Subjective Well-being Across One Year of Living Through the COVID-19 Pandemic: A 3-Wave Longitudinal Study

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Abstract

People worldwide have been impacted by the COVID-19 global pandemic since March 2020, but it is unclear how people's subjective well-being (SWB) has changed during this pandemic. Recent studies have reported both change and stability in SWB, but most of these studies have examined only short periods of time or were limited to only a few dimensions of SWB. Moreover, prior findings have been somewhat inconsistent. To address these issues, this study ($N = 972$) tracked five SWB indicators (i.e., life satisfaction, positive and negative emotions, depression, and anxiety) over three waves of data that covered about one year following the pandemic declaration. Using latent growth curve models, we found that SWB remained stable during the study period, and that there was great variability in people's initial levels of SWB (about three months post-pandemic declaration). We did not find that different SWB indicators displayed different change patterns.

Keywords: COVID-19 pandemic, subjective well-being (SWB), positive emotions, negative emotions, life satisfaction, depression, anxiety

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On March 11th, 2020, COVID-19, the respiratory illness caused by the novel coronavirus SARS-CoV-2, was declared a state of pandemic by the World Health Organization (WHO). It swept the world and made an unprecedented impact on people's health and well-being. By April 2022, the pandemic had resulted in more than 503 million confirmed cases worldwide, and more than 80 million confirmed cases and over 988,000 deaths in the U.S. (Dong et al., 2020). Historically, research on pandemic and epidemics, including severe acute respiratory syndrome (SARS), Ebola, and Middle East respiratory syndrome-related coronavirus (MERS), has also documented a negative psychological impact on subjective well-being in various samples due to quarantine restrictions (see Brooks et al., 2020 for a review). These prior findings may not be surprising given that pandemics and epidemics tend to impact many aspects of people's lives. For example, the COVID-19 pandemic had deep impacts across different life domains, including changes in work environments or job loss, changes in family routines or bereavement, changes in health, and community changes like shortages, generalized loss, or structural changes. Thus, it is reasonable to predict that the generalized disruption may have had a lasting impact on well-being.

Subjective well-being (SWB) refers to the extent to which individuals are subjectively happy and functioning normally (Lucas et al., 1996). SWB is an important predictor of a series outcomes, including health, longevity (Diener & Chan, 2011), better work performance, relationships, and creativity (Diener et al., 2018). Low levels of SWB could transform to worse objective health, for example, chronic high levels of negative emotions and/or low levels of positive emotions may lead to mental and physical issues (Boehm, 2018). Therefore, a high level of SWB is very desirable. SWB comprises of two distinct components of well-being (Lucas et al., 1996): the cognitive evaluation of one's own life, which is usually operationalized as life satisfaction, and the emotional evaluation, which is usually operationalized as the positive and negative emotions. Therefore, the most widely employed measures for SWB are life satisfaction, positive emotions, and negative emotions. However, this model received criticism for not being able to decompose negative well-being into more measures (Fischer & Boer, 2011), such as depression and anxiety, which have been observed to increase during the pandemic quarantine (Brooks et al., 2020). Thus, to achieve a comprehensive understanding of SWB, it is best to also include measures of depression and anxiety.

Prior theory and empirical work on well-being changes in response to adverse events have proposed four main patterns of change: resilience, recovery, chronic distress, and delayed reactions (Bonanno et al., 2010). First, resilience refers to bouncing back to a normal functioning level after relatively short, minor disruption. Second, recovery refers to recovering to a normal level within a year or two since the individuals suffered a decline in well-being when the event happened. Third, chronic distress refers to developing chronic psychopathology after the event, where individuals suffer from worse well-being for a long period of time. Fourth, delayed reactions refer to a delayed decrease in well-being. Resilience and recovery are the first and second most typical response patterns to a traumatic life event, with 35%-65% and 15%-25% of the population typically falling in these two categories, respectively (Bonnano et al., 2011). Those who suffer severe psychological decline from a traumatic event are usually less than 30% of the population (Bonnano et al., 2010).

Therefore, it follows that if one tracked people's SWB across one year and beginning shortly *after* a traumatic event occurred, the average pattern of change expected will likely be remaining stable (not statistically significant since the disruption is minor) or increasing gradually, which correspond to resilience or recovery. The reason for these expected average patterns would be that the well-being dip might have already occurred when the traumatic event happened. Two complications in making predictions in the context of the COVID-19 pandemic are that (1) the pandemic is not a single event but a continuous series of potentially traumatic events and that (2) different countries declared emergency and/or lockdown at different time points. Thus, the above predictions assume that the "traumatic event" is the declaration of the pandemic by the World Health Organization along with the first "peak" which lasted from March to May 2020 (see 1Point3Acres, 2021). This assumption is supported by the available empirical evidence reviewed later in this thesis (e.g., Ruggieri et al., 2021; Shanahan et al., 2020; Zimmermann et al., 2021).

Moreover, different dimensions of SWB tend to show different developmental trends across the lifespan and in response to trauma (Diener et al., 2006). For example, although positive emotions tend to decline with age, life satisfaction tends to increase. Furthermore, the same traumatic event may be associated with different developmental trends in different dimensions of SWB (Infurna, & Luthar, 2017); for example, after losing their spouse, most participants had a minor disruption in life satisfaction and returned to their baseline level soon, but they suffered from a big decline in positive emotions and needed years to recover. Therefore, the investigation of SWB, including in the context of the COVID19 pandemic, must include a careful scrutinization of its different dimensions.

