Trajectories of depressive symptoms and subjective well-being before and after the onset of the COVID-19 pandemic: Two six-year longitudinal studies

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ABSTRACT

Previous research investigated the trajectories of mental health and well-being during and after the onset of the COVID-19 pandemic. However, less is known about the trajectories of mental health and well-being before, during, and two years after the onset of the pandemic. The aim of the current study was to investigate the trajectory of depression symptoms and subjective well-being (i.e., life satisfaction and positive and negative affect) trajectories over six time points (2017–2022), three before the pandemic and three after the onset of the pandemic. To increase the robustness of our overall conclusions and avoid reliance on data from only one country, we used data from two nationwide representative longitudinal surveys conducted in Germany (GESIS Panel study; $N = 5184$) and Switzerland (Swiss Household Panel study; $N = 17,074$). Using covariance pattern mixture models, the results revealed that a four-class model best fit the data. The Stable/resilient trajectory was the most common across outcomes (74.2%–90.1% of participants). Three additional trajectories of Chronic/Low, Upright U-shaped, and Inverted U-shaped emerged in the analysis of negative affect and depression symptoms, while distinct trajectory classes of Worsening, Improving/Stable, and Upright U-shaped also emerged for analyses of positive affect and life satisfaction shaped. In conclusion, there was no evidence of a long-term impact of the pandemic for the vast majority of participants (about 90%). For the remaining participants, the COVID-19 pandemic (along with its exceptional circumstances) was a turning point or a catalyst that reversed, accelerated, or flattened a pre-pandemic trend. These changes in trends were not only negative (e.g., greater depression symptoms), but also positive (e.g., less depression symptoms).

1. Introduction

The COVID-19 pandemic was not only a health threat but impacted virtually all aspects of daily life, required adaptations to multiple challenges, and imposed social and economic costs from premature mortality, social isolation, financial losses, and unemployment (e.g., Li et al., 2023; Rathnayaka et al., 2023; Silva et al., 2023; Su et al., 2023). This complex array of stressors and exceptional conditions had psychological costs for the population. For instance, persistent forms of social disengagement and avoidance behavior have been reported in different countries after lockdowns were lifted (Prati and Mancini, 2023b). Systematic reviews and meta-analyses of longitudinal studies in the early phase of the pandemic identified a small but consistent deterioration of mental health in the general population (e.g., Prati and Mancini, 2021;

Witteveen et al., 2023). Moreover, there is also evidence of a small increase in happiness levels from before to after the onset of the pandemic, suggesting a rebound effect of relief that the pandemic is over (Prati and Mancini, 2023a).

The most common response pattern in studies conducted after the onset of the COVID-19 pandemic has been a resilient one of stable adaptive functioning (Bonanno et al., 2024; Bonanno et al., 2023). Specifically, a resilient trajectory was the most common pattern among samples from Israel (Kimhi et al., 2021; Shilton et al., 2023), the United States (Shilton et al., 2023), the Republic of Ireland (Hyland et al., 2021), the United Kingdom (Ellwardt and Präg, 2021; Shevlin et al., 2023), France (Pellerin et al., 2022), Poland (Gambin et al., 2023), Argentina (Fernández et al., 2022), China (Chen et al., 2022), and Germany (Ahrens et al., 2021). (PTE). A recent review of 28 studies on

mental distress trajectories during COVID-19 (Schäfer et al., 2022) further confirmed that resilience was the prevailing response with a prevalence estimated at 66%. In addition, consistent with the idea of heterogeneity (Mancini, 2020), this review found evidence of other prototypical outcome trajectories (e.g., Bonanno, 2004; Bonanno et al., 2024). These included patterns of recovery (estimated at 13%), chronicity (estimated at 11%), delayed onset (estimated at 12%), and moderate-mild persistent distress (estimated at 27%). Compared to trajectory studies following major life stressors and potential trauma (Galatzer-Levy et al., 2018), the moderate–mild persistent distress and the chronicity trajectories were more prevalent, and the recovery trajectory was less prevalent in studies during COVID-19 pandemic (Schäfer et al., 2022). According to Bonanno et al. (2024), the differences in findings might be due to the longer duration of the pandemic. However, the prevalence of the resilient trajectory largely accorded with prior estimates of the impact of major life stress and potential trauma (Bonanno et al., 2011; Mancini and Bonanno, 2009).

