COVID-19 Pandemic Impacts on Adolescent Affect and Mobility: A Six-Year, Smartphone-Based Intensive-Longitudinal Panel Study of 887 Twins.

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Abstract

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Abstract

At the beginning of the COVID-19 pandemic, U.S youth faced major challenges to their emotional well-being and daily routines. Less well known are the patterns and persistence of those effects, especially over the pandemic's multi-year course. Here, we analyzed smartphone-based biweekly affect surveys, using an abbreviated Positive and Negative Affect Survey (PANAS), and GPS location data collected from 887 Colorado-based twin youth over the course of six years, from 06/01/2016 – 04/18/2022. We observed mean declines in affect and mobility in the months following the pandemic onset, including a 29% decline in daily locations visited, a 60% decline in daily travel distance, and 0.3 SD changes in affect. Mean affect and mobility levels fluctuated considerably over subsequent years, with daily locations visited and positive affect remaining slightly below (standardized β=[0.10-0.20], *P*=[*.008;.004]*) and negative affect slightly above (standardized β=0.14, *P*=.04) pre-pandemic levels through April 2022. Weekly county-level COVID-19 transmission rates were negatively associated with mobility and positive affect and positively with negative affect, though these effects were greatly weakened later in the pandemic (e.g., early 2022) or when transmission rates were high (e.g., >200 new cases per 100,000 people per week). Findings demonstrated modest to large pandemic-onset and local case count effects on affect and mobility that attenuated with time but did not revert to pre-pandemic levels. Results highlight both youth resilience and ongoing challenges in the pandemic's aftermath, and inform theories of hedonic adaptation which predict a return to an emotional baseline following stressful life events.

Keywords: Adolescence; Intensive Longitudinal Assessment; COVID-19; Affect; GPS Mobility Measures

Introduction

Individuals throughout the world faced widespread disruptions and uncertainty during the COVID-19 pandemic. From January 2020 – March 2023, the United States confirmed more than 100,000,000 cases and 1,100,000 deaths from COVID-19 (Dong et al., 2023). Beginning in March 2020, many states closed schools and nonessential businesses and encouraged residents to minimize trips away from home (Bergquist et al., 2020). Youth in particular faced unique stressors during the pandemic, most notably disruptions to developmental milestones, such as transitioning into college or the workforce, peer group formation, and parental separation (Breaux et al., 2023; de Figueiredo et al., 2021; Furlong, 2016).

Declines in positive emotional experiences and increases in negative emotional experiences following the pandemic's onset are widely reported, with especially strong impacts reported for adolescents and younger adults (Bera et al., 2022; Blasco-Belled et al., 2022; Brooks et al., 2020; Deng et al., 2021; Klaiber et al., 2021; Lades et al., 2020). While such findings have been widely replicated, studies of the pandemic's psychological impacts are frequently limited by measurement and study design concerns. Most lack pre-COVID data, and report perceived changes in emotional well-being, which may be especially prone to recall biases in the context of traumatic events like the pandemic (Paulus & Vazire, 2007; Russell & Russell, 2021), rather than actual changes in emotional experiences before and after the pandemic's onset. Furthermore, such studies were generally collected at only a few timepoints, often during the first few months of 2020, limiting their ability to observe changes in well-being over the multi-year course of the pandemic.

Psychological theories of adaptation to stressful experiences offer different predictions on the persistence of pandemic-related distress. Hedonic adaptation theory (Frederick &

Loewenstein, 1999) predicts that, following stressful life events, emotional well-being may initially be substantially impacted, but will recover to a pre-existing “set point” over the subsequent months or weeks (Diener et al., 2009; Lyubomirsky, 2010). This theory predicts that pandemic-related impacts on emotional experiences gradually attenuated over subsequent weeks and months as individuals adjusted to the event. Contrastingly, theories regarding the psychological impact of traumatic experiences assert that sufficiently distressing events may have lasting emotional consequences, suggesting many individuals may have faced lasting distress in the pandemic’s aftermath (Goldmann & Galea, 2014; Norris & Wind, 2009)