Empirical, longitudinal studies documenting SWB changes in response to the COVID-19 pandemic have been rapidly emerging since 2020. At the beginning of the pandemic, the overall pattern observed was that people suffered from a dip of SWB (Fruehwirth et al., 2021; Möhring et al., 2021; Shanahan et al., 2020) and higher mental illness prevalence was found in both the US (Twenge & Joiner, 2020) and worldwide (Xiong et al., 2020). A good number of large-scale studies had previously collected one or more waves of online surveys on one or more SWB indicators, so these existing data were used as a baseline and their last wave of data was usually collected online shortly after the declaration of the pandemic. For example, Möhring and colleagues (2021) found that compared to September 2019, in April 2020 German adults had significantly lower family satisfaction ($N = 2{,}639$) and work satisfaction ($N = 1{,}663$). Similar patterns were found for other SWB indicators, including increased negative emotions, stress (Shanahan et al., 2020), anxiety, and depression (Fruehwirth et al., 2021; Twenge & Joiner, 2020). These results were also replicated in studies with data collected right before the pandemic declaration (Castellini et al., 2020; Zacher & Rudolph, 2021), some smaller studies or studies with a specific age group (De France et al., 2021; Ruggieri et al. 2021; Saraswathi et al., 2020; Wettstein et al., 2021; Zimmermann et al., 2021). For example, a US study ($N = 205$; Zimmermann et al., 2021) collected three self-report surveys seven months before the pandemic declaration, five months before, one month before, and one month after. Compared to the pre-pandemic time, participants reported higher levels of depression and anxiety one month after the pandemic declaration.

Nevertheless, for some SWB indicators, different change patterns were observed at the beginning of the pandemic. For example, some studies found that depression symptoms did *not* increase significantly (Saraswathi et al., 2020; Wettstein et al., 2021), possibly because people were still digesting the changes in such a short period of time. Although Saraswathi and colleagues (2020) found increased levels and prevalence of anxiety and stress in undergraduate Indian students (*N* = 217) from Dec 2019 to June 2020, the level and prevalence of depression were found to remain stable. Another study (Wettstein et al., 2021) tracked senior Germans (*N* =10,323) across three time points in 2014, 2017, and 2020. They found that the level of depressive symptoms was stable from 2014 to 2017 and suffered an increase from 2017 to 2020; however, life satisfaction remained stable from 2014-2020. O'Conner and colleagues (2021) even found the portion of people who had anxiety *decreased* right after the pandemic. They collected three waves of online surveys from British adults (*N* = 3,077) in March (T1), April (T2), and May (T3) 2020, and compared to the T1, at T2 and T3 a smaller portion of people were having mid to severe level of anxiety; more people were having suicidal ideas, but at the same time, more people were having positive well-being. Moreover, the portions of people with mid-to-severe levels of depressive symptoms or loneliness did not change.

To provide further detail into the existing empirical evidence on SWB during the pandemic, I have divided it based on the number of assessments and the length of time covered by the published longitudinal studies.

In the first several months of the COVID-19 pandemic, the evidence of SWB changes was mixed. These studies in general collected two or more waves of data in a short period of time around, or, shortly after the declaration of the pandemic; a few of them compared pre- and post-pandemic SWB. Most studies found that people's well-being recovered after the initial shock of the pandemic (Bachtiger et al., 2021; Fancourt et al., 2021; Kuhn et al., 2021;

Megalakaki et al., 2021; Pieh et al., 2021; Quaglieri et al., 2021; van der Velden et al., 2021; Wang et al., 2021). For example, a large UK panel study that included weekly assessment (*N* = 36,520; Fancourt et al., 2021) found that both anxiety and depressive symptoms decreased across five months from the pandemic declaration. In contrast, other studies found that people's SWB declined during roughly the similar period (Bathina et al., 2021; Kimhi et al., 2020; Shiloh et al., 2021). For example, Kimhi and colleagues (2020) found that Israeli adults' (*N* = 906) distress increased, whereas their well-being and resilience decreased in July compared to May 2020. A few studies also found that SWB stayed stable during the first several months of the pandemic (Groarke et al., 2021; Kuhn et al., 2021; McPherson et al., 2021; Wang et al., 2021), and according to these results, most people are resilient. For example, another three-wave UK study (*N* = 1,958; Groarke et al., 2021) found that loneliness and depression remained stable from the beginning of the pandemic to two months later. Using the same data, McPherson and colleagues (2021) found that over 70% participants had low and stable levels of depression, anxiety and stress across the same period. Moreover, other studies found that different aspects of SWB displayed different change patterns. For instance, Willroth et al. (in press) found that from March to September 2020, positive emotions stayed relatively low but negative emotions bounced back quickly after the start of the pandemic. In sum, previous studies investigating SWB changes at the very beginning of the pandemic support mostly a recovery pattern, with the caveat that not all SWB indicators show the same developmental patterns and that some studies did not show signs of recovery. Despite these important contributions, we are left asking what happened after the initial few months. Now that the pandemic has been ongoing for two years, what happened next?