These studies have provided crucial insight into patterns of adaptation during the pandemic, but they are largely based on post-pandemic research designs. This is problematic for several reasons. In the absence of a pre-pandemic assessment, for example, it is not possible to distinguish a pattern of continuous pre- and post-pandemic distress from a pattern of increased distress due to the pandemic onset. Similarly, a pattern of improved functioning due to the onset of the pandemic cannot be distinguished from a resilient pattern of continuous adaptive functioning (Mancini, 2019; Mancini et al., 2024; Prati and Mancini, 2023a). Finally, post-pandemic designs have weaker internal validity, and pre- and post-pandemic approaches are far better suited to establish the overall population-level effects of the pandemic (Shadish et al., 2002). Nevertheless, relatively few trajectory studies have investigated pre- and post-pandemic trajectories. Ellwardt and Präg (2021) identified four different trajectories of distress: Continuously low, repeatedly elevated, temporarily elevated, and continuously elevated distress. Two trajectories (i.e., continuously low and repeatedly elevated) included the vast majority of the participants (77%) and were relatively unaffected by the first year of the pandemic. While the continuously low trajectory continued to be unaffected until 2021 (the last assessment point), the likelihood of psychological distress in the repeatedly elevated trajectory tended to peak in the third lockdown (i.e., January 2021). In another study on pre- and post-pandemic trajectories in France, Lu et al. (2022) found three trajectory classes for depressive symptoms (consistently low, 56.1%; consistently very low, 34.6%; increasing and clinically significant at the second lockdown, 9.3%) and two distinct classes for anxiety symptoms (no pre-pandemic anxiety, slightly increase, 58.9%; consistently fair, 41.1%). Three of these trajectories (i.e., consistently very low, consistently low, and consistently fair) did not seem to be affected by the pandemic. Finally, in their analysis of the impact of the COVID-19 pandemic on the mental health of middle-aged and older Canadian adults, Raina et al. (2021) found three depressive symptom trajectories: High-increasing (8.0%), moderate-increasing (35.5%), and low-consistent (56.6%). The low-consistent trajectory indicated most participants were unaffected by the pandemic. Taken together, these findings suggest that most people experienced modest to no psychological consequences of the pandemic, even among those who reported less than optimal mental health. A more robust assessment of pre-pandemic functioning can help to establish the degree of impact of the pandemic.

1.1. Purpose of the present study

In the present study, we investigated trajectories of well-being and depression among two representative samples of Swiss and German participants. Switzerland and Germany were epicenters of the pandemic, both in the early acute phase (Jamshidi et al., 2023) and again in late 2021 (WHO, 2021). Both Switzerland and Germany are federal states, and therefore, COVID-19 response measures partly belonged to the cantons (Switzerland) and the Länder (Germany). Notwithstanding, in both countries, the most important COVID-19 response measures were decided at the federal level. Lockdown measures have been imposed around mid-March 2020 and lifted gradually since the end of April 2020. Policy measures in both Germany and Switzerland were comparable and comprised national closures of borders, schools, cafes, bars, restaurants, and non-essential shops. Compared to most European countries, general curfews were not implemented (Zimmermann et al., 2022). Switzerland and Germany experienced comparably more favorable health outcomes (e.g., mortality and case fatality rates) than those in the rest of Europe (Desson et al., 2020). Switzerland and Germany opened around the time fatalities started to decline and their speed of reopening was faster compared to most European countries (Desson et al., 2020). In contrast to other European countries, Switzerland and Germany relied on solidarity and personal responsibility to comply with policy measures (Zimmermann et al., 2022).

We examined longitudinal changes in depression, life satisfaction, positive affect, and negative affect over six waves of data collection in the pre-pandemic period until 2022. We used covariance pattern mixture models (CPMMs) to identify distinct patterns of change over time. Compared to latent class growth models and growth mixture models, CPMMs result in improved convergence rates and class enumeration and less biased class-specific growth trajectories (McNeish and Harring, 2020; McNeish et al., 2023).

We included age and income as covariates in the models. Younger age and lost or lower income have both been found to be associated with more elevated patterns of distress and thus a lower likelihood of resilience during the pandemic (Ellwardt and Präg, 2021; Shilton et al., 2023). Thus, they can help both to specify the patterns and to provide support for their validity (Muthén, 2003). Because variation in outcomes would be expected, we sought to identify distinct and heterogeneous trajectories over time. Although we expected to identify a subset of participants who experienced worse functioning after the onset of the pandemic, as well as participants with sub-optimal functioning who were unaffected by the pandemic, we also expected a majority of participants to report minimal change from the pre-to post-pandemic assessments, a pattern of response consistent with psychological resilience. The use of pre-pandemic data is needed to understand whether trajectories were affected by the onset of the pandemic.

2. Method

2.1. Sample and procedure

We used data from two sources: the GESIS Panel study (Bosnjak et al., 2018; GESIS, 2023) and the Swiss Household Panel study (Tillmann et al., 2018). These studies are nationwide representative longitudinal surveys conducted in Germany (i.e., GESIS Panel study) and Switzerland (i.e., Swiss Household Panel study). Both studies have been running annually. Informed consent was obtained from each participant and the study complied with ethical standards. See Bosnjak et al. (2018) and Tillmann et al. (2022) for detailed information on the data collection, sampling methodology, compliance with ethical standards, and response rate of these two surveys. The representativeness of both the GESIS Panel study and the Swiss Household Panel study has been demonstrated in previous research (Bosnjak et al., 2018; Tillmann et al., 2016).

In the current study, we selected data for the period starting from 2017 to 2022 to ensure an adequate longitudinal assessment of pre-pandemic functioning and sufficient statistical power. Six time points are appropriate when the turning point is at the third or fourth time point (Diallo and Morin, 2015; Moerbeek, 2022). Data on depression in the GESIS Panel study has been assessed every year in February–March until 2020 and in February–April since 2021. Data collection in the Swiss Household Panel has been conducted annually from September to

February.

