# Original research

# Trajectories of mental health among UK university staff and postgraduate students during the pandemic

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#### ABSTRACT

these trajectory types.

**Objectives** The COVID-19 pandemic has disrupted

have highlighted worsening mental health during the

pandemic, but often rely on small samples or infrequent

follow-up. This study draws on fortnightly assessments

from a large occupational cohort to describe differing

trajectories of mental health between April 2020 and

Methods King's College London Coronavirus

Health and Experiences of Colleagues at King's is

an occupational cohort study at a large university in

London, UK. Participants (n=2241) completed online

April 2021. Symptoms of anxiety and depression were

assessed using Generalised Anxiety Disorder (GAD-7)

**Results** On average, participants reported low levels

of anxiety and depression (GAD-7 and PHQ-9 scores

symptoms) throughout the year, with symptoms highest

in April 2020 and decreasing over the summer months

when no lockdown measures were in place. However,

among subgroups of participants. Four trajectory types

for anxiety and depression were identified: 'persistent high severity' (6%-7% of participants), 'varying

symptoms, opposing national cases' (4%-8%), 'varying

symptoms, consistent with national cases' (6%–11%)

and 'persistent low severity' (74%-84%). Younger age,

**Conclusions** These data highlight differing individual

responses to the pandemic and underscore the need to

consider individual circumstances when assessing and treating mental health. Aggregate trends in anxiety and depression may hide greater variation and symptom

The COVID-19 pandemic is a threat to well-being,

not only from infection with the SARS-CoV-2 virus

itself, but also indirectly through public health

measures such as social isolation and changes to

associated with higher severity trajectory types.

female gender, caring responsibilities and shielding were

of 0-9, consistent with 'none', 'minimal' or 'mild'

we observed more severe and variable symptoms

questionnaires fortnightly between April 2020 and

and Patient Health Questionnaire (PHQ-9).

April 2021 and individual characteristics associated with

the social and working lives of many. Past studies

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home working and schooling. The potential impact of the pandemic on mental health was highlighted early in 2020.<sup>1</sup> Since then, numerous studies have

severity among subgroups.

INTRODUCTION

Key messages

#### What is already known about this subject?

► Research among the general population during the pandemic has highlighted worsening anxiety, depression, and other symptoms of distress, with people tending to report more severe symptoms during the early phases of the pandemic. However, few studies have assessed individual variation among these averages, particularly from an occupational cohort perspective. Employers play a key role in navigating the 'new normal'.

#### What are the new findings?

 During the first year of the pandemic, on average, participants reported low levels of anxiety and depression, with symptoms improving when restrictions were lifted. However, these averages hid substantial variability within subgroups of participants. We identified two subgroups experiencing persistent high or low severity symptoms and two subgroups with symptoms that fluctuated in line with the easing and tightening of national lockdown restrictions.

## How might this impact on policy or clinical practice in the foreseeable future?

When considering how best to support the mental health of staff and students during the pandemic, policymakers and employers across the higher education sector need to account for individual variability and provide support that accommodates the needs of specific subgroups

assessed symptoms of distress, depression and anxiety, with mixed methodological rigour and heterogeneous findings.<sup>1-3</sup> The consensus has been that, on average, people in the early phases of the pandemic reported significantly higher levels of symptoms, compared with before the pandemic, but that the impact on mental health was unevenly felt across the population.<sup>4–6</sup>

Insights from a single point in time are limited. Mental health is dynamic and support needs to reflect individual experiences that evolve alongside the pandemic and public health response. Longitudinal assessments of mental health to identify vulnerable groups are therefore important for policy makers when planning for COVID-19 response and recovery.<sup>7 8</sup> Support from employers is also important for well-being when navigating the 'new normal' after the more acute phases of the pandemic.<sup>19 10</sup>

Universities are large employers comprising a variety of staff roles.<sup>11</sup> Individual experiences of the pandemic, and the impact on mental health, are likely to vary across roles. For example, between those who have regular contact with members of the public vs those working remotely. Factors associated with poor mental health in populations prior to the pandemic include younger age, female gender, belonging to an ethnic minority group,<sup>12</sup> prior diagnosis of mental disorder, and caregiving responsibilities.<sup>13</sup> In addition, recent studies have identified specific determinants of mental health that are caused or exacerbated by the pandemic. These include living alone, being a key worker, or having children at home, particularly school age children who are affected by school closures.<sup>7</sup>

