

RESEARCH ARTICLE

Mental Health Trends in the United Kingdom, 1991–2025: A Time-Series Analysis

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Introduction: There is ongoing debate regarding increasing trends in mental health symptoms, particularly among younger people.

Aim: This study examined mental health trends in the United Kingdom from 1991 to 2025.

Methods: Calendar-year aggregated data from 120,001 participants in the nationally representative Understanding Society survey, including the British Household Panel Survey and the UK Household Longitudinal Study, were analyzed. Mental health symptoms were measured using the GHQ-12.

Results: Mental health symptoms increased from 1991 to 1996, remained relatively stable from 1997 to 2013, and increased thereafter, with the steepest rise around the onset of the COVID-19 pandemic. Post-2020 scores remained elevated. Although the BEAST-fitted trend was slightly upward, a complementary discontinuity model found no statistically significant slope in the final segment. The timing and direction of some trends differed by gender and age. Among participants aged 16–24 years, symptoms showed a gradual upward trend from 1991 to 2014. The posterior probability of a three-changepoint solution was 99.6% in the full sample, with greater uncertainty in subgroup analyses.

Conclusions: Mental health symptoms increased from the mid-2010s and rose particularly sharply around the onset of the COVID-19 pandemic. These patterns may be consistent with contextual influences, including austerity and the pandemic.

Keywords: time trends, secular change, mental health, United Kingdom, crisis

Introduction

Several studies have investigated changes in mental health over time (Bai et al., 2022; Botha et al., 2023; Collishaw, 2015; Gagné et al., 2022; Keyes et al., 2014; Mojtabai & Olfson, 2020; Moreno-Agostino et al., 2021; Olfson et al., 2014; Twenge et al., 2019). Although there is some evidence of substantial secular change in child and adolescent mental health problems, it is important to consider methodological issues (Collishaw, 2015). Increases in the diagnosis and treatment of mental health disorders in clinical practice in high-income countries do not necessarily reflect a decline in mental health. In addition, Costello et al. (2006) found no evidence of an increase in the prevalence of depression among child and adolescent participants when concurrent assessment, rather than retrospective recall, was used. Some studies have found a decline in mental health since the mid-2000s and have linked this trend to the rise of digital media and electronic communication (Twenge et al., 2019).

While most of these studies focused on children and young people, relatively few studies have reported trends in mental health among adults. Among Swedish adults, Calling et al. (2017) found an increase in mental health symptoms over a 25-year period from 1980/81 to 2004/05. In their analysis of a nationally representative panel

survey of Australian adults, Botha et al. (2023) found that population mental health had been worsening over two decades before the COVID-19 pandemic. Moreover, they revealed that the negative effect of time on mental health was stronger among younger participants, whereas no time trend was observed for participants aged 65 years and older. Among adults living in the UK in the period between 1991 and 2019, Zhang et al. (2023) found that mental health worsened from around 2015 onward, thereby predating the negative impact of the COVID-19 pandemic. It is worth noting that different trends and age effects were observed in other countries. Using data from the United States and Canada from 1997 to 2010, Keyes et al. (2014) did not find a clear trend in mental health. Specifically, the highest level of mental health symptoms was observed in 2001 and the lowest level in 2007. In the decades preceding the COVID-19 pandemic, the incidence and prevalence of depression decreased among younger age groups and increased among older individuals (Bai et al., 2022; Ren et al., 2020).

In these studies, trends in mental health were investigated in the years preceding 2020 or during the COVID-19 pandemic. There is evidence that the COVID-19 pandemic had an impact on population mental health (Prati & Mancini, 2021). However, the effect was heterogeneous, with people reporting either a decline or an improvement in mental health after the onset of the COVID-19 pandemic (Prati & Mancini, 2024). Trends in mental health during and after the COVID-19 pandemic have rarely been compared with historical trends, which limits the possibility of placing the pre- and post-pandemic periods in historical perspective. One exception is the study by Gagné et al. (2022), who compared changes in mental health in the UK between 1991 and 2018 and between 2018–2019 and 2020. They found that mental health deteriorated in the early pandemic period (April 2020), although a return to pre-pandemic levels was observed by September 2020. In addition, based on a descriptive examination of the trend, they distinguished three periods between 1991 and 2018. First, between 1991 and 2006–2010, the trends differed across gender and age groups. Second, between 2006–2010 and 2015–2016, there was a decline in mental health, especially among women. Third, from 2015–2016 to 2018, there was a second and more pronounced decline in mental health affecting both women and men. However, these trends were not formally tested. Therefore, it is unknown whether these fluctuations reflect underlying changes in mental health or whether they are merely random variation.

Purpose of the Present Study

In the present study, mental health trends in the UK were examined over the period from 1991 to 2025. This extended time frame allows comparison of the magnitude of changes over time and places the pre- and post-COVID-19 pandemic periods in historical perspective. Following previous studies (Gagné et al., 2022; Zhang et al., 2023), trends were also examined by gender and by age group (16–24, 25–34, 35–64, and ≥65 years).

Method

Data Sources

The current study used data from *Understanding Society* spanning the period from 1991 to 2025. *Understanding Society* includes the *British Household Panel Survey* (BHPS), with fieldwork spanning 1991 to 2009, and the *UK Household Longitudinal Study* (UKHLS), which has been ongoing since 2009 (University of Essex, 2026). *Understanding Society* is a panel survey that incorporates refreshment samples and is designed to provide a representative sample of UK households, including individuals aged 16 years and older. As both the BHPS and the UKHLS are panel surveys that include refreshment samples, the same respondents are followed over time, while new respondents are added in later waves to maintain representativeness, compensate for attrition, or restore population coverage. Different modes of data collection were employed, including pen-and-paper personal interviews (PAPI), online questionnaires, and computer-assisted personal interviews (CAPI). Complete and detailed information on sampling and survey methodology, including wave response rates and attrition, can be found elsewhere (e.g., Cabrera-Álvarez & Lynn, 2025; Taylor et al., 2017). All data collection for the *Understanding Society* main study was approved by the University of Essex Ethics Committee. Study materials are publicly available for consultation (<https://beta.ukdataservice.ac.uk/datacatalogue/studies/study?id=6614#!documentation>). The data used in the current study are available through the UK Data Service (<https://doi.org/10.5255/UKDA-SN-6614-22>). Although the transition from the BHPS to the UKHLS involved changes in sampling and panel structure, both surveys provide samples that are representative of the general population. Moreover, the current

study used harmonized BHPS and UKHLS data, which were adapted to enable joint analysis. Finally, the sample composition did not change substantially across years; the small observed variations reflected broader changes in UK society, such as a slight increase in the mean age of the population (see [Appendix Figures 1 and 2](#)).

All available data were used, comprising 120,001 unique participants contributing 749,193 person-year observations across 35 calendar years. Because fieldwork periods overlapped across waves, data collected in the same calendar year were combined across waves to represent participants' responses for that year, irrespective of wave. The study therefore analyzed calendar-year aggregated summed-score data. The time-series decomposition was performed on a single aggregated vector comprising 35 annual time points. Calendar year served as the time index for the aggregated series. The year 2025 is based on a smaller number of observations for that calendar year and should therefore be interpreted with appropriate caution.

Measures

The 12-item version of the General Health Questionnaire (GHQ; Goldberg et al., 1997) was used to measure mental health symptoms. The GHQ is a widely used and validated instrument for assessing mental health symptoms (Goldberg et al., 1997; Jackson, 2007) and has been validated for use in the United Kingdom (Goldberg et al., 1997; Shevlin & Adamson, 2005). Goldberg et al. (1997) demonstrated that the performance of the GHQ was not materially affected by gender, age, or educational level. Moreover, several studies have demonstrated the invariance of the GHQ across several groups in the UK (e.g., King et al., 2023; Schlechter & Neufeld, 2024; Shevlin & Adamson, 2005; Ushakova et al., 2025). Finally, longitudinal measurement invariance of the GHQ-12 has also been established in both the UKHLS (Prati, 2025c) and the BHPS (Prati, 2025a). Likert scoring (0, 1, 2, and 3) was used to calculate the total GHQ scores. Specifically, responses to all items were summed to yield a total score ranging from 0 to 36, with higher scores indicating greater levels of mental health symptoms.

