**ORIGINAL PAPER**

# Trajectories of common mental disorders symptoms before and during the COVID-19 pandemic: findings from the ELSA-Brasil COVID-19 Mental Health Cohort

Daniel Fatori[1] · Paulo Suen[1] · Pedro Bacchi[1] · Leonardo Afonso[1] · Izio Klein[1] · Beatriz A. Cavendish[1] ·
Younga H. Lee[2] · Zhaowen Liu[2] · Joshua Bauermeister[3] · Marina L. Moreno[1,4] · Maria Carmen Viana[6] ·
Alessandra C. Goulart[4] · Itamar S. Santos[4,5] · Sarah Bauermeister[3] · Jordan Smoller[2] · Paulo Lotufo[1,4] ·
Isabela M. Benseñor[1,4] · André R. Brunoni[1,5]

## Abstract

**Aim** Evidence indicates most people were resilient to the impact of the COVID-19 pandemic on mental health. However, evidence also suggests the pandemic effect on mental health may be heterogeneous. Therefore, we aimed to identify groups of trajectories of common mental disorders' (CMD) symptoms assessed before (2017–19) and during the COVID-19 pandemic (2020–2021), and to investigate predictors of trajectories.

**Methods** We assessed 2,705 participants of the ELSA-Brasil COVID-19 Mental Health Cohort study who reported Clinical Interview Scheduled-Revised (CIS-R) data in 2017–19 and Depression Anxiety Stress Scale-21 (DASS-21) data in May–July 2020, July–September 2020, October–December 2020, and April–June 2021. We used an equi-percentile approach to link the CIS-R total score in 2017–19 with the DASS-21 total score. Group-based trajectory modeling was used to identify CMD trajectories and adjusted multinomial logistic regression was used to investigate predictors of trajectories.

**Results** Six groups of CMD symptoms trajectories were identified: low symptoms (17.6%), low-decreasing symptoms (13.7%), low-increasing symptoms (23.9%), moderate-decreasing symptoms (16.8%), low-increasing symptoms (23.3%), severe-decreasing symptoms (4.7%). The severe-decreasing trajectory was characterized by age < 60 years, female sex, low family income, sedentary behavior, previous mental disorders, and the experience of adverse events in life.

**Limitations** Pre-pandemic characteristics were associated with lack of response to assessments. Our occupational cohort sample is not representative.

**Conclusion** More than half of the sample presented low levels of CMD symptoms. Predictors of trajectories could be used to detect individuals at-risk for presenting CMD symptoms in the context of global adverse events.

**Keywords** Cohort study · Anxiety · Depression · Trajectories · COVID-19 pandemic

✉ Daniel Fatori
daniel.fatori@gmail.com

[1] Faculdade de Medicina da, Universidade de São Paulo, R. Dr. Ovídio Pires de Campos, 785-Cerqueira César, CEAPESQ, Sala 9, São Paulo, SP 05403-903, Brazil

[2] Department of Psychiatry, Harvard Medical School and Department of Epidemiology, Harvard School of Public Health, Boston, MA, USA

[3] Department of Psychiatry, University of Oxford, Oxford, UK

[4] Centro de Pesquisa Clínica E Epidemiológica, Hospital Universitário, Universidade de São Paulo, São Paulo, Brazil

[5] Departamento de Clínica Médica, Faculdade de Medicina da Universidade de São Paulo, São Paulo, Brazil

[6] Department of Social Medicine, Postgraduate Program in Public Health, Center of Psychiatric Epidemiology (CEPEP), Federal University of Espírito Santo, Vitória, Brazil

# Background

The COVID-19 pandemic brought concerns about an increase in common mental disorders (CMD) among populations worldwide [1, 2]. Studies conducted in the early stages of the pandemic showed rates of CMD (depression and anxiety disorders) above 30% [3], higher than pooled global estimates from multinational studies conducted in the last decades [4]. However, initial studies performed during the pandemic did not use longitudinal data, therefore, hindering the possibility of detecting change in prevalence of CMD during the COVID-19 pandemic. They also relied mostly on sampling methods (e.g., snowball sampling) prone to selection bias. Later, longitudinal studies comparing pre-pandemic with pandemic data conducted in 2020 showed an increase in mental symptoms in the beginning of the pandemic and a later decrease to similar levels prior to 2020 [5]. Meta-analytic data have shown that the impact of the COVID-19 pandemic and quarantine measures implemented in countries on population mental health was heterogeneous and small in terms of effect size [6], indicating most people are resilient to the changes brought by the pandemic.