King's College London (KCL) is a large university with five campuses in central London, United Kingdom (UK). On 23 March 2020, KCL closed its campuses to all except essential workers and moved most activities online. In April 2020, the university set up the 'KCL Coronavirus Health and Experiences of Colleagues at King's' (KCL CHECK) project to understand the impact of the pandemic on staff and postgraduate research students (PGR) and inform policy making within the university.<sup>14</sup> We have previously reported on symptoms of depression and anxiety collected at the baseline questionnaire in April 2020.<sup>15</sup>

This study aimed to describe patterns of mental health among staff and PGRs between April 2020 and April 2021. We drew on fortnightly questionnaires to (1) describe aggregate trends in anxiety or depression; (2) identify subgroups with differing symptom trajectories and (3) consider how these trajectory types were associated with individual characteristics such as age or gender. This is an important population to study partly because most occupational studies during the pandemic have focused on healthcare settings, but also because of the growing awareness within the higher education sector of the need to support staff and student mental health.<sup>16</sup> The 2020–2021 period was a challenging and uncertain time for staff and students and these challenges come on top of, and interact with, existing risk factors for mental ill health.

# METHODS

#### Data

Data were collected from staff and PGR students participating in the KCL CHECK longitudinal survey. Participants were invited via email to complete the baseline survey in April 2020. Those completing the baseline survey were also invited to participate in longitudinal surveys. All surveys were conducted online. Longitudinal surveys included shorter fortnightly questionnaires as well as longer questionnaires every 2 months. Between April 2020 and March 2021, there were 6 longer questionnaires and 21 fortnightly questionnaires (see online supplemental table 1). Of 2590 staff and PGR students responding to the baseline survey, 2508 agreed to participate in longitudinal follow-ups and are included in this analysis. Contextual data on the strictness of lockdown measures in the UK were obtained from the Oxford COVID-19 Government Response Tracker.<sup>17</sup>

# Weighting

The target population was all staff and PGR students at KCL. Described in detail elsewhere,<sup>15</sup> survey respondents represented

the population in terms of age, but female gender and White ethnicity were over-represented. We used administrative information for staff and PGR student populations to construct a 'baseline weight' accounting for differences in age, gender and ethnicity between the baseline cohort and the target population. We also constructed a longitudinal weight to account for differential non-response at longitudinal follow-up (see online supplemental materials). Baseline statistics and trajectory models were weighted using the baseline weight only; longitudinal statistics were additionally weighted to account for non-response.

## Measures

The outcomes were reports of symptoms associated with depression and anxiety measured using the Patient Health Questionnaire (PHQ-9)<sup>18</sup> and the Generalised Anxiety Disorder (GAD-7)<sup>19</sup> scales, respectively. Where participants partially completed measures, up to two items were person-mean imputed for PHQ-9 and one for GAD-7.<sup>20</sup> In our analyses these outcomes were treated continuously, but scores of 5–9 are typically labelled as 'mild anxiety' or 'mild depression' and scores  $\geq 10$  used to indicate 'Probable anxiety' or 'Probable depression'.<sup>18 19</sup>

Covariates were self-reported by participants at baseline. These included factors previously linked to anxiety and depression as well as factors likely to be associated with increased vulnerability during the pandemic: (1) demographic characteristics (age, gender, ethnicity, partnership status); (2) living arrangements and housing tenure; (3) health status (chronic health conditions, shielding, previous mental health diagnoses); (4) caring roles (children at home, young children aged  $\leq 6$ , other caring responsibilities); and (5) occupational role and key worker status. 'Shielding' was defined in the survey as 'a type of self-isolation, which involves not leaving your home for any reason for at least 12 weeks to reduce your risk of contracting COVID-19' (see online supplemental materials for details). Ethnicity was used to describe the sample but was omitted from regression models due to small numbers of participants in minority ethnic groups which would have produced unreliable estimates.

For visualisation purposes, information on the strictness of government lockdown policies was extracted from Oxford COVID-19 Government Response Tracker.<sup>1</sup> Periods of lockdown were defined as days where there was a national requirement to stay at home (defined as 'not leaving house with exceptions for daily exercise, grocery shopping, and 'essential' trips' or 'not leaving house with minimal exceptions (eg, allowed to leave once a week, or only one person can leave at a time)').