Statistical Analysis

The estimand was the annual population-weighted mean GHQ score by calendar year of interview. The analysis was therefore conducted as a repeated series of annual population estimates rather than as an analysis of within-person change among a fixed longitudinal cohort. Cross-sectional weights were used to estimate the population mean GHQ score in each year. Longitudinal weights were not used in the primary analysis, as they would target a different population: respondents who remained eligible and observed across a specified set of waves. Such weights are appropriate for analyses of longitudinal change among continuing respondents, but not for estimating annual population means. A Bayesian model averaging time-series decomposition algorithm (BEAST), available through the R package Rbeast (Zhao et al., 2019), was used. Specifically, the annual time series was represented as a trend component that could contain abrupt changepoints, plus a noise component. BEAST estimates both the underlying trend and the posterior probabilities of changepoints in that trend as formulated in the following equation:

$$y_i = T(t_i; \theta_T) + \varepsilon_i$$

where the parameter θ_T specifies trend signals and implicitly encodes abrupt changes; y and t represent the dependent and independent variables, respectively; ε represents noise; θ_T is a parameter to be estimated from the time series data. Following the recommendations of Parpoula and Karagrigoriou (2022), a minimum segment length of five annual time points was selected to reduce the risk of overfitting while preserving the ability to detect short, transient periods of instability. The model posterior probabilities were approximated using the BIC-type approximation proposed by Kim and Kim (2016), which has been shown to provide consistent estimation of the number of changepoints. The BEAST algorithm was used to capture the trend in GHQ-12 summed scores for each calendar year (i.e., aggregated data). Specifically, BEAST analysis was applied not to individual-level trajectories, but to a single aggregated time-series vector (1×35) of calendar-year GHQ-12 scores derived from the underlying individual-level observations. Because the weights adjust for differential nonresponse and unequal selection probabilities, weighted means of GHQ-12 scores were calculated. The appropriate cross-sectional adult survey weights supplied by the harmonized dataset were applied (<https://doi.org/10.5255/UKDA-SN-6614-22>). Cross-sectional weights were used rather than longitudinal weights, as the estimand was the population mean for each calendar year, not change among a balanced panel. Since item-level missingness was very low (approximately

1%), available-case analysis was used as recommended in the methodological literature when missingness is minimal (e.g., Parent, 2013).

To assess the robustness of the results, level and slope discontinuity latent growth models (Rioux et al., 2021) were applied to the identified changepoints. Specifically, the models were used to estimate whether a changepoint was associated with a change in mean scores (i.e., levels) as well as with a different growth pattern (i.e., slope) before and after the changepoint. In a slope discontinuity model with two linear slopes, the knot is estimated as an intercept, centered by assigning a common loading of 0 for the two slopes. Here, both slopes have a loading of 0 for the wave representing the changepoint. The loadings of the first slope factor are constrained to follow a linear pattern from 0 to 3 across the four calendar years preceding the changepoint, with loadings fixed to 0 after the changepoint. The loadings of the second slope factor are constrained to follow a linear pattern from 0 onward. Detailed information regarding the specification of level and slope discontinuity latent growth models is provided by Rioux et al. (2021). The full information maximum likelihood (FIML) approach was employed to handle missing data (e.g., Lee & Shi, 2021). To ensure an adequate assessment of trajectories before the changepoint and sufficient statistical power, the trend changepoint should occur at the third or fourth time point (Diallo & Morin, 2015; Moerbeek, 2022; Prati & Mancini, 2024). Because changepoints were detected near both the beginning and the end of the time series, no substantive exclusion criteria were applied beyond the availability of valid GHQ-12 data and the relevant survey weight for a given year. The level and slope discontinuity latent growth model was applied to all identified changepoints, which were estimated simultaneously within a single unified piecewise growth model.

As a sensitivity analysis, the main time-series analysis was repeated after item-level multiple imputation of missing GHQ-12 items. Multiple imputation was applied to respondents with at least one observed GHQ item, excluding proxy cases and respondents with no observed GHQ items. For each imputed dataset, GHQ Likert scores were computed by summing the 12 GHQ items, and survey-weighted annual mean GHQ scores were then estimated. These annual estimates were pooled across imputed datasets and used as input for the time-series analysis. The substantive time-series conclusions were unchanged, indicating that the findings were robust to item-level missingness in GHQ responses.

To assess whether changes in sample or population composition could account for the observed GHQ time-series pattern, we conducted a covariate-standardized sensitivity analysis. First, observed survey-weighted annual mean GHQ scores were estimated. We then estimated covariate-standardized annual means using a survey-weighted linear model with calendar year entered as a categorical variable. The model adjusted for harmonized sociodemographic covariates: gender, age group, educational attainment, employment status, marital status, region, and household structure. Detailed categorical variables were harmonized into broader categories where necessary to improve comparability across waves. Predicted annual GHQ means were standardized to a pooled equal-year reference population, so that each calendar year contributed equally to the reference covariate distribution. This approach estimated the annual GHQ series that would be expected if the distribution of the measured sociodemographic covariates were held constant over time. We then compared the observed weighted annual GHQ series with the covariate-standardized annual series. The compositional component of change was calculated as the difference between observed change from baseline and covariate-standardized change from baseline. Finally, the time-series changepoint analysis was repeated using the covariate-standardized annual GHQ series to evaluate whether the main temporal findings were robust to measured compositional change.

Results

Measurement Invariance

To test whether the GHQ-12 functioned equivalently across time and survey modes between the BHPS and the UKHLS, we conducted measurement invariance tests using data from participants who took part in both the first wave of the BHPS and the latest wave of the UKHLS ($N = 1,667$). For invariance tests, Chen (2007) recommended a change of $\geq .010$ in CFI, paired with a change of $\geq .015$ in RMSEA, as a criterion for indicating non-invariance. Metric invariance was supported, as the differences in fit indices between the configural model (CFI = .957, RMSEA = .074) and the metric model (CFI = .955, RMSEA = .074) were below these cutoffs, $|\Delta\text{CFI}| = .002$, $|\Delta\text{RMSEA}| = .000$. There was also support for scalar invariance, given that the differences in fit indices between the metric model (CFI = .955, RMSEA = .074) and the scalar model (CFI = .946, RMSEA = .077) were below the cutoffs, $|\Delta\text{CFI}| = .009$, $|\Delta\text{RMSEA}| = .003$. Therefore, the GHQ-12 demonstrated sufficient in-