Even though a growing body of evidence derived from well-designed longitudinal studies indicates most people are resilient to the changes brought by the pandemic, some specific groups may have been impacted differently. For instance, a meta-analysis investigating the effects of the COVID-19 pandemic on various maternal outcomes reported that depression symptoms, when compared to pre-pandemic levels, were elevated during the pandemic [7]. Recent longitudinal studies have highlighted that the pandemic effect on mental health may be heterogeneous [8, 9]. Understanding different patterns of change in mental health before and during the pandemic and detecting vulnerable groups at risk for developing CMD, as well as risk and protective factors associated with poor trajectories are key to comprehending the impact of the pandemic on populations and to plan interventions.

In this context, cohort studies present the optimal design for leveraging longitudinal data to identify trajectories of CMD symptoms before and during the pandemic. For instance, in a study using data from a United Kingdom sample, three groups of depression symptom trajectories in the early period of the pandemic were identified: low, moderate, and severe [10]. Likewise, a study in Australia identified 4 trajectories of anxiety (resilience, improving, worsening, and sustained) and 3 trajectories of depression (low, moderate, and severe then declining) [11]. The only trajectory study with mental health data before and during the pandemic was conducted in the United Kingdom (UK) [12]. The UK Household Longitudinal Study used

the 12-item General Health Questionnaire (GHQ-12) to assess general mental health in 2016–2019 and across six time-points in 2020, from April to October ($N = 19{,}763$). The authors reported finding five groups of trajectories: consistently poor, consistently good, consistently very good, deteriorating, and recovery [12]. Among trajectory studies conducted during the pandemic, predictors of poor trajectories included younger age, ethnicity, lower socioeconomic status, living in a city, experiences of physical or psychological abuse, preexisting mental disorder, chronic health problem, social support, empathy, loneliness, financial distress related to the pandemic, functional impairment, and intolerance of uncertainty [10–13].

The aforementioned CMD trajectory studies were conducted in high-income countries (HIC), albeit more than 80% of the world population lives in low- and middle-income countries (LMIC) [14]. HICs and LMICs are different not only in the epidemiology of mental disorders; but also in several social, economic, and health aspects that impact CMD [15–17]. Evaluating CMD trajectories during the pandemic in a LMIC can provide unique insights by assessing predictors, such as low educational level, poverty, and frequent adverse events, which could be generalizable to other LMICs. Such findings could lead to a better understanding of the heterogeneity of the impact of the pandemic on mental health and the development of interventions tailored to the specific needs of LMIC populations worldwide.

In this context, our study the Brazilian Longitudinal Study of Health (ELSA-Brasil) [18, 19] represents one of the few LMIC cohorts that is systematically collecting data on mental health since the pandemic inception, while providing data of several predictors collected in pre-pandemic assessments. Here, our aims were twofold. First, to identify trajectory groups of CMD symptoms assessed at five time-points before and during the COVID-19 pandemic: 2017–19, May to July 2020, July to September 2020, October to December 2020, and April to June 2021. We hypothesized we would find at least three groups of trajectories characterized by low, moderate, and chronic high symptomatology, with at least one group distinguished by a decreasing pattern of symptoms. Our second aim was to investigate the role of sociodemographic characteristics, health-related characteristics, and adverse life events as predictors of trajectories. We hypothesized that age and family income would play a protective role, decreasing the odds of individuals presenting high symptomatology or increasing the odds of a recovery pattern, while previous mental disorders and adverse life events would increase the odds of individuals presenting chronic symptomatology.

## Methods

### Study design and participants

We are conducting the ELSA-Brasil COVID-19 Mental Health Cohort study, based on the larger ELSA-Brasil occupational cohort that, at baseline (2008–2010), recruited 35–74-year-old employees from six universities ($N = 15,105$) in major Brazilian cities (São Paulo, Rio de Janeiro, Salvador, Belo Horizonte, Vitoria, and Porto Alegre), with the objective of investigating determinants of mortality and chronic diseases. Since its inception, the ELSA-Brasil conducted three waves of assessment: 2008–2010 (w1), 2012–2014 (w2), and 2017–2019 (w3). Each wave consisted of comprehensive onsite assessments comprising clinical interviews, medical examinations, and laboratory tests, collecting information on sociodemographic variables, clinical history, family history of diseases, lifestyle factors, anthropometric measurements, and biomarkers. Additional details regarding the ELSA-Brasil study can be found elsewhere [18, 20, 21].