# **Statistical analyses**

The analyses were in four parts:

- 1. We compared the analytical sample with excluded respondents using  $\chi^2$  tests (categorical variables) and t-tests (continuous variables).
- 2. We described the cohort using weighted summaries of baseline characteristics and the two outcomes (GAD-7 anxiety and PHQ-9 depression) at each follow-up survey.
- 3. We used growth mixture models (GMMs) to identify subgroups of participants with differing trajectories of anxiety and depression symptoms. GMMs are an extension of latent growth curve models (LGCMs) and are estimated within a structural equation modelling framework.<sup>21</sup> The LGCM allows us to model repeated measures of an observed variable (eg, symptoms of anxiety) by using latent variables to represent the intercept (the initial level of the observed variable) and slope (the change over time). A GMM extends this

model to allow identification of subgroups ('latent classes') with different intercepts and slopes, reflecting differing trajectories of symptoms over time. The GMM proceeds in two stages: (1) We first fit LGCMs to identify the most appropriate functional form of growth (eg, linear, quadratic) for our data; (2) We then fit GMMs with increasing numbers of latent classes and choose the optimal number of classes based on relative model fit and substantive interpretability. Modelling was conducted separately for anxiety symptoms and depression symptoms. Relative model fit was assessed based on the Akaike information criterion (AIC), sample size adjusted Bayesian information criterion (SABIC;<sup>22</sup>), and the Lo-Mendell-Rubin test.<sup>23 24</sup> For AIC and SABIC, lower values indicated a better fit.

4. Fourth, we considered how covariates measured at baseline were associated with membership to trajectory classes using the R3STEP method in Mplus.<sup>25</sup> This used a multinomial logistic regression model to estimate how the odds of assignment to a particular trajectory class were associated with a unit change in each baseline predictor. We considered each covariate separately, adjusted for age, gender, and previous mental health diagnosis.

Descriptive statistics were calculated using R V.4.1.2.<sup>26</sup> GMM models were estimated using Mplus 8.4 using the MplusAutomation package<sup>27</sup> for R. Survey weights were generated using the survey package for R.<sup>28</sup> All code used in these analyses can be found online (https://osf.io/7d9ts).

#### **Missing data**

We excluded participants without any outcome data (7%) or missing information on baseline covariates (4%). Descriptive statistics were calculated based on the available sample at each time point. GMM models used full information maximum likelihood information to retain all participants with at least one postbaseline measurement of the outcome.<sup>29</sup>

# RESULTS

#### **Cohort characteristics**

Of 2508 participants agreeing to longitudinal follow-up, we excluded 176 participants without follow-up information on PHQ-9 and GAD-7 and 91 without information on baseline covariates. The analytical sample therefore included 2241 participants (1851 staff; 390 PGR students), representing 19% and 16% of all staff and PGR students at KCL, respectively. Excluded participants tended to be older (mean age=39.6 vs 38.3 years; p=0.08) and female (70% vs 60%; p<0.001). A small number of staff (n=107) and PGR students (n=24) left KCL during the fieldwork period but continued to complete follow-up questionnaires (online supplemental table 3).

Table 1 presents sociodemographic characteristics of the analytical sample at baseline. Figure 1 presents weighted mean scores for GAD-7 anxiety and PHQ-9 depression at each survey period. On average, participants reported low levels of anxiety and depression (scores consistent with 'none' or 'mild' symptoms) over time. Symptoms were highest in April 2020, decreased over the summer months and increased again in December 2020 at a time of rising case numbers and reinstated national lockdown measures. When stratifying by age, younger individuals scored higher on both anxiety and depression than older participants. On average, males and females reported similar levels of anxiety and depression throughout the year, but females presented with higher scores at each survey period.