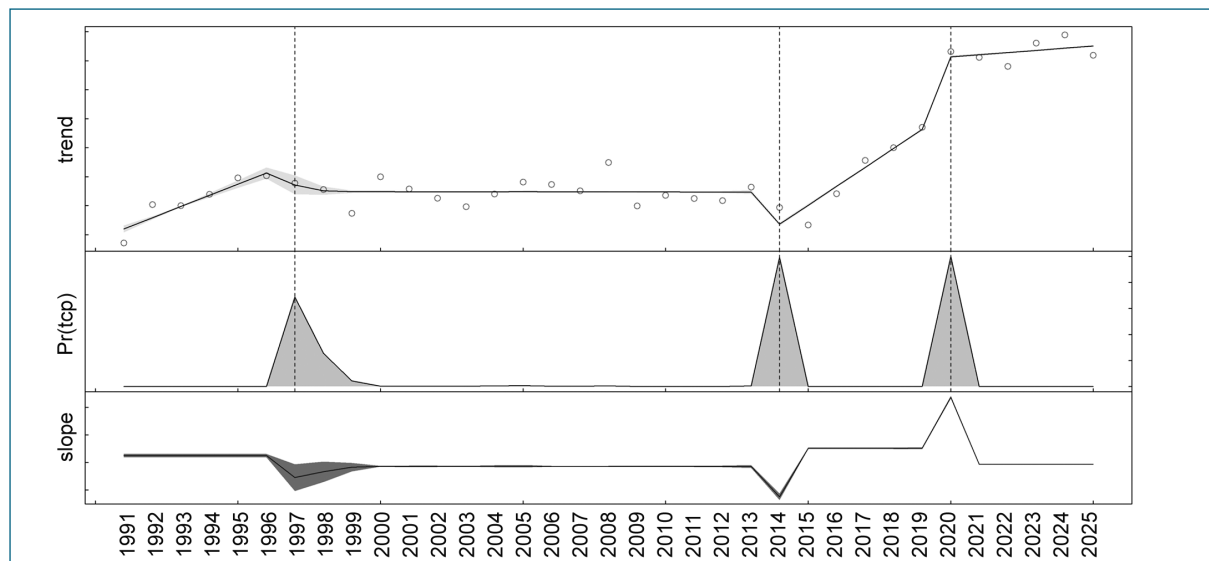
variance, indicating that it measured the same construct in the same participants across years and survey modes in the BHPS and the UKHLS.

Trends in the UK Population

Table 1 presents the descriptive statistics for GHQ-12 scores across the calendar years. Figure 1 shows the results of the changepoint and trend analyses. There was a 99.6% probability that the trend component had three changepoints, resulting in four segments. The first segment represented an initial period of increase in GHQ scores from 1991 to 1996. Starting in 1997, a period of relatively stable mean scores was observed until 2013. The segment from 2014 to 2019 was characterized by a rise in GHQ scores, which became steeper between 2019 and 2020. The BEAST-fitted trend remained slightly upward from 2020 to 2025, although the increase was substantially more gradual than during the preceding segment.

Table 1. Descriptive Statistics for the GHQ-12 Scores across the Calendar Years

Year	N	M	SD	Minimum	Maximum
1991	9,613	10.771	4.914	0	36
1992	8,954	11.083	5.111	0	36
1993	8,705	11.018	5.217	0	36
1994	8,877	11.121	5.234	0	36
1995	8,629	11.220	5.391	0	36
1996	9,153	11.223	5.369	0	36
1997	10,500	11.241	5.557	0	36
1998	10,328	11.212	5.434	0	36
1999	11,368	11.038	5.378	0	36
2000	13,439	11.325	5.528	0	36
2001	19,407	11.321	5.513	0	36
2002	16,042	11.225	5.474	0	36
2003	16,099	11.062	5.379	0	36
2004	14,196	11.173	5.504	0	36
2005	14,202	11.282	5.500	0	36
2006	13,740	11.201	5.553	0	36
2007	13,320	11.191	5.591	0	36
2008	12,777	11.413	5.578	0	36
2009	20,831	11.069	5.381	0	36
2010	43,582	11.137	5.443	0	36
2011	42,417	11.095	5.471	0	36
2012	39,172	11.054	5.573	0	36
2013	37,060	11.146	5.648	0	36
2014	36,667	10.976	5.525	0	36
2015	37,730	10.866	5.465	0	36
2016	37,603	11.029	5.526	0	36
2017	34,438	11.203	5.540	0	36
2018	32,753	11.313	5.625	0	36
2019	31,531	11.410	5.631	0	36
2020	30,459	11.923	5.753	0	36
2021	28,059	11.836	5.805	0	36
2022	28,958	11.759	5.795	0	36
2023	33,398	11.930	5.866	0	36
2024	14,674	11.996	5.853	0	36
2025	512	11.678	5.965	0	36

Figure 1. Illustration of the Changepoints and Trends in Mental Health Scores

Note. Trend denotes the estimated trend; $Pr(tcp)$ denotes the posterior probability of a trend changepoint; slope denotes the estimated trend slope. Vertical dashed lines indicate estimated changepoint locations.

Stratification by Gender

Figures 2 and 3 show the changepoints and trends in mental health scores for women and men, respectively. Among women, the trend exhibited three changepoints, resulting in four distinct segments. Specifically, there was a 99.9% probability that the trend component had three changepoints. The first segment comprised the period between 1991 and 1999, during which mental health symptoms increased. The second segment represented a period of relatively stable scores from the end of the 1990s to 2009. The beginning of the UKHLS corresponded to a drop in mental health scores, followed by an increasing trend. Mean mental health scores then increased slowly and subsequently rose sharply between 2019 and 2020. In the fourth segment, a modest decreasing trend was observed.

Figure 2.
Illustration of
the Change-
points and
Trends in
Mental Health
Scores among
Women

Note. Trend denotes the estimated trend; $Pr(tcp)$ denotes the posterior probability of a trend changepoint; slope denotes the estimated trend slope. Vertical dashed lines indicate estimated changepoint locations.