In 2020, all participants from the São Paulo research center (active or retired public servants from the University of São Paulo, USP; $N = 4,712$) were invited to respond to online assessments conducted at four time-points: May to July 2020 (COVID-19 wave 1, c1), July to September 2020 (c2), October to December 2020 (c3), and April to June 2021 (c4). Eligibility criteria included having access to the internet via smartphone, tablet, or personal computer. Research Electronic Data Capture (REDCap) [22] online electronic questionnaires were sent to participants by email or text message. Participants who did not reply to three emails sent at weekly intervals were contacted via three text messages or telephone calls also in a weekly interval. Participants with difficulties understanding, accessing or completing online questionnaires were interviewed via phone call. More details and initial findings from our study can be found in [19, 23].

Our study was approved by the Local Ethics Committee of the University Hospital, USP. All participants provided electronic informed consent. Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) guidelines were used to report the present study [24].

### Assessments and variables

We used two instruments to assess CMDs. In 2017–2019 (w3), CMD was assessed using the Clinical Interview Schedule-Revised (CIS-R) [25], a widely used structured instrument designed to measure non-psychotic mental disorders based on the International Classification of Disease 10th edition (ICD-10) criteria in population studies. The CIS-R has been adapted and validated in Brazil [26] and has been used in multiple studies [27–29]. The symptom domains assessed by the CIS-R are somatic complaints, fatigue, concentration and forgetfulness, sleep disturbance, irritability, worry about physical health, depression, depression ideas, worry, anxiety, phobias, panic, compulsions, and obsessions. Each domain has a score ranging from 0 to 4 (except depressive ideas that range from 0 to 5). These scores can be summed up to achieve a CMDs total score ranging from 0 to 57 [25].

During the COVID-19 pandemic, we used the Depression, Anxiety, and Stress Scale (DASS-21) [30] to assess CMD. The DASS-21 is a self-report instrument with a Likert four point scale (from 0 "strongly disagree" to 3 "totally agree") indicating the frequency or severity of symptoms. Each of its three domains are composed of 7 items. A total score summing items from the three domains was calculated, with higher scores indicating greater severity (ranging from 0 to 63). The DASS-21 was translated and validated to Brazilian Portuguese [31] and has been used extensively in Brazil [32, 33].

We identified potential predictors of trajectories in three domains: sociodemographic characteristics (age, sex, skin color, income, marital status), health-related characteristics (physical activity, obesity, active smoking, alcohol abuse, mental disorders), and experience of adverse life events (e.g., race discrimination, childhood adverse events). This selection was based on our previous works [19, 27, 34], as well as on reviews of mental symptoms' trajectories studies during the COVID-19 pandemic [10, 11, 13, 35]. Predictors were derived from data collected in 2017–2019 and 2008–2010. Table 1 provides a description of all predictors. For additional details on how each variable was assessed and coded, see online supplementary material.

### Analysis

Analyses were conducted using Stata 17 and R. Statistical significance was set under an alpha threshold of 0.005 [36–38]. Parameters are reported using a confidence interval of 99.5% (99.5% CI).

Since CMD was measured before the pandemic using the CIS-R and during the pandemic using the DASS-21, we used equi-percentile linking (R package equate) [39, 40], a statistical procedure designed to identify comparable scores on different scales measuring the same construct. This procedure is adequate when item endorsement may have a nonlinear relationship between scales [41]. First, we calculated a modified version of the CIS-R total score, excluding symptoms of compulsion, obsession, sleep disturbance, and phobias, leading to a range of 0 to 41, since there are no equivalent items in the DASS-21. Then, the modified CIS-R

**Table 1** Description of predictors

| Predictors | Time-point | Description |
| --- | --- | --- |
| Age | 2017–2019 | < 60 years old or ≥ 60 years old |
| Sex | 2017–2019 | Male or female |
| Ethnicity | 2017–2019 | Non-white or white |
| College degree | 2017–2019 | College degree or below college degree |
| Family income | 2017–2019 | Total family income in deciles |
| Married | 2017–2019 | Married or not married |
| Physical activity | 2017–2019 | Physically active or sedentary based on the IPAQ data |
| Obesity | 2017–2019 | BMI of 30 kg/m2 or higher based on weight and height measurement by a trained assessor |
| Active smoker | 2017–2019 | Active smoking or not active smoking |
| Alcohol abuse | 2017–2019 | Alcohol abuse present if women reported taking > 1 dose/day and men > 2 doses/day during a given week |
| Previous mental disorders | 2008–2010 | CIS-R total score (0–57) |
| Race discrimination | 2017–2019 | Total score of the EDS of participants that reported being discriminated against because of ancestry, national origins or race |
| Childhood adverse events | 2017–2019 | Participants who reported at least one of the following events: (a) lived with someone who abused drugs/alcohol/medicines, (b) lived with someone who was arrested/convicted (c) lived with someone with depression or other mental disorder, (d) parents separated/divorced, (e) parents or guardians died before he was 14 years old, (f) worked during childhood |
| Adverse life events | 2008–2010 | Participants who reported at least one of the following life events: (a) being robbed, (b) being hospitalized, (c) bereavement/mourning due to the death of a relative, (d) experienced severe financial problems, and (e) ending up an intimate relationship |

