemics during phases of additional economic vulnerability (e.g., lockdown periods). Echoing previous studies (Pierce et al., 2021) and consistent with ongoing national and global reports (Ose & Kaspersen, 2021; Santomauro et al., 2021), the findings highlight that mental health services may expect to see an increase in referrals, necessitating careful considerations and logistical planning by health and government agencies.

Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of this article.

Author Contributions

OVE: conceptualization, data curation, formal analysis, investigation, methodology, project administration, visualization, writing – original draft, writing – review & editing. RF:

formal analysis, visualization, writing – review & editing. SUJ: investigation, project administration, supervision, writing – review & editing. AH: investigation, supervision, writing – review & editing. OAS: supervision, writing – review & editing. DC: methodology, supervision, writing – review & editing.

Transparency and Openness

In accordance with the Transparency and Openness Promotion (TOP) guidelines, all used methods in this study are detailed and cited in the article. These analytical strategies are further detailed in the supplementary materials, with the code available on request from the corresponding author.

Data Availability Statement

Our received ethical approval from the Norwegian Centre for Research Data (NSD) and The Regional Committee for Medical and Health Research Ethics (REK) precludes submission of raw data to public repositories. Access to the data can be granted from the principal investigators Omid V. Ebrahimi and Sverre Urnes Johnson following ethical approval of a suggested project plan for the use of data granted by NSD and REK.

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Figure Captions

Figure 1

The Latent Change Score Mixture Model (LCSMM) along with the demographic and contextual predictors of class membership

Note. The covariance between η_{t1} and the latent change scores $\delta\eta_{t2-t9}$, the estimated parameter labels of the class predictors, covariances between class predictors, and the regression estimates from the class predictors to η_{t1} and $\delta\eta_{t2-t9}$ are omitted from the figure for visualization purposes. All estimated parameters are class-specific, and the subscript '$_C$' was omitted to enhance visualization. Within-class variance is restricted to zero to obtain latent classes, with all variability in latent change captured by between-class differences. Bin. drin.: Binge drinking; Edu: Education; ES: Ethnic status; Info. freq.: Information seeking frequency; LA: Living alone; Psy. d.: Psychiatric diagnosis; Rel. stat.: Relationship status; Phy. act.: Physical activity; WJE: Worry about job and economy.

Figure 2

Differential Depressive Response Patterns Across the 24-Month Study Period

Note. The dashed line presents the validated cutoff for moderate levels of depression.

Figure 3

Probability of Psychiatric Treatment-Seeking Behavior and Psychiatric Diagnoses for Adults with Different Depressive Symptom Change Patterns at the end of the Two-Year Study Period (T9)

Note. CH = Consistently High (Class 2); CR = Consistent Resilience (Class 5); MD = Mild Deterioration (Class 3); SD = Strong Deterioration (Class 1); SR = Shock to Resilience (Class 4).

Supplementary Material

Supplementary Figure S1

Population-Level Change Patterns in Depressive Symptoms Across the Pandemic Period

Supplementary Figure S2

Raw Scores of Depressive Symptom Severity (PHQ-9) for 100 a Random Subset of 100 Individuals Belonging to Each of the Five Profiles of Depressive Symptom Change Patterns During the COVID-19 Pandemic

Supplementary Appendix

Additional Details About the Class Enumeration Procedure

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Table 1

Demographic Information of the Participants

Subgroups	*N* (%)
All	4361 (100%)
Sex	
Female	2152 (49.34%)
Male	2183 (50.06%)
Missing	26 (0.60%)
Age, years (*M* = 37.48, *SD* = 14.81)	
18-30	1983 (45.47%)
31-44	1108 (25.41%)
45-64	1037 (23.78%)
65+	233 (5.34%)
Education level	
Compulsory School	522 (11.97%)
Upper secondary high school	1786 (40.95%)
Currently studying	510 (11.70%)
Any university degree	1543 (35.38%)
Relationship status	
Single or divorced	1765 (40.47%)
In a relationship	2596 (59.53%)
Ethnic status	
Non-minority	4136 (94.84%)
Ethnic minority	225 (5.16%)
Preexisting psychiatric diagnosis	
Yes	850 (19.49%)
No	3511 (80.51%)

Table 2

Results of the Latent Change Score Mixture Model (LCSMM)

	Estimate	*SE*	*z*	*p*
Class 1: Strong Deterioration (*N* = 295; 6.77%)				
Means				
η_{t1}	5.22	0.82	6.40	< .001*
$\delta\eta_{t2}$	13.07	0.75	17.45	< .001*
$\delta\eta_{t3}$	0.73	0.69	1.05	.294
$\delta\eta_{t4}$	1.41	0.54	2.63	.009*
$\delta\eta_{t5}$	-1.11	0.49	-2.26	.024*
$\delta\eta_{t6}$	-1.08	0.65	-1.67	.096
$\delta\eta_{t7}$	0.29	0.94	0.31	.758
$\delta\eta_{t8}$	1.26	0.72	1.76	< .079
$\delta\eta_{t9}$	-1.43	0.81	-1.77	< .076
Class 2: Consistently High (*N* = 371; 8.50%)				
Means				
η_{t1}	14.36	1.92	7.47	< .001*
$\delta\eta_{t2}$	-0.13	0.98	-0.13	.897
$\delta\eta_{t3}$	1.85	0.65	2.83	.005*
$\delta\eta_{t4}$	-0.34	0.47	-0.71	.475
$\delta\eta_{t5}$	-0.27	0.52	-0.52	.601
$\delta\eta_{t6}$	-2.23	0.56	-3.96	< .001*
$\delta\eta_{t7}$	0.37	0.72	0.51	.612
$\delta\eta_{t8}$	0.76	0.82	0.93	.354
$\delta\eta_{t9}$	-0.81	0.68	-1.18	.237
Class 3: Mild Deterioration (*N* = 1267; 29.04%)				
Means				
η_{t1}	5.99	0.51	11.76	< .001*
$\delta\eta_{t2}$	2.43	0.33	7.39	< .001*
$\delta\eta_{t3}$	1.57	0.23	6.90	< .001*
$\delta\eta_{t4}$	0.02	0.20	0.08	.935
$\delta\eta_{t5}$	-0.26	0.22	-1.22	.224
$\delta\eta_{t6}$	-1.56	0.25	-6.14	< .001*
$\delta\eta_{t7}$	0.39	0.29	1.33	.183
$\delta\eta_{t8}$	0.88	0.30	2.92	.003*
$\delta\eta_{t9}$	-0.70	0.29	-2.45	.014*
Class 4: Shock to Resilience (*N* = 574; 13.17%)				
Means				
η_{t1}	17.33	0.38	46.05	< .001*
$\delta\eta_{t2}$	-13.50	0.48	-28.32	< .001*
$\delta\eta_{t3}$	1.43	0.23	6.18	< .001*
$\delta\eta_{t4}$	0.10	0.23	0.46	.649

$\delta\eta_{t5}$	-0.24	0.25	-0.96	.337
$\delta\eta_{t6}$	-1.25	0.25	-5.07	< .001*
$\delta\eta_{t7}$	0.25	0.27	0.93	.353
$\delta\eta_{t8}$	0.14	0.28	0.51	.609
$\delta\eta_{t9}$	-0.11	0.29	-0.39	.694
Class 5: Consistent Resilience (*N* = 1854; 42.52%)				
Means				
η_{t1}	4.76	0.13	37.46	< .001*
$\delta\eta_{t2}$	-1.67	0.22	-7.75	< .001*
$\delta\eta_{t3}$	0.58	0.10	6.10	< .001*
$\delta\eta_{t4}$	0.08	0.09	0.85	.394
$\delta\eta_{t5}$	-0.23	0.10	-2.30	.022*
$\delta\eta_{t6}$	-0.58	0.11	-5.19	< .001*
$\delta\eta_{t7}$	0.01	0.11	0.06	.954
$\delta\eta_{t8}$	0.40	0.12	3.24	.001*
$\delta\eta_{t9}$	-0.27	0.14	-1.99	.046*

Note. η_{t1} = Latent intercept at T1 (March 2020); $\delta\eta_{t2}$ = Latent change from T1 to T2 (March to July, 2020); $\delta\eta_{t3}$ = Latent change from T2 to T3 (July to December, 2020); $\delta\eta_{t4}$ = Latent change from T3 to T4 (December 2020 to February, 2021); $\delta\eta_{t5}$ = Latent change from T4 to T5 (February to May, 2021); $\delta\eta_{t6}$ = Latent change from T5 to T6 (May to August, 2021)); $\delta\eta_{t7}$ = Latent change from T6 to T7 (August to November, 2021); $\delta\eta_{t8}$ = Latent change from T7 to T8 (November, 2021 to January, 2022); $\delta\eta_{t9}$ = Latent change from T8 to T9 (January to March, 2022).

Table 3

Odds Ratios (OR) for the Different Predictors of Class Membership Relative to the Reference (Consistent Resilience) Class Along With the 95% Confidence Intervals of ORs

Predictor	Class	OR	Lower CI	Upper CI	*p*
Age	1 (SD)	0.93	0.70	1.22	.593
	2 (CH)	0.43	0.29	0.65	< .001*
	3 (MD)	0.69	0.56	0.84	< .001*
	4 (SR)	0.45	0.34	0.60	< .001*
Living alone	1 (SD)	2.98	1.65	5.40	< .001*
	2 (CH)	3.13	1.52	6.44	.002*
	3 (MD)	2.36	1.46	3.82	< .001*
	4 (SR)	2.03	1.14	3.59	.015*
Relationship	1 (SD)	1.02	0.58	1.81	.936
	2 (CH)	0.51	0.27	0.97	.040*
	3 (MD)	0.98	0.65	1.48	.929
	4 (SR)	0.52	0.32	0.83	.006*
Education	1 (SD)	0.78	0.60	0.99	.044*
	2 (CH)	0.81	0.58	1.12	.199
	3 (MD)	0.89	0.74	1.07	.203
	4 (SR)	0.73	0.58	0.92	.009*
Information seeking	1 (SD)	1.12	0.86	1.46	.403
	2 (CH)	1.16	0.83	1.62	.393
	3 (MD)	1.22	1.01	1.47	.036*
	4 (SR)	1.30	1.06	1.56	.013*
Ethnic minority	1 (SD)	3.66	1.36	9.81	.010*
	2 (CH)	2.59	0.56	11.93	.223
	3 (MD)	2.30	0.95	5.54	.064
	4 (SR)	1.11	0.36	3.43	.855
Binge drinking	1 (SD)	16.78	2.86	98.52	.002*
	2 (CH)	13.99	2.28	85.92	.004*
	3 (MD)	6.84	1.17	39.88	.033*
	4 (SR)	1.76	0.22	13.89	.590
Physical activity	1 (SD)	0.88	0.73	1.06	.183
	2 (CH)	0.59	0.46	0.77	< .001*

	3 (MD)	0.84	0.73	0.97	.018*
	4 (SR)	0.67	0.57	0.79	< .001*
Psychiatric diagnosis	1 (SD)	1.03	0.45	2.34	.944
	2 (CH)	12.21	6.02	24.76	< .001*
	3 (MD)	1.42	0.79	2.55	.237
	4 (SR)	11.35	6.57	19.61	< .001*
Sex	1 (SD)	1.00	0.58	1.73	.995
	2 (CH)	0.58	0.30	1.12	.106
	3 (MD)	0.80	0.53	1.20	.279
	4 (SR)	0.68	0.42	1.10	.113
Worry about job and economy	1 (SD)	1.03	0.86	1.24	.748
	2 (CH)	1.51	1.26	1.80	< .001*
	3 (MD)	1.07	0.96	1.20	.237
	4 (SR)	1.53	1.35	1.74	< .001*

Note. * $p < .05$. CH = Consistently High (Class 2); MD = Mild Deterioration (Class 3); SD = Strong Deterioration (Class 1); SR = Shock to Resilience (Class 4).