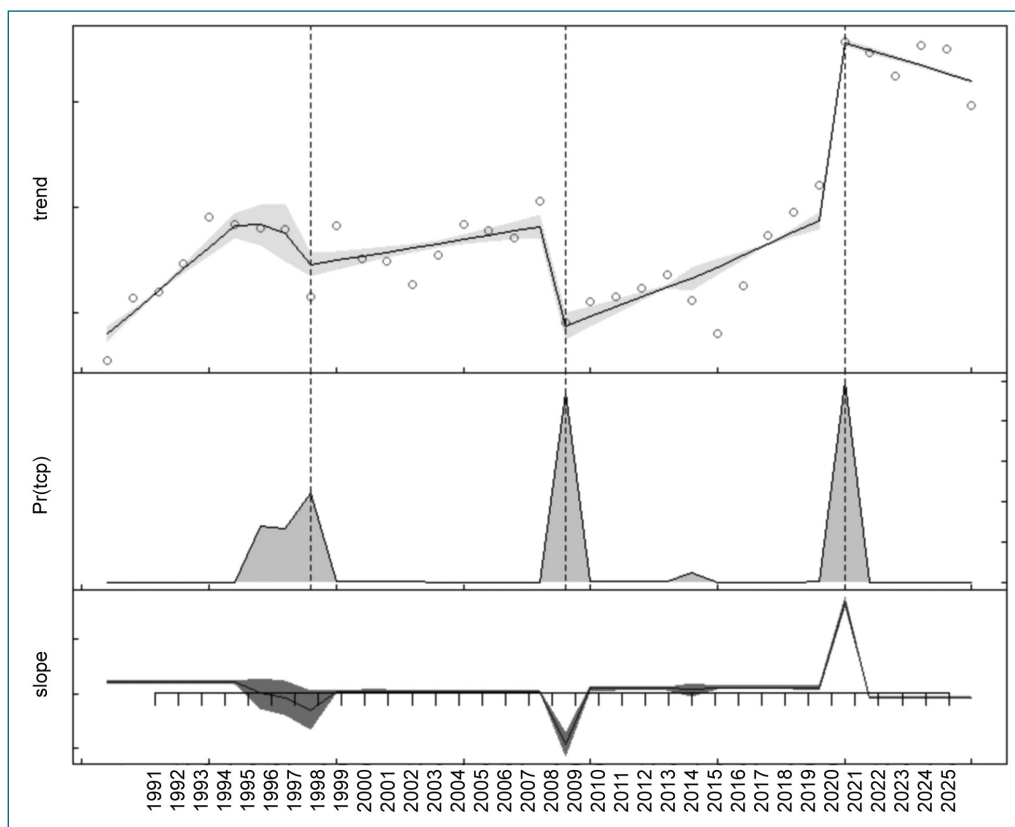
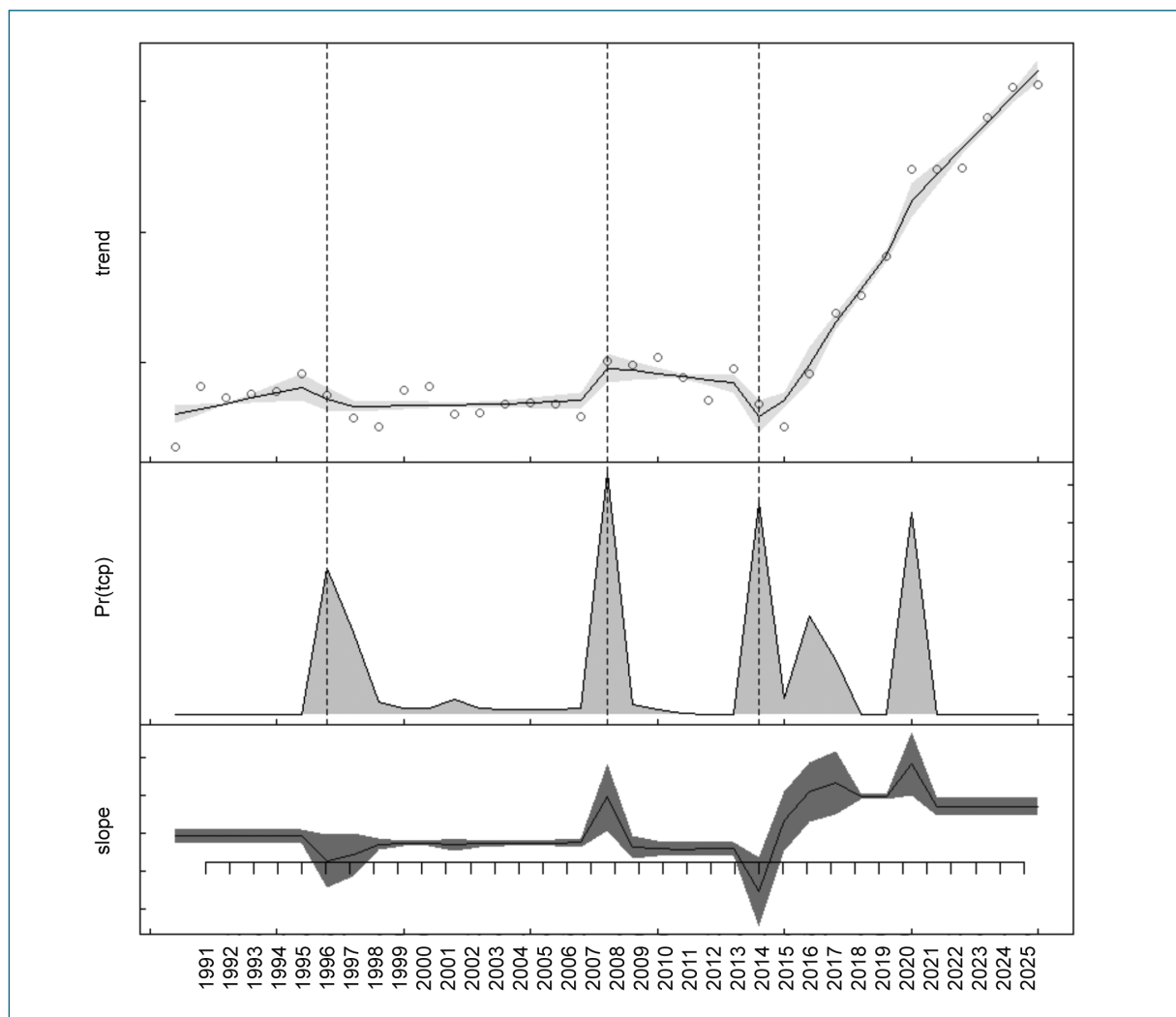


Figure 3. Illustration of the Changepoints and Trends in Mental Health Scores among Men



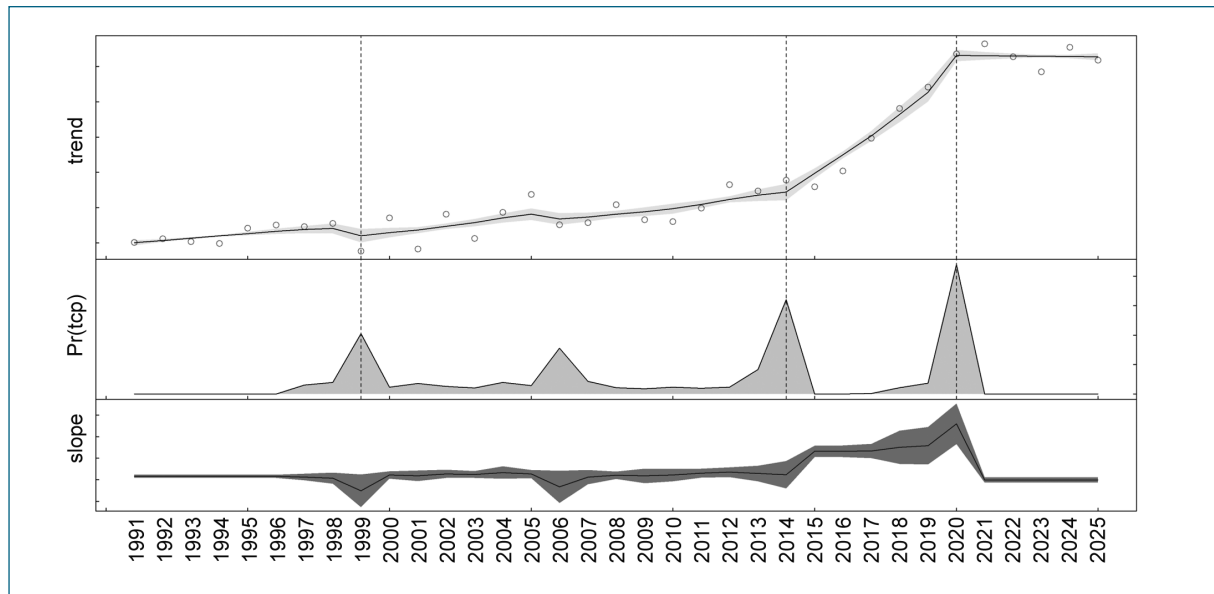
Note. Trend denotes the estimated trend; $\text{Pr}(\text{tcp})$ denotes the posterior probability of a trend changepoint; slope denotes the estimated trend slope. Vertical dashed lines indicate estimated changepoint locations.

Among men, there was a 91.8% probability that the trend component had three changepoints. The first segment comprised the period between 1991 and 1997, during which mental health symptoms slightly increased. The second segment represented a period of relatively stable scores from 1997 to 2009. The beginning of the UKHLS corresponded to an increase in mental health scores, followed by a slight downward trend. Mental health scores then increased between 2014 and 2025. The probability associated with the identified trend component was lower among men than among women, leaving comparatively more uncertainty in the male subgroup analysis.