*IPAQ* International Physical Activity Questionnaire; *BMI* body mass index; *CIS-R* Clinical Interview Schedule-Revised; *EDS* Everyday Discrimination Scale

total score was linked to the DASS-21 total score at c1, generating a CIS-R total score equivalent to the DASS-21 total score with a range from 0 to 63.

We used group-based trajectory modeling (GBTM) [42, 43] to identify CMD symptoms trajectories over five time-points before and during the COVID-19 pandemic (w3, c1 to c4). GBTM is a finite mixture method designed to identify clusters of individuals with similar trajectories of an outcome of interest assessed over time. Selection of the best GBTM model was based on the following criteria: (1) Bayesian Information Criteria (BIC), (2) average posterior probabilities (APP), (3) domain knowledge (previous studies), and (4) interpretability. The largest BIC score (less negative) and APP above 0.7 were considered indicators of a good model fit [43]. The shape of trajectories was modeled using polynomial functions. The number of measurements minus 1 (time-1) defined the polynomial functions used [44]. We tested whether each CMD symptoms trajectory presented a constant, linear, quadratic, cubic, or quartic relationship. The p-values of trajectory shape parameters across different models were used to determine the best combination and order of polynomial functions. Different combinations of number of groups and trajectory shapes were tested.

Since the distribution of DASS-21 scores presented zero-inflation (Fig. S1), all tested models used zero-inflation Poisson (ZIP) as the probability distribution of the dependent variable (CMD symptoms). ZIP models presented better BIC scores when compared to models with Gaussian distribution. All participants with at least one DASS-21 report were included in the models. The selected model was plotted with parametric bootstrap confidence intervals.

Considering some participants had missing data on predictor variables (see Table S1 for distribution of missing values), we used multiple imputation by chained equations (MICE) [45–47]. MICE takes into account uncertainty in the imputation procedures, while the chained equations strategy can deal with different types of variables, making predictions more accurate. To determine the number of imputations, we ran a model including all variables of interest with five imputations to determine the fraction of missing information (FMI). The FMI indicates the proportion of the total sampling variance related to missing data. The largest FMI found was 0.54, indicating the necessity of at least 40 imputations to prevent loss of statistical power [48]. Our outcome of interest and all predictors were inserted in the MICE models, generating 40 imputations. Data were assumed to be missing at random [49]. We used multinomial logistic regression to investigate predictors of trajectories. Separate models were run for each predictor, adjusting for sex at birth, age, educational level, and skin color. The dependent variable was the identified group trajectories. We reported results of the pooled log odds ratio (lOR) considering imputations. lOR estimates were plotted by trajectory groups.

# Results

## Participants

Out of 4712 eligible participants, we obtained CMD data from 2,705 (57.4%). Non-inclusion reasons were unwillingness to participate, impossibility of making contact, and deaths (Fig. 1). We compared participants who provided CMD data in at least one time-point (included) vs. participants who did not provide CMD data (not included). The included sample had a significantly higher percentage of women (included = 57.2% vs. not included = 52.2%), younger participants (≥ 60 year: included = 40.3% vs. not included = 55.3%), higher educational level (college degree: included = 58.8% vs. not included = 28.0%), and presented higher score of CMD (mean CIS-R total score difference = 0.9) (Table S2). The mean age of the included sample was 58.3 (99.5% CI [58.0, 58.6]) years, while 57.2% were female (99.5% CI [55.3, 59.0%]) and 33.5% were non-white (99.5% CI [31.7, 35.3%]) (Table S3). The mean CMD total score at w3 was 8.0 (7.9); c1 was 8.1 (9.4); at c2 was 7.2 (8.7); at c3 was 6.9 (8.4); at c4 was 7.6 (9.1) (Table S3).