All available data from both the Swiss Household Panel study and the GESIS Panel study were used. Data for depression symptoms were taken from the GESIS Panel study, while data for life satisfaction, positive affect, and negative affect were taken from the Swiss Household Panel study. The sample size for depression symptoms (GESIS Panel study) was 5184, for life satisfaction (Swiss Household Panel study) was 17069, for positive affect (Swiss Household Panel study) was 17073, and for negative affect (Swiss Household Panel study) was 17074. Table 1 displays the demographic characteristics of participants.

Among the participants of the first wave (2017) of the Swiss Household Panel, 89% participated in the second wave, 80% in the third wave, 74% in the fourth wave, 68% in the fifth wave, and 62% in the sixth wave. Among the participants of the first wave (2017) of the GESIS Panel study, 88% participated in the second wave, 82% in the third wave, 77% in the fourth wave, 74% in the fifth wave, and 70% in the sixth wave. Drop-out analysis (Table S1) revealed no meaningful differences in study variables. Specifically, according to the interpretation grids proposed by Cohen (1992), the effect size of the differences was very small and, therefore, negligible.

2.2. Measures

To assess *depression symptoms*, we used the eight-item Centre for Epidemiologic Studies Depression Scale (CES-D-8; Schlechter et al., 2022). Participants were asked to report their experience of depressive symptoms on a six-point scale ranging from $1 = never$ to $6 = always$. Item-level missingness was very low. Specifically, the percentage of item nonresponse was lower or equal to 0.7%. Given the very small amounts of missing data, available-case maximum likelihood was used as the technique for dealing with item-level missing data (Chen et al., 2020; Parent, 2013). Scale reliability was satisfactory across waves ($\alpha = .86$–0.88). After accounting for the reverse-scored items, we computed a mean score with high scores indicating high levels of depression symptoms.

Table 1
Demographic characteristics of the participants in the GESIS Panel study and the Swiss Household Panel study.

Variable	M	SD	N	%	Census data 2022
Swiss Household Panel study					
Age	49.43	19.33			44.6
Gender (Female)			7205	51.7%	50.3%
Yearly total personal income, net (CHF)	61292.30	57834.97			
Years of Education (ISCED Classification)	11.94	4.93			
Employed			6612	47.5%	53.3%
GESIS Panel study					
Age	53.54	14.45			44.6
Gender (Female)			2102	50.4%	50.7%
Monthly net income (€)	3702.20	1250.20			
Education					
Polytechnic secondary school			472	11.3%	
Lower secondary school			670	16.1%	
Secondary school			938	22.5%	
Advanced technical college			530	12.7%	
Degree from a university			1507	36.1%	
Other			53	1.3%	
Employed			2778	67.33	54.0%

Note. Census data for Germany were provided by Statistisches Bundesamt (www.destatis.de/), while Census data for Switzerland were provided by Federal Statistical Office (https://www.bfs.admin.ch/bfs/en/home.html).

Life satisfaction was assessed by asking participants to rate how satisfied they were with their lives in general on an eleven-point scale ranging from $0 = not\ at\ all\ satisfied$ and $10 = completely\ satisfied$. We assessed *positive* and *negative affect* by asking participants to report the frequency of experiencing four items representing four markers of *negative* (i.e., depression, blues, anxiety; anger; sadness; and worry) and two items representing two markers (i.e., joy; plenty of strength, energy, and optimism) of *positive affect* (Ryser and Wernli, 2017).[1] An eleven-point scale ranging from $0 = never$ to $10 = always$ was used. The items measuring positive and negative affect were adapted from the positive and negative feelings subscales of the World Health Organization Quality of Life Survey (WHOQOL-100; The Whoqol Group, 1998). The use of a single question to measure life satisfaction is widely accepted in the subjective well-being literature (e.g., Raudenská, 2023) and its validity is similar compared to the use of multiple-item (Cheung and Lucas, 2014; Jovanović and Lazić, 2020). Specifically, Cheung and Lucas (2014) found that a single-item measure of life satisfaction demonstrated a substantial degree of criterion validity with the Satisfaction with Life Scale (SWLS) and that single-item measures did produce similar correlations with theoretically relevant variables compared to the SWLS. Jovanović and Lazić (2020) provided evidence of validity (e.g., convergent and criterion-related validity) and test-retest reliability of both the single-item measure of life satisfaction and the SWLS. Finally, the validity and reliability of the positive and negative affect scales as well as the single question to measure life satisfaction used in the current study was examined and demonstrated (Gondek et al., 2024). In the current study, the correlation coefficients between the two items of positive affect ranged from 0.40 to 0.43 across waves. The percentage of item nonresponse was lower or equal to 0.3%. As the technique for dealing with item-level missing data, available-case maximum likelihood was used (Chen et al., 2020; Parent, 2013). We calculated a mean score for negative affect and positive affect, with a high score indicating a greater frequency of experiencing positive and negative affect. The correlation coefficients between the two items of positive affect ranged from 0.40 to 0.43 across waves. Cronbach's alphas for the negative affect scale ranged from 0.76 to 0.78 across waves.