Figure 1

The Latent Change Score Mixture Model (LCSMM) Along With the Demographic and Contextual Predictors of Class Membership

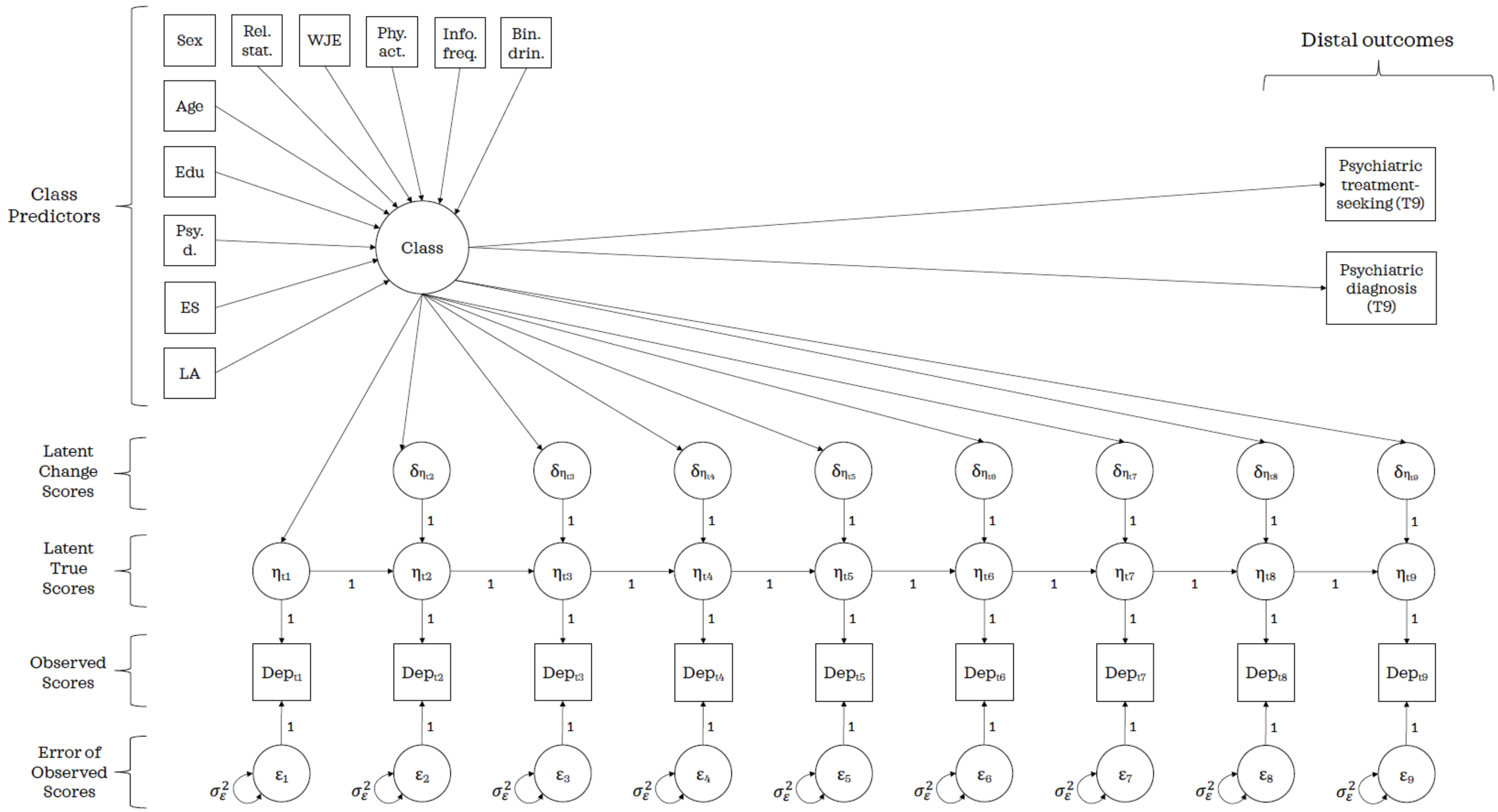
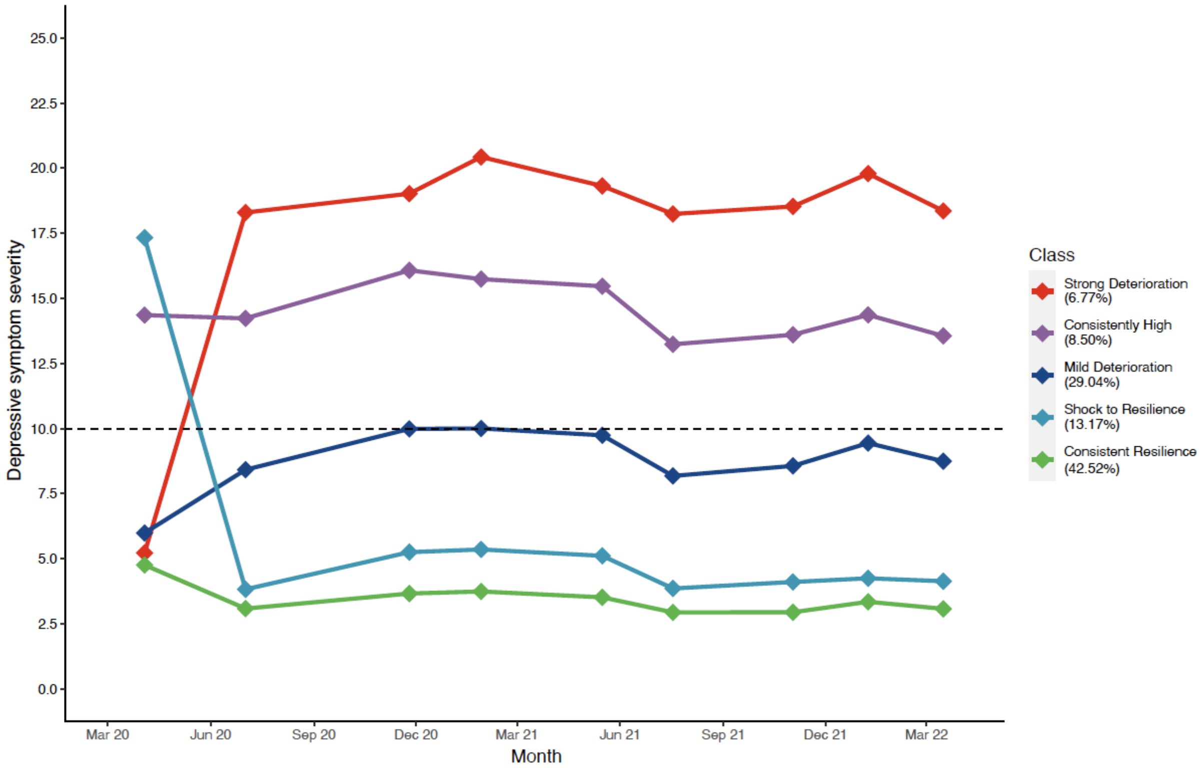


Figure 2

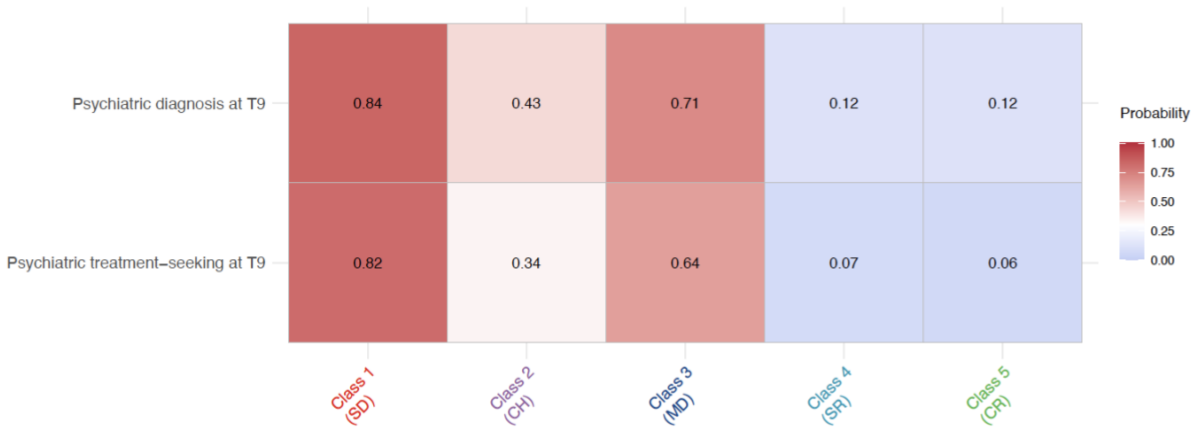
Differential Depressive Response Patterns Across the 24-Month Study Period



Note. The dashed line presents the validated cutoff for moderate levels of depression.

Figure 3

Probability of Psychiatric Treatment-Seeking Behavior and Psychiatric Diagnoses for Adults with Different Depressive Symptom Change Patterns at the end of the Two-Year Study Period (T9)



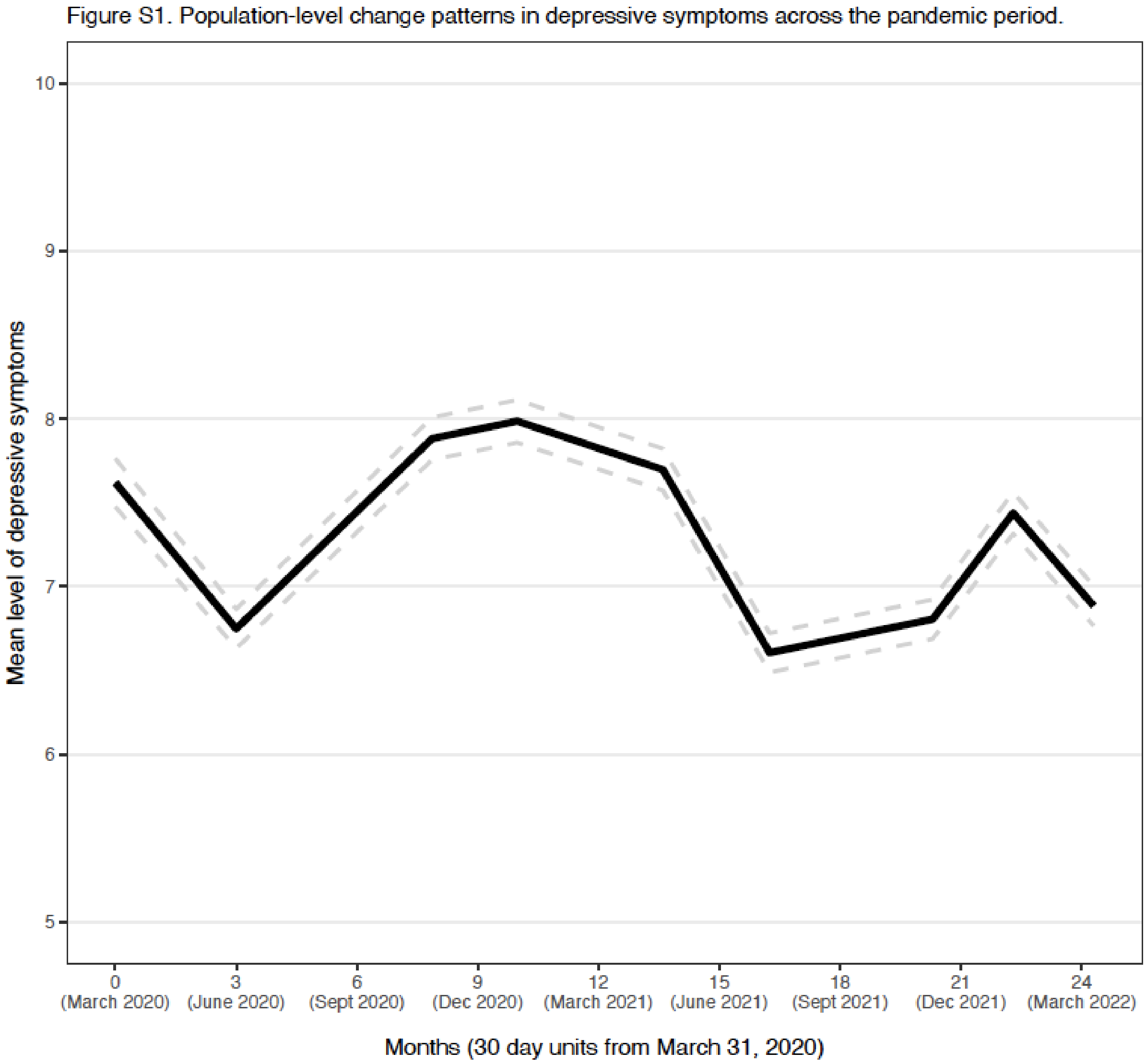
Note. CH = Consistently High (Class 2); CR = Consistent Resilience (Class 5); MD = Mild Deterioration (Class 3); SD = Strong Deterioration (Class 1); SR = Shock to Resilience (Class 4).

Supplementary Figure S1: Population-Level Change Patterns in Depressive Symptoms Across the Pandemic Period

(Article 2)

Supplementary Figure S1

Population-Level Change Patterns in Depressive Symptoms Across the Pandemic Period