Table 1      Cohort characteristics at baseline (n=2241)			
	Count	Weighted proportion	95% CIs
Gender			
Female	1581	0.57	(0.54 to 0.60)
Male	660	0.43	(0.40 to 0.46)
Age group			
16–34	941	0.43	(0.40 to 0.46)
35–54	979	0.43	(0.41 to 0.46)
55+	321	0.14	(0.12 to 0.15)
Ethnicity			
White	1907	0.71	(0.68 to 0.74)
Black	32	0.04	(0.03 to 0.06)
Asian	156	0.14	(0.12 to 0.17)
Mixed	90	0.05	(0.04 to 0.06)
Other	56	0.06	(0.04 to 0.08)
Role			
Staff	1851	0.82	(0.80 to 0.85)
PGR students	390	0.18	(0.15 to 0.20)
Pre-existing major depressive disorder	519	0.22	(0.20 to 0.24)
Pre-existing generalised anxiety disorder	512	0.21	(0.19 to 0.23)
Living alone	250	0.12	(0.10 to 0.13)
Number of children living with you			
0	1600	0.72	(0.70 to 0.75)
1	276	0.12	(0.10 to 0.14)
2	316	0.14	(0.12 to 0.15)
3+	49	0.02	(0.01 to 0.03)
Participant is key worker*	283	0.13	(0.11 to 0.14)

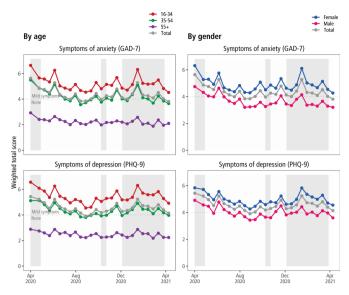
\*Key worker status was assessed by asking participants 'Are you currently fulfilling a 'key worker' role as identified by the government?' The possible responses were: (1) Health, social care or relevant related support worker (including laboratory staff); (2) Worker involved in medicines or protective equipment production or distribution; (3) Public safety or national security worker; (4) Key public services worker (eg, justice staff, religious staff, public service journalist or mortuary worker); (5) Local or national government worker delivering essential public services; (6) Teacher or childcare worker still travelling in to work (7) Transport worker; (8) Food chain worker (eg, production, sale, delivery); (9) Utility worker (eg, energy, sewerage, postal service) or (10) Other key worker.

#### Trajectories of anxiety and depression symptoms

Based on model fit and substantive interpretability, we chose a four-class model for both anxiety and depression. While model fit could be improved by going beyond four classes (see online supplemental table 2), this was at the expense of interpretability. Additional classes indicated similar types of trajectory but at higher or lower levels of severity, compared with the existing four classes. Figure 2 presents the four-class trajectories for symptoms of anxiety and depression. For both outcomes, the four classes can be characterised as follows:

**Class 1:** 'Persistent high severity symptoms' (n=145 (6%) and 153 (7%) for symptoms of anxiety and depression, respectively). This class reported scores consistent with 'probable' anxiety and depression' (>10) throughout the year. Mean scores increased consistently from April 2020 onwards, with the exception of depressive symptoms which started to decline in early 2021.

**Class 2:** 'Varying symptoms, opposing national cases' (n=176 (8%)) and 82 (4%) for anxiety and depression, respectively). This class experienced fluctuating symptoms over the year, meeting and exceeding thresholds for 'probable' anxiety and



**Figure 1** Fortnightly mean scores for anxiety (GAD-7) and depression (PHQ-9) stratified by age group and gender (n=2241). Periods of national lockdown are shaded in grey, based on the Oxford COVID-19 government response Tracker. GAD-7, Generalised Anxiety Disorder; PHQ-9, Patient Health Questionnaire.

depression. Notably, this class reported symptoms that ran counter to national COVID-19 case numbers and hospitalisations. Between April and September 2020, as COVID-19 cases in the UK declined, this class experienced a worsening of symptoms of anxiety and depression. Conversely, as UK case numbers rose in December 2020 and lockdown measures returned, this class experienced improving symptoms.

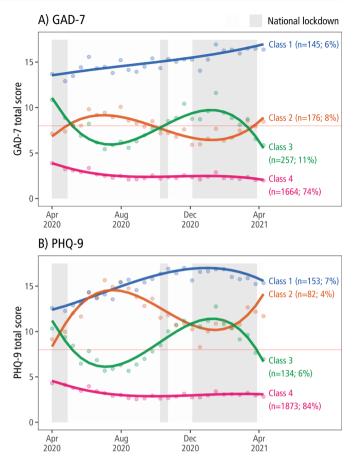
**Class 3:** 'Varying symptoms, consistent with national cases' (n=257 (11%) and 134 (6%) for anxiety and depression, respectively). Like Class 2, this class experienced fluctuating symptoms over the year, but these fluctuations mirrored changes in the number of COVID-19 cases and hospitalisations in the UK. As COVID-19 cases declined from April to August 2020, this class experienced reductions in symptom severity. During the winter months, as COVID-19 cases in the UK rose, this class reported increasing symptoms of anxiety and depression.