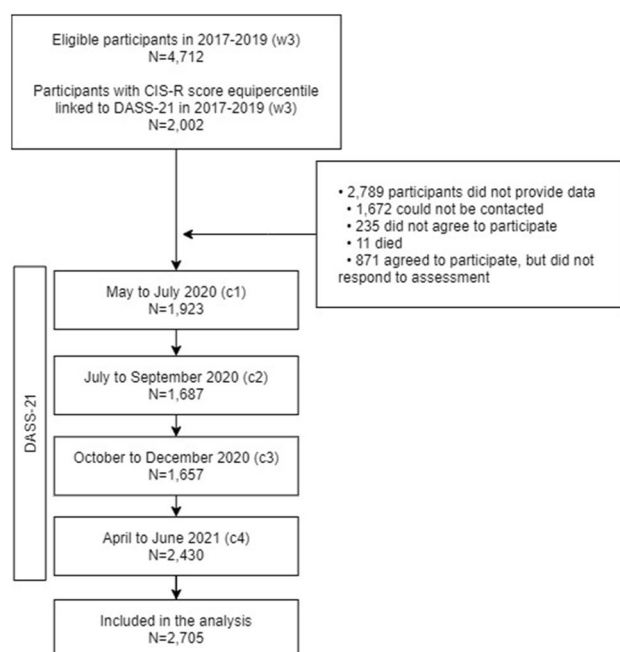## Trajectories of common mental disorders symptoms

Among simple models specifying linear shapes of trajectories, we selected the six-group model. Additional groups improved BICs slightly, but due to interpretability and domain knowledge (no previous study identified more than six groups), we chose the six-group model. Thus, we explored different combinations of polynomial functions among six-group models. The best fit presented a BIC of -30,973.36 with all groups APP above 0.8. Table S4 depicts the goodness of fit of tested models, while table S5 presents parameter estimates of the best fitting model.

The following groups (Fig. 2) were identified and labeled according to levels of CMD symptoms and shape of trajectories: Group 1 (17.6%) low symptoms; Group 2 (13.7%) low-decreasing symptoms; Group 3 (23.9%) low-increasing symptoms; Group 4 (16.8%) moderate-decreasing symptoms; Group 5 (23.3%) low-increasing symptoms; Group 6 (4.7%) severe-decreasing symptoms. Table S6 depicts group means of CMD by time-point.
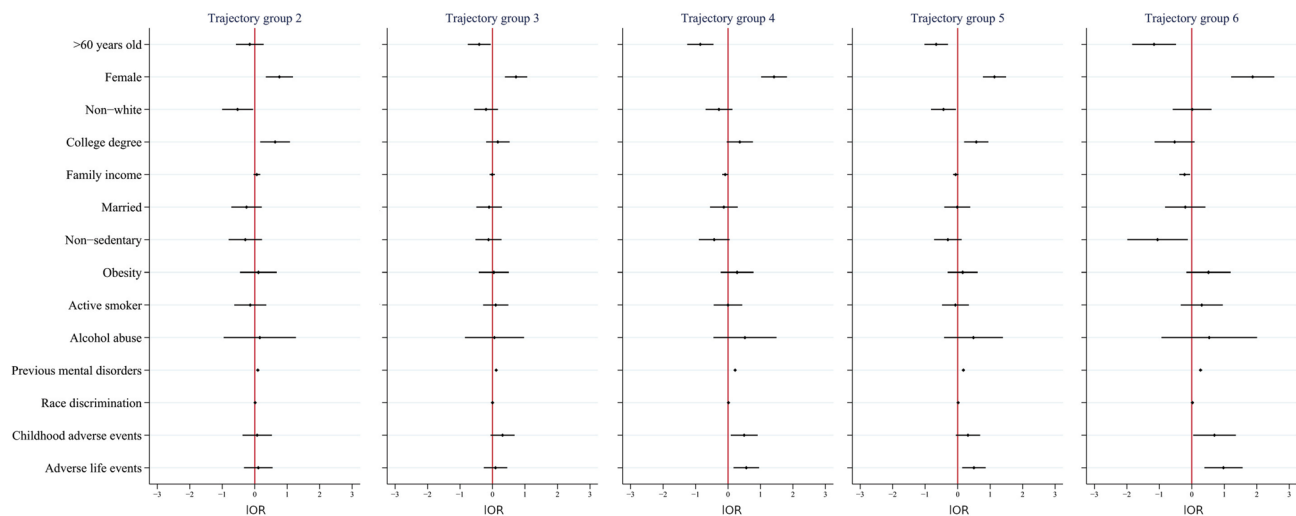
## Predictors of trajectories

Table S7 describes the distribution of predictors by CMD symptoms trajectory groups. Figure 3 and Table S8 depict results of the predictors analyses by trajectory group (multinomial logistic regressions). Below, we describe significant results from models. All 5 groups, when compared to Group 1, were negatively associated with female sex and previous mental disorders. Being older predicted decreased risk of membership in Groups 3, 5, and 6, while increased the risk of membership in Group 4. Participants who reported being non-white were at a decreased risk of membership in Groups 2 and 5. Having a college degree increased the risk of membership in Groups 2 and 5. Higher family income decreased the risk of membership in Group 6. Participants physically active were more likely to have severe-decreasing symptoms (Group 6). Having experienced at least one childhood adverse event increased the risk of membership in Groups 4, 5, and 6. Participants that reported adverse life events were more likely to present moderate-decreasing