When looking at studies with longer time spans, where the last wave of data was collected in late 2020 or 2021, there are fewer studies and the diverse patterns of SWB change continued (most of them involved only two time points). In general, people's SWB seemed to suffer another dip when winter came with higher flu susceptibility and cross-infection between the flu and COVID-19. People had lower mental well-being scores and higher perceived stress compared to the pre-pandemic time, and the portion of people with worse mental well-being states increased (Savage et al., 2021; Thygesen et al., 2021). For example, a study with UK college students ($N = 255$; Savage et al., 2021) found that students had lower mental well-being and higher perceived stress seven months after the pandemic started as opposed to five months before. Moreover, some studies found that even compared to the first dip in SWB observed at the beginning of the pandemic, SWB declined later on (Rogowska et al., 2021). Rogowska and colleagues (2021) found that their student participants had a higher level of stress and lower level of life satisfaction late 2020 (November to December 2020) than at the beginning of the pandemic (March to April 2020). Later, people's anxiety, depression and stress seemed to hit a plateau and remained stable from November 2021 to February 2021 (Jordan et al., 2021).

To my knowledge, only four studies tracked longitudinal SWB changes with three or more time points that reached or spanned beyond late 2020. Krautter and colleagues (2022) tracked two cohorts of students ($N = 162{,}114$), each with four waves of data in seven months, and both cohorts reported worse SWB during the lockdowns in April 2020 and January and April 2021, with greater declines in cognitive (i.e., life satisfaction) than emotional SWB. Hansen and colleagues (2021) collected self-report data of SWB from Norwegian elders ($N = 2{,}831$), and observed relatively stable well-being from three months before the pandemic to three months after the pandemic, but significant lower levels of psychological well-being, positive emotions, and higher levels of negative emotions from three months to nine months into the pandemic. Li and colleagues (2021) collected four waves of data at China ($N = 715$) and US ($N = 247$) in Feb (T1), April (T2), July (T3), and Dec 2020 (T4), respectively. Participants' emotional states declined (no data for China, T1-2 for US) but then quickly bounced back after the start of the pandemic (T1-T2 for China; T2-4 for US) and then became stable (T2-4 for China); Life satisfaction fluctuated but the effect sizes were very small, so it seems that people's life satisfaction was more resilient. Lastly, Joshi and colleagues (2021) collected six waves of monthly data from Canadian university employees ($N = 131$) from April to November 2020, and found that participants' depression symptoms demonstrated two major change patterns. About one third of them exhibited high and increasing depressive symptoms, and about two thirds of them exhibited low and consistent depressive symptoms during their study period.

Overall, there seems to be a major pattern that people's SWB declined at the beginning of the pandemic, gradually rebounded but suffered another decline in late 2020; and after that, SWB seems to stabilize again, but not much data is available past late 2020. Given that different time periods of the pandemic appear to be accompanied by different patterns of change in SWB, and that different SWB indicators tend to show different patterns of change, studies that include more SWB indicators and longer periods of time during the pandemic are needed.

Present Study

Although previous longitudinal studies have investigated changes in SWB in the context of the COVID-19 pandemic, many of them either looked at a relatively short period of time or made comparisons between the past and a time point shortly after the pandemic onset. Few of them reported long-term changes of SWB after the declaration of the pandemic, and the focus of most papers has been primarily on clinical measures, such as depression and anxiety. Thus, to better understand the multi-aspect, lasting impact on SWB within the population in the wake of this public traumatic event (Bonanno et al., 2011), a longitudinal study over a longer period of time and looking at more dimensions of SWB is needed. Moreover, because two types of patterns have been found in previous longitudinal studies (resilience and recovery) and COVID-19 is a complex traumatic event, currently we do not know whether resilience is still the most prevailing response pattern in the general population, so more evidence is needed. Therefore, the current study investigates change in 1,000 people's SWB across one year shortly after the pandemic was declared. Given the empirical evidence presented for both resilience and recovery patterns and the complex nature of COVID-19 as a traumatic event, I tested the following competing hypotheses: individuals' SWB (1) remained relatively stable or (2) gradually increased in a year. Moreover, I also predicted that (3) different dimensions of SWB will display different patterns of change, although I did not have specific predictions for each of the measures.

To take the multiple dimensions of SWB into account, the following indicators were included in this study: life satisfaction, positive and negative emotions, depression, and anxiety. In addition to these measures, several demographic factors were also included because they can be usefully correlated with SWB, as indicated in the following studies. Castellini and colleagues (2021) found that perceived economic damage was positively related to the worsening of sleep and sexual functioning. In Shanahan and colleagues' (2020) study, female participants reported higher emotional distress than males prior to and during the pandemic; economic disruptions and loss of education or employment were associated with greater increases in emotional distress. In another study (Zimmermann et al., 2021), female students also reported greater disruption of daily activities and greater negative impact on their health during the pandemic compared to male students; Asian and Asian Americans reported lower levels of anxiety and depression than their White/European American counterparts, and Hispanic participants reported greater depression symptom severity. Therefore, I included age, gender, racial/ethnic background, and income as control variables in this study.

Methods

The current study used data from a larger three-wave longitudinal study of human functioning across the COVID-19 pandemic, to understand how people's SWB has changed across one year of living through the pandemic in the United States. This study was pre-registered after data collection but before accessing the data—the pre-registration can be found at: https://osf.io/bz6w5.