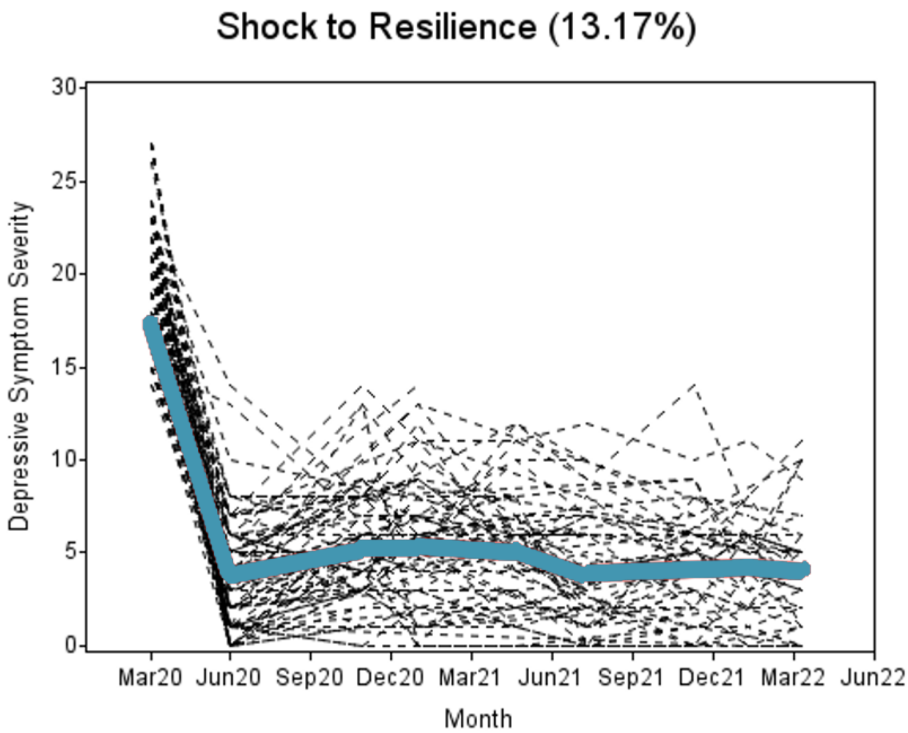


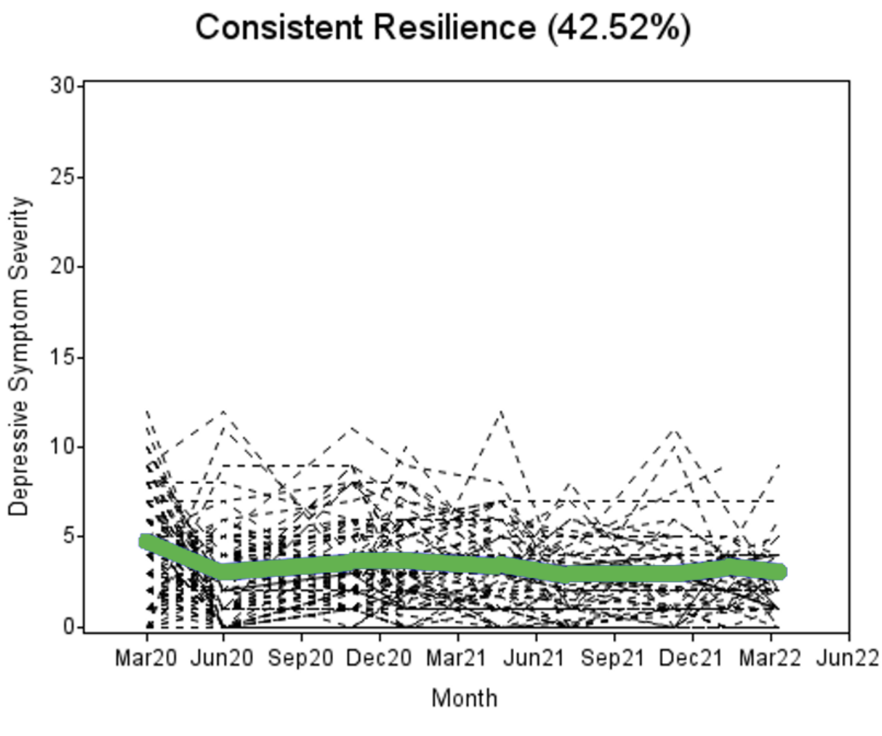
Supplementary Figure S2: Raw Scores of Depressive Symptom Severity for Random Subsets of Individuals for Each Depressive Symptom Response Profile

(Article 2)

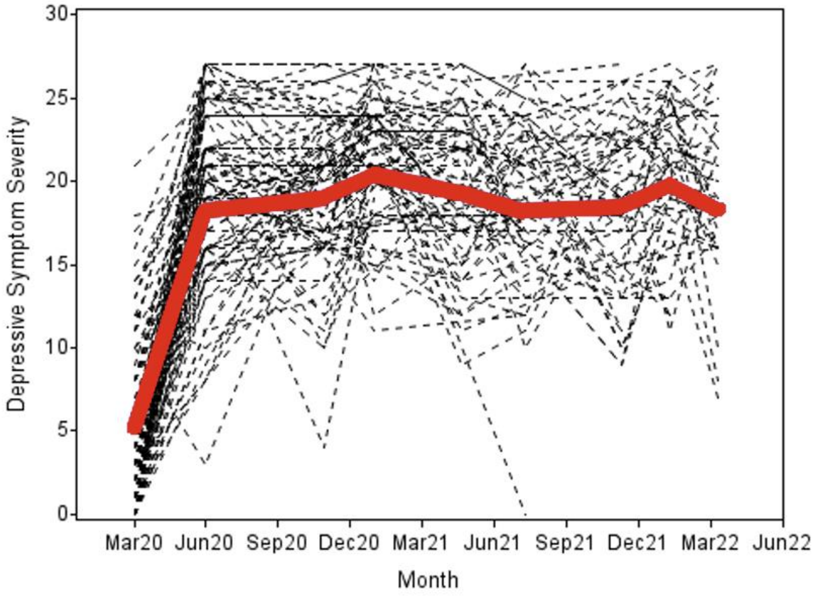
Figure S2

Raw Scores of Depressive Symptom Severity (PHQ-9) for 100 a Random Subset of 100 Individuals Belonging to Each of the Five Profiles of Depressive Symptom Change Patterns During the COVID-19 Pandemic

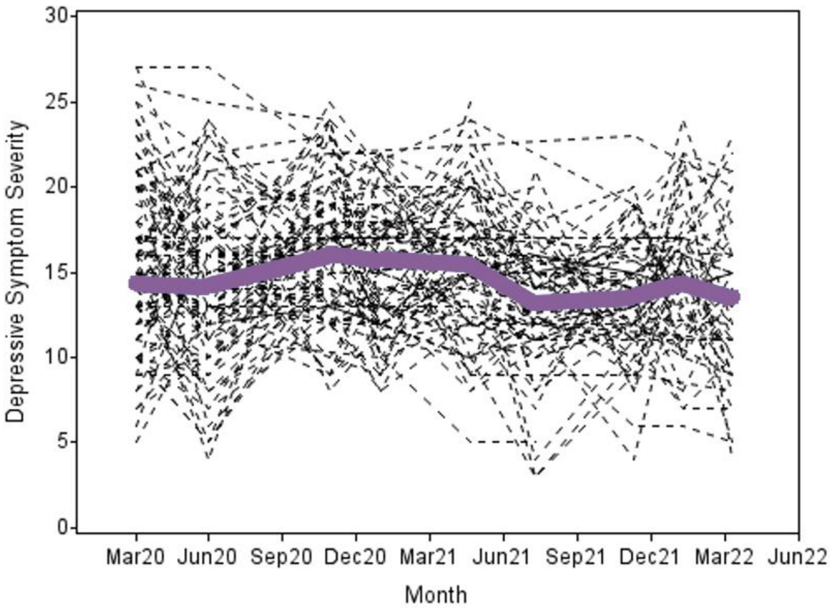


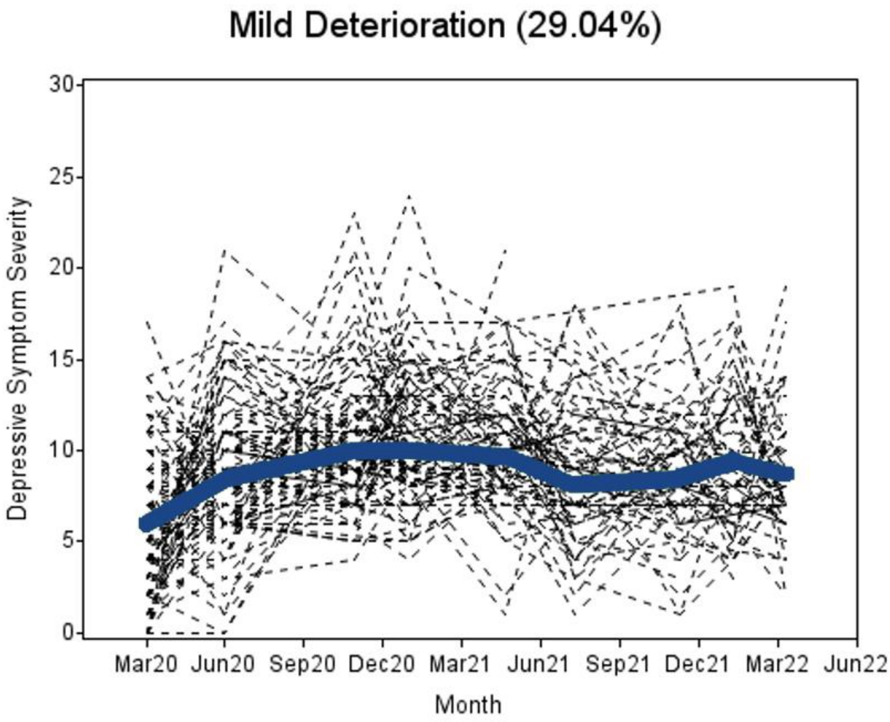


Strong Deterioration (6.77%)



Consistently High (8.50%)




Mild Deterioration (29.04%)
Depressive Symptom Severity
30
25
20
15
10
5
0
Mar20 Jun20 Sep20 Dec20 Mar21 Jun21 Sep21 Dec21 Mar22 Jun22
Month

Supplementary Appendix

(Article 2)

Supplementary Appendix: Additional Details About the Class Enumeration Procedure

Class Enumeration

Table S1 below presents the model performance metrics for each of the eight models tested. Overall, as described in the Results section, the preponderance of our class selection criteria (cf. Methods section) favored a five-class solution, which was further revealed as a robust and stable solution consistent with the literature. As expected, given the large sample size of the study and its high power to detect additional classes based on trivial changes in mean levels, information criteria continued to decrease upon addition of more classes. These decreases however, portrayed diminished returns following five classes and this, coupled with increasing model instability, argued for selection of no more than five classes (Nylund-Gibson & Choi, 2018; Sinha et al., 2021).

Additional sensitivity analyses were conducted comparing these quantitative results to theory and previous empirical findings which further supported the selection of a five-class model. First, the five-class solution was found to correspond with previously identified number of classes in the literature during the early stages of the pandemic, investigating mental health up to October 2020 (Pierce et al., 2021). Second, we compared the final five-class solution to the four-class model, the latter of which failed to retrieve the subgroup of individuals with pre-existing and chronic depressive problems (cf. Consistently High class; Figure 1 in the manuscript). The five-class model estimates this group to comprise 8.5% of the population, a figure that is closely corroborated by the Norwegian Institute of Public Health (2016) estimate that 10% of the population of Norway suffered from depressive problems pre-pandemic. Finally, when introducing the six-class model and additional models, no novel unique patterns were retrieved, with additional classes revealing unstable results (cf. replication of loglikelihood values) and further splitting up previously identified classes (i.e., two similar pairs of the identified Mild Deterioration class; Figure 1 in the manuscript) into more granular subgroup with solely minimal differences in mean levels, further suggesting that the principal patterns in the data were successfully retrieved with the five-class model.

Table S1

Clustering Criteria and Information Criteria per class derived from the Latent Change Score Mixture Model.

Classes	BIC	AIC	CAIC	ssBIC	Entropy	P-BLRT	Class proportion (%)
1[a]	112837.49	112773.68	112847.49	112805.71	-	-	100
2[a]	107049.66	106922.05	107069.66	106986.11	0.68	17331.50*	74.42, 25.58
3[b]	105549.80	105358.39	105579.80	105454.47	0.66	1583.66*	57.06, 29.71, 13.23
4[a]	103646.37	103391.15	103686.37	103519.26	0.69	1987.24*	45.37, 13.81, 12.12, 28.70
5[a]	103012.21	102693.19	103062.21	102853.34	0.71	717.96*	8.50, 29.04, 6.77, 13.17, 42.52
6[b]	102550.82	102167.99	102610.82	102360.16	0.66	545.20*	4.90, 16.21, 25.67, 33.45, 5.98, 13.79
7[b]	102209.96	101763.32	102279.96	101987.52	0.67	424.67*	5.01, 31.01, 6.27, 14.83, 5.44, 26.26, 11.18
8[b]	101981.49	101471.06	102061.49	101727.29	0.67	312.27*	10.67, 29.71, 14.62, 5.40, 1.32, 25.94, 6.19, 6.15

Note. [a] Best loglikelihood consistently replicated; [b] Best loglikelihood did not consistently replicate; BIC: Bayesian Information Criterion; AIC: Akaike Information Criterion; CAIC: Consistent Akaike Information Criterion; ssBIC: sample size adjusted Bayesian Information Criterion; P-BLRT: Parametric Bootstrapped Likelihood Ratio Test. * $p < .05$.

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Study 3

Ebrahimi, O. V., Burger, J., Hoffart, A., & Johnson, S. U. (2021). Within and across-day patterns of interplay between depressive symptoms and related psychopathological processes: A dynamic network approach during the COVID-19 pandemic. *BMC Medicine, 19*(317), 1-17. https://doi.org/10.1186/s12916-021-02179-y

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https://doi.org/10.1186/s12916-021-02179-y

BMC Medicine

RESEARCH ARTICLE Open Access

Within- and across-day patterns of interplay between depressive symptoms and related psychopathological processes: a dynamic network approach during the COVID-19 pandemic

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Abstract

Background: In order to understand the intricate patterns of interplay connected to the formation and maintenance of depressive symptomatology, repeated measures investigations focusing on within-person relationships between psychopathological mechanisms and depressive components are required.

Methods: This large-scale preregistered intensive longitudinal study conducted 68,240 observations of 1706 individuals in the general adult population across a 40-day period during the COVID-19 pandemic to identify the detrimental processes involved in depressive states. Daily responses were modeled using multi-level dynamic network analysis to investigate the temporal associations across days, in addition to contemporaneous relationships between depressive components within a daily window.

Results: Among the investigated psychopathological mechanisms, helplessness predicted the strongest across-day influence on depressive symptoms, while emotion regulation difficulties displayed more proximal interactions with symptomatology. Helplessness was further involved in the amplification of other theorized psychopathological mechanisms including rumination, the latter of which to a greater extent was susceptible toward being influenced rather than temporally influencing other components of depressive states. Distinctive symptoms of depression behaved differently, with depressed mood and anhedonia most prone to being impacted, while lethargy and worthlessness were more strongly associated with outgoing activity in the network.

Conclusions: The main mechanism predicting the amplifications of detrimental symptomatology was helplessness. Lethargy and worthlessness revealed greater within-person carry-over effects across days, providing preliminary indications that these symptoms may be more strongly associated with pushing individuals toward prolonged depressive state experiences. The psychopathological processes of rumination, helplessness, and emotion regulation only exhibited interactions with the depressed mood and worthlessness component of depression, being unrelated

(Continued on next page)

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(Continued from previous page) to lethargy and anhedonia. The findings have implications for the impediment of depressive symptomatology during and beyond the pandemic period. They further outline the gaps in the literature concerning the identification of psychopathological processes intertwined with lethargy and anhedonia on the within-person level.