One response to the challenge of validly capturing pandemic-related impacts via retrospective self-report was the use of behavioral “proxy” measures, like smartphone-based GPS location data, for which prospective data were available and which did not utilize self-report (Harari et al., 2016). Such data can capture features of daily routine mobility patterns, including their frequency, distance, duration, and regularity (Alexander et al., 2022; Andrade et al., 2019; Barbosa et al., 2018; González et al., 2008). This research has identified widespread changes in mobility patterns following the pandemic’s onset and the implementation of lockdown policies, including fewer locations visited and shorter travel distance and, frequently, a gradual recovery toward pre-pandemic mobility patterns following the first few months of the pandemic (Dahlberg et al., 2020; Galeazzi et al., 2021; Hu et al., 2021, 2021; Klein et al., 2020; Pullano et al., 2020; Santana et al., 2023, 2023; Wellenius et al., 2021). Several studies found that mobility changes were moderated by factors like local pandemic severity, and sociodemographic characteristics like age, race/ethnicity, and income levels (Bonaccorsi et al., 2020; Galeazzi et al., 2021; Hu et al., 2021; Santana et al., 2023; Showalter et al., 2021; Weill et al., 2020).

Pandemic-related mobility disruptions are widely studied amongst adults though little research has investigated effects on youth mobility. Youth are less risk averse than adults, (Crone & van Duijvenvoorde, 2021; Leather, 2009) experienced lower risk of severe illness from COVID-19 (Starke et al., 2021), and were likely differentially impacted by pandemic-related policies (e.g. school closures). Hence, youth and adults likely experienced a different set of salient restrictions and motivations impacting their daily routines .

GPS location data are useful for identifying changes in daily routines, though they cannot capture the pandemic's psychological impacts. Such impacts are predominantly studied via self-report instruments, though, as previously discussed, the rapid onset of the pandemic precluded prospective data collection for many studies, leading much of the literature on COVID-19 related psychological impacts especially prone to recall biases. Ongoing longitudinal studies with prospectively measured psychological surveys, especially those conducted over multiple years before and during the pandemic, are a key source of such prospective data. Such studies are well suited to improve and expand upon the COVID-19 literature, allowing for the measurement of the pandemic's impact on psychological outcomes with greater robustness to self-reporting biases and greater information on the persistence of pandemic-related effects.

The present study investigated the magnitude and persistence of changes in youth affect and daily mobility patterns following the COVID-19 pandemic, utilizing GPS mobility data and biweekly affect surveys collected for up to 70 months between June 2016 and April 2022 from a sample of Colorado-based adolescent and young adult twins. We had two primary aims. First, to investigate the magnitude of COVID-19 related disruptions to youth daily routines, measured via GPS-based mobility measures, and emotional experiences, measured by biweekly surveys measuring positive and negative affect, and the persistence of these effects over the pandemic's multi-year course. Second, we estimated the effect of local pandemic severity (measured by the weekly incidence of county-level COVID-19 cases) on daily routine and affect, as well as whether case count effects differed over the course of the pandemic.

Consistent with similar work in adults (Santana et al., 2023), we predicted sharp declines in measures of daily mobility in March 2020, following the implementation of COVID-19 mitigation policies in many US states, and a gradual return to pre-pandemic mobility patterns over the following months, as COVID-related restrictions eased, vaccines became available, and attitudes toward social gatherings grew more permissive. Similarly, we predicted moderate-to-large declines in positive affect and increases in negative affect in early 2020, with a return to baseline over the following months due to hedonic adaptation and increasing opportunities for enjoyment and social engagement with the loosening of pandemic-related restrictions. Lastly, we predicted reduced mobility and poorer emotional well-being in areas with greater COVID-19 transmission rates and that this relationship would be strongest during the initial months of the pandemic, reflecting greater fear and uncertainty about the pandemic's impacts.