Participants and Procedure

We have already collected three waves of data in July 2020, November 2020, and April 2021. For Wave 1, we recruited 1,000 participants from Amazon Mechanical Turk. According to a sensitivity power analysis, 1,000 participants would provide us with 80% power (α = .05) to detect effects as small as a correlation of .1, which indicates that practically significant effects will also be statistically significant. Also, power seems adequate because this effect of .1 is smaller than previously observed effects in the literature on adversity (as the larger study was primarily designed to investigate the effects of COVID-19 related adversity on various outcomes). Frankly, it was also the largest sample the team could afford. For Waves 2 and 3, there was attrition, where 669 and 434 of the participants in the original sample completed the follow-ups, respectively. For each wave of survey, participants completed the consent form and then a 45-minute survey.

Measures

The measures in this study included Satisfaction with Life Scale, PANAS, depression scale, anxiety scale, and the demographics (full scales available in the Appendix).

Satisfaction with Life Scale. Diener and colleagues (1985) developed this five-item scale to measure global life satisfaction. Participants indicated their agreement with the statements on a five-point Likert scale ranging from *strongly disagree* (1) to *strongly agree* (5). A sample item was "In most ways my life is close to my ideal". Higher score indicates higher level of life satisfaction. The internal reliability for this scale in this study from wave 1 to wave 3 are .92, .93, and .93, respectively.

PANAS. Watson and colleagues (1988) developed the Positive and Negative Affect Schedule (PANAS) to measure individuals' self-report positive and negative emotions. The participants indicated the extent to which they feel the listed emotions in the current moment. They responded to a five-point Likert scale ranging from *very slightly or not at all* (1) to *extremely* (5). There were 10 positive emotions and 10 negative emotions listed, such as interested, excited, irritable, and nervous. Higher score stands for higher level of the emotions. The reliability for positive emotions scale in this study from wave 1 to wave 3 are .93, .93, and .94. The reliability for negative emotions scale from wave 1 to wave 3 are .95, .93, and .94.

For positive emotions and negative emotions, we modeled separate single latent factors with 3 subscale indicators each, where each indicator consisted of a parcel (two parcels with 3 items each and one parcel with 4 items) following Kunzmann et al. (2002). Parcels with the same items were allowed to correlate across time points.

Depression. Kroenke and colleagues (2001) developed the Patient Health Questionnaire (PHQ), and we used one of their modules PHQ-9, a nine-item scale that was designed to measure depression. Participants indicated how often they experienced the stated symptoms in the past two weeks, and responded to a four-point scale ranging from *not at all* (0) to *nearly every day* (3). A sample item was "Feeling tired or having little energy". Higher score indicates higher level of the depression symptoms. The internal reliability for PHQ-9 in this study from wave 1 to wave 3 are .93, .90, and .91.

We modeled a single latent factor with 3 subscale indicators. The make-up of the indicators was determined by radial parceling (Rogers & Schmitt, 2002), where the 3 initial parcels were created as described next. Two items with the closest factor loadings were grouped into parcel 1, the next closest pair were grouped into parcel 2, and then the third closest pair were grouped into parcel 3. Then, in the second iteration, the 3 remaining items were each assigned to a parcel having closest primary factor loadings to their own, during which each parcel got 1 item, resulting in 3 items in each parcel. Parcels with the same items were allowed to correlate across time points. Items 5, 8 and 1 were included in the first parcel, items 6, 2, and 9 were included in the second parcel, and items 7, 4, and 3 were included in the third parcel.

Anxiety. Spitzer and colleagues (2006) developed the Generalized anxiety disorder (GAD-7), a seven-item scale to measure anxiety. Participants indicated how often they experienced the stated symptoms in the past two weeks, and responded to a four-point scale ranging from *not at all* (0) to *nearly every day* (3). A sample item was "Feeling nervous, anxious, or on edge". Higher score indicates higher level of the anxiety symptoms. The internal reliability for GAD-7 in this study from wave 1 to wave 3 are .94, .93, and .93.

We modeled a single latent factor with 3 subscale indicators. The make-up of the indicators was also determined by radial parceling, like we did for the PHQ-9 (Rogers & Schmitt, 2002). Parcels with the same items were allowed to correlate across time points. Specifically, items 3 and 4 were included in the first parcel, items 1 and 2 were included in the second parcel, and items 5, 6, and 7 were included in the third parcel.

Demographics. Participants provided their age, gender, racial/ethnic background, education, and income in the survey. Gender was coded as 0 = male, 1 = female. The racial/ethnic background was coded as 0 = White/European American, 1 = Person of Color (POC), where POC included Latino/Hispanic, Native American/American Indian, Black/African American, Asian/Asian American, Native Hawaiian/Pacific Islander, Multi-Race, and Other. Participants also indicated their annual household income in US dollars. Since the linearity assumption was violated for income, we log-transformed the variable.

Data Analysis

R (version 4.1.3; R Core Team, 2022) and SPSS were used to conduct the analyses. The R packages used are the *jmv* (v0.9.6.1; Selker, Love, & Dropmann, 2019), the *psych* (v2.2.3; Revelle, 2018), the *lavaan* (v0.6-10; Rosseel, 2012), the *semTools* (v0.5-5; Jorgensen et al., 2021), the *parameters* (v0.17.0; Lüdecke et al., 2020), and the *dplyr* (v1.0.8; Wickham et al., 2022).