2.3. Analytic strategy

Mplus 8.11 was used for data analysis. As estimator, we chose MLR (maximum likelihood) parameter estimates with standard errors and a chi-square test statistic (that are robust to non-normality). Missing data were handled using a full information approach. We first analyzed the overall patterns of change before and after the onset of the pandemic in depression symptoms, life satisfaction, and positive and negative affect. To this end, we estimated the average growth trajectory from the level and slope discontinuity latent growth model with the knot estimated like an intercept centered using a common 0 loading for the two slopes for the year 2020 assessment (Rioux et al., 2021). Then, to identify trajectories, we fit covariance pattern mixture models (CPMMs). CPMMs result in improved convergence rates and class enumeration and less biased class-specific growth trajectories (McNeish and Harring, 2020; McNeish et al., 2023). In the selection of the model, theoretical coherence, interpretability, and model parsimony were taken into account, as well as commonly used information criteria (Nylund-Gibson and Choi, 2018), such as Bayesian Information Criterion (BIC), sample size adjusted BIC (SABIC), consistent AIC (CAIC), and Approximate Weight of Evidence Criterion (AWE). Entropy was used for evaluating how well the classes were differentiated. Age and income were added as predictors of the trajectories (i.e., covariates) to help specify the model and identify the proper number of classes (Muthén, 2003).

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[1] In response to an anonymous Reviewer's comment "Do you mean to say that different markers of negative and positive affect were assessed at different timepoints?", the authors state that the same items were used in each timepoint.

3. Results

3.1. Overall patterns of change

A preliminary analysis was conducted to examine the overall patterns of change for the population. Fig. 1 shows the overall patterns of change for all study variables. The growth factor means for depression symptoms were not significantly different from zero for the first slope (pre-pandemic), coefficient = −0.01 ($SE = 0.01$, $p = .059$), while they were significantly different from zero for the event level (pandemic onset), coefficient = −0.02 ($SE = 0.01$, $p = .003$), and for the second slope (post-pandemic), coefficient = 0.05 ($SE = 0.01$, $p < .001$). Also, the growth factor means for negative affect were not significantly different from zero for the first slope, coefficient = 0.01 ($SE = 0.01$, $p = .176$), while were significantly different from zero for the event level (pandemic onset), coefficient = 0.04 ($SE = 0.01$, $p < .001$), and for the second slope (post-pandemic), coefficient = 0.03 ($SE = 0.01$, $p < .001$). These findings indicate that the average level of depression symptoms and negative affect did not change before the pandemic, but slightly increased after the onset of the pandemic. Moreover, depression symptoms increased at the pandemic onset, while negative affect decreased for the same period. The growth factor means for life satisfaction were significantly different from zero for the first slope, coefficient = −0.02 ($SE = 0.01$, $p = .012$) and the second slope, coefficient = −0.07 ($SE = 0.01$, $p < .001$), but not for the event level, coefficient = −0.05 ($SE = 0.01$, $p = .053$). These results indicate that the average level of life satisfaction slightly decreased both before and after the onset of the pandemic, but not at the onset of the pandemic. The growth factor means for positive affect were significantly different from zero for the first slope, coefficient = −0.03 ($SE = 0.01$, $p < .001$), for the event level, coefficient = −0.08 ($SE = 0.01$, $p < .001$), and for the second slope, coefficient = −0.06 ($SE = 0.01$, $p < .001$). These findings indicate that the average level of positive affect slightly decreased before, at the onset, and after the onset of the pandemic.

3.2. Trajectories of depression symptoms

We next tested one to four class solutions for depression symptoms (Table 2). The four-class solution yielded an increased fit in all indices and was theoretically interpretable. Therefore, it was selected as optimal. The entropy was 0.80. The average posterior probabilities of each class can be found in Table S2 (supplemental material).

Table 2
Fit indices for mixture models.

Classes	BIC	SABIC	AWE	CIAC	Entropy
Depression					
1	41,944	41,881	42,175.26	41964.20	–
2	41,820	41,757	42,051.13	41840.06	0.69
3	41,661	41,579	41,961.83	41687.44	0.76
4	41,486	41,384	41,855.31	41517.60	0.80
Life satisfaction					
1	191,464	191,401	191,719.10	191484.2	–
2	189,654	189,591	189,908.97	189674.1	0.94
3	187,953	187,871	188,284.52	187979.1	0.90
4	186,946	186,844	187,353.50	186977.7	0.88
Positive affect					
1	187,964	187,901	188,219.38	187984.5	–
2	186,682	186,619	186,937.26	186702.4	0.85
3	185,766	185,684	186,097.60	185792.2	0.82
4	185,188	185,086	185,596.03	185220.2	0.80
Negative affect					
1	204,759	204,696	205,014.15	204779.2	–
2	203,689	203,625	203,943.80	203708.9	0.66
3	203,098	203,015	203,429.29	203123.9	0.68
4	202,514	202,412	202,921.51	202545.7	0.72