Keywords: Dynamic network analysis, Depression, Psychopathological mechanisms, Longitudinal study, Nomothetic time series analysis, General adult population, COVID-19 pandemic

Background

The global pandemic caused by the SARS-CoV-2 virus has been accompanied by substantial augmentations in psychiatric symptoms in the general population, with scholars denoting this homologous co-occurrence as a parallel pandemic of detrimental psychiatric symptomatology [1]. Among the studied symptom domains, the cross-continental elevations in depressive symptoms have been deemed an area of concern warranting further investigation [2–5]. To date, the preponderance of the pandemic literature has concerted its efforts toward the identification of prevalence estimates and demographic risk factors accompanied by the alterations in depressive symptom levels [3, 6, 7]. Consequently, knowledge remains exiguous concerning the psychopathological mechanisms that are interconnected with psychiatric symptom expressions during the pandemic [7].

Psychopathological mechanisms refer to processes which contribute to the amplification and maintenance of psychiatric symptomatology. Within the processes encapsulated in this phenomenon, behavioral and cognitive-affective mechanisms connote a prime category of interest, as they are loanable to manipulation by a wide range of psychiatric treatment modalities aimed at alleviating depression. Notably, such mechanisms (e.g., rumination) entail processes that are tied to fluctuations in symptoms *within* individuals. By contrast, risk factors provide information about the likelihood of experiencing detrimental symptoms *compared to peers* in the population with other dispositional or circumstantial disparities. Accordingly, investigations of mechanistic processes versus risk factors of depression yield distinctive pieces of information not necessarily compatible with the other, with their separation requiring the deployment of the appropriate level of analysis to disaggregate between what is referred to as *within-person* and *between-person* relationships, respectively [8]. As reflected by recent research calls [7, 9], however, much of the pandemic literature encompasses of study designs and analytical tools that are precluded from appropriate separation of these pivotal relationships.

Several scholars have denoted the substantive necessity of disentangling within- from between-person relationships [8, 10–14], with an example from the field of medicine highlighting its importance. Although the risk of heart attack is lower among physically active people (i.e., a *between-person* relationship), the chances of an individual having a heart attack is higher while exercising (i.e., a *within-person* relationship). Consequently, the presence of these opposing effects with the same set of variables (termed Simpson's paradox, e.g., [14]) accentuates the importance of their appropriate and distinctive investigation. From this perspective, knowledge concerning the formation of depressive symptoms and their patterns of interconnection with psychopathological mechanisms warrants investigations at the within-person level of analysis, presenting a key step toward the identification and impediment of the escalatory processes tied to the aforementioned increases in detrimental depressive symptomatology during the present pandemic. Mapping out such interrelations is further of utility beyond the pandemic period, as more knowledge is needed concerning the multitudinous processes involved in the maintenance of deleterious mental health states in non-clinical populations. As such, calls have been made for the adaptation of multi-level dynamic network approaches using longitudinal designs and time series data [4, 7, 15–17], yielded with the aptitude of detecting the different components involved in the maintenance of depressive symptomatology while appropriately separating within- from between-person effects across time.

A suitable dynamic network approach incorporating these properties includes the use of the multi-level vector autoregressive (VAR) model, further allowing investigations of relationships among variables occurring across specific time lags and within a given time window [18–20]. These patterns of interaction may further be interpreted through the lens of the network theory of mental disorders [21, 22], conceptualizing psychiatric symptoms and related components as networks of causally interacting entities. The time-lagged relationships in such dynamic network models are indicative of *Granger causal* relationships [23], denoting a variable's ability to predict another variable at the consecutive time point, yielding important information about which variable temporally precedes another in a system. Simultaneously, such network models provide information concerning interactions between variables occurring within a given time window, providing information about processes that may unfold at a faster rate than the studied temporal window of measurement [24]. In summary, the adaptation of dynamic network models allows for investigations of within-person relationships between symptoms and mechanisms, while providing information about their temporal order and preliminary indications concerning the time windows which they interact on.

The present preregistered study uses multi-level VAR networks to investigate the day-to-day and within-day fluctuations of depressive symptoms during the COVID-19 pandemic, with the aim of identifying the mechanistic processes involved in the amplification and maintenance of deleterious depressive symptomatology in the general adult population. In adapting a multi-level approach, the study further disentangles within-person from between-person relationships to identify and separate between processes of change and risk factors, respectively. Such investigations represent tests of theorized connections between depressive symptomatology and its constituents, advancing the insight concerning the patterns of interplay present among symptoms and mechanistic and contextual variables in detrimental depressive states.

As detailed in the preregistered protocol of this study, a comprehensive range of psychopathological mechanisms and contextual variables were investigated, with the aim of advancing the insight concerning how these theorized variables interact with specific symptoms of depression. Several psychopathological theories predict rumination to be a key process involved in depressive dynamics. As proposed by metacognitive theory [25], rumination may arise as an attempt to understand the reasons of depressed mood, only to operate as a maintaining mechanism of depressive symptomatology with individuals remaining stuck in the depressed state through engagement in repetitive cognitive processes rather than functional problem solving. Among other psychopathological mechanisms, helplessness may play a particularly prominent role in maintaining depressive states during pandemic periods, with learned helplessness theory predicting depressive symptomatology to arise when individuals perceive to have limited influence over the circumstances they are exposed to [26]. Additionally, emotion regulation difficulties are theorized as a maintaining mechanism in depressive states, with increased proneness of employing maladaptive emotion regulation strategies presenting greater difficulties of recovering from negative emotions, sustaining the depressed mood [27, 28]. Finally, contextual variables previously tied to depressive states in prepandemic periods were investigated, including loneliness [29], physical activity [30], social media use [31], interpersonal conflict [32], sleep quality [33], relatedness needs [34], and productivity [35]. As the preponderance of these aforementioned variables has been subject to fluctuation during the present pandemic, an investigation of their relevance in the maintenance of depressive states is important. Examples include fluctuation in loneliness levels tied to social distancing protocols [36], changes in productivity related to transitions from work to home office, and sleep disturbances connected to perturbations in daily routine [37]. Finally, access to information [4] and social contact [38] was investigated, both of which have been related to depressive symptoms in pandemic settings.

Methods

The preregistered protocol of this study can be found at the online repository of the Center for Open Science (https://osf.io/trf2y). All elements of the submitted study adhere to its preregistered protocol. Ethical approval for this study was granted by the Regional Committee for Medical and Health Research Ethics (reference: 125510).

Study design and time period description

The present study comprises an intensive longitudinal design conducting daily measures of depressive symptomatology and related mechanistic and contextual constituents for 40 consecutive days during the COVID-19 pandemic. This data collection method is referred to as a diary study and falls under the area of ambulatory assessment techniques [39], which also encompass the experience sampling method (ESM) and ecological momentary assessment (EMA). In the clinical empirical literature, these terms are often used interchangeably and commonly referred to as the sampling of intensive longitudinal data in the participant's real life using portable devices.

The measurement period (i.e., February 17 to March 28, 2021) was characterized by several periodic-specific events, encompassing (a) three longer and continuous periods of national holidays (i.e., days 6 to 12, days 13 to 19, and day 38 onward) and (b) a consecutive and uninterrupted period with implemented viral mitigation protocols where no modifications in national protocols occurred (i.e., days 20 to 37). This uninterrupted viral mitigation period was characterized by a stable set of protocols, such as quarantine upon contact with infected individuals, isolation upon infection, closure of schools and universities, restriction on social gatherings, public activities and events, and visitation restrictions. Several of these implemented protocols (e.g., social gatherings, domestic travel, and visitation restrictions) were slightly lightened during the three holiday intervals encompassed in the study period (i.e., the two winter and the Easter holidays).

Participants and procedure

This study is part of the Norwegian COVID-19, Mental Health and Adherence Project, a large ongoing longitudinal investigation of psychiatric symptomatology in the general adult population. Eligible participants included all adults (i.e., age $\geq$ 18 years) residing in Norway. Prior to the aforementioned daily measurements conducted for the present study, the participants provided responses at four measurement waves since the onset of the pandemic. Upon initial recruitment to the project (i.e., the first wave of data collection, March 2020), the participants responded through an online survey disseminated to a random selection of Norwegian adults through a Facebook business algorithm, in addition to systematic dissemination of the survey via national, regional, and local information platforms (i.e., television, radio, and newspapers). This procedure is elaborated in detail elsewhere [4]. The same participants were recontacted at each wave of measurement. At the fourth wave of data collection (i.e., January 2021), the participants were queried concerning their interest in participating in an upcoming 40-day study about mental health (i.e., the present study). A total of 2383 participants expressed interest to partake in the study, of which 1706 individuals formally enrolled in the study. Daily measures were conducted across a 40-day period, encompassing of a 24-h sampling frequency with the participants receiving the set of time-variant items each evening at 18:30 (6:30 PM). The sampling frequency was held constant throughout the measurement period, and daily measures were conducted to investigate temporal effects (i.e., relationships across days) and contemporaneous effects within the same time window (i.e., relationships within a day) [24]. The daily sampling frequency was deemed as appropriate given its direct relation to the assessment of depressive symptom endorsement in the Diagnostic and Statistical Manual of Mental Disorders (DSM-V), querying about the presence of symptomatology during and across days [40].

Measurement

Time-invariant variables

The participants reported their age, sex, education, civil status, preexisting mental health status, and region of residence.

Time-variant variables: item selection procedure and response scale

The item selection procedure in the present study was designed to accommodate for critical topics in the dynamic network analytic literature. First, all items were selected with the aim of avoiding topological overlap and thus possible inflation in centrality estimates [41]. Second, this theoretically grounded selection was proceeded by a data-driven approach, affirming the correlation matrix to be positive definite and that the included items were not linear combinations of one another. Subsequently, the goldbricker algorithm [42] was used to search for pairs of highly intercorrelated items, in addition to items displaying similar behavioral patterns with the other items in the network. Dependent correlations were investigated using the Hittner method [43]. The data analytical approach was congruous with the theoretical selection, identifying no redundant items.

Another topic that has received notable attention in the (dynamic) network literature includes utilization of validated items, which were predominantly adapted in this study (cf. preregistration protocol). Finally, these aforementioned topics were coupled with selections of theorized psychopathological mechanisms and contextual variables of potential relevance to depressive symptom dynamics. Overall, the item selection process followed a consensus procedure consisting of six meetings between the authors, yielding the following preregistered study protocol (https://osf.io/rekzm) containing the full details of each investigated variable and the theoretical rationale underlying item selection.

The full list of items measuring the depressive symptoms and related mechanistic and contextual constituents is provided in Table 1. All items were adapted to capture daily patterns of interplay. Following Fried and colleagues [44], the items were measured on a 5-point response scale, with all variables and their full measurement details presented in the table note of Table 1.

Statistical analyses

Time series analyses and data pre-processing for network models

All statistical analyses were performed using R version 4.1.0 [45]. The R code and the correlation matrices necessary to regenerate the estimated models may be found here https://osf.io/trf2y/. Period-specific patterns across the different periods of the study (i.e., holiday periods and uninterrupted period of viral mitigation) were investigated using multilevel models, with a two-sided alpha level of .001 set as the inference criteria. Along with the time series visualizations, these auxiliary analyses provide descriptions of the investigated variables across the 40-day measurement period to be briefly presented in the "Results" section.

Prior to the estimation of the main analyses of the study (i.e., estimation of networks), pre-processing steps common for dynamic network models were performed. First, these analyses require a minimum number of observations per person. Because the procedure is based on within-person centering using sample means per person, it is generally not recommended to include individuals with less than 20 measurements [19, 46]. To find an optimal balance between including participants with minimal missingness and retaining as many participants as possible, the number of completed diaries was visualized as a function of the cumulative number of participants (see Additional file 1: Figure S1). The plot indicated that any more lenient cutoff for completed diaries than about 30 would not lead to substantially larger numbers of included participants. Accordingly, participants who completed at

Table 1 All Items were measured on a 5-point scale (1–5). Items 1–13: 1 (not at all), 2 (slightly), 3 (moderately), 4 (very), and 5 (extremely). Items 14–16: 1 (0 min), 2 (1–15 min), 3 (15–60 min), 4 (1–2 h), and 5 (over 2 h). Item 17: 1 (0 min), 2 (10–15 min), 3 (15–30 min), 4 (30–60 mi), 5 (over 1 h)

No.	Abbreviation	Item
1	Depressed mood	Today, I felt down, depressed or hopeless.
2	Anhedonia	Today, I had little interest or pleasure in doing things.
3	Lethargy (energyless)	Today, I felt tired or that I had little energy.
4	Worthlessness	Today, I felt bad about myself or felt like a failure.
5	Rumination	Today, I thought negatively about things that have happened in the past.
6	Emotion regulation difficulties	Today, it has been difficult to cope with my emotions.
7	Helplessness	Today, I felt helpless with regard to my problems.
8	Loneliness	Today, I felt lonely.
9	Sleep satisfaction	Today, I was satisfied with my sleep.
10	Productivity	Today, I felt productive or useful.
11	Relatedness	Today, I felt close to other people.
12	Sufficient information	Today, I received enough information on how to deal with the pandemic and its associated protocols.
13	Interpersonal conflict	Today, I argued or had negative discussions with someone.
14	In-person social contact	Today, I spent ... minutes/hours on physical social gatherings (i.e., meeting others face-to-face, offline).
15	Digital social contact	Today, I spent ... minutes/hours on digital social gatherings.
16	Social media	Today, I spent ... minutes/hours scrolling social media just to make the time pass.
17	Physical activity	Today, I spent ... minutes/hours physically exercising to the extent that it lead to increased pulse or at least minimal sweating.

least 30 out of 40 diaries were selected. This resulted in including 1368 out of 1706 participants.