**Class 4:** 'Persistent low severity symptoms' (n=1664 (74%) and 1873 (84%) for anxiety and depression, respectively). This class comprised the majority of respondents who reported lower symptoms throughout the year, at or below 'Mild' anxiety and depression. Symptoms for this group were highest in April 2020 but declined thereafter.

#### Baseline predictors of trajectory class membership

We used multinomial logistic regression to estimate the odds of assignment to each class for a unit change in each covariate. Figure 3 presents ORs for assignment to classes 1–3, where class 4 ('persistent low severity') was treated as the reference category. Each covariate was tested in a separate model, adjusted for age and gender. Age was scaled such that a one unit change represents a 10-year difference in age. These results are also presented in online supplemental table 4.

For anxiety, 'persistent high severity' symptoms were associated with younger age, female gender, having a chronic condition, and having a caring role. Shielding was strongly associated with the high severity trajectory although without reaching statistical significance. 'Varying, opposing national cases' was associated with younger age, having a chronic condition and shielding. 'Varying,



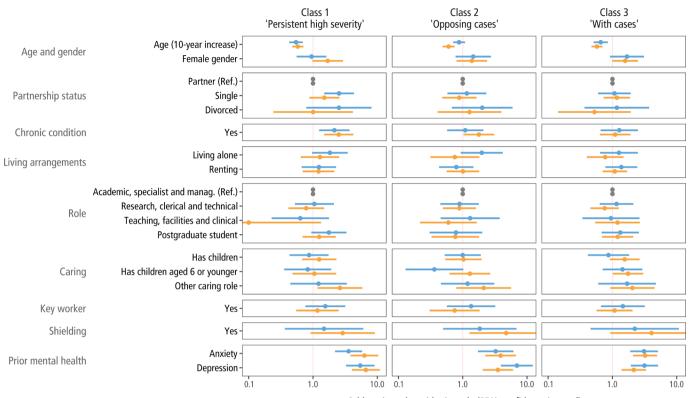
**Figure 2** Trajectory classes from four-class GMM model for symptoms of anxiety and depression (n=2241). Lines represent model estimated values; points represent observed data. Shaded regions indicate periods of lockdown based on the COVID-19 government response Tracker (OxCGRT), defined as days where there was a national requirement to stay at home. GMM, growth mixture model; OxCGRT, Oxford COVID-19 Government Response Tracker; PHQ-9, Patient Health Questionnaire.

consistent with national cases' was associated with younger age and female gender. All three trajectory types were positively associated with having prior anxiety or depression, compared with the reference 'persistent high severity' class.

For depression, 'persistent high severity' was positively associated with younger age, having a chronic condition, and living alone, although the latter did not reach statistical significance. 'Varying, opposing national cases' was positively associated with being divorced and living alone and negatively associated with having young children. 'Varying, consistent with national cases' was positively associated with younger age. All three trajectories were again positively associated with prior anxiety or depression.

#### DISCUSSION

In a large occupational cohort with fortnightly follow-up and consistently high response rates, we described trajectories of anxiety and depression symptoms in the first year of the COVID-19 pandemic in the UK. Symptoms were highest at the start of the pandemic, eased over the summer months, and increased again in December, mirroring national patterns of lockdown and case numbers. While average levels of anxiety and depression were low throughout the year (scores consistent with 'none' or 'mild' symptoms), these hid much greater variation among subgroups. Using GMMs, we identified four trajectory types for anxiety and depression. Most participants were assigned to the 'persistent low-level



Odds ratio on logarithmic scale (95% confidence interval)

**Figure 3** Associations of baseline variables with trajectory class assignment (n=2241). ORs representing odds of class assignment, compared with reference class of 'persistent low severity'. ORs also presented in online supplemental table 4. GAD-7, Generalised Anxiety Disorder; PHQ-9, Patient Health Questionnaire.

symptoms' trajectory class, but others experienced more severe and variable symptoms. One group reported high severity symptoms throughout the year ('persistent high severity') whereas two groups reported fluctuating, moderate symptoms. Notably, these were in opposing directions. Some respondents reported reductions in symptom severity as lockdown measures eased, while at the same time, others experienced increasing anxiety and depression.