Methods

Participants

Participants in the present study were 887 twins living in Colorado and neighboring US states who were between the ages of 14 and 17 at their initial intake visit and owned their own Android or iOS smartphone device (see **Table 1** for participant demographics). Parents and children both provided informed consent and assent prior to participation and the study was approved by Institutional Review Boards at both the University of Minnesota and the University of Colorado, Boulder. Intake visits for the first 670 participants were conducted between April 2015 and October 2016. These participants were initially recruited to participate for one year with the opportunity to continue for an additional year. Participating youth and their parents provided demographic information and baseline youth/parent-report data during an initial in-person assessment visit, which included cognitive testing, interviews, and both youth and parent-report questionnaires. (Freis et al., 2023). Youth participants then completed routine surveys and provided GPS data via a smartphone application for the duration of their participation in the study. A second wave of recruitment occurred between October 2018 and July 2021, with participants agreeing to participate for an additional three years. Of the original 670 twins, 76% participated in this wave, and 217 new participants were recruited. Due to COVID-19 University-mandated lockdowns, no intake visits occurred between February 2020 and February 2021, though new participants were still recruited at this time and participated via the smartphone app, providing survey and location data like all other participants at this time. Data collection was completed in April 2022.

Procedure

CoTwins participants completed an in-person intake visit that included baseline assessments and the installation of the CoTwins smartphone application. This application was then used to administer regular self-report assessments and collect time-stamped GPS location data for the duration of the study. Study staff regularly reviewed questionnaire completion rates and GPS data collection and contacted twins to assist with technical issues as needed. Additional information on the CoTwins study procedure is available in both Alexander et al. (2022) and Freis et al. (2023).

Table 1. CoTwins Sample Demographics

Sex	*n* (%)
Female	478 (53.9%)
Male	409 (46.1%)
Race	***n* (%)**
American Indian/Alaska Native	12 (1.4%)
Asian	4 (0.5%)
Black/ African American	12 (1.4%)
Native Hawaiian/other Pacific Islander	2 (0.2%)
White	715 (80.6%)
More than one race	90 (10.2%)
Declined to provide	56 (6.3%)
Ethnicity	***n* (%)**
Hispanic/Latino	138 (15.6%)
Not Hispanic/Latino	749 (84.4%)
Annual Family Income	***n* (%)**
Less than $30,000	30 (3.4%)
$31,000 - $60,000	98 (11.0%)
$61,000 - $100,000	162 (18.3%)
$100,000 - $150,000	208 (23.4%)
Greater than $150,000	225 (25.4%)
Declined to provide	164 (18.5%)
Highest Attained Parent Education	***n* (%)**
Less than high school	4 (0.1%)
High school diploma/ GED	42 (4.7%)
Some college/ Associate's degree	230 (25.9%)
Bachelor's degree	310 (34.9%)
Master's degree or Higher	249 (28.1%)
Declined to provide	52 (5.9%)
Age	Mean (SD)
Age on January 1st, 2020	19.18 (1.54)
Total	887

Participant Demographic information was collected via parent-report during an initial in-person intake assessment.

Measures

Positive and Negative Affect

Positive and negative affect surveys were deployed to participants' smartphones once every two weeks via an abbreviated form of the Positive and Negative Affect Schedule (PANAS; Crawford & Henry, 2004; Watson et al., 1988). The abbreviated PANAS consisted of five items assessing negative affect and five items assessing positive affect. Example items include "indicate to what extent you have felt afraid over the past few days" (negative affect) and "indicate to what extent you have felt inspired over the past few days" (positive affect). Each PANAS item was answered on a five-point scale from "Very Slightly" (1) to "Extremely" (5).

Average past week positive/negative affect were both computed by taking the mean score of all the positive/negative items.