Trajectories of depression symptoms for the 4-class solution are shown in Fig. 2. The predominant response pattern was a Stable/resilient trajectory (82.9%) characterized by low levels of depression symptoms throughout the six years. The Stable/resilient class was characterized by a low intercept ($b = 2.50$, $p < .001$), a significant linear slope ($b = −0.02$, $p = .021$), and a significant quadratic slope ($b = 0.01$, $p < .001$). In addition to a resilient class, a smaller subset of participants revealed a Chronic/low functioning pattern (12.1%). This class was characterized by a high intercept ($b = 3.61$, $p < .001$), a flat, non-significant linear slope ($b = 0.08$, $p = .070$), and a non-significant quadratic slope ($b = 0.01$, $p = .078$). The Upright U-shaped class (3.1%) was characterized by a relatively high intercept ($b = 3.28$, $p < .001$), a significant linear slope ($b = 0.63$, $p = .002$), and a significant quadratic slope ($b = 0.16$, $p < .001$). Finally, the Inverted U-shaped class (1.9%) was characterized by a low intercept ($b = 2.51$, $p < .001$), a significant linear slope ($b = 1.10$, $p < .001$), and a significant quadratic slope ($b = 0.22$, $p < .001$).

To compare the scores obtained using this version of the 8-item CESD with that measured on a scale from 0 to 3, we should take into account the different response options. Considering that the first two response
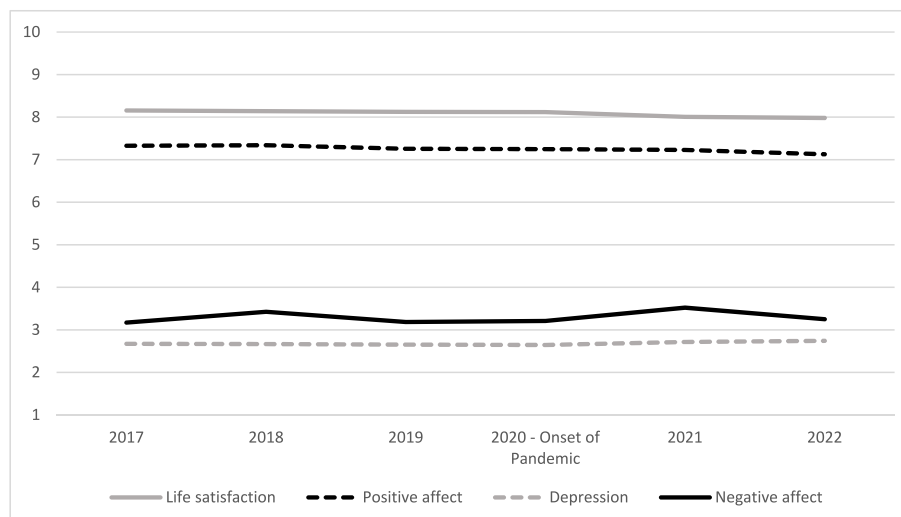
Overall Patterns of Change

Fig. 1. Overall patterns of change.
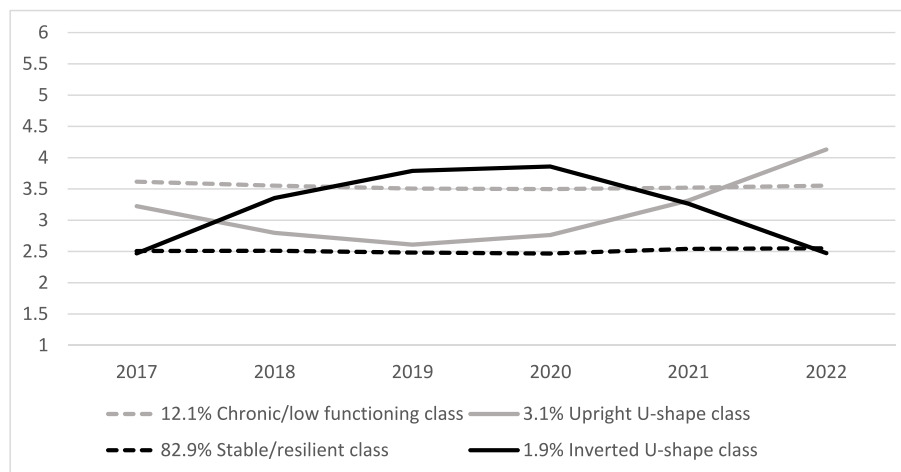
Depression Trajectories by Class

Fig. 2. Depression trajectories by class.

options of this version of the 8-item CESD correspond to the first response option (i.e., Rarely or none of the time) of the CESD measured on a scale from 0 to 3 and using the proportion of maximum scaling transformations (Little, 2013), the cut-off of 9 would correspond to a score of 3.5. however, the validity of this transformation is limited, and results interpretation needs to be cautious.