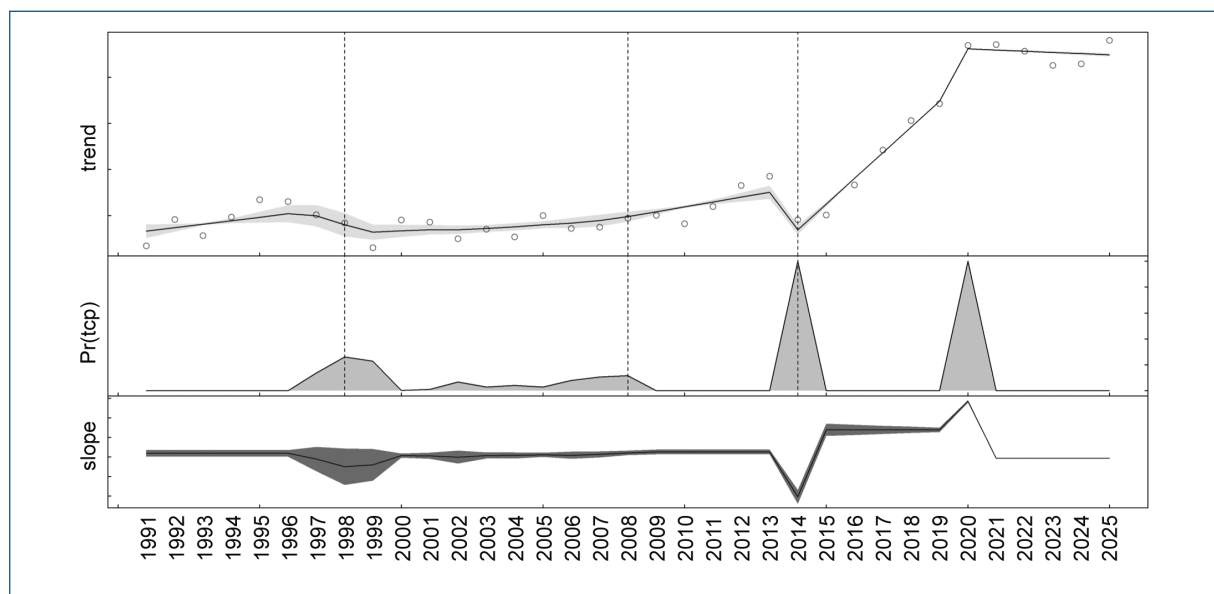
Stratification by Age

Among participants aged 16–24 years, three trend changepoints were observed (Figure 4). The posterior probability was 51.3%, indicating considerable uncertainty regarding the three-changepoint solution. The first and second segments were characterized by increasing trends, which became steeper over time. The third segment, covering the period from 2014 to 2020, exhibited an increasingly steep upward trend. The final segment, from 2020 to 2025, was characterized by a stable trend.

Among participants aged 25–34 years, three changepoints emerged, resulting in four segments with a probability of 96.9% (Figure 5). The first segment, from 1991 to 1998, displayed a slightly increasing trend, followed by a drop in scores. The second segment, from 1998 to 2014, was characterized by an increasing trend. The third segment, from 2014 to 2020, exhibited an increasingly steep upward trend, followed by a fourth segment characterized by a slightly decreasing trend.

Figure 4. Illustration of the Changepoints and Trends in Mental Health Scores among Participants Aged 16–24 Years

Note. Trend denotes the estimated trend; $\text{Pr}(\text{tcp})$ denotes the posterior probability of a trend changepoint; slope denotes the estimated trend slope. Vertical dashed lines indicate estimated changepoint locations.

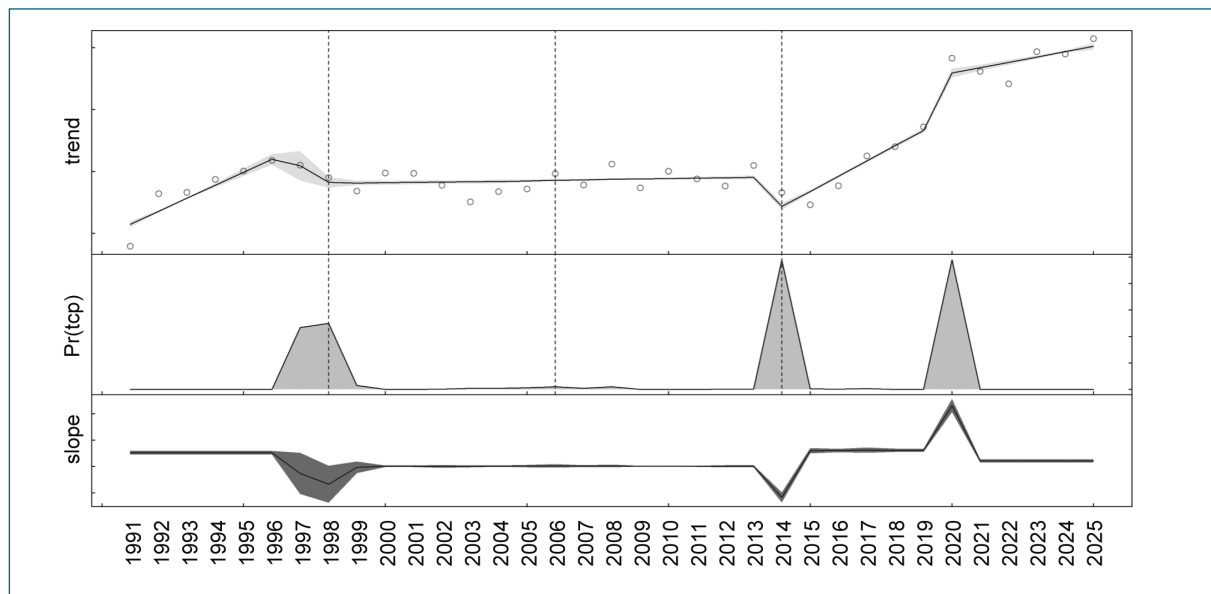
Figure 5. Illustration of the Changepoints and Trends in Mental Health Scores among Participants Aged 25–34 Years

Note. Trend denotes the estimated trend; $\text{Pr}(\text{tcp})$ denotes the posterior probability of a trend changepoint; slope denotes the estimated trend slope. Vertical dashed lines indicate estimated changepoint locations.

Among participants aged 35–64 years, there was a 92.2% probability that the trend component had three changepoints (Figure 6). While the first segment, from 1991 to 1998, was characterized by an increasing trend, the second segment, from 1998 to 2006, and the third segment, from 2006 to 2014, were relatively flat. The fourth segment was characterized by an increasingly steep upward trend.

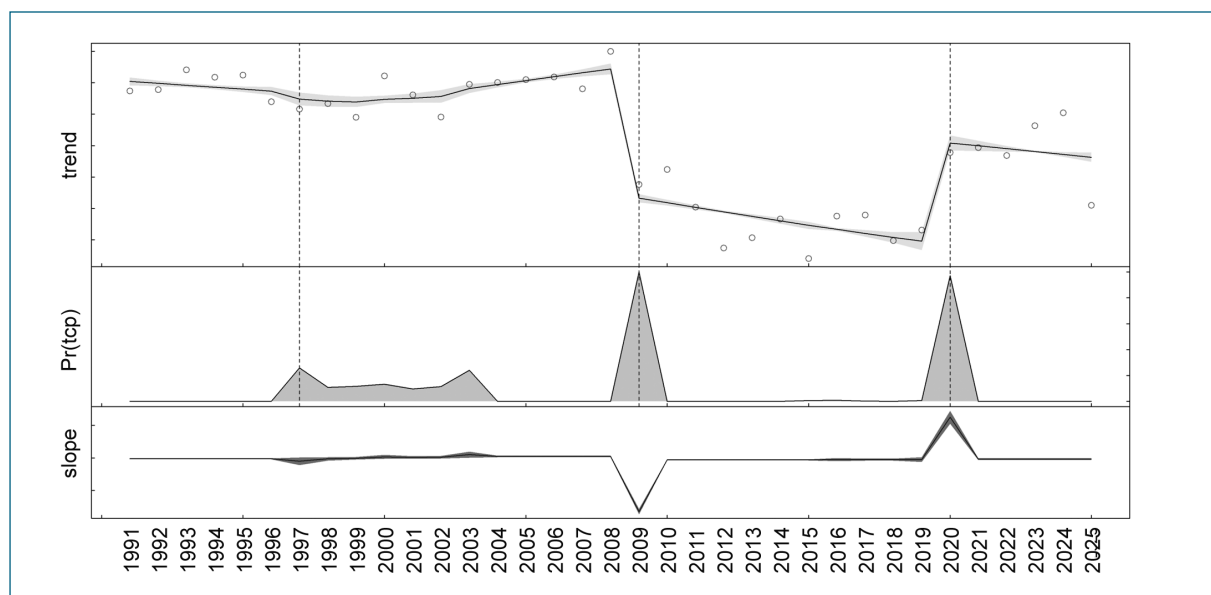
Finally, among participants aged 65 years or older, there was an 87.3% probability that the trend component had three changepoints (Figure 7). The first segment, from 1991 to 1997, was characterized by a gradual decreasing trend, followed by a second segment, from 1997 to 2009, which exhibited an increasing trend. The third segment, from 2009 to 2020, was characterized by a drop in mental health scores followed by a decreasing trend. The final segment was characterized by a slightly decreasing trend. In the age-stratified subgroup analyses, the probabilities associated with the estimated trend components were generally lower than the corresponding probability in the main sample, leaving some uncertainty.