Data cleaning. Prior to any analyses, we excluded participants who failed to pass more than 2 attention check questions in the larger survey, and this resulted in a final sample of 972. Missing data were estimated by Full Information Maximum Likelihood (FIML). For all analyses, we assessed model fit indicators including chi-square and degrees of freedom, the root mean square error of approximation (*RMSEA*; where values smaller than .05 indicate a close fit, values between .05 and .08 indicate an acceptable fit, and values between .08 and .10 indicate a mediocre fit), and *CFI* values (where values greater than .95 indicate a close fit, values between .90 and .95 indicate an acceptable fit, and values between .85 and .90 indicate a mediocre fit) (Little et al., 2013). The model fit conclusions were informed by *Δ CFI* being less than or equal to .01 (Meade et al., 2008).

Measurement invariance. To ensure that the changes over time observed are due to real changes in constructs instead of measurement errors, it is necessary to establish measurement invariance (Schmitt & Kuljanin, 2008; Schmitt et al., 2010). For each SWB indicator, we tested measurement invariance (configural, metric, and strong) by comparing a set of increasingly restrictive models to ensure that the same construct is being measured across time. Specifically, we compared three measurement models for each SWB indicator: (1) freely estimating the factor loadings for the latent factors at each time point (i.e., configural invariance); (2) constraining the respective factor loadings to be equal at each time point (i.e., weak/metric invariance); and (3) constraining the factor loadings and intercepts to be equal at each time point (i.e., strong invariance). The model fit standards were that change in comparative fit index (*Δ CFI*) less than or equal to 0.01 (Meade et al., 2008), because they are more accurate and less biased fit indices for large sample sizes. For all SWB indicators, the more constrained models did not fit worse than the lesser constrained models, so the structures of the SWB indicators are the same over time. Table 1 shows the results of measurement invariance, where all SWB indicators showed strict invariance.

Latent growth curve models. To test our two competing hypotheses – to estimate whether SWB remained stable or increased across one year, we conducted a series of second-order univariate latent change models for each SWB indicator, respectively (for a review, see Duncan, et al., 2006). For each SWB indicator, we tested (1) a latent basis model, where the slope of the 1st and 3rd time point was fixed at 0 and 2, and the slope of the 2nd time point was freely estimated; (2) a no growth model, where the slope is fixed to be zero over time; and (3) a linear growth model, where the slope linearly increases by one unit over time, with the 1st time point centered at '0', the 2nd time point fixed at '1', and the 3rd time point fixed at '2'. In all models, path coefficients from the intercept to the repeated assessments were fixed at 1, and the intercept and slope were allowed to covary.

Prediction models. To estimate the effect of the demographic factors on SWB indicators, we predicted the intercepts and slopes obtained from the latent change models, separately for each SWB indicator, with the following manifest variable predictors (all assessed at baseline): age, gender, race/ethnicity, and income.

Results

Attrition analysis

We compared the mean-level differences of all study variables at Wave 1, between those who stayed and those who dropped out at Wave 3. For race, we conducted a binary logistic regression. We adjusted the p value to .006 because we did nine comparisons altogether. People who dropped out were not in a different racial composition (note that we only had two groups, 0 = White/European American, 1 = Person of Color), and did not have different levels of income, positive emotions, or anxiety compared to people who did not drop out; however, the former were younger ($\Delta M = 3.90$, $t = 4.96$, $p < .001$, $d = .33$), more likely to be men (ΔM = .10, where male = 0, female = 1, t = 3.10, p = .002, d = .21), had higher life satisfaction (ΔM = .23, t = 3.44, p < .001, d = .23), higher levels of depression (ΔM = .39, t = 8.38, p < .001, d = .54), and higher levels of negative emotions (ΔM = .46, t = 7.74, p < .001, d = .49).

Intercorrelations

Table 2 shows the intercorrelations of the main study variables, where SWB indicators were averaged across time. Age and gender were negatively associated with all SWB indicators, being a Person of Color was positively associated with all SWB indicators, and log-transformed income was not associated with any of the SWB indicators.

Latent growth curve models

Table 3 shows the results of latent growth curve models for the five SWB indicators. Based on the CFI index, all latent change models showed mediocre fit, except for models of life satisfaction; based on the RMSEA index, only models for positive emotions and negative emotions showed mediocre fit, and models for anxiety showed close to mediocre fit. We compared a latent basis model, a no growth model, and a linear growth model for each SWB indicator. For all indicators, the no growth model provided the best fit, indicating that participants' SWB did not change significantly a year after the pandemic declaration. Therefore, our hypothesis 1 (SWB remained stable) was supported, but hypotheses 2 (SWB gradually increased) and 3 (different SWB indicators displayed different change patterns) were not. The variance in level was statistically significant for each SWB indicator, indicating that there were significant individual differences in participants' initial levels of SWB.

Prediction models

Table 4 shows the results of prediction models where we predicted the levels and slopes taken from latent growth models with demographics: age, gender (being female), race/ethnicity (being a Person of Color), and income. Although “no growth” models showed a better fit than “linear growth” models, we still included the slopes in these analyses as per the pre-registration, but the effects of the predictors on slopes should be interpreted with great caution. When predicting initial levels of SWB (about three months after the pandemic began), I found that age predicted lower scores on negative emotions, depression, and anxiety, indicating that older people were in better SWB states compared to younger people during one year after the pandemic declaration. Being a Person of Color predicted higher scores on negative emotions, depression, and anxiety, indicating that White/European Americans were in better SWB states compared to People of Color. Income predicted higher scores on life satisfaction, and positive emotions, indicating that people with higher income were in better SWB states. When predicting slopes (i.e., rates of change in SWB across one year of the pandemic), I found that no demographic factors were significant predictors for any of the SWB indicators.