Daily Mobility Measures

Participant location was collected via the CoTwins smartphone application, installed on each twin's personal phone. To limit battery drain, the "significant change" location API was used on iOS devices, such that a participant location was recorded each time the device registered a "significant" change in location (e.g., a movement greater than roughly 100-200 meters). On Android devices, the application was designed to record the participant's location once every five minutes.

After visual inspection and data cleaning steps, which included removing duplicated, incomplete, inaccurately measured, or highly improbable locations (such as those implying participant movement speeds greater than 600 kilometers per hour), locations were aggregated into points of interest, also called "staypoints," which were locations where participants were estimated to have spent at least 30 min within a 200 m radius (Zheng et al., 2011). This was done to help standardize the number and meaning of GPS locations observed each day between Apple and iOS participants or between participants living in urban or rural areas. To allow for harmonization with COVID-19 case count data, all locations recorded outside the United States were removed from analyses. From an initial sample of 42.0 million unique GPS locations, data cleaning and aggregation procedures yielded a dataset of 2.1 million staypoints from 598,966 participant-days.

Two daily mobility measures were computed from these staypoints: daily locations visited, defined as the number of staypoints recorded by a participant on a given day, and daily travel distance, the straight-line distance (in km) between a day's consecutively recorded staypoints. Travel days, in which the daily travel distance exceeded 500 km, were excluded from analyses to reduce the effect of outlying values. Additional information on the computation and measurement properties of these measures is available in Alexander et al. (2022).

COVID-19 Case Count

The Johns Hopkins Coronavirus research center provided daily data on the number of new COVID-19 cases recorded in each United States county between January 20th, 2020 and March 10th, 2023 (Dong et al., 2020). These were mapped to participants' modal county each day (defined as the county where a participant recorded the greatest number of staypoints) to measure the degree of COVID-19 transmission in a participant's environs. To help account for reporting artefacts (e.g., counties reporting weekend cases on the following Monday) daily county-level case count was aggregated by week and standardized by the county's population as weekly county-level case count per 100,000 people.

Date

A date term was used to model changes in affect and mobility over time both before and during the pandemic. This was included in statistical models as the number of days since 01/20/2020, the date of the first US COVID case. Data collected prior to pandemic onset were assigned negative date values. Several follow up analyses included a categorical effect of date to compare affect and mobility levels between January and April (corresponding to the first four months of the COVID-19 pandemic) in 2019 – 2022. Categorical date effects were restricted to data from January-April each year. This was done to account for seasonality effects, to isolate the especially large effect of the first months of the pandemic in early 2020, and to account for the lack of available data after April 18th, 2022. This categorical date variable had four levels: indicating whether an observation was recorded from 2019/01/20 – 2019/04/30, from 2020/01/20

– 2020/04/30, from 2021/01/20 – 2021/04/30, or from 2022/01/20 – 2022/04/18 (the final day with available affect or mobility data in the study).

Model Covariates

Participant sex was coded as male (0) or female (1). Participant age on 01/20/2020 (included as a constant to reduce collinearity with date effects) was recorded in years. Weekday/weekend status was coded as (0) weekday or (1) weekend. Operating system was recorded as either Apple iOS (0) or Android OS (1).

Missing Data

To help account for any systematic missingness in either the affect or mobility measures, a common challenge in intensive longitudinal research (Hicks et al., 2019), we included the proportion of missing days of location data and the proportion of missed PANAS responses as model covariates. The proportion of missing days of location data was defined as the proportion of days between a participant's first and last recorded location with no recorded staypoints. The proportion of missed PANAS surveys was computed as one minus the number of recorded affect surveys divided by a "theoretical maximum" number of affect surveys a person could have recorded, defined as the number of surveys a participant would have completed if they had completed one affect survey every two weeks between the date of their first and last survey response (rounded upwards to the nearest integer to prevent fractional values).