Figure 6. Illustration of the Changepoints and Trends in Mental Health Scores among Participants Aged 35–64 Years



Note. Trend denotes the estimated trend; $\text{Pr}(\text{tcp})$ denotes the posterior probability of a trend changepoint; slope denotes the estimated trend slope. Vertical dashed lines indicate estimated changepoint locations.

Figure 7. Illustration of the Changepoints and Trends in Mental Health Scores among Participants Aged 65 Years or Older



Note. Trend denotes the estimated trend; $\text{Pr}(\text{tcp})$ denotes the posterior probability of a trend changepoint; slope denotes the estimated trend slope. Vertical dashed lines indicate estimated changepoint locations.

Robustness Analysis

A level and slope discontinuity latent growth model was used to estimate whether the three changepoints were associated with changes in mean scores, as well as with different growth patterns (i.e., slopes) before and after each changepoint. Compared with the estimated value at the first assessment, 10.69, the estimated mean differences at the three changepoints were 0.40 ($p < .001$), 0.30 ($p < .001$), and 1.36 ($p < .001$), respectively. The first slope before the first changepoint was estimated at 0.10, $p < .001$. The second and third slopes also significantly differed from zero and were estimated at 0.01, $p = .001$, and 0.12, $p < .001$, respectively. The fourth slope was not statistically significant, 0.00, $p = .978$, providing no evidence of a systematic linear change during this period. Thus, although the BEAST-fitted trend showed a slight upward trajectory after 2020, the discontinuity model

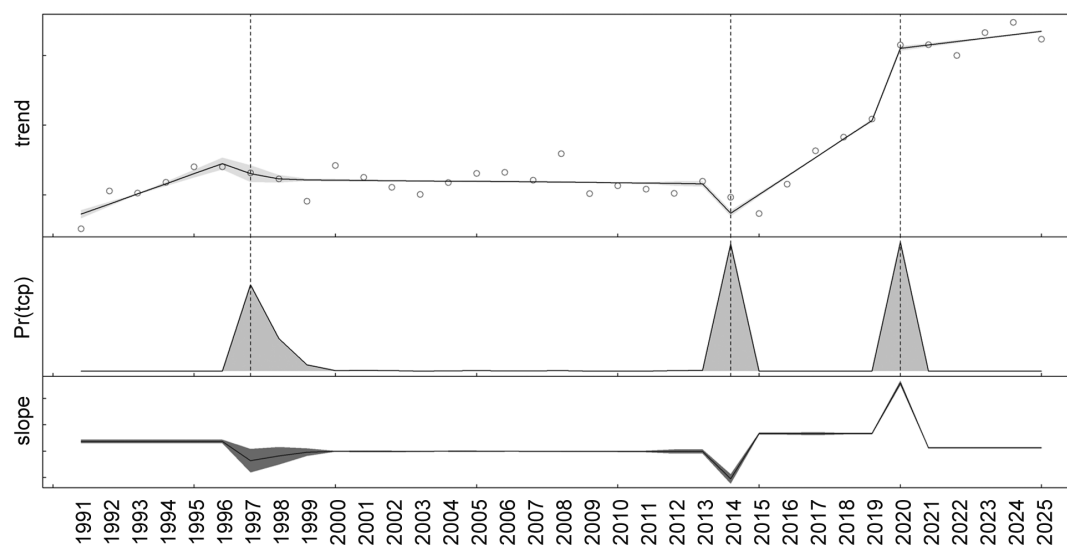
did not provide evidence that the post-2020 slope differed reliably from zero. The level and slope discontinuity latent growth model was also estimated after excluding the 2025 assessment. Relative to the estimated mean at the first assessment (10.69), the estimated mean-level changes at the first, second, and third changepoints were 0.40 ($p < .001$), 0.30 ($p < .001$), and 1.36 ($p < .001$), respectively. The slope preceding the first changepoint was positive and statistically significant (estimate = 0.10, $p < .001$). The slopes in the second and third segments also differed significantly from zero, with estimates of 0.01 ($p = .001$) and 0.12 ($p < .001$), respectively. Similarly, the slope in the final segment was not statistically significant (estimate = 0.00, $p = .904$), providing no evidence of systematic change during this period.

Sensitivity Analysis

As a sensitivity analysis, the main time-series analysis was repeated after item-level multiple imputation of missing GHQ-12 items. Figure 8 shows that the imputed annual GHQ series closely tracked the annual GHQ series obtained using available-case analysis. Repeating the time-series analysis using the multiply imputed GHQ estimates produced the same substantive conclusions, indicating that the results were robust to item-level missingness in GHQ responses.

A covariate-standardized sensitivity analysis was conducted to assess whether changes in measured sample or population composition could account for the observed GHQ time-series pattern. Covariate standardization altered annual GHQ estimates modestly. Across years, the mean absolute difference between the observed weighted annual GHQ mean and the covariate-standardized weighted mean was 0.53 points on the 0–36 GHQ scale, with a maximum absolute difference of 0.62 points. When changes from the 1991 baseline were compared, the mean absolute compositional component was 0.52 points, and the maximum was 1.03 points.

Figure 8. Illustration of the Changepoints and Trends in Mental Health Scores Using Multiple Imputation