# Comparison with past studies

Our findings are consistent with several studies identifying trajectories of mental health in general population samples during the pandemic. Pierce *et al*<sup>30</sup> identified remarkably similar trajectories using the nationally representative UK Household Longitudinal Study (UKHLS). Based on the General Health Questionnaire-12, they identified five classes: most respondents (77%) were assigned to 'consistently good' or 'consistently very good' classes, whereas a minority (4%) belonged to a 'Consistently very poor' class. Like us, they also identified two classes with moderate symptoms that experienced opposing trajectories, mirroring our 'varying symptoms' classes. One ('deteriorating') saw worsening symptoms in the period from April to July, when national case numbers declined, whereas another ('recovery') saw improving symptoms. Whereas Pierce et al incorporated data until September 2020, our trajectories extended until April 2021. Our findings suggest that the 'deterioration' and 'recovery' trajectories identified in the UKHLS may have subsequently reversed course in December 2020 amidst worsening national circumstances. Consistent with our findings, Pierce et

*al* found more adverse trajectories to be associated with female gender, younger age, prior mental health condition, living alone and shielding.

Our findings are also consistent with those from the UCL Social Study,<sup>31</sup> an online survey of over 70 000 respondents, that found levels of anxiety (GAD-7) and depression (PHQ-9) to be highest in April at the start of the pandemic, declining over the summer months, and increasing again from December 2020. They similarly found more severe symptoms those with younger age, female gender and prior mental health diagnosis. Saunders *et al*<sup>32</sup> identified four trajectory classes for anxiety and depression among adults in England from March to July 2020. As in our study, most respondents were assigned to a 'low symptom severity' class (70%) whereas a smaller proportion experienced moderate or severe symptoms (6%–17%). A fourth class experienced symptoms that worsened during national lockdown but improved after lockdown measures were eased, mirroring our 'varying symptoms, opposing national cases' class.

# **Policy implications**

Our findings should be considered within the context of higher education, a sector that has previously acknowledged the need to support the mental health of its staff and students.<sup>16</sup> The pandemic has exacerbated existing challenges in this sector<sup>33</sup> and created a renewed need for action on mental health. However, as our results highlight, individual experiences of the pandemic were heterogeneous and aggregate trends hide considerable

interindividual variation. Policies must reflect the diverse needs of each subgroup.

Notably, we found that as lockdown measures eased and national case numbers fell, some individuals reported improving symptoms whereas others reported worsening symptoms. This latter group is particularly relevant since this directionality (worsening symptoms amidst 'improving' national circumstances) may appear counterintuitive and thus be easily overlooked when designing policies to help staff and students resume in-person activities. While it is difficult to make specific policy recommendations from our analysis, such individuals may benefit from measures allowing greater autonomy in the return to work, for example, allowing individuals to return at their own pace and offering long-term hybrid working options. Individuals in the 'opposing cases' group, who reported worsening symptoms as lockdown measures eased, may have experienced reduced stressors while working from home. For example, stressors associated with in-person working, travelling to work, or negotiating health-related adjustments in the workplace.

We found shielding to be associated with both 'varving' trajectory types and thus a greater sensitivity to contextual factors such as COVID-19 policy. This group is likely to be strongly affected by future policy changes, suggesting a need for employers to offer greater support and accomodation in policy making. Shielding was one of several factors including younger age and female gender that were associated with more severe trajectory types. While this suggests a need for preventative action-for example, creating peer support networks for younger employees or offering flexibility for those with caring responsibilities-we are wary of making specific policy recommendations. In part, because it was difficult to empirically distinguish between the two 'varying' trajectory types and directionality was often unclear: shielding was associated with both improving and worsening symptoms as lockdown measures eased. But also because of broad categories used in our analyses (eg, 'caring role' vs 'no caring role') that grouped heterogeneous individual experiences. This calls for more detailed analyses that can address the underlying mechanisms. For example, qualitative studies of individuals in both 'varying' trajectories to explore their feelings around the return to work vs periods of lockdown.

Our research also underlines two further points that are important for future work in this area. First, our findings regarding the variability of mental health over time underscore the importance of frequent data collection to understand the temporality of mental health. Second, the importance of a welldefined population and access to reliable information on population characteristics to understand representativeness and derive sampling weights.