3.3. Trajectories of life satisfaction

Among the one to four class solutions of life satisfaction (Table 2), the four-class solution was chosen because of a better fit in all indices and theoretical interpretability. The entropy was 0.88. Trajectories of life satisfaction for the 4-class solution are shown in Fig. 3. Again, the largest class was a Stable/resilient trajectory (90.1%) characterized by high levels of life satisfaction throughout the six years. The Stable/resilient class was characterized by a high intercept ($b = 8.35, p < .001$), a significant linear slope ($b = -0.02, p = .003$), and a non-significant quadratic slope ($b = 0.00, p = .818$). The Worsening class (4.0%) was characterized by a relatively high intercept ($b = 7.71, p < .001$), a significant linear slope ($b = 0.56, p < .001$), and a significant quadratic slope ($b = 0.25, p < .001$). The Improved/stable class (3.3%) was characterized by a relatively low intercept ($b = 4.55, p < .001$), a significant linear slope ($b = 1.47, p < .001$), and a significant quadratic

slope ($b = -0.20, p < .001$). Finally, the Upright U-shaped class (2.5%) was characterized by a relatively high intercept ($b = 7.22, p < .001$), a significant linear slope ($b = 2.32, p < .001$), and a significant quadratic slope ($b = 0.43, p < .001$). Stable/resilient class Improving/stable class Worsening class.

3.4. Trajectories of positive affect

Again, the four-class solution was chosen because of a better fit in all indices compared to the other classes and theoretical interpretability (Table 2). Moreover, entropy was 0.80. Trajectories of life satisfaction for the 4-class solution are shown in Fig. 4. The most prevalent class was a Stable/resilient trajectory (86.0%) characterized by high levels of positive affect for all the 6-year period. The Stable/resilient class was characterized by a high intercept ($b = 7.52, p < .001$), significant linear slope ($b = -0.06, p < .001$), and quadratic slope ($b = 0.01, p = .001$). The Worsening class (5.6%) was characterized by a high intercept ($b = 7.28, p < .001$), a significant linear slope ($b = 0.53, p < .001$), and a non-significant quadratic slope ($b = 0.22, p < .001$). The Improving/stable class (4.7%) was characterized by a relatively low intercept ($b = 4.76, p < .001$), a significant linear slope ($b = 1.40, p < .001$), and a significant quadratic slope ($b = -0.20, p < .001$). Finally, the Upright U-shaped class (3.7%) was characterized by a relatively high intercept ($b = 6.72, p <$
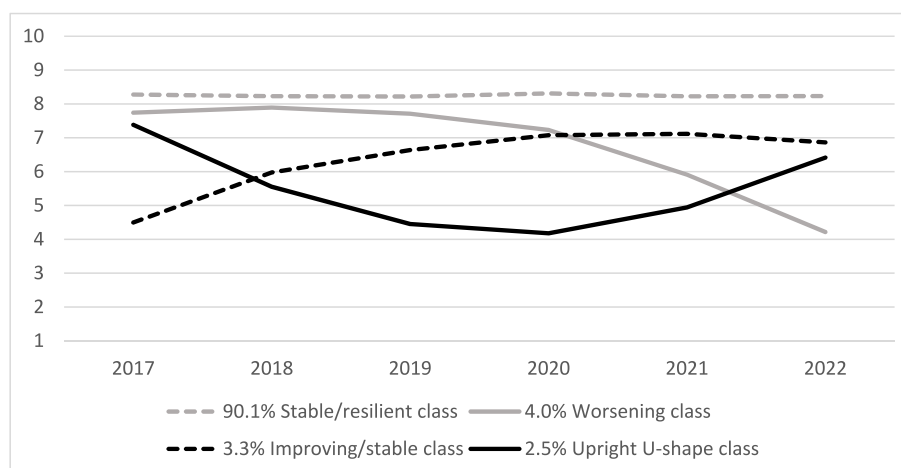
Life Satisfaction Trajectories by Class

Fig. 3. Life satisfaction trajectories by class.
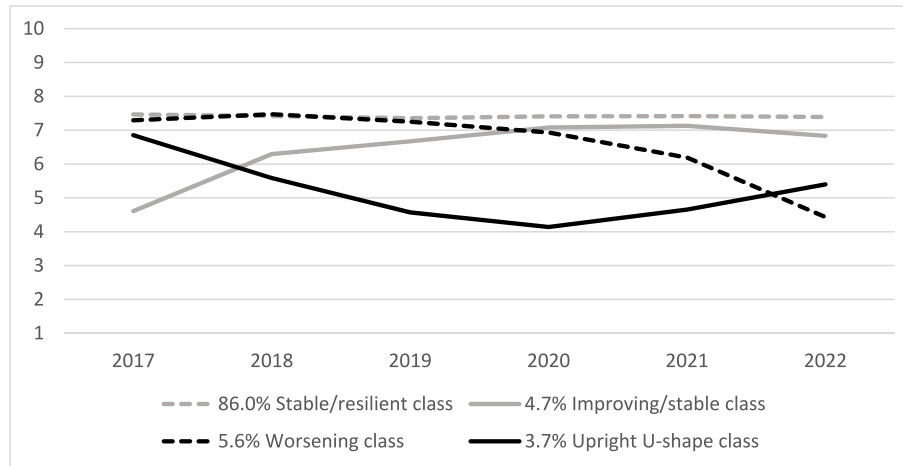
Positive Affect Trajectories by Class

Fig. 4. Positive affect trajectories by class.

.001), a non-significant linear slope ($b = 1.70$, $p = .105$), and quadratic slope ($b = 0.29$, $p = .144$).