Analyses

All models reported in the results section are presented in **Table 2** along with their corresponding interpretation. A variety of statistical approaches were considered to model changes in affect and mobility patterns following the onset of the COVID-19 pandemic and in response to local COVID-19 cases, including linear mixed effects models, structural equation-based latent growth curve models, and generalized additive mixed models ("GAMMs"). Mobility and affect data were correlated at the individual and family level, were collected frequently at unevenly spaced intervals, and were expected to exhibit highly non-linear trajectories both over time and in response to local COVID cases. We therefore determined that GAMMs were best suited to accommodate these correlated, time unstructured data and expected non-linear relationships (McNeish & Matta, 2018; Wood & Scheipl, 2020).

As seen in **Table 2**, these GAMMs, which were fit using the gamm4 package in r (Wood & Scheipl, 2020), included parametric fixed effects of sex, age, smartphone operating system, and the proportion of missing location and survey data, nested random intercepts of individuals within families, and nonlinear "smooth" terms (fit via penalized regression splines) of either date or case count. Models of daily mobility further included a covariate indicating whether the observation was recorded on a weekday or a weekend. Smooth effects for date were fit using thin plate regression splines with k = 35 basis functions, while smooth effects for case counts were fit with k = 10 basis functions. Selection of the number of basis functions was supported via the k-basis dimension test to prevent model under-identification. (Wood, 2017; Wood & Scheipl, 2020). To assess whether mobility and affect were significantly increasing or decreasing at a given date or case count level, we computed first derivatives and 99% confidence intervals of the smooth date and case count terms at 10,000 equally spaced points on the smooth's curve using the R package gratia (Simpson, 2014; Simpson & Singmann, 2023).

Such GAMMs are useful for visualizing complex mean trajectories, but they consequently do not provide readily interpretable fixed effects coefficients for date or case count effects. Hence, complementary to these generalized additive models, we further fit linear mixed effects models, via the R package lme4, (Bates et al., 2014) which included all fixed effects covariates included in the GAMMS, nested random intercepts for individuals nested within families, and both fixed and random effects of year (see the measures section) or local COVID-19 transmission rates. Similarly, to assess whether affect or mobility differed in their responsiveness to local case count over time, we also fit mixed effects models with these same covariates along with a linear case count effect, year effect (where year indicated whether an observation was recorded in 2020, 2021, or 2022), and a case count × year interaction effect (see **Table 2**. for formal and text-based descriptions of each model).

Table 2. Description of models, terms included, and related research aims.

Research Aim	Model	Terms
Quantify mean changes in affect/ mobility over time or across COVID-19 transmission levels.	$Y_{ij}=f_1(u_{1ij})+X_{1ij}\beta_1+Z_{1ij}b_1$ (1)	Y_{ij}: Vector of participant *i* in family *j*'s affect/mobility. $f_1(u_{1ij})$: Smoothing function representing the nonlinear effect of date or local case counts on affect/mobility $X_{1ij}\beta_1$: Linear effect β_1 of covariates X_{1ij} $Z_{1ij}b_1$: Random effects (intercept) b_1 for individual j nested in family *j* ϵ_{ij}: Random error term

Obtain parameter estimates for affect and mobility changes by year and across COVID-19 transmission levels.	$Y_{ij} = X_{2ij}\beta_2 + Z_{2ij}b_2 + \epsilon_{ij}$ (2)	Y_{ij}: Vector of participant *i* in family *j*'s affect/mobility. $X_{2ij}\beta_2$: Linear effect β_2 of covariates X_{2ij}, including an effect of year or local case count.. $Z_{2ij}b_2$: Nested random effects b_2 of individual i within family *j*, including a random slope of year or local case count. ϵ_{ij}: Random error term
Test whether the effect of local COVID-19 case counts on affect/mobility are moderated by year.	$Y_{ij} = X_{3ij}\beta_3 + Z_{3ij}b_3 + \epsilon_{ij}$ (3)	Y_{ij}: Vector of participant *i* in family *j*'s affect/mobility. $X_{3ij}\beta_3$: *Linear effect* β_3 *of covariates* X_{3ij}, including an effect of year, local case count, and a year by local case count interaction term. $Z_{3ij}b_3$: *Nested random effects* b_3 *of individual i within f* including random slopes of year and case count. ϵ_{ij}: Random error term