#### **Strengths and limitations**

Our study benefited from a well-defined population and large sample that captured one fifth of KCL staff and PGR students. All participants were working or studying at KCL at baseline, and therefore, are likely to have received similar communications from the university and experienced similar workplace policies. Follow-up information was collected fortnightly for 12 months and response rates remained high throughout the study. We used administrative data to describe sample representativeness and derive weights. Our use of LGCM made efficient use of the available data and retained all participants with at least one follow-up assessment. We used validated measures of mental health and adjusted for several important confounders. However, there are several limitations. First, male gender and minority ethnic groups were under-represented. We derived weights to account for differences between sample and population, but these cannot make up for the missing experiences from smaller, intersectional groups that are present in very small numbers. Small numbers from minority ethnic groups also prevented us from assessing associations with trajectory class assignment.

Second, occupational studies have been shown to report higher levels of psychological stress, compared with population studies.<sup>34</sup> Our study captures a single occupational cohort at a large London university, which may not reflect patterns in other workplaces. Respondents had more years of education and higher socioeconomic position compared with the general population. There will also be a healthy worker effect<sup>35</sup> since employees and PGR students are, by definition, well enough to work.

Third, while the GAD-7 and PHQ-9 questionnaires are widely used and have been validated for the general population,<sup>18</sup> <sup>19</sup> studies validating these scales for use in a global pandemic are yet to be published. During extremely adverse events such as pandemic and lockdown, it is not known how questionnaire scores relate to clinical disorder.

Fourth, we lacked prepandemic assessments of GAD-7 and PHQ-9 and cannot say how the observed trends compare to previous years.<sup>36</sup> It is also important to stress that we identified variables associated with mental health during a pandemic, rather than specific causal effects of COVID-19 on mental health. Many of the observed risk factors are likely to have existed in 2019 and earlier.<sup>5</sup>

Fifth, and relatedly, although we described patterns of mental health in relation to wider contextual factors such as lockdown or rising cases, we did not test these relationships empirically. For example, participants may have experienced improving symptoms alongside easing of lockdown or declining cases, but this improvement could be attributable to any number of contemporaneous, unmeasured variables. For example, seasonal changes in mood may have contributed to the trends observed during November 2020 to January 2021.

Lastly, as reported above, a small number of staff and PGR students continued to participate in the survey after leaving KCL. Although completing a PGR programme or leaving a job may have consequences for mental health, this is unlikely to have impacted our findings due to the small number of participants and assessments involved.

#### CONCLUSIONS

Our findings highlight differing individual responses to the pandemic and the need to consider individual circumstances when supporting mental health of staff and students. Aggregate trends in anxiety and depression can hide greater variation and symptom severity experienced by subgroups. As university campuses resume in-person activities it will be important to ensure staff and students are adequately supported. Particular attention should be placed on individuals likely to report worsening mental health alongside easing restrictions, as well as those with identified risk factors, such as having young children, caring roles, a history of mental illness or shielding.

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**Contributors** All authors contributed to the design of the study. EC and CO carried out the data analysis and wrote the manuscript. All authors made substantive revisions to and approved the final manuscript. KD, GB-C, GL, DL, CO, CP, VV and AW carried out the data collection. SS, RR and MH supervised the project. EC is the guarantor of the study.

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**Disclaimer** The views expressed are those of the author(s) and not necessarily those of the NHS, the NIHR or the Department of Health and Social Care.

**Competing interests** MH receives funding from Janssen as part of the RADAR-CNS consortium, which includes a project on depression. He is a principal investigator of RADAR-CNS, a precompetitive public private partnership co-funded by Innovative Medicines Initiative (European Commission) and European Federation of Pharmaceutical Industries and Associations (EFPIA). He has also been an independent expert witness in group litigations instructed by claimants against pharmaceutical companies for alleged harmful effects of their products. Authors have no other conflict of interest to declare.

Patient consent for publication Obtained.

**Ethics approval** Ethical approval for KCL-CHECK was obtained from King's College London's Psychiatry, Nursing and Midwifery Research Ethics Committee (HR-19/20-18247). Participants gave informed consent to participate in the study before taking part.

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**Data availability statement** Deidentified participant data are available for research purposes on request to the study authors, subject to approval. Please see https://kcl-check.org for further information.

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