3.5. Trajectories of negative affect

We fitted one to four class solutions of negative affect (Table 2). The four-class solution was selected because of its higher fit in all indices and theoretical interpretability. Moreover, entropy was highest for the four-class solution compared to the other classes. Trajectories of negative affect for the 4-class solution are shown in Fig. 5. The largest class was a Stable/resilient trajectory (74.0%) characterized by low levels of negative affect throughout the six years. The Stable/resilient class was characterized by a low intercept ($b = 2.68$, $p < .001$), a significant linear slope ($b = 0.05$, $p = .016$), and a significant quadratic slope ($b = -0.01$, $p < .001$). The Chronic/low functioning class (16.6%) was characterized by a high intercept ($b = 5.11$, $p < .001$), a flat, non-significant linear slope ($b = 0.02$, $p = .747$), and a non-significant quadratic slope ($b = 0.00$, $p = .813$). The Upright U-shaped class (5.6%) was characterized by a medium intercept ($b = 3.90$, $p < .001$), a significant linear slope ($b = -1.05$, $p = .016$), and a significant quadratic slope ($b = 0.28$, $p < .001$). Finally, the Inverted U-shaped class (3.8%) was characterized by a relatively low intercept ($b = 3.04$, $p < .001$), a significant linear slope ($b = -2.05$, $p < .001$), and a significant quadratic slope ($b = -0.42$, $p < $

.001).

4. Discussion

The main aim of the current study was to investigate depression symptoms and subjective well-being trajectories before and after the onset of the COVID-19 pandemic over six time points (2017–2022). The results revealed that about 90% of participants were unaffected by the pandemic in the long-term. These results are corroborated by the analysis of the average growth trajectories (i.e., the level and slope discontinuity latent growth model) which documented only small changes before, at the onset, and after the onset of the pandemic. This finding is in line with previous research documenting a limited impact of the pandemic on mental health and well-being (e.g., Prati and Mancini, 2021; Witteveen et al., 2023). However, the fact that 90% of participants were essentially unaffected by the pandemic does not mean that all of these participants would be considered resilient. A Stable/resilient trajectory of flat and relatively high levels of mental health/well-being across the six years comprised 74%–90% of the participants across samples, consistent with the notion that resilience is the most prevalent trajectory (Bonanno et al., 2011; Mancini and Bonanno, 2009). However, in addition to a Stable/resilient trajectory, we also found a low-functioning but stable trajectory (chronic) that is composed of
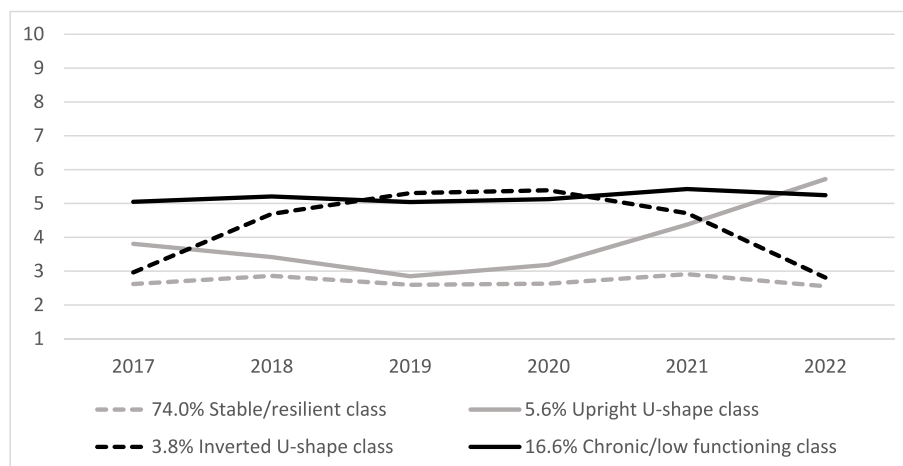
Negative Affect Trajectories by Class

Fig. 5. Negative affect trajectories by class.

individuals who were also relatively unaffected by the pandemic. In the absence of pre-pandemic data, such participants might be assumed to have been substantially affected by the pandemic. Instead, our findings clearly indicate that their low functioning preceded the pandemic onset. This trajectory underscores the possibility that the impact of the pandemic on mental health and well-being can be overestimated when there are no pre-pandemic assessments.

We note that the Chronic/low functioning trajectory was only found for depression symptoms and negative affect. When using these measures, we found that the vast majority of participants (95% for depression symptoms and 90% for negative affect) were not affected by the pandemic in the long-term. For the remaining participants, the pandemic was a life event (or series of events) that disrupted their pre-pandemic trend and catalyzed a change in an opposite direction in the form of two U-shaped trajectories. Participants exhibiting an Upright U-shaped trajectory were experiencing a decline in depression symptoms and negative affect during the pandemic period. However, the COVID-19 pandemic onset was associated with a rebound in depression symptoms and negative affect. Consistent with diathesis-stress models (Zuckerman, 1999), such rebound and consequent increase in depressive symptoms and negative affect may be the result of an interaction between a vulnerability and the stress caused by the pandemic. Participants exhibiting an Inverted U-shaped trajectory, on the contrary, were experiencing an increase in depressive symptoms and negative affect before the pandemic and such a trend was reversed after its onset. Such a rebound effect suggests that, contrary to a stress process perspective, the onset of the pandemic acted as a positive catalyst for psychological functioning. This positive catalyst perspective is consistent with models of the positive consequences after stressful events (Mancini, 2019; Tedeschi and Calhoun, 2006) and with studies documenting an increase in well-being following the pandemic (Mancini et al., 2024; Prati and Mancini, 2021, 2023a). We note that the starting points of the two trajectories were different: the Inverted U-shaped class was characterized by lower levels of depression symptoms and negative affect, while higher scores on depression symptoms and negative affect were found in the Upright U-shaped class.