We considered several different strategies to reduce the impact of missing surveys and location data. The proportion of missing affect surveys and missing days of GPS location data for each participant were recorded as model covariates. Relationships between missingness, participant demographics, and affect and mobility measures were explored to identify possible attrition effects on outcomes. Additional strategies were considered, such as running analyses in a latent growth curve modelling framework with full information maximum likelihood estimation (Enders & Bandalos, 2001) or multiply imputing missing data . However, given that predictor variables were only rarely missing, measurement occasions were irregularly spaced, and affect and mobility trajectories were highly non-linear, we concluded that Generalized Additive Mixed Models remained better suited to modelling these relationships (McNeish & Matta, 2018; Wood & Scheipl, 2020). Similarly, multiple imputation was ultimately not utilized due to computational constraints and to the large number of missing days of data, implying a large fraction of missing information impacting the accuracy of imputation results (Madley-Dowd et al., 2019).

Results

Descriptive Statistics

Descriptive statistics for affect and mobility measures are provided in **Table 3.** To assess the extent of reliability of the remote affect surveys over the multi-year duration of the study, Cronbach's alphas were computed at each assessment for participants' first 70 remote affect surveys. These alphas ranged from 0.67 to 0.91 for positive affect (mean α = 0.78) and from 0.75 to 0.89 (mean α = 0.83) for negative affect, indicating affect surveys were adequately reliable for the duration of the study. Intraclass correlation coefficients (ICCs; single random raters) for the affect surveys over time were 0.52 for average positive affect and 0.55 for average negative affect, indicating that individuals' self-reported positive and negative affect varied between assessments but was moderately-highly correlated with affect measurements at other timepoints. Mobility measure ICCs were 0.14 for daily locations visited and 0.04 for daily travel distance, suggesting highly variable mobility patterns over the multi-year duration of the study. A greater percentage of both location data and affect surveys were missing for younger participants *(β= [-0.40 – -1.12], all P<.001)* and Android users *(β= [0.97 – 44.05],* all *P<.001).* Missing location data was significantly more prevalent in females *(β=0.22, P<.001)* while missing affect surveys were more common among males *(β=2.88, P<.001).*

Table 3. Descriptive Statistics for Affect and Mobility Measures

Variable	Grand Mean (Mean, SD; IQR)	Within-Subject Mean (Mean, SD; IQR)	N_{Total}	$N_{Participant}$ (Mean, SD; IQR)	% Missing (Mean, SD; IQR)
Daily Locations Visited	3.5, 2.1; (2.0 – 5.0)	3.4, 0.9; (2.8 – 3.9)	592,834	689.3, 498.4; (271.5 – 1090.5)	46.1% (23.7% – 62.0%)
Daily Travel Distance (km)	20.3, 42.0; (0.6 – 21.2)	18.1, 9.4; (11.5 – 23.4)	592,834	689.3, 498.4; (271.5 – 1090.5)	46.1% (23.7% – 62.0%)

Positive Affect (0-5)	2.9, 0.7; (2.4 – 3.4)	2.9, 0.6; (2.5 – 3.2)	15,501	23.3, 18.0; (8 – 36)	47.1% (25.0% – 66.8%)
Negative Affect (0-5)	2.0, 0.8; (1.4 – 2.6)	2.1, 0.6; (1.6 – 2.5)	15,500	23.3, 18.0; (8 – 36)	47.1% (25.0% – 66.8%)

Grand Mean: the average value for a measure across all participants and days.
Within-Subject Mean: The mean of participant-mean values for a measure.
N_{total}: The total number of recorded observations across all participants for a measure.
$N_{Participant}$: The average number of observations recorded per participant.
% Missing: The mean participant's portion of missing days of location data/completed affect surveys. (See the "Missing Data" section for additional information on missingness).
IQR: "Interquartile Range"