Second, the presence of trends in the data may lead to lower specificity or sensitivity in the resulting networks [24]. Accordingly, a linear trend analysis was performed for each variable using two components; a cumulative linear trend over the assessment period, and a week-day versus weekend trend. Such trends can be identified by performing a regression of the item scores on the assessment time (linear trend), as well as on a dummy variable coding week-days versus weekend-days (weekend trend). For a detailed, reproducible work flow of the trend removal, the reader is directed to the R code found in the "Code availability statement" section. In the subsequent analyses, these trends were removed from each variable by subtracting the linear trends and weekend effects from each observation. Note that the time series visualized in Fig. 1 portray the data prior to the detrending procedure.

Main analyses

We used the multi-level vector autoregressive model implemented in the *mlVAR* package in R [47] to estimate the network models from the data. The algorithm implemented in *mlVAR* is based on a two-step procedure. First, (*within-person*) temporal and *between-subjects* effects are computed based on a node-wise multi-level regression, and second, (*within-person*) contemporaneous effects are obtained by performing a subsequent node-wise multi-level regression from the residuals in step 1. In line with the recommendations for networks with more than six nodes [19, 47], *orthogonal* estimation was chosen for both the temporal and contemporaneous networks.

This results in three types of networks, visualized in Fig. 2. (1) A *fixed-effect temporal network* (top panel of Fig. 2), in which average within-person effects indicate predictions of different nodes at the consecutive time point (i.e., lag-1), capturing the potential across-day temporal interactions between depressive symptomatology and related components. The temporal network provides directed statistical relationships (i.e., one-headed arrows) that are interpreted as Granger-causal [23], representing whether a node at time t predicts another at the subsequent time point (i.e., $t + 1$), while controlling for all other nodes in the network. (2) A *fixed-effect contemporaneous network* (middle panel of Fig. 2), indicating average within-person effects between variables that are

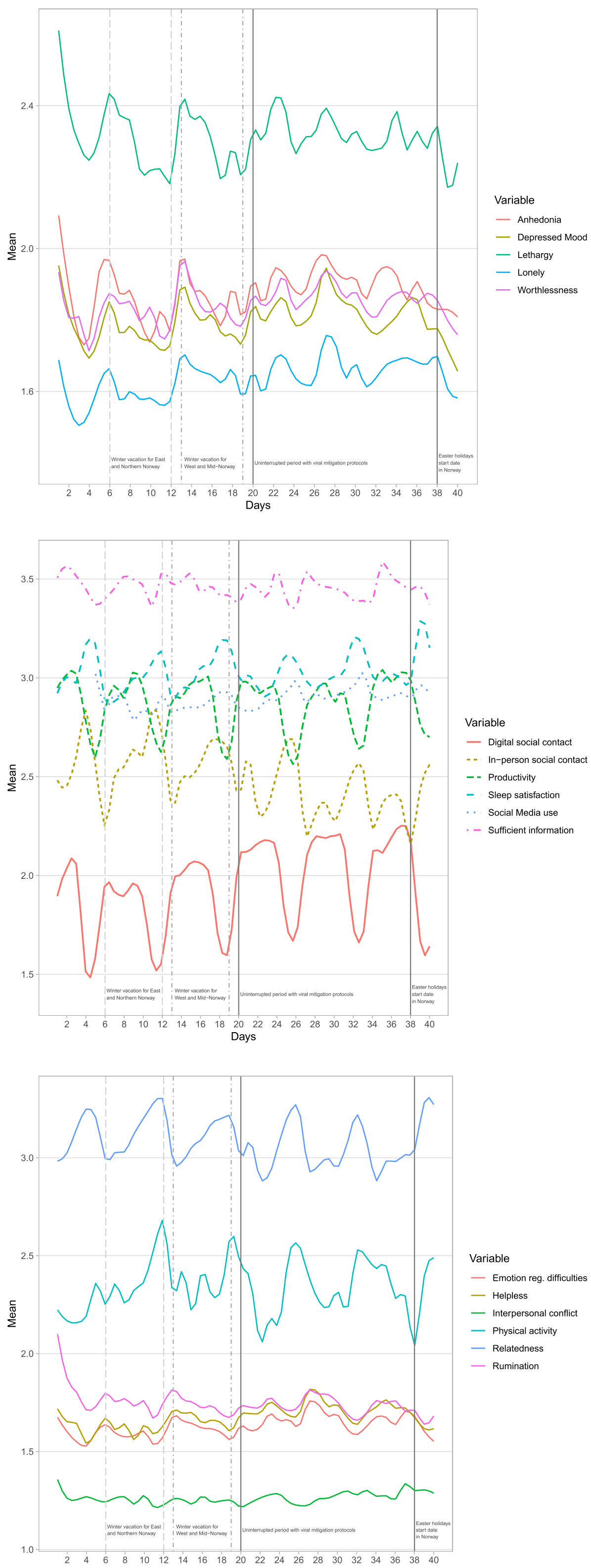

Fig. 1 Nomothetic time series visualizations of all investigated variables through the measurement period, further depicting period-specific patterns across the 40-day study period

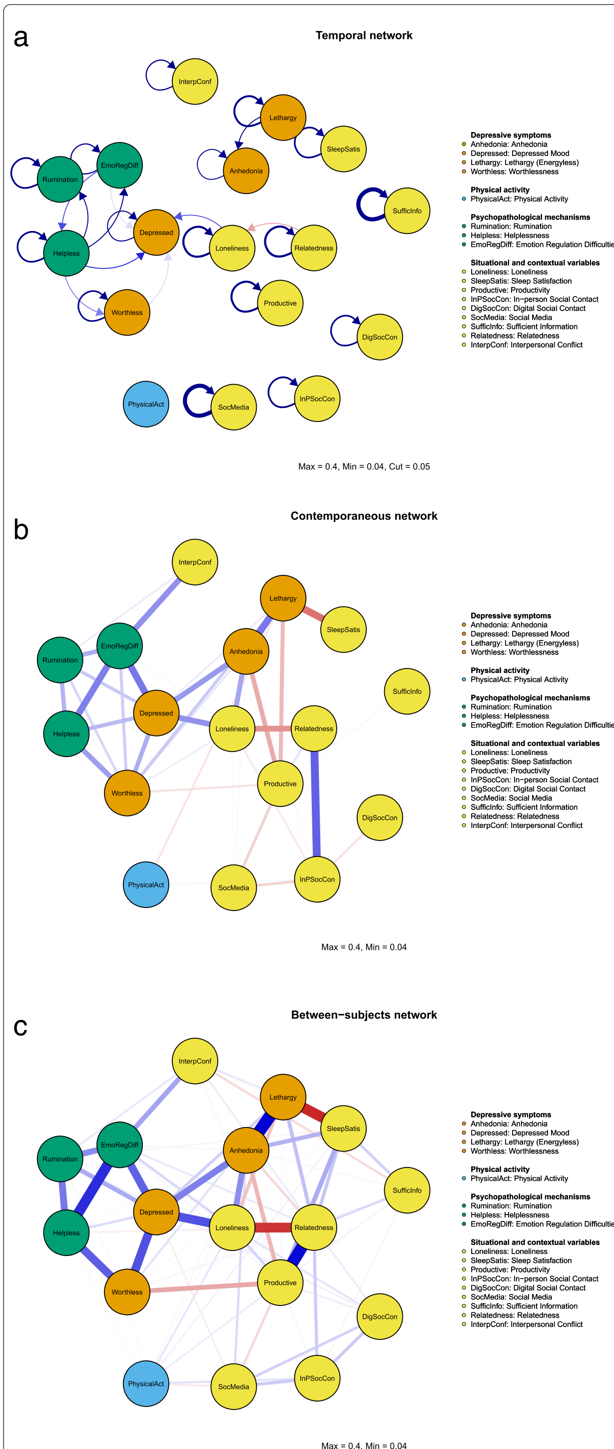

Fig. 2 Temporal (top), contemporaneous (middle), and between-subject (bottom) networks derived from the multi-level vector autoregressive (VAR) model showing the connection between nodes while controlling for all other nodes in the network. The strongest edges include the temporal network coefficient = 0.27 (SufficInfo → SufficInfo), the contemporaneous network coefficient = 0.26 (InpSocCon ↔ Relatedness), and the between-subject network coefficient = 0.45 (Anhedonia ↔ Lethargy)

not captured in the temporal network, which estimates the unique interactions between all nodes within the same time window. In the dynamic network literature, these effects have been interpreted as dynamics that are potentially faster than those captured in the lag-1 temporal effects [24], indicative of interactions between nodes within the same day in the present study. (3) The *between-subjects network* (bottom panel of Fig. 2) indicates relationships between variables based on the person-wise means of each variable. The between-subject network concerns average *between-person effects*, revealing how higher average levels on a variable *compared to peers* (i.e., compared to other subjects) is related to the mean levels in another variable compared to others in the population (e.g., people who on average are more physically active compared to their peers also likely have lower average heart rate than their peers). The temporal and contemporaneous networks concern average *within-person effects* across and within measured time windows respectively, both revealing how people displaying higher scores on a variable *compared to their own average* may display average within-person level changes on another variable (e.g., when individuals exert more physical activity than their own average, they also experience higher heart rate than their own average). The within-person effects provide insight into the patterns of interplay between symptoms and mechanisms of change in a depressive system, while the between-subject effects provide information concerning risk factors associated with depressive symptoms across subjects.

Each network consists of sets of nodes (i.e., variables) listed in Table 1 and sets of edges describing the relationships between nodes. Blue and red edges portray positive and negative relationships, respectively. Importantly, each network model estimates the unique relationships among nodes while controlling for all other variables in the network. The main focus of the present study includes the average *within-subject* relationships (i.e., temporal and contemporaneous networks).

Centrality metrics [48] aim to quantify the role of individual nodes for the overall information flow in the networks. Strength centrality enhances the interpretation of network models through highlighting how strongly a node is directly connected to other nodes in the network. As a directed graph, the temporal network model enables estimation of the outstrength and instrength centrality, quantifying the sum of all outgoing and incoming absolute edge weights (i.e., excluding the autoregressive effect) from and to a node, respectively. Instrength thus reveals which nodes are more likely of being influenced by fluctuations in other nodes in the network at the previous day, while outstrength centrality quantifies the magnitude of a node in influencing other nodes in the network at the consecutive day. The undirected between-subject and contemporaneous networks provide estimations of strength centrality, computing the sum of all absolute edge weights connected to a node to quantify the overall weighted connectivity of the node in the network. All aforementioned strength centrality metrics reflect the average conditional associations between a node and the other nodes in a network. In the present study, we introduce a novel approach in *visualizing* centrality metrics using radar charts in order to enhance visual comparisons of centrality indices in a given network (i.e., outstrength versus instrength centrality in the temporal network) and across networks containing the same nodes. In line with the recommended reporting standards for network studies [49], we use raw centrality scores as opposed to standardized estimates, as the latter may inflate dissimilarity between centrality indices.

Sensitivity to demographic composition

The proportion of all demographic characteristics was investigated and compared to their known rate in the population. All characteristics not fully representative of the Norwegian adult population were adjusted in sensitivity analyses encompassing of a random selection of participants fully matching the population characteristics. The similarity and degree of replicability between the results from the main sample and the adjusted proportional subsample representative of the population were compared through correlating the respective matrices containing any estimated effects in the study, with its range reported at the beginning of the "Results" section.

Robustness and replicability of networks

Additional analyses were performed to assess the robustness and replicability of the network models. These analyses were conducted across four subdivisions of the dataset. First, all participants were randomly separated into two groups prior to re-estimation of the network models and assessment of the replicability of the findings across the two subsamples. Second, two additional subdivisions of the dataset were created, separating the data into an early subsection consisting of all participants using the first half of the time series and a second subsection encompassing of data of all participants using the latter half of the time series. Thus, the network models were further re-estimated to assess the replicability of the findings across the time-specific subsamples.

In each of the four aforementioned subsamples, three main analyses were conducted to assess the robustness of the findings, with each subsample compared to its respective counter-subsample as detailed above. First, following previous research [50], the global replicability and consistency of edges of each of three estimated networks (i.e., temporal, contemporaneous, and between-subjects network) was assessed through correlating the estimated edge weights in each subsample. Second, to assess the stability of centrality values, estimated centrality indices were compared through correlations across each respective pair of subsamples. Finally, the rate of consistency among the nodes with the highest centrality was assessed through comparing the total number of times the most central nodes identified by the main analyses were replicated across all four subsamples described above, used as a proxy to obtain estimations approximating the rank-order stability of the centrality indices.

In using such proposed assessments of robustness across subsamples, a previous study [50] found moderate replicability across subsample networks through correlations of .61 when comparing edge weights, toward which the present findings will be benchmarked against. The range of correlations derived from these robustness analyses is to be presented in the "Results" section labeled *network replicability*.

Network visualization

All networks have been visualized using the *qgraph* package in R [51]. The maximum edge weight across the three networks was set to correspond to the largest edge weight across the networks (i.e., *partial* $r \approx .4$). Correspondingly, to filter out weaker from more notable effects, the minimum edge weight was set to one-tenth (i.e., .04) of the maximum value. Note that the set minimum merely hides edges in the network figures for visualization and interpretation-enhancing purposes and does not remove them from the model. As common across dynamic network studies [44, 52], the temporal network generally exhibited smaller effects than the other two networks. Therefore, for visualization purposes, a cut value of .05 was set to more clearly separate the effects above and below this threshold. The arrangement of the nodes is based on the average layout of the three networks that have been established via the Fruchterman-Reingold algorithm [53]. The matrices containing all edge weights and the raw networks displaying all edges (i.e., including the weaker effects) can be found at the online repository of the Center for Open Science (https://osf.io/trf2y) and in Additional file 2: Figure S2-S4, respectively.