While the Upright U-shaped trajectory was also found with respect to life satisfaction and positive affect, the Inverted U-shaped was not. Worsening and Improving/stable trajectories characterized the patterns of life satisfaction and positive affect. The Worsening trajectory indicates that the COVID-19 pandemic acted as a catalyst in affecting a (pre-pandemic) decreasing trajectory. In other words, the pandemic affected their rate of change. On the contrary, the Improving/stable trajectory reveals that the COVID-19 pandemic flattened a pre-pandemic trend.

Our findings have implications for public health efforts during a pandemic. Given that public health interventions should be prioritized to those who are affected by the pandemic, the current study provides a realistic estimate of people most likely to be harmed by the pandemic. Moreover, our findings have implications for evidence-based public health communication efforts in future global emergencies. Alarming messages such as a 'tsunami' of mental disorders caused by the COVID-19 pandemic may not only lack a sound scientific basis, but also be counterproductive (e.g., potentially capable of generating useless fears in the population).

Among the potential limitations of our study, participants from this study were from a specific region (Central Europe) and the generalizability of the study findings to other countries and cultures is limited. It should be noted that the findings were coherent among the two countries. However, the extent to which the findings are generalizable to other cultures is unknown. For this reason, replication of trajectory patterns is imperative. Another limitation was the use of a one-item scale to measure life satisfaction and a two-item scale to assess positive affect. In addition, the data may be affected by response biases such as social desirability. Given that previous research demonstrated that response biases do not significantly affect the investigation of the relationship

between life events and psychological symptoms (Lakey and Heller, 1985), we believe that the impact of response bias on the findings is limited. An additional limitation was that the analysis of data with missing values implicitly assumed that data were missing at random (MAR). However, the MAR assumption cannot be empirically tested from the observed data (Little, 2021). To make the MAR assumption more plausible, the current study used auxiliary variables (i.e., age and income) in the analysis (Enders, 2008). Finally, the current study was based on yearly assessments and, therefore, is silent about the impact of the pandemic on shorter time scales of weeks or months after the pandemic onset. Different findings may be obtained when examining the impact of the pandemic days, weeks, or months after the pandemic onset.

5. Conclusion

The key finding of this study was that about 90% (and up to 95% for depression symptoms) of participants exhibited trajectories that were not affected by the COVID-19 pandemic in the long term. In addition, the findings contribute to the existing body of knowledge by showing that the prototypical patterns following exposure to potentially traumatic events (e.g., Bonanno, 2004; Bonanno et al., 2024; Bonanno et al., 2023; Galatzer-Levy et al., 2018) were not found when examining the long-term consequences of the pandemic and by taking into account pre-pandemic trends. This does not mean that people did not report negative consequences as a result of the pandemic. It is possible that within a shorter time span, we can find some of the prototypical patterns. However, their duration is likely to be transient and to subside relatively quickly. For instance, in the study of Shilton et al. (2023), the trajectories of the recovery and delayed onset seem to suggest a return to previous levels in the long run. Therefore, it is possible that after one year, people tended to return to their baseline levels. Based on these results, we argue that the COVID-19 pandemic can be considered in all respects a potentially traumatic event at the population level. Of course, in the context of the COVID-19 pandemic, there are some individual cases that can fit within the framework of a potentially traumatic event such as a person experiencing a loss of a loved one due to COVID-19 or a patient with severe or critical illness from COVID-19. We note, however, that, as this study reported data on two countries, we cannot rule out the hypothesis that the COVID-19 pandemic had long term impact and that the prototypical patterns following exposure to potentially traumatic events can be found in other contexts.

Our findings contribute to the existing body of knowledge by documenting that for a small minority of participants (about 10%) the COVID-19 pandemic was a turning point or a catalyst leading to both negative and positive consequences. We note that some of these classes included less than 5% of the sample. There is evidence in the methodological literature that the risk of low power, unstable class solution, and lack of statistical precision is a function of actual sample size rather than the percentage (e.g., Lubke and Neale, 2006; Morgan, 2015). We note that the Improving/stable class (positive affect) contains less than 5% of the sample but includes more than 800 participants. In addition, we believe that an important factor to consider is the interpretability of these class trajectories. These class trajectories are clearly distinct and separate from other classes and are also clearly interpretable and consistent with our theory of a turning point/catalyst.

Author note

We have no conflicts of interest to disclose.

CRediT authorship contribution statement

Gabriele Prati: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Conceptualization. **Anthony D. Mancini:** Writing – review & editing, Supervision, Formal analysis, Conceptualization.

Declaration of competing interest

We have no conflicts of interest to disclose.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jpsychires.2024.08.024.

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