Discussion

There are three contributions of this study. First, we examined changes in SWB across one year following the COVID-19 pandemic onset, which is a longer period compared to most other studies currently available in the literature. Second, we used a relatively large US sample (N = 972). Although MTurk samples cannot be said to be representative of the population, some of their demographics are representative, such as gender and education level (Berinsky et al., 2012). Therefore, the sample provided a relatively good representation on key demographic aspects at a low cost. Third, we collected information of multiple dimensions of SWB in this study, including life satisfaction, positive and negative emotions, depression, and anxiety, enabling a more comprehensive depiction of the construct. Fourth, we used well-validated measures of SWB, and we showed strict invariance in all measurements.

With the latent growth curve models, we found significant individual differences in participants' initial levels of SWB measured about three months after the pandemic declaration. For each SWB indicator, we found the no growth model to fit better with the data compared to linear growth model, so people's SWB remained stable, on average, for one year following the pandemic declaration. This finding is consistent with some of the previous research (Groarke et al., 2021; Kuhn et al., 2021; McPherson et al., 2021; O'Conner et al., 2021; Saraswathi et al., 2020; Wang et al., 2021; Wettstein et al., 2021). We did not find that different SWB indicators displayed different change patterns. This is somewhat inconsistent with the previous findings (Diener et al., 2006; Infurna, & Luthar, 2017).

With the prediction models, we found age, gender, and income as significant predictors, each for at least two SWB indicators. These results confirmed the patterns—that young people, People of Color, and people with lower income suffered more from the pandemic, as observed in previous research (Castellini et al., 2021; Shanahan et al., 2020). However, gender was not a significant predictor for any SWB indicators in this study, despite previous studies having found that women suffered more (Zimmermann et al., 2021).

This thesis served as a first step of a bigger project that aims to identify the predictors for and explain the pattern of well-being development after the pandemic. Now we described the overall pattern of SWB for a year after the pandemic, for the next step we will identify predictors in multiple aspects of life that influence our subjective and physical well-being (i.e., occupational/financial, family, personal health, and community factors). If it is financially and timely feasible, we will continue to collect a fourth wave of data, so that the whole study spans over an even longer period following the pandemic.

Limitations

This study has several limitations. First, we had no data collected before the pandemic. This potentially prevented us from observing the initial dip in subjective well-being followed by recovery, a pattern that has commonly been observed in the context of the COVID19 pandemic (Fruehwirth et al., 2021; Möhring et al., 2021; Shanahan et al., 2020; Twenge & Joiner, 2020; Xiong et al., 2020). Second, participants who dropped out from the study were younger, more likely to be men, and they had higher levels of life satisfaction, negative emotions, and depression compared to people who did not drop out. Attrition is common in longitudinal studies (average attrition rate being close to 30%; Teague et al., 2018), and longer study periods tend to bring about higher attrition rates. Under the circumstance of the pandemic, participants had an even harder time staying in the same study. Since different people's SWB were influenced by the pandemic to a different extent, it is relatively reasonable that specific types of people are more likely to drop out during the pandemic. Nevertheless, the sample used cannot be considered representative and thus, all conclusions should be limited to this sample and not overgeneralized to the whole US population.

Conclusion

This study tracked a large sample of participants ($N = 972$) with online surveys across three waves of data, and found evidence supporting for that people's SWB remained stable for a year following the pandemic. We also found significant variability of the starting points of people's SWB levels (measured about three months after the pandemic declaration). As a next step, we will identify predictors of different life aspects of the SWB patterns.

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List of Tables

Table 1

Assessing measurement invariance across time

	Model	χ^2	***df***	***p***	**RMSEA**	**90% CI**	**FI**	**CFI**	**Model Evaluation**
Life Satisfaction	Configural/Pattern Invariance	1793.02	88	.000	.141	[.136, .147]	.828		
	Weak/Loading/Metric Invariance	1795.77	96	.000	.135	[.130, .140]	.828	.001	Pass
	Strong/Scalar/Intercept Invariance	1811.31	104	.000	.130	[125, .135]	.828	.001	Pass
	Strict Invariance	1818.25	114	.000	.124	[.119, .129]	.828	.000	Pass
Positive Emotions	Configural Invariance	388.49	25	.000	.122	[.112, .133]	.941		
	Weak Invariance	393.58	29	.000	.114	[.104, .124]	.941	.000	Pass
	Strong Invariance	404.14	33	.000	.108	[.098, .117]	.940	.001	Pass
	Strict Invariance	410.02	39	.000	.099	[.090, .108]	.940	.000	Pass
Negative Emotions	Configural Invariance	221.31	25	.000	.090	[.079, .101]	.971		
	Weak Invariance	234.03	29	.000	.085	[.075, .096]	.970	.001	Pass
	Strong Invariance	238.59	33	.000	.080	[.071, .090]	.970	.000	Pass
	Strict Invariance	266.31	39	.000	.077	[.069, .086]	.967	.003	Pass
Depression	Configural Invariance	917.66	25	.000	.192	[.181, .203]	.875		
	Weak Invariance	960.80	29	.000	.182	[.172, .192]	.869	.005	Pass
	Strong Invariance	981.06	33	.000	.172	[.163, .182]	.867	.002	Pass
	Strict Invariance	1042.79	39	.000	.163	[.155, .172]	.859	.008	Pass
Anxiety	Configural Invariance	434.63	25	.000	.130	[.119, .141]	.937		
	Weak Invariance	452.59	29	.000	.123	[.113, .133]	.935	.002	Pass
	Strong Invariance	473.23	33	.000	.117	[.108, .127]	.932	.003	Pass
	Strict Invariance	505.82	39	.000	.111	[.103, .120]	.928	.004	Pass