**Fig. 1** Flow diagram of the present study
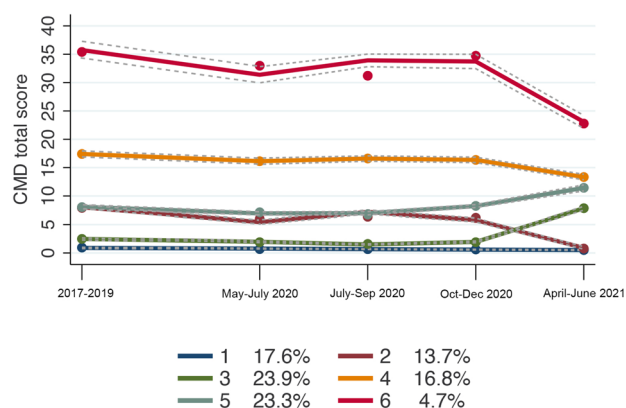


**Fig. 2** Trajectories of common mental disorders before and during the COVID-19 pandemic (*N* = 2705)

**Fig. 3** Coefficient plot depicting the association of analyzed predictors with trajectories of common mental disorders ($N = 2,705$). Association was measured using log odds ratios (lORs) and 99.5% CIs. Models were adjusted by age, sex, skin color, and educational level

symptoms (Group 4), low-increasing symptoms (Group 5), and severe-decreasing symptoms (Group 6) trajectories. The following predictors were unrelated to membership in any of the Groups: being married, obesity, active smoking, alcohol abuse, and race discrimination.

## Discussion

We sought to identify CMD symptom trajectories before (2017–2018) and during the COVID-19 pandemic (from May 2020 to June 2021) in a large Brazilian cohort. Our findings showed that 55% of the sample presented low levels of CMD symptoms (55%, Groups 1 to 3), while 4.7% of the sample was classified in the most severe trajectory. This finding is similar to previous pre-pandemic studies that investigated trajectories of depression and anxiety, showing the majority of the population do not develop high levels of symptoms [50, 51]. It is also in line with studies that used latent trajectories analysis during the pandemic [10–13].

In line with our hypothesis, we found groups showing decreasing levels of symptoms over time. The severe-decreasing group (Group 6, 4.7% of the sample) presented a clinically significant decline in CMD symptoms, from a mean of 35.4 to 22.8, resulting in a 35.6% change. Previous studies before the pandemic showed that trajectory patterns of decreasing symptoms over time are common [50]. In the context of the COVID-19 pandemic, a cohort study in Ireland found one trajectory group of a composite measure of depression, anxiety, and post-traumatic stress symptoms that improved over time (18%) [13]. In Australia, a cohort study assessed depression and anxiety symptoms online across seven time-points in 2020, finding a group

with severe levels of depression symptoms declining over time (9%) and a group with moderate decreasing levels of anxiety (5%) [11]. The UK Household Longitudinal Study, a study with pre-pandemic and pandemic depression data also identified a group with decreasing symptoms (12%) [12]. One notable difference from our findings is that the decline in symptoms occurred in 2021. Before this time-point, the severe-decreasing group CMD means fluctuated around 31 to 35. However, our findings may not be directly comparable to the aforementioned studies, since our measure is a composite score of depression and anxiety disorders, while most studies assessed only depression.

Our data showed CMD trajectories were mostly stable across time. This could be because our sample was composed of older adults (mean age of 58.3 years). Trajectory studies of depression symptom trajectories in adolescence and early adulthood show less stability, with models revealing increasing and decreasing trajectories [52], compared to studies with older adults [50]. The stability of symptoms in our sample, especially during 2020, could also be explained by our time-point intervals, since assessments in 2020 occurred a few months apart. However, other studies had similar intervals but presented less stability [8, 12].

Furthermore, different from other studies [8, 12], we did not find a group characterized by severe-chronic symptoms. Diminishing rates of new cases and mortality by COVID-19 in Brazil, as well as the start of the vaccination campaign, may have buffered the negative impact of the pandemic on mental health, therefore explaining the decreasing pattern in the most severe group. Also, in the early stages of the pandemic, mental health awareness increased in Brazil due to campaigns and various institutions started offering free remote mental health care for the population [53];

thus, participants may have benefited from these measures by seeking and receiving treatment during the pandemic. Another explanation for this finding could be related to participants being retired or active public servants who had no changes to their income during the pandemic, while also having access to mental health care provided by the university.