Change over Time and Pandemic Onset Effects on Affect and Mobility

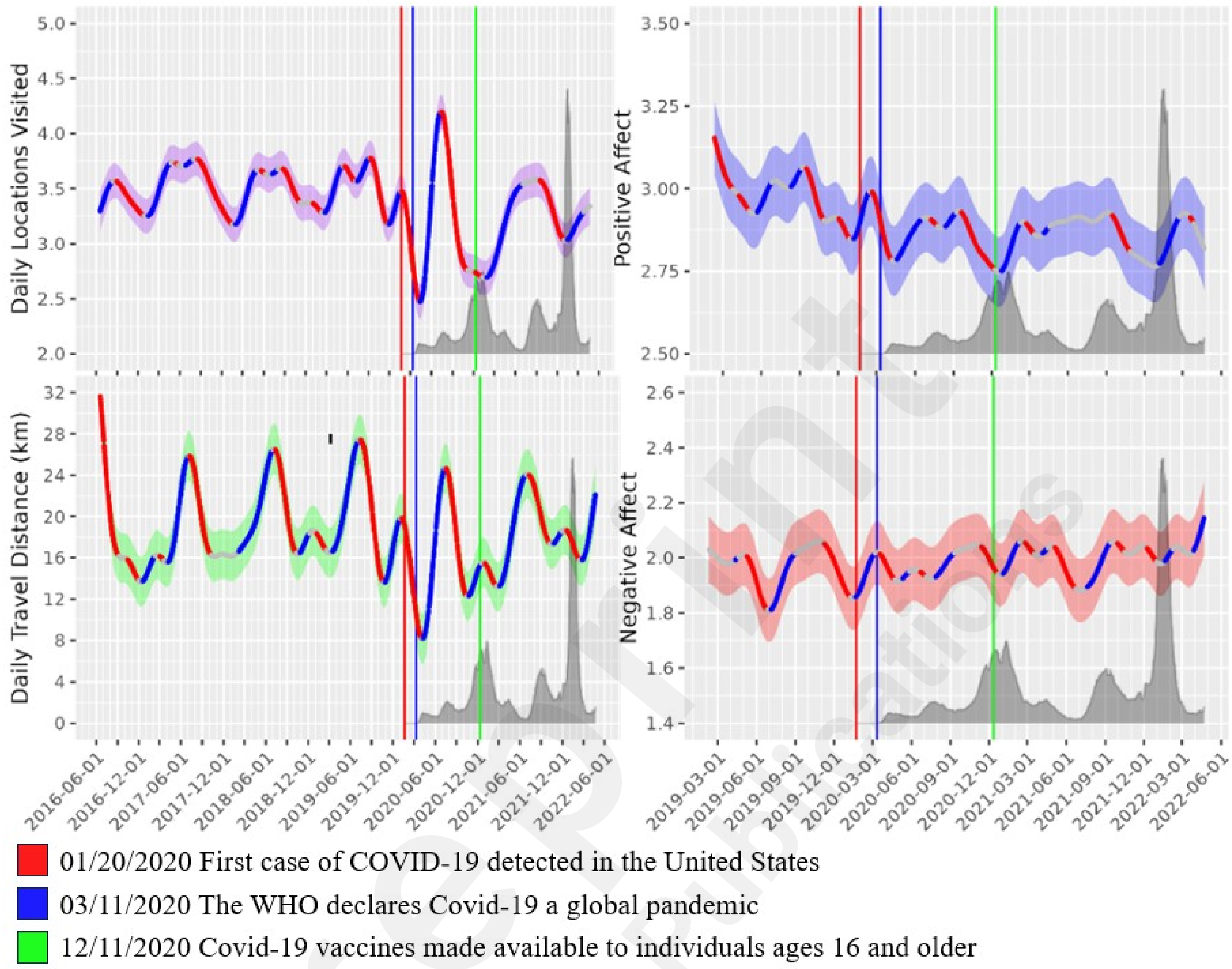
Supplementary Table S1. reports the results of GAMMs of daily locations visited, daily travel distance, positive affect, and negative affect conditioned on a smooth Date term, fixed effects covariates, and random intercepts of individuals nested in families. Significant fixed effects of covariates are reported in **Supplementary Table S1.** and included male sex (positive affect, negative affect), age on 1/20/2020 (locations visited, travel distance), weekend day (locations visited, travel distance), Android OS (locations visited, positive affect, negative affect), percent missing location data (locations visited, travel distance) and percent missing affect surveys (locations visited, travel distance). Effective degrees of freedom ("edf") tests of non-linearity (Wood, 2017) indicated that date smooths were significantly non-linear for all outcome variables (edf =31.2–33.8, F=29.0–400.7, all P<.001) while k-basis dimension tests (Wood, 2017) suggested basis dimensions were sufficient to prevent underfitting (k =0.98–1.01, P=.14–.81).