Results

A total of 1706 participants enrolled in the study. The age of the participants ranged from 18 to 86 years ($M_{age} = 37.30$), with 1336 (78.54%) of the participants being female, 962 (56.89%) having a university degree, and 830 (49.43%) being married or in a civil partnership. A total of 1368 of the 1706 (80.19%) participants provided sufficient data to be included the study, with no pattern of difference identified between initiators and those with sufficient data. The percentage of individuals with preexisting mental health conditions in this sample was 16.62%, representative of the known rate of psychological disorders in the adult population of Norway, which is between 16.66 and 25.00% [54]. The sample was further geographically representative of Norway, with the quota of participants sampled from each region being proportional to region size. With the exception of sex and education (i.e., oversampling females and those with a university degree), the preponderance of demographic characteristics were representative of the Norwegian adult population. To fully match all demographic characteristics (i.e., including sex and education) to the known proportions in the population, sensitivity analyses were conducted on a randomly drawn set of 598 individuals fully matching the population parameters. These sensitivity analyses replicated the results from the main sample across all analyses below, with the correlation between the matrices containing the results of the representative sample and main sample ranging from .96 to .99.

Time series analyses and time-specific patterns across the study period

Figure 1 provides a visualization of the time-specific patterns of depressive symptomatology and related constituents across the 40-day study period. Overall, mental health-promoting associations were identified during the holiday periods where pandemic protocols were lightened (i.e., days 6–12, 13–19, and 38 and onward), while detrimental associations were found during the period encompassing of uninterrupted viral mitigation protocols (i.e., days 20–37). Specifically, all unfavorable variables (e.g., loneliness, depressed mood, interpersonal conflict, helplessness) revealed linear decreases during holiday periods (*ps* $< .001$) while increasing during the continuous viral mitigation period (*ps* $< .001$). All favorable variables (e.g., relatedness) revealed linear increases during holiday periods (*ps* $< .001$), while decreasing during the uninterrupted viral mitigation period. The only notable exceptions from these patterns included (a) productivity (i.e., increasing during uninterrupted viral mitigation period, decreasing during holidays, *ps* $< .001$) and (b) lethargy, information access needs, sleep satisfaction, and rumination which did not reveal any significant fluctuations during the continuous viral mitigation period (*ps* $> .05$).

In-person (i.e., offline face-to-face) and digital social contact demonstrated opposite patterns, with in-person social contact decreasing during the continuous viral mitigation period and increasing during holidays, while digital social contact decreased during holidays and increased during the continuous viral mitigation period (*ps* $< .001$).

Patterns of interplay between depressive symptoms and related components

The *within-person* patterns of interplay obtained in the temporal and contemporaneous network models

(Fig. 2) provide insight concerning the potential processes involved in the maintenance and amplification of depressive symptomatology.

Figure 2 (top panel) displays the temporal network revealing the average *within-person* connections between nodes *from one day to the next*, with the radar plots in Fig. 3 depicting each variable's outstrength and instrength centrality. The radar plots depicting outstrength and instrength displayed distinctive patterns, indicating differences in the extent to which nodes were associated with having outward influencing roles versus susceptibility of being influenced on an across-day basis. Loneliness, helplessness, and in-person social contact had the greatest outstrength centrality. Depressed mood, anhedonia, and emotion regulation difficulties had the greatest instrength centrality. Concerning node connections, specific across-day patterns unfolded between lethargy and anhedonia, with greater within-person levels of lethargy temporally predicting increases in within-person levels of anhedonia at the consecutive day and anhedonia further reinforcing itself across days in a vicious self-loop. This pattern of interwovenness also involved an autoregressive carry-over effect in lethargy, in which low energy levels carried over across days. The across-day interplay among depressive symptomatology was coupled and separated, with lethargy and anhedonia representing one pair, while depressed mood and worthlessness represented the other. Helplessness was among the nodes revealing the highest outstrength centrality across days, with higher within-person levels of helplessness being involved in the amplification of other detrimental mechanistic processes (i.e., increases in rumination and emotion regulation difficulties) in addition to key symptoms of depression (i.e., increases in depressed mood and worthlessness), all further involved in detrimental self-loops across days. A vicious cycle was identified between helplessness and emotional regulation difficulties, with higher within-person levels of each predicting greater increases in the other at the consecutive day. Examples of across-day patterns with smaller magnitude included the directed effects from relatedness to loneliness (i.e., higher within-person levels of relatedness at the previous day predicted less loneliness at the consecutive day), greater helplessness predicting more worthlessness the next day, and more emotion regulation difficulties and loneliness predicting higher depressed mood at the following day. Additionally, although having smaller magnitude in its outgoing effects, in-person social contact demonstrated widely distributed across-day influence on the other nodes in the network, as reflected by its position among the nodes with greatest outstrength (Fig. 3). This widely distributed outgoing connectivity is visible in the raw network containing all effects found in Additional file 2: Figure S2.

Inspecting the contemporaneous network (Fig. 2, middle panel) provides indications of average *within-person* relationships among the investigated nodes occurring *within the same window of measurement*, which in the present study reflects a within-day time window. All abovementioned relationships between depressive symptoms and related constituents were present within the same window of measurement. In contrast to the across-day patterns including separate clusters of interaction among depressive symptoms, all depressive symptoms were related with one another in the contemporaneous network. Notable unique patterns of interconnection were found within a daily window of measurement, with within-person sleep satisfaction inversely related to lethargy, within-person increases in loneliness associated with higher within-person levels of anhedonia and lower

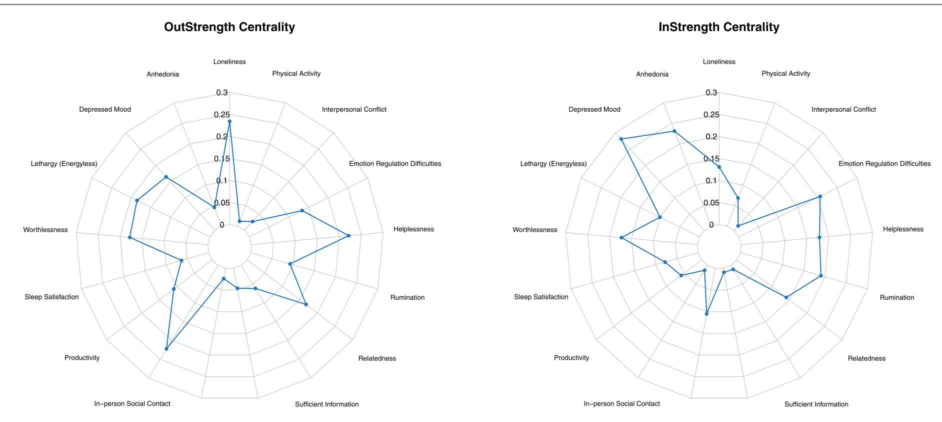

Fig. 3 Radar chart depicting the OutStrength (i.e., sum of all outgoing absolute edge weights from a node) and InStrength centrality (i.e., sum of all incoming absolute edge weights to a node) of the variables in the temporal network model. The across-day directed involvement of a node is revealed through the extent of which a node influences other nodes (i.e., OutStrength) at the consecutive day or is influenced by other nodes in the network at the previous day (i.e., InStrength)

relatedness, and greater emotion regulation difficulties being associated with more interpersonal conflict and worthlessness. Additionally, productivity portrayed negative within-day relationships with both anhedonia and lethargy. Importantly, the relationship between rumination and key depressive symptoms (i.e., worthlessness and depressed mood) predominantly occurred within the same window of measurement (i.e., within a day), revealing weak effects across days. Among the contextual variables prominent during the pandemic, in-person social contact and relatedness were further strongly interwoven in the same time window. The most central (i.e., strength centrality; Fig. 4, left panel) nodes in contemporaneous network were depressed mood, anhedonia, and emotional regulation difficulties, outlining the nodes with the strongest overall connectivity within a day among the nodes in the network.

Risk factors associated with depressive symptoms

The between-subjects network (Fig. 2, bottom panel) is suitable in the identification of risk factors across subjects in a population. Several distinctive associations were derived from this network, predominantly involving the contextual variables of the study. Particularly, the relationship between information access needs and sleep quality was highlighted, revealing that people who on average feel well-informed about the pandemic also report greater sleep satisfaction compared to other adults in the population. Higher relatedness was associated with greater productivity across subjects. Similarly, there was a negative association between productivity levels and perceptions of worthlessness, and a positive association between productivity levels and sleep satisfaction. Overall, the nodes with the highest strength centrality (Fig. 4, right panel) in the between-subject networks were relatedness, depressed mood, and anhedonia.

Network replicability

The estimated network models and their corresponding computed parameters were yielded as robust, replicating the main findings. Specifically, the correlation between edge weights comparing the two random subsamples of participants was $r = .93$ for the temporal network, $r = .99$ for the contemporaneous network, and $r = .97$ for the between-subjects network. Correspondingly, the correlation between edge weights comparing the first half of the time series compared with the latter half was $r = .92$ for the temporal network, $r = .99$ for the contemporaneous network, and $r = .99$ for the between-subjects network. Centrality estimates were further robust across both aforementioned pairs of subsamples, with correlations ranging from $r = .89$–$.96$ (i.e., instrength) to $r = .80$–$.88$ (i.e., outstrength) for the temporal network, stable at $r = .99$ for the contemporaneous network, and ranging from $r = .88$ to $.97$ for the between-subject network.

Finally, the edges revealing the highest centrality were consistent across all subsamples (cf. Additional file 3: Table S1), with 96.67% of the edges with the highest centrality re-obtained in the subsample analyses across all networks.

Discussion

As discussed by multiple scholars [8, 11–14], a study of within-person relationships is required to understand the mechanisms of change in human behavior and psychopathological research. The disentanglement of such within- and between-person relationships are imperative, as conclusions from one level do not necessarily generalize to the other, where in extreme cases, these relationships can convey opposite patterns [8, 11, 12, 14]. Consequently, understanding the maintaining components involved in depressive states necessitates the study of within-person relationships.

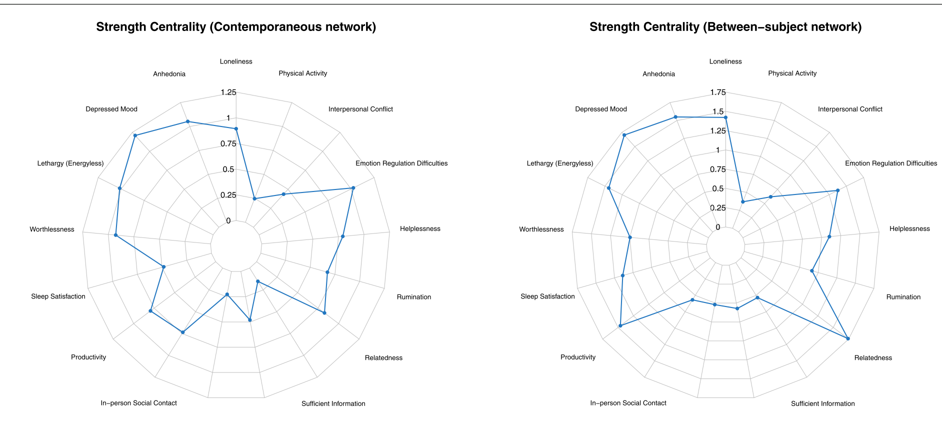

Fig. 4 Radar chart revealing the strength centrality (i.e., the sum of all absolute edge weights connected to a node), quantifying the overall weighted connectivity of the node in the contemporaneous (left) and between-subject (right) network models

Maintaining mechanisms of depressive symptomatology

The main purpose of the present study was to examine the *within-person* relationships present in the temporal and contemporaneous models of depressive symptoms and its constituents. As these networks model average within-person connections between nodes, they provide insight into potential mechanisms of change involved in the amplification and impediment of depressive symptomatology, providing directions toward further study and identification of targets for interventions aimed at alleviating these detrimental mental health problems.

Although all depressive symptoms were well-connected on a between-subject level and further interacted within the same window of measurement, the findings of present study indicate that interactions between depressive symptoms to a greater extent are separated and uniquely coupled across days. Specific across-day connections were identified between anhedonia and the somatic symptom lethargy, while two cognitive-affective symptoms, perceptions of worthlessness and depressed mood, were more strongly interconnected on an across-day basis. Additionally, the relationship between these symptoms were directed, revealing the predominant temporal influence of lethargy on anhedonia, and worthlessness on depressed mood. These findings have implications for efforts aimed at impeding escalations of depressive states, suggesting that lethargy and worthlessness have a greater likelihood of contributing as catalysts in the escalation of deleterious depressive states from one day to the next. As a key feature putting individuals at risk of developing depressive syndrome involves the prolonged constellation and experience of multiple symptoms [40], insight into the specific symptoms that more likely yield carry-over effects across time is of importance from an epidemiological and clinical perspective in more successfully preventing the development of a depressive state. The present study identifies that the two most prominent depressive symptoms that may be involved in such detrimental carry-over effects in the non-clinical population are worthlessness and lethargy. This finding is consistent with cross-sectional network studies identifying worthlessness and lethargy as central nodes in depressive states [16, 17], with the present study advancing insight concerning the directed temporal involvement and coupled interaction between these symptoms.

This investigation further extended the applications of network theory through the introduction of relevant psychopathological mechanisms and contextual factors in the networks, yielding novel insights concerning the specific patterns that these processes exhibit in their interactions with depressive symptomatology. Loneliness, helplessness, and in-person social contact had the greatest outward temporal influence (i.e., outstrength centrality) on the other variables in the network on an across-day basis. Studies during the present pandemic have found undirected associations between loneliness and depressive symptomatology in the general population [55, 56]. The present longitudinal study advances the literature by identifying the direction of this association, further identifying that loneliness interacts with depression through its directed association with the depressed mood component of depression, carrying over across days.