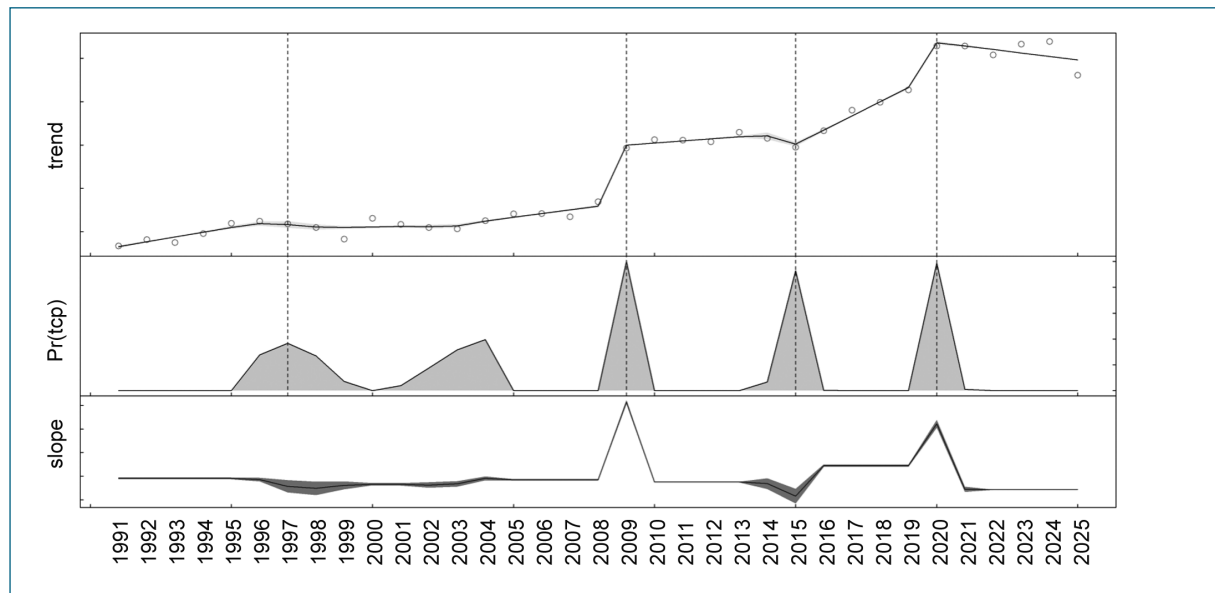


Note. Trend denotes the estimated trend; $\text{Pr}(\text{tcp})$ denotes the posterior probability of a trend changepoint; slope denotes the estimated trend slope. Vertical dashed lines indicate estimated changepoint locations.

In addition, the main temporal pattern was not materially altered after standardization for measured socio-demographic composition. The time-series analysis of the covariate-standardized GHQ series produced the same substantive findings as the analysis of the observed weighted series, including a changepoint around 2014 followed by an increasing trend until 2020 (Figure 9). The standardized series additionally identified a changepoint in 2009, which coincided with the transition from the BHPS to the UKHLS and may therefore reflect the panel transition rather than a substantive population change. The 2014–2020 increase was virtually identical in the two series: the observed weighted GHQ mean increased by 1.08 points, whereas the covariate-standardized mean increased by 1.06 points. The compositional component for this segment was only 0.02 points, indicating that

measured compositional change did not materially affect the post-2014 slope. Taken together, these results suggest that measured sociodemographic composition modestly influenced annual GHQ levels but did not account for the 2014 changepoint or materially alter the subsequent increase in GHQ scores. The post-2014 increase remained after measured composition was held constant.

Figure 9. Illustration of the Changepoints and Trends in Covariate-Standardized Mental Health Scores



Note. Trend denotes the estimated trend; $\text{Pr}(\text{tcp})$ denotes the posterior probability of a trend changepoint; slope denotes the estimated trend slope. Vertical dashed lines indicate estimated changepoint locations.

Discussion

The principal aim of the current study was to investigate mental health trends in the UK from 1991 to 2025. In the general population, three trend changepoints emerged. The trend and changepoint analyses revealed an initial period of increasing scores from 1991 to 1996, followed by a period of relatively stable mean scores from 1997 to 2013. This period was followed by an increasing trend that became markedly steeper around the onset of the COVID-19 pandemic. Thereafter, the BEAST-fitted trend remained slightly upward, but the complementary discontinuity analysis provided no evidence of a statistically detectable post-2020 slope.

Excluding the first years of the 1990s, the findings of the present study suggest that mental health symptoms in the UK population were fairly stable until the mid-2010s. It is noteworthy that the austerity policies following the Great Recession were not followed by immediate changes in GHQ scores or slopes in the general population. Although there is debate in the literature concerning mental health outcomes during economic recessions, most research has employed cross-sectional designs, which substantially limit causal inference (Frasquilho et al., 2016). Furthermore, the findings of the present study are in line with those of Katikireddi et al. (2012), who did not find a deterioration in population mental health in the first years after the 2008 economic crisis. Rather than suggesting a direct and short-term impact of the recession, the findings of the present study are more consistent with the possibility of an indirect and longer-term influence via austerity (Alexiou et al., 2021). Following the 2008 financial crisis, the UK government introduced measures to reduce public spending, which disproportionately affected local government services (Alexiou et al., 2021; McCartney et al., 2022). Therefore, the increasing trend starting around the mid-2010s may be consistent with the possible effects of cuts in central government funding for a wide range of services, including public health, housing, and social care. In addition, Wickham et al. (2020) found that the introduction of Universal Credit in 2013, a major UK welfare policy change, led to an increase in mental health symptoms among unemployed individuals affected by the policy. There is also evidence that measures such as minimum income schemes during macro-level crises, such as the COVID-19 pandemic, can have beneficial effects on mental well-being (Prati, 2025b).

The onset of the COVID-19 pandemic was accompanied by a clear increase in mental health symptoms. Nevertheless, the increase was small in magnitude, consistent with previous studies documenting a small, albeit statistically significant, impact of the COVID-19 pandemic on mental health in the European general population (e.g., Prati & Mancini, 2021, 2024). There is also some evidence, especially among male participants, of an increasing trend in mental health symptoms even before the COVID-19 pandemic (i.e., starting in the mid-2010s). This finding is consistent with evidence that deterioration in population psychological-distress indicators began before the COVID-19 pandemic (Zhang et al., 2023).

Austerity and the onset of the COVID-19 pandemic represent major contextual changes experienced by the population during the study period. However, these contextual factors should be understood as possible interpretations of the observed trends, not as causal conclusions established by the present analyses. It should also be noted that people aged 65 years or older did not show an increasing trend during the second half of the 2010s. Although participants aged 16–24 years reported fewer mental health symptoms in the earliest surveys, this age group showed a gradual increase in symptoms across successive surveys. This slow but continuous increase in mental health symptoms from the beginning of the survey was not observed in other age groups. This change among young adults may be consistent with evidence of secular changes in child and adolescent mental health problems (Collishaw, 2015). The rise of digital media and electronic communication may have affected mental health (Sharma et al., 2020; Twenge et al., 2019); however, the slow deterioration in mental health among young adults began well before the widespread diffusion of the Internet and social media. Moreover, there was no clear evidence that the trend changed following the advent of digital media and electronic communication. Although the rise of social media has influenced society and individuals, the debate over its effects is still ongoing (Sharma et al., 2020). The observed changepoint pattern does not provide obvious temporal support for a simple account in which the rise of digital media corresponds to a discrete change in population mental health. Other explanations therefore warrant consideration. A notable change in cultural values, including neoliberalism and competitive individualism, has occurred in the UK in recent decades and has coincided with an increase in multidimensional perfectionism among young people (Curran & Hill, 2019). Perfectionism has been implicated as a transdiagnostic risk and maintenance factor in psychopathology (Egan et al., 2011; Limburg et al., 2017). In addition, perfectionistic individuals are not only more likely to experience mental health problems but also more likely to hold stigmatizing attitudes toward mental health and, consequently, to be more reluctant to seek treatment for psychological difficulties (Shannon et al., 2018). Clearly, multifactorial models are needed to account for mental health trends. Changes in socioeconomic and cultural factors, such as inequality, consumerism, and individualistic values; family and extrafamilial life, such as changes in parenting norms and concerns about school performance; and individual vulnerabilities, such as declines in sleep duration and changes in personality traits, may all help explain mental health trends among younger people (Collishaw, 2015).

Strengths and Limitations

A major strength of the present study is its use of a large, nationally representative dataset spanning more than three decades, with repeated measurements of mental health using the same well-validated instrument and population-weighted annual estimates that allow long-term trends to be examined within a consistent measurement framework. The current study has some limitations that should be considered when interpreting the findings. First, the extent to which the findings are generalizable to other countries is difficult to ascertain. Research conducted in countries that experienced different impacts of the pandemic may yield different findings. Second, the potential for response biases, such as recall bias and social desirability bias, should be acknowledged. Third, the number of time points available for the time-series analysis was limited. There is no consensus regarding the minimum number of time points required for time-series analysis with a single unit. Nevertheless, the robustness of the results was supported by level and slope discontinuity latent growth models. Moreover, the large number of participants in the level and slope discontinuity latent growth models may partially compensate for the relatively small number of time points (Hecht & Zitzmann, 2021; Schultzberg & Muthén, 2018). Specifically, the sample size is consistent with the sample size recommendations provided by Hecht and Zitzmann (2021).