Notes. These analyses used a FIML estimation based on $N = 972$. A relative model pass was determined based on ΔCFI being < .01 (a negative ΔCFI means the more restricted model fit better, which also means that model should be selected).

Table 2

Intercorrelations for the main variables (N = 972)

Variables	1	2	3	4	5	6	7	8	9
age	-								
Female	**.19**	-							
POC	**-.20**	**-.10**	-						
Income_ln	.03	**-.13**	.03	-					
SWLS_M	**-.16**	**-.08**	**.12**	-.06	-				
PE_M	**-.13**	**-.10**	**.14**	-.05	**.85**	-			
NE_M	**-.13**	**-.10**	**.14**	-.05	**.85**	**.99**	-		
Depression_M	**-.16**	**-.11**	**.11**	-.03	**.86**	**.87**	**.87**	-	
Anxiety_M	**-.16**	**-.11**	**.13**	-.02	**.84**	**.86**	**.86**	**.88**	-

Notes. Bold indicates $p < .05$. Gender and race were dummy coded, 0 = male, 1 = female; 0 = White/European American, 1 = Person of Color (POC). _M means the average score across three time points. _ln means log transformed. SWLS = life satisfaction; PE = positive emotions; NE = negative emotions.

Table 3

Latent Growth Curve Models

Latent growth curve models		Intercept		Slope		Model Fit		
SWB indicator	models	Mean (*p*-value)	Variance (*p*-value)	Mean (*p*-value)	Variance (*p*-value)	χ^2(*df*, *p*-value)	RMSEA (90% CI)	CFI
Life Satisfaction	No growth	**.20**(.001)	**28.60**(.000)	N/A	N/A	1808.13(116, .000)	.123[.118, .128]	.829
	Linear growth	**-.25**(.000)	**32.12**(.000)	-.07(.282)	.14(.584)	1804.87(113, .000)	.124[.119, .129]	.829
	Latent basis	**3.94**(.000)	52.54(.035)	-.07(.298)	.54(.300)	1804.77 (112, .000)	.125[.120; .130]	.829
Positive Emotions	No growth	.07(.133)	**6.94**(.000)	N/A	N/A	409.12(43, .000)	.094[.085, .102]	.941
	Linear growth	**.30**(.000)	**7.45**(.000)	.06(.186)	.06(.526)	406.75(40, .000)	.097[.089, .106]	.941
	Latent basis	**.50**(.000)	**10.44**(.000)	.04(.289)	.23(.051)	398.21(39, .000)	.097[.089, .106]	.942
Negative Emotions	No growth	.10(.028)	**7.98**(.000)	N/A	N/A	297.52(43, .000)	.078[.070, .087]	.963
	Linear growth	**.77**(.000)	**8.94**(.000)	**-.20**(.000)	.12(.177)	273.17(40, .000)	.077[.069, .086]	.966
	Latent basis	**.28**(.000)	**9.33**(.000)	**-.23**(.000)	.18(.047)	270.24(39, .000)	.078[.069, .087]	.966
Depression	No growth	.02(.347)	**.70**(.000)	N/A	N/A	1047.48(41, .000)	.159[.151, .168]	.859
	Linear growth	.04(.157)	**.72**(.000)	**-.05**(.000)	.004(.822)	1021.99(38, .000)	.163[.155, .172]	.862
	Latent basis	**.10**(.000)	**.73**(.000)	**-.05**(.000)	.01(.738)	1021.73(37, .000)	.166[.157, .175]	.862
Anxiety	No growth	**.28**(.000)	**8.54**(.000)	N/A	N/A	509.21(43, .000)	.106[.098, .114]	.928
	Linear growth	**.44**(.000)	**11.09**(.000)	**-.17**(.001)	.27(.033)	489.60(40, .000)	.108[.099, .116]	.931
	Latent basis	**2.52**(.000)	**10.10**(.000)	**-.20**(.000)	.16(.228)	487.96(39, .000)	.109[.100, .118]	.931

Note. These analyses used a FIML estimation based on $N = 972$. Bold indicates statistical significance at $p < .01$, because as pre-registered, we adjusted the *p* value upon the plan to fit 5 comparisons.