The main psychopathological mechanism temporally associated with the maintenance and amplification of depressive dynamics on an across-day basis was helplessness. Accordingly, when an individual reported being more helpless than their own average at a given day, they reported within-person increases in depressed mood, rumination, and worthlessness at the consecutive day. This finding provides support for helplessness as an important mechanistic variable in the maintenance and change of depressive symptoms in the general population. This is consistent with the learned helplessness theory of depression [26], postulating that when an individual comes to believe that their efforts to modify their circumstances are ineffective, developed perceptions of helplessness may incite depressive symptomatology. The finding is further consonant with a central meta-theory of psychopathology proposed by Jerome Frank, suggesting that demoralization (i.e., experienced helplessness or inability to cope) is a key aggravator of psychiatric symptomatology [57]. As perceptions of helplessness are theorized by several scholars to be the main reason for individuals seeking psychiatric treatment [57, 58], directing efforts toward reducing helplessness may be warranted. The present study provides preliminary indications that such efforts may have the ability to impede deleterious depressive states, although such assertions warrant further investigation using controlled designs.

Aside from being uniquely associated with within-person increases in key depressive symptoms and rumination at the next day, helplessness was further engaged in a vicious cycle with emotional regulation difficulties across days, with emotion regulation problems also associated with heightening of depressed mood from one day to the next within individuals. Combined with the finding that emotion regulation difficulties were the most central psychopathological process in the contemporaneous network, revealing strong interactions with depressive symptoms within a day, this finding suggests it may be important to devote simultaneous attention toward the detrimental role that emotional regulation difficulties may play in depressive mental health states. Notably, this study provides indications that the interaction between depressive symptoms and emotional regulation difficulties may predominantly operate on a faster time scale than helplessness with depressive symptoms. This finding is meaningful, given that emotional regulation problems likely are more situationally contingent and probable of occurring within a more encapsulated time period. Consequently, these findings distinguish between the proximal role that emotion regulation difficulties play in its interaction with depressive symptoms, while identifying helplessness as having a more prominent role in terms of prolonged depressive symptom experience. More granular approaches are called for in future studies to refine the understanding of the possible directed role that emotion regulation difficulties may play within a day.

Among the aforementioned psychopathological mechanisms, rumination was peripheral and did not have any notable interaction with depressive symptomatology on an across-day basis. This finding is consistent with a previous study [59] identifying rumination to be on the receiving end of predictive temporal relationships in a network of mechanistic variables, in addition to another study not finding any temporal relationship between rumination and depressive symptoms [60]. In the present study, the only notable connection with rumination included a directed effect from helplessness predicting rumination at the consecutive day. This finding suggests that helplessness may play a more prominent role in the maintenance and across-day constellation of depressive symptomatology in the non-clinical population, consistent with the goal progress theory of rumination proposing rumination to be a response to failure in achieving a certain task rather than an outgoing mechanistic process [61]. Consistent with existing studies [16], rumination revealed undirected associations to some symptoms of depression (e.g., weaker associations with worthlessness) on both a between-subject level and within a day. However, the present findings in combination with findings from directed network studies investigating within-day relationships involving depression and rumination [59, 60] provide indications that these associations may to a greater extent be indicative of rumination being an influenced node rather than the influencing node, with implications for interventive efforts aimed at alleviation of depressive symptoms. This finding is further partially consistent with metacognitive perspectives on depression [25], postulating rumination to be a process *ensuing* depressive symptoms as a reactional attempt to understand the reason for their presence and in attempts of identifying solutions to the problem. However, the present study does find indications of rumination subsequently influencing depressive symptoms in turn, which is also postulated by the theory. Still, given the multimodal complexity of rumination [62, 63], the literature will benefit from further temporal examinations of depressive symptoms simultaneously investigating rumination along with other psychopathological mechanisms of relevance, to better understand its specific as well as comparative interaction with depressive components.

The findings of the present study further shed some light on the interactions between depressive symptomatology and mechanistic processes that operate on a faster time scale than an across-day basis. In the present study, this reflects the identified interactions in the contemporaneous network, which cautiously provide indications of associations among nodes that may occur within person during a given day. Meaningful connections emerged between lethargy within individuals in its association with reduced sleep satisfaction within the same time window, while being more productive than usual was associated with lower anhedonia and lethargy. Loneliness was a central node with important connections to depressive symptoms and contextual variables across all three networks. On a within-person level, loneliness displayed its largest connectivity within a day, with the findings indicating that while individuals felt greater loneliness than their own average, this was associated with greater within-person intensity of depressed mood and anhedonia. Consistent with a study by Fried and colleagues [44] on the student population, the present study found higher within-person levels of loneliness to be associated with reduced relatedness and in-person contact. The present study supports and adds to these findings by extending the time period of investigation to later stages of the pandemic and a broader demographic composition of participants, in addition to identifying detrimental associations between loneliness and depressed mood.

Notably, on the within-person level, the three psychopathological processes (i.e., helplessness, rumination, and emotion regulation difficulties) only exhibited interactions with the depressed mood and worthlessness component of depression, being unrelated to lethargy and anhedonia. These findings highlight the connection between these aforementioned cognitive-affective mechanisms with particular depressive components, providing important insights on the patterns of interaction between depressive symptoms and mechanistic processes. Simultaneously, they also leave important gaps in the literature concerning the identification of pathological processes more closely intertwined with lethargy and anhedonia on the within-person level.

Risk factors associated with depressive symptoms across subjects

Across subjects, in-person social contact was revealed as the type of social interaction with the strongest association with relatedness, with those who reported being more frequently engaged with such face-to-face contact compared to their peers also reporting greater relatedness. Moreover, individuals who on average felt more connected to their peers during the pandemic reported greater levels of productivity, further mirrored by within-person relationships to outline several beneficial associations of relatedness. However, although relatedness was connected to anhedonia on a between-subject level, this connection was not present in any of the within-person networks (i.e., temporal and contemporaneous network). This demonstrates the importance of separating between- and within-person effects [8, 11, 12, 14], with this finding implying that it is unlikely that relatedness is directly associated with anhedonia. Rather, as also revealed by the within-person networks, relatedness is more indirectly connected to depressive symptoms through its association with loneliness.

Between-person associations were further identified between information access and sleep, with those who on average reported sufficient access to information about the pandemic situation reporting greater sleep satisfaction compared to their peers. Still, no within-person relationships emerged for this association. Moreover, no social contact component other than in-person social contact revealed notable beneficial associations across any of the investigated networks, with other social contact components additionally portraying detrimental associations to depressive states. Specifically, consistent with previous findings [31, 64], individuals who compared to their peers who were more engaged in passive social media use had a greater risk of being associated with higher levels of anhedonia, in addition to lower productivity. Yet, again, however, no meaningful within-person detrimental association emerged between social media use and anhedonia, suggesting the limited likelihood of this factor being associated with within-person fluctuations in depressive states when controlling for all other variables in the network. Additionally, no beneficial within-person associations were identified with digital social contact. Taken together, these findings highlight solely in-person social contact as having a potentially important role on a within-person basis through this variable association with loneliness and relatedness. As loneliness is an important problem in itself [36] and further was found to be connected to depressed mood across days on the within-person level in this study, this finding implies that attempts to find an optimal balance between strength of viral mitigation protocols and appropriate levels of in-person social contact, the latter of which the present findings reveal to be hard to substitute by other social contact types, may be of utility in combating the concurrently ubiquitous presence of loneliness. Clever behavioral interventions at the population level, including the use of social bubbles, may serve as utile strategies that can simultaneously reap the psychological benefits of reduced loneliness while maintaining control over viral spread [65]. As for depressive symptoms, however, the present study does not identify any direct within-person relationship between social contact and depressive symptomatology, suggesting that efforts toward alleviation of depressive symptoms may be more fruitful when aimed at other identified mechanistic and contextual variables.

Other notable findings

The social contact components were negatively associated in the contemporaneous network, reflecting that while an individual is engaged in a greater extent of in-person social contact than their own average, they are less involved in digital social contact within the same window of time. This stands in informative contrast with the positive associations between these components in the between-subject network, which highlights that people who on average are more engaged with in-person social contact compared to their peers likely also are people who to a greater extent are engaged in both social media use and digital social contact. In other words, social individuals are sociable, likely to report higher levels of engagement compared to their peers among a wide range of social activities (i.e., between-subject network), but being engaged with one social activity in a given time window reduces the opportunities of being engaged with another social activity within the same time window (i.e., contemporaneous network). This contrasting finding between the two networks highlights the importance and utility of disentangling between within-person and between-person relationships. This is further emphasized through the positive connection identified between emotion regulation difficulties and worthlessness on a within-person level, while this relation was absent across individuals. In other words, while individuals experienced greater emotional regulation difficulties than their own average, this was associated with increased feelings of worthlessness during that day (i.e., a within-person effect). However, individuals who have greater emotion regulation difficulties compared to their peers are not likely to be individuals who feel worthlessness. Within-person and between-person relationships are not necessarily coherent, and the inappropriate generalizations from the between- to the within-level has been referred to as ecological fallacy [8, 66]. In its investigation of within-person relationships among multiple theorized detrimental processes, the present study fills the gaps [7, 17] in progressing the understanding of psychopathological mechanisms connected to depressive symptomatology in the general population.

Moreover, physical activity and digital social contact were consistently among the least central and influential node across all networks, outlining their limited relevance and involvement in depressive states when controlling for all other nodes in the network during the present pandemic context. Specifically, as no particularly notable within-person relationship was present between these variables and depressive symptoms, the present findings suggest that future efforts toward identification of variables that may impede deleterious symptoms within subjects best are aimed at other central components of symptom maintenance, such as helplessness and emotion regulation skills building. The findings of the present study thus imply that promising interventive targets warranting investigation in future controlled studies may include testing whether and how techniques such as cognitive restructuring and behavioral activation may temporally interact and impact perceptions of helplessness and lethargy, respectively.

Finally, this study introduces the usage and utility of radar plots in visualizing key information about network centrality metrics, with the results of the temporal network model outlining the comparative extent of involvement of a given node as an outgoing node at an across-day basis versus as a node more strongly tied to being influenced from other nodes at the previous day. Both loneliness, helplessness, and lethargy had greater strength as outgoing nodes in contrast to being influenced. As relationships in temporal networks are indicative of Granger causal effects, these findings preliminary indicate the greater likelihood that helplessness, loneliness, and lethargy may play in serving as engines in the network, to a greater extent being associated with activation of other nodes. However, as Granger causal effects do not necessarily equate true causal processes and only satisfy its temporal criterion, these findings warrant further investigation in future studies. Other drastic differences were found for in-person social contact in terms of its relative position as an influential node versus being influenced, a finding which is meaningful in the present pandemic setting.

Both anhedonia and depressed mood were more likely to be impacted by other nodes at the previous day than having across-day carry-over effects. Across three of four centrality estimations (i.e., with the exception of out-strength centrality), depressed mood and anhedonia were the most central nodes in the networks, which provides support for their position as the key identifiers of depression [40]. Importantly, however, these findings illuminate their more limited outgoing involvement in depressive states, highlighting lethargy and worthlessness to have stronger outgoing impact on other symptoms.

Strengths and limitations

The present paper consists of several limitations. First, the conclusions of this paper have to be interpreted in light of the underlying assumptions of the statistical model. More specifically, we interpreted a lack of relationships in the temporal network as indicative of potentially faster interactions between depressive symptoms and related components [24]. This interpretation assumes that meaningful interactions can in principle be captured using linear lag-1 models. An alternative explanation for the lack of detected temporal relationships is that these could be nonlinear or time-varying [67–70], which calls for further investigations using other modeling approaches. Furthermore, although the study investigated some of the most central theorized mechanisms in the psychopathological literature, the edge weights were generally smaller in the temporal network than the other networks, as commonly the case in multi-level network analytic studies [44, 52]. This further highlights the necessity of advancing current and building novel theories through formalization and incorporation of the time-scales which phenomena may operate on [70, 71]. Finally, the modeled relationships in the present paper are on the average within-person level, calling for idiographic efforts [72] in inspecting how closely such within-person aggregations correspond to the level of the individual.

This study consists of several strengths, including that it was pre-registered with a clear rationale preceding the selection of variables. Additional strengths include the use of validated measures, its focused time window of measurement corresponding to the DSM-V depressive symptom endorsement assessment, longitudinal design, broad demographic composition of participants, and conducted sensitivity analyses on a fully representative sample replicating the main findings. Moreover, the robustness and replicability of the network models and their corresponding estimated parameters were assessed across four additional subsamples, revealing high robustness of the results. Importantly, the investigation of psychopathological mechanisms in a non-clinical population provides insight into the processes that may be involved in the formation and maintenance of detrimental depressive states which may turn to more enduring problems. A major strength of the present study includes the focus on within-person rather than between-person relationships. This is an asset because theories in psychopathology concern how within-person change in a mechanism variable relates to within-person change in symptoms. Important differences were identified between these two divergent types of relationships, providing clearer directions concerning promising targets for intervention that should be investigated in future studies. The present study is among the largest intensive longitudinal investigations of psychopathology in the adult population, contributing to the stability of its results. Further efforts to assess the replicability of the presented findings in independent samples and in the clinical population would benefit the literature. Finally, the use of longitudinal data and multi-level approach is powerful and overcomes many of the shortcomings experienced in dynamic modeling.