Notably, apart from the severe-decreasing group, CMD symptom levels were below 20 points. Participants in this severity range were probably not facing impairment typical of full criteria depression and anxiety disorders. The moderate-decreasing group may have had subclinical CMD with some impairment, while the low-increasing group had a slight deterioration that could potentially lead to subclinical CMD. Even though these two groups have trajectories of low and moderate levels of symptoms, they may benefit from mental health care attention to prevent further deterioration. Considering a stepped care approach, individuals with low but increasing levels of symptoms could benefit from low intensity interventions, such as self-guided psychotherapy and psychoeducation [54]. Cases with further deterioration would then benefit directly from more intensive interventions (e.g., cognitive-behavioral therapy, pharmacological intervention, etc.). Future assessments of our sample will be needed to further understand post-pandemic trajectories.

Our second aim was to investigate predictors of CMD trajectories. Our findings show the most severe trajectory of CMD symptoms was characterized by age < 60 years, female sex, low family income, non-sedentary behavior, previous mental disorders, and the experience of adverse events in life. Pre-pandemic studies have shown older age is associated with a significant decline in the proportion of individuals with more severe trajectories. A systematic review of depression trajectories showed that 2–7% of older adults are classified in the chronic high levels of symptoms trajectory, compared to 14–32% in adolescents, and 2 to 28% in adults [50]. Previous trajectories studies conducted during the pandemic also found women are more likely to present depression and anxiety symptoms [11, 12]. A systematic review of studies conducted in the early stages of the pandemic found a consistent association between female sex and risk for mental disorders in general [35]. This is not surprising, since this is a well-known risk factor for CMD [55, 56]. It is worth noting a previous study analyzing our sample in the early stage of the pandemic showed increased age and male sex were protective factors for CMD [19].

Higher family income was a protective factor against the severe-decreasing trajectory of CMD symptoms. Socioeconomic status (SES) is a well-known factor associated with mental disorders. Robust evidence shows income has a dose–response relationship with depression [57]. Even though the mechanism behind this association is not yet fully understood, evidence suggests that low SES is commonly associated with exposure to several negative conditions, such as unhealthy work conditions, adverse living conditions, material deprivation, daily hassles, lack of cultural or leisure activities, among others [58, 59]. The persistent exposure to these conditions may be related to the onset and maintenance of CMD symptoms. Studies investigating the impact of the COVID-19 pandemic also revealed that income is negatively associated with mental health outcomes [35, 60].

Physically active participants presented a lower risk of pertaining to the most severe trajectory of CMD. Evidence shows there is a link between depression and sedentary behavior [61, 62]. People with depression on average spend less time doing physical activities and this pattern is stronger in older adults [63]. Even though the relationship between these variables is not totally understood, recent evidence suggests there is a causal link between being physically active and reduced risk for depression [64]. Interestingly, physical activity is a modifiable risk factor that can be the target of effective interventions to reduce depression symptoms [65]. Such interventions could be adapted and implemented in contexts similar to the pandemic.

In addition, preexisting mental disorders (measured in 2017–2019) were also a predictor of the more severe trajectories of mental symptoms, drawing attention to the need of offering or maintaining treatment for these individuals during the pandemic, as previously demonstrated by other studies [19, 66]. Most importantly, the group of individuals with mental health problems is at-risk for developing persistent CMD symptoms in the context of a global pandemic and should be prioritized to receive interventions.

Participants who experienced adverse life events in childhood and adulthood were at a higher risk of presenting the most severe trajectory of CMD symptoms. Adverse or stressful life events are of the most studied risk factors linked to the onset of CMDs. Multiple adverse events early in life (physical abuse, neglect, family conflict, household criminality, etc.) are negatively associated with anxiety and depression [67, 68]. These early adversities may alter physiological processes that can lead to impairments in the development of brain functions that are later in life associated with negative outcomes [69, 70]. In addition, adversities later in life may also negatively impact mental health [71, 72]. Meta-analytic evidence shows negative life events are also linked to depression in older people, such as in the case of our sample [73]. Screening of experiences of adverse life events could be used to detect individuals at risk for severe trajectories of CMD symptoms to plan and deliver interventions.