Table 4

Prediction models

	Life satisfaction				Positive emotions				Negative emotions				Depression				Anxiety			
	Level		Slope		Level		Slope		Level		Slope		Level		Slope		Level		Slope	
Predictors		95% CI		95% CI		95% CI		95% CI		95% CI		95% CI		95% CI		95% CI		95% CI		95% CI
age	.02	[-.05, 0.09]	.18	[-.54, .89]	.07	[.00, .14]	.20	[-.29, .69]	**-.11**	[-.17, -.04]	-.16	[-.40, .07]	**-.13**	[-.20, -.06]	-.05	[-.21, .10]	**-.14**	[-.21, -.07]	-.05	[-.23, .14]
female	.03	[-.04, .09]	-.18	[-.90, .54]	-.06	[-.13, .01]	.09	[-.32, .51]	-.03	[-.10, .04]	.20	[-.06, .45]	-.05	[-.12, .02]	.04	[-.12, .20]	.03	[-.04, .10]	.09	[-.10, .28]
POC	.01	[-.06, .08]	.71	[-1.35, 2.76]	.06	[-.01, .13]	-.05	[-.47, .38]	**.25**	[.18, .31]	-.28	[-.54, -.02]	**.19**	[.13, .26]	-.21	[-.37, -.04]	**.18**	[.11, .24]	-.22	[-.42, -.02]
income	**.28**	[.21, .34]	-.18	[-.98, .61]	**.25**	[.18, .31]	.13	[-.34, .60]	-.05	[-.12, .01]	-.17	[-.43, .10]	-.06	[-.13, .00]	-.14	[-.31, .03]	-.08	[-.15, -.01]	.06	[-.15, .27]
Model fit	$\chi^2(df, p)$ = 1900.95(167, .000)				$\chi^2(df, p)$ = 466.63(68, .000)				$\chi^2(df, p)$ = 307.15(68, .000)				$\chi^2(df, p)$ = 1054.99(66, .000)				$\chi^2(df, p)$ = 531.52(68, .000)			
	CFI = .821				CFI = .934				CFI = .965				CFI = .859				CFI = .927			
	RMSEA[90% CI] = .106[.101, .110]				RMSEA[90% CI] = .079[.073, .086]				RMSEA[90% CI] = .061[.055, .069]				RMSEA[90% CI] = .127[.120, .134]				RMSEA[90% CI] = .086[.079, .092]			

Notes. These analyses used a FIML estimation based on N = 927, with 45 cases list-wise deleted due to missing data in demographics. Latent levels and slopes were included as outcome in the models. Gender and race/ethnicity were dummy coded: 0 = Male, 1 = Female; 0 = White/European American, 1 = Person of Color (POC). Bold indicates statistical significance at p < .005, because it was adjusted to fit a total of 10 regression models as pre-registered.

Appendix: Questionnaires used in the study

Satisfaction with Life Scale (Diener et al, 1985)

Below are five statements regarding how you feel about your life, please indicate the extent to which you disagree or agree with each statement.

1 - Strongly disagree; 2 – Disagree; 3 - Slightly disagree; 4 - Neither agree nor disagree; 5 - Slightly agree; 6 – Agree; 7 - Strongly agree

In most ways my life is close to my ideal.
The conditions of my life are excellent.
I am satisfied with my life.
So far, I have gotten the important things I want in life.
If I could live my life over, I would change almost nothing.

PANAS (Watson et al., 1988)

This scale consists of several words that describe different feelings and emotions. Read each item and then indicate to what extent you felt this way in the **past month**, including today:

1	**2**	**3**	**4**	**5**
very slightly or not at all	a little	moderately	quite a bit	extremely

__________ 1. Interested __________ 11. Irritable
__________ 2. Distressed __________ 12. Alert
__________ 3. Excited __________ 13. Ashamed
__________ 4. Upset __________ 14. Inspired
__________ 5. Strong __________ 15. Nervous
__________ 6. Guilty __________ 16. Determined
__________ 7. Scared __________ 17. Attentive
__________ 8. Hostile __________ 18. Jittery
__________ 9. Enthusiastic __________ 19. Active
__________ 10. Proud __________ 20. Afraid

Depression PHQ-9 (Kroenke et al., 2001)

Over the last 2 weeks, how often have you been bothered by any of the following problems?

0 (not at all); 1 (several days); 2 (more than half the days); 3(nearly every day)

1. Little interest or pleasure in doing things
2. Feeling down, depressed, or hopeless
3. Trouble falling or staying asleep, or sleeping too much
4. Feeling tired or having little energy
5. Poor appetite or overeating
6. Feeling bad about yourself, or that you are a failure, or have let yourself or your family down

7. Trouble concentrating on things, such as reading the newspaper or watching television
8. Moving or speaking so slowly that other people could have noticed. Or the opposite- being so fidgety or restless that you have been moving around a lot more than usual
9. Thoughts that you would be better off dead, or of hurting yourself in some way

Anxiety GAD-7 (Spitzer et al., 2006)

Over the last 2 weeks, how often have you been bothered by any of the following problems?

0 (not at all); 1 (several days); 2 (more than half the days); 3(nearly every day)

1. Feeling nervous, anxious, or on edge
2. Not being able to stop or control worrying
3. Worrying too much about different things
4. Trouble relaxing
5. Being so restless that it is hard to sit still
6. Becoming easily annoyed or irritable
7. Feeling afraid as if something awful might happen

Demographics and Background Questions

1. What is your age? __________
2. What is your gender? (a) male, (b) female, (c) Other:_____
3. What is your racial background?
    - (a) White/Caucasian, (b) Latino/Hispanic, (c) Native American/American Indian, (d) Black/African-American, (e) Asian/Asian American, (f) Native Hawaiian/Pacific Islander, (g) Multi-Race, (h) Other: ________________.
4. What is your current annual *household* income (i.e., combined income of your home)? *[if you live alone, the amount you enter below should be the same as your personal annual income]*_____