The use of the GHQ to measure mental health symptoms is also a limitation, as mental health is a multifaceted construct encompassing a wide range of disorders and symptoms. Because a continuous score was used, the findings of the current study refer to symptom severity and should not be interpreted as prevalence estimates, which would require a diagnostic measure. Although nonresponse could potentially explain changes in the observed

trends, analyses of nonresponse in *Understanding Society* did not provide evidence of changes in nonresponse indicators before and after the changepoints (Cabrera-Álvarez & Lynn, 2025).

The identified segments should not be regarded as definitive, as they are contingent on several factors, including the data used, the algorithm employed, and survey methodology. For instance, in the gender- and age-stratified subgroup analyses, the probabilities associated with the identified trend components were generally lower than the corresponding probability in the main sample, leaving some uncertainty. In addition, age, period, and cohort influences are difficult to fully disentangle in long-running population panel data; therefore, the observed trends should not be interpreted as unambiguous evidence of purely historical or societal effects.

Finally, the combination of BHPS and UKHLS data may have introduced a methodological artifact in some subgroup analyses. Although the current analysis cannot determine whether the observed changes in mental health are attributable to a methodological artifact, such as selection-bias mechanisms, or to contextual factors, three points should be highlighted. First, as a matter of caution, these changes were not presented as resulting from contextual factors. Second, a methodological artifact may explain a sudden drop; although the survey transition could plausibly generate a discontinuity, it is less clear whether it could account for slope changes emerging and persisting several years later. Nevertheless, this possibility cannot be completely excluded. The primary focus of the present study was not on isolated changes in mean scores, but on changepoints associated with durable changes in slopes across multiple years. Third, the main analysis involving the entire sample did not provide evidence of a changepoint occurring during the transition period.

Conclusion, Implications, and Future Directions

An accurate understanding of mental health trends is important for both theory and practice. Although the factors influencing these trends are complex and multifaceted, the findings indicate that after increasing during the first half of the 1990s, mental health symptom scores remained relatively stable from 1997 to 2013 before increasing again from the mid-2010s and rising particularly sharply around the onset of the COVID-19 pandemic. After 2020, scores remained elevated, but evidence for a further systematic increase was limited: the BEAST-fitted trend was slightly upward, whereas the discontinuity model did not detect a statistically significant slope during the final segment. Although these increases were small in magnitude, their timing coincided with major contextual changes.

These findings underscore the importance of monitoring population mental health over extended historical periods, as short-term changes may be difficult to interpret without a longer-term context. Future research should examine whether similar changepoint patterns emerge in other countries and should more explicitly disentangle age, period, and cohort influences. In addition, studies incorporating direct measures of candidate contextual mechanisms, such as economic conditions, welfare policies, digital-media exposure, and broader cultural change, are needed to determine which factors may account for the observed temporal shifts.

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Author contribution

Gabriele PRATI: conceptualization, design, methodology, investigation, project administration, data management, formal analysis, interpretation, supervision, writing—original draft; writing—review and editing.

Declaration of interest statement

The author has no relevant financial or non-financial interests to disclose.

Ethical statement

This manuscript is the author's original work.

All data collection for the Understanding Society main study was approved by the University of Essex Ethics Committee.

The University of Essex Ethics Committee has approved all data collection on Understanding Society main study and innovation panel waves, including obtaining consent for all data linkages except to health records. Requesting consent for health record linkage was approved at Wave 1 by the National Research Ethics Service (NRES) Oxfordshire REC A (08/H0604/124), at BHPS Wave 18 by the NRES Royal Free Hospital & Medical School (08/H0720/60) and at Wave 4 by NRES Southampton REC A (11/SC/0274). Approval for the collection of bio-social data by trained nurses in Waves 2 and 3 of the main survey was obtained from the National Research Ethics Service (Understanding Society – UK Household Longitudinal Study: A Biosocial Component, Oxfordshire A REC; Reference: 10/H0604/2).

Data availability statement

The data analyzed in this study were obtained from a third party, the University of Essex, Institute for Social and Economic Research, through the UK Data Service. Study materials are publicly available at <https://beta.ukdata-service.ac.uk/datacatalogue/studies/study?id=6614#!/documentation>.

Declaration on using artificial intelligence in research and manuscript preparation

The author acknowledges the use of ChatGPT 5.6 for manuscript drafting, editing, and formatting. All AI-generated suggestions were reviewed, revised, and approved by the author, who takes full responsibility for the accuracy and integrity of the work.

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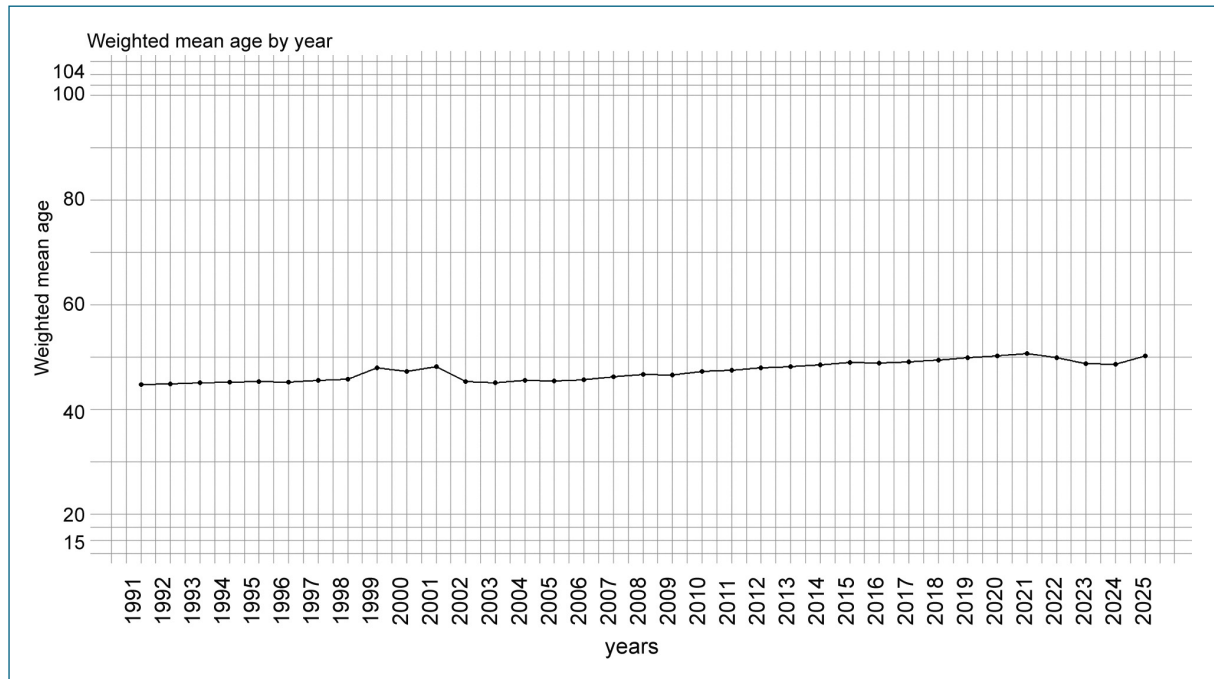
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Appendix

Appendix Figure 1.



Appendix

Appendix Figure 2.