Conclusions

In identifying psychopathological mechanisms and central symptoms involved in the maintenance of depressive states, investigations of within rather than between-

-person relationships are needed. This intensive longitudinal study identified helplessness as the main mechanism interwoven with depressive symptomatology on an across-day basis, while emotion regulation difficulties had more proximal associations with depressive symptoms. While depressed mood and anhedonia were identified as symptoms most susceptible toward being influenced by other nodes in the network, the present study identified that the two most prominent symptoms displaying outward temporal influence were worthlessness and lethargy. These symptoms had greater within-person carry-over effects across days, putting individuals at greater risk of prolonged depressive state experiences. This suggests that not all symptoms of depression should be viewed as equal in their role in maintaining this deleterious mental health state. Finally, rumination was to a greater extent susceptible to being influenced rather than temporally influencing other components involved in depressive states. These findings outline several associations between symptoms and mechanisms that are important to investigate further toward advancing the etiological understanding of depression.

Abbreviations
mlVAR: Multi-level vector autoregressive (VAR) model; DSM-V: Diagnostic and Statistical Manual of Mental Disorders, fifth edition

Supplementary Information
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Additional file 1: Figure S1: Cumulative length of time-series per person across the study participants.

Additional file 2: Figure S2-S4: Figure S2 - Supplementary temporal network with all effects. Figure S3 - Supplementary contemporaneous network with all effects. Figure S4 - Supplementary between-subjects network with all effects.

Additional file 3: Table S1: Consistency amongst highly central nodes across replicability analyses.

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Authors' contributions
Study design (OVE) and feedback on design (AH, SUJ). Study conceptualization (OVE) and preregistration (OVE, JB). Study administration, management, and coordination (OVE). Data acquisition and curation (OVE). Data cleaning and preparation (OVE). Data analysis (OVE, JB). Writing—original draft preparation (OVE). Writing—review and editing (OVE, JB, AH, SUJ). All authors contributed to the interpretation of the data. All authors read and approved the final manuscript.

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Availability of data and materials
The materials necessary to regenerate the estimated models of the present study may be found at the online repository of the Center for Open Science (https://osf.io/trf2y). As our received ethical approval from the Norwegian Centre for Research Data (NSD) precludes submission of raw data to public repositories, the matrices underlying the model estimation are provided. Access to the data can be granted from the principal investigators Omid V. Ebrahimi and Sverre Urnes Johnson following ethical approval of a suggested project plan for the use of data granted by NSD and REK.

Code availability
All code for the present study is uploaded at the online repository of the Center for Open Science (https://osf.io/m2zhu/). We also provide a step-by-step guide for conducting radar plot visualizations of centrality metrics, readily available in the code.

Declarations

Ethics approval and consent to participate
Ethical approval for this study was granted by the Regional Committee for Medical and Health Research Ethics (reference: 125510). All participants provided their consent for their data to be used in this research.

Consent for publication
Not applicable.

Competing interests
The authors declare that they have no competing interests.

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Publisher's Note

Supplementary Table S1: Consistency Amongst Highly Central Nodes

Across Replicability Analyses

(Article 3)

Table S1. Consistency Amongst Highly Central Nodes Across Replicability Analyses

Main Analysis

OutStrength	InStrength	Contemporaneous	Between
Loneliness	Depressed mood	Depressed mood	Relatedness
Helplessness	Anhedonia	Anhedonia	Depressed mood
In-person social contact	EmoRegDiff	EmoRegDiff	Anhedonia

Split-half Time-series Replicability Analysis 1

OutStrength	InStrength	Contemporaneous	Between
Loneliness	Depressed mood	Depressed mood	Relatedness
Helplessness	Anhedonia	Anhedonia	Depressed mood
In-person social contact	EmoRegDiff	EmoRegDiff | Lethargy	Anhedonia

Split-half Time-series Replicability Analysis 2

OutStrength	InStrength	Contemporaneous	Between
Loneliness	Depressed mood	Depressed mood	Relatedness
In-person social contact	Anhedonia	Anhedonia	Depressed mood
Helplessness | Lethargy	EmoRegDiff	EmoRegDiff	Loneliness | Anhedonia

Random Split-half Replicability Analysis 1

OutStrength	InStrength	Contemporaneous	Between
Loneliness	Depressed mood	Depressed mood	Depressed mood
Helplessness	Anhedonia	Anhedonia	Anhedonia
In-person social contact	EmoRegDiff	EmoRegDiff | Lethargy	Loneliness

Random Split-half Replicability Analysis 2

OutStrength	InStrength	Contemporaneous	Between
Helplessness	Depressed mood	Depressed mood	Relatedness
Worthless	Anhedonia	Anhedonia	Depressed mood
In-person social contact	EmoRegDiff	EmoRegDiff	Anhedonia

Number of centrality indices consistent across all replicability analyses

	N	Percentage (%)
Total number of central edges (Top 3) across five analyses	**60**	**100%**
Number of central edges uniquely consistent across five analyses	**54**	**90%**
Number of central edges consistent across five analyses	**58**	**96,67%**

Descriptive note:

The vertical line ' | ' refers to cases where two nodes where equally ranked in centrality.

Uniquely consistent was defined as cases where the top 3 most central nodes where exactly the same across all analyses.

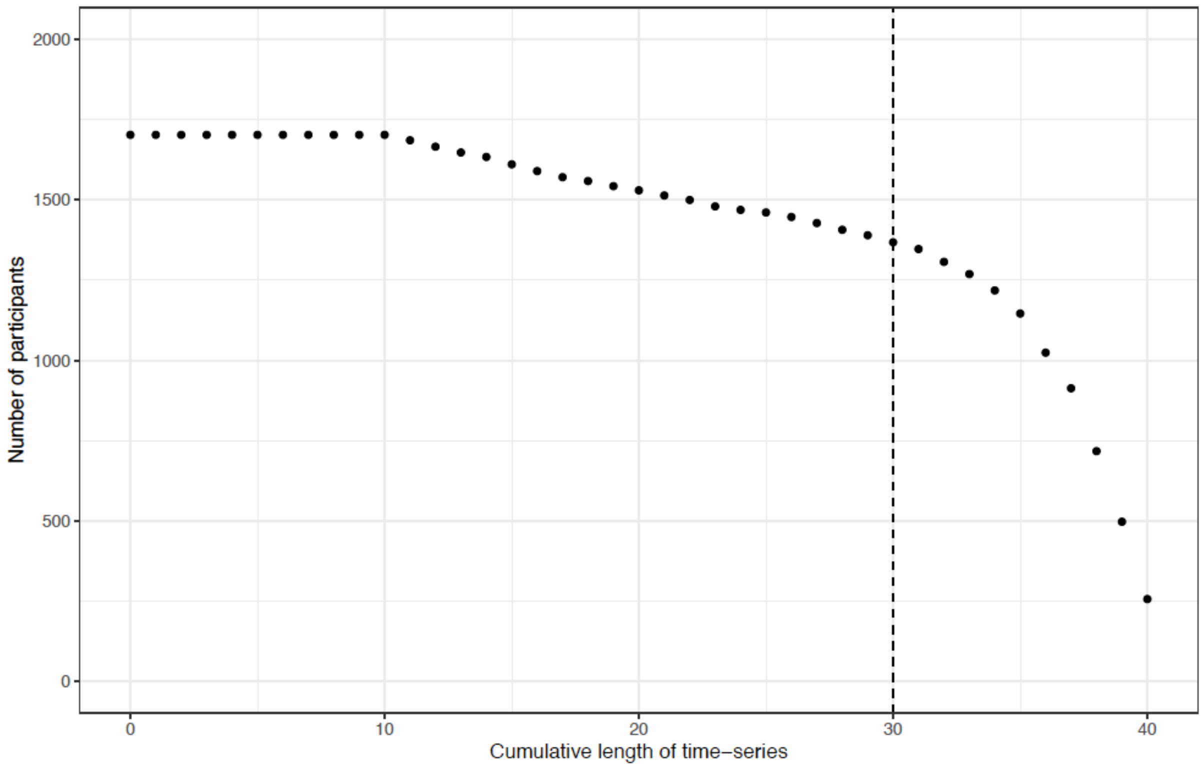
Color code:	
Green	Fully and uniquely replicated (i.e., the central node retrieved is identical as main analysis).
Yellow	Replicated (i.e., central node from main analysis is retrieved, but shares its position with an additional node).
Red	Not replicated (i.e., central node from main analysis not retrieved, but another node obtained).

Supplementary Figure S1: Cumulative Length of Time-Series per Person Across the Study Participants

(Article 3)

Figure S1

Cumulative Length of Time-Series per Person Across the Study Participants



Supplementary Figure S2-S4: Network Plots With all Effects

(Article 3)

Figure S2

Supplementary Temporal Network With all Effects

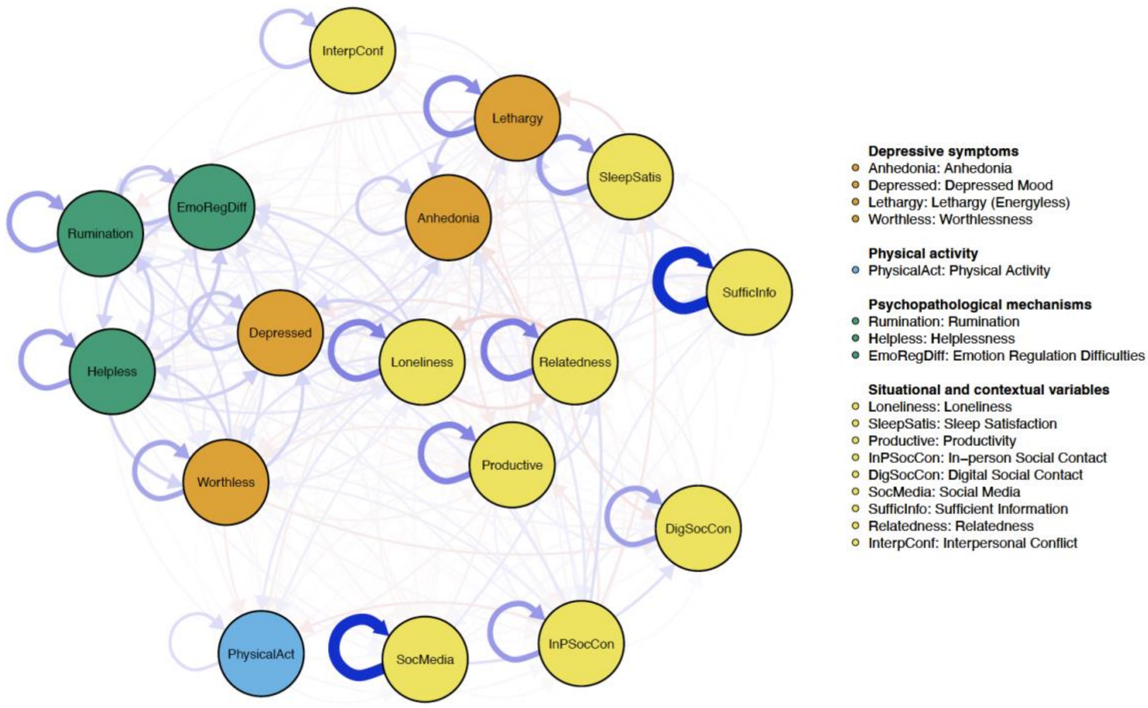


Figure S3

Supplementary Contemporaneous Network With all Effects

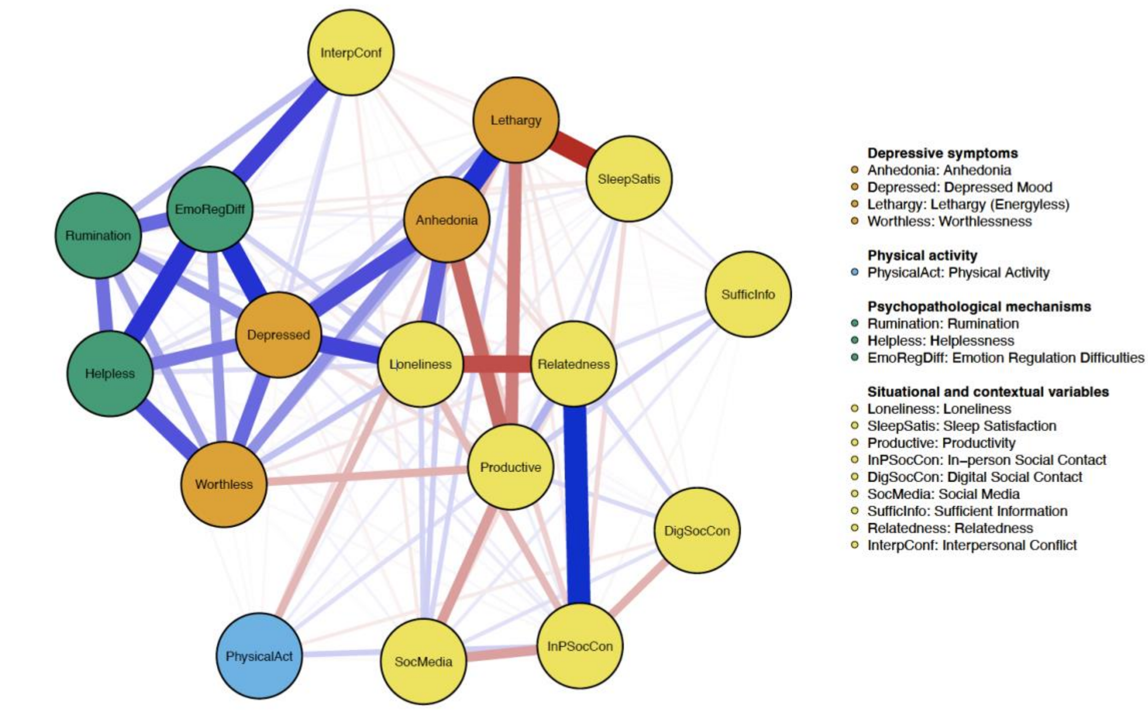


Figure S4

Supplementary Between-Subject Network With all Effects