Interestingly, our data suggest not only that the impact of the pandemic on CMD trajectories is heterogeneous, but it is also characterized by different pre-pandemic predictors. For instance, the moderate-decreasing group was characterized by increased age, female sex, previous mental disorders, and

the experience of adverse events in life. In this case, no predictor showed a protective effect. Also, predictors impacted specific groups differently. Older age, for example, acted as a protective factor against the severe-decreasing trajectory, but increased the odds of the moderate-decreasing trajectory. Noticeably, preexisting mental disorders presented a consistent pattern, increasing the risk of all trajectory groups, showing it may be a predictor not ideal to differentiate types of trajectories of CMD symptoms.

Our findings should be viewed in light of some limitations. First, we found that sex, age, educational level, and mental health were characteristics associated with not responding to assessments, although these differences were small to moderate. In the case of the CIS-R total score the differences were less than one unit. Additionally, approximately half of the eligible sample responded to assessments during the pandemic. Even though this is in line with other cohort studies [12, 66, 74], those who did not respond may be more likely to present a deteriorating trajectory of CMD symptoms or have more pandemic-related problems (e.g., financial issues, stress, etc.). Second, our findings may not be generalizable to other contexts, since our sample is not representative of the country's population. Our sample is composed of public servants of the University of Sao Paulo. Compared to national indicators in 2019, our sample has significant differences in the same year. While 58.8% of our sample had a college degree, only 17.4% of Brazilians had a college degree. In our sample, 57.3% reported non-white skin color, while in Brazil 33.5% of the population was non-white. Moreover, 51.8% of the Brazil population was female, while in our study 57.2% was female [75]. Also, the income of participants (working or retired) may have been mostly unaffected by the pandemic. Therefore, caution is needed when interpreting and generalizing our findings. However, our study was based on a well-defined 13-year large cohort of participants systematically assessed by trained professionals before the COVID-19 pandemic. We consider these aspects a strength compared to online surveys without pre-pandemic data and studies using snowball sampling. Also, our findings are relevant because they add to the growing body of evidence from developing countries, especially those that struggled to contain the COVID-19 pandemic, as it was the case of Brazil. Third, adverse life events and childhood adverse events were not derived from validated questionnaires, yet these were standardized questionnaires based on well-known measures. In addition, childhood adverse events were measured retrospectively when participants were adults, therefore this measure was prone to memory bias. Fourth, CMD symptoms before the pandemic were measured using a different scale when compared to pandemic data. To account for this discrepancy we used equipercentile linking, deriving a modified CIS-R total score equivalent to the DASS-21 total score. Our findings may have been different if the same measure was used across all time-points. However, equipercentile linking methods are known to be robust and have previously been effectively used in the field of psychiatry [76–78]. Fifth, our analytical approach combined depression and anxiety symptoms in a single domain. However, these symptoms may have distinct trajectories. Future studies could investigate these symptoms separately using a multi-trajectory strategy [79]. Sixth, our analysis did not include variables measured during the pandemic, such as COVID infection and economic impact. Previous studies showed CMD symptoms were greatly influenced by such variables [12, 19]. However, to establish a temporal link between CMD trajectories and predictors, we opted to include only variables measured before the pandemic. Seventh, we did not measure trauma symptoms during the pandemic. The pandemic was a major life-changing event that could be a potential trauma affecting general mental health or even causing post-traumatic stress disorder, as previous studies indicated [80, 81]. Eighth, we identified groups of trajectories using statistical models. Even though we followed guidelines and objective metrics to identify the best fitting model, we cannot be certain the same model would be identified in a different sample or context. Also, overall, models with more groups revealed larger BIC scores, although above six groups the increase was slight. So we based our decision on interpretability (more groups would be a challenge for the predictors analysis) and domain knowledge (no previous study identified more than six groups). Additionally, more groups can lead to smaller groups, resulting in model misspecification and problems to run multinomial regression models.

## Conclusion

We longitudinally assessed symptoms of CMD in adults at five time points before and during the pandemic in São Paulo, Brazil. Six trajectories of CMD symptoms emerged from our data. More than half of the sample presented low levels of mental symptoms, meaning resilience to the challenges brought by the COVID-19 pandemic is a prevalent feature of our sample. However, approximately 5% of the sample presented severe symptomatology that attenuated over time. The severe-decreasing levels of CMD symptoms was characterized by increased age, female sex, low family income, previous mental disorders, and the experience of adverse events in life. These pre-pandemic risk and protective factors could be used to detect individuals at risk for presenting clinically significant CMD symptoms in the context of global adverse events such as the COVID-19 pandemic.

## Declarations

**Conflict of interest** The authors declare that they have no conflict of interest.

**Ethical standards** The authors assert that all procedures contributing to this work comply with the ethical standards of the relevant national and institutional committees on human experimentation and with the Helsinki Declaration of 1975, as revised in 2008.

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