Smooth date effects (adjusted for fixed effects covariates), characterizing the change in mean affect and mobility levels over time are presented in **Figure 1.** Prior to the onset of the pandemic in January 2020, mobility measures were largely stable over time, though with seasonal fluctuations of higher mobility in the summer months and lower mobility during the winter. During the first several months of the COVID-19 pandemic, from January - May 2020, both daily locations visited and daily travel distance fell sharply to their lowest levels observed during the study, falling by 29%, from 3.5 to 2.5 locations per day, and by 60%, from 20 km to 8 km per day, respectively. Both mobility measures sharply rebounded during the Summer of 2020, with daily locations visited increasing 68% and daily travel distance increasing by 200%. They then plummeted between September and December, with mean daily locations visited falling from a high of 4.2 to a low of 2.8 locations per day and mean daily travel distance falling from a high of 24km to a low of 12km per day, coincident with a large outbreak of COVID-19 cases. Beginning in December 2020 and January 2021, roughly coincident with when COVID-19 vaccines were first made broadly available to adults over age 16, daily mobility measures steadily increased for much of 2021 and 2022, though with significant decreases of ~0.6 locations/day and ~8km/day between September 2021 and January 2022, possibly reflecting the return of seasonal declines in mobility during the winter observed prior to the pandemic's onset. By mid-April 2022 participants visited an average of 3.3 locations per day with a daily travel distance of 28km, both of which were similar to levels observed in Spring, 2019.

During 2019, positive affect significantly increased during the Summer months and significantly decreased during the Fall and Winter months (all $P < .01$). In contrast, negative affect significantly decreased during the Summer of 2019, significantly increased in the late Summer and Fall, and significantly declined in the late Fall and Winter (all $P < .01$). Average positive affect saw modest changes following the pandemic's onset in early 2020, initially increasing from a mean of 2.85 in January to 3.0 in February 2020 before declining to 2.79 by April 2020 (a decline of 0.3 standard deviations), its lowest observed level during the study period. Contrastingly, mean negative affect initially increased from 1.85 to 2.10 between January and March 2020 (an increase of 0.3 standard deviations) before declining slightly to 1.91 in April and May 2020, concurrent with the implementation of COVID-19 lockdown policies. Over the subsequent two years, positive affect remained consistently below pre-pandemic levels, though with significant fluctuations: declining significantly during two large COVID outbreaks in the Fall and Winter 2020 and 2021 and increasing significantly in late 2020/early 2021 (coincident with the rollout of the COVID-19 vaccine) and in early 2022. In contrast, mean negative affect levels continued to modestly fluctuate over the subsequent months and years of the pandemic, though generally remaining slightly above levels observed prior to the pandemic's onset.

The results of mixed effects models quantifying differences in average affect/mobility from January-April in 2019-2022 are presented in **Supplementary Table S2** as well as in **Figure 2.** Fixed effects covariate estimates were largely consistent with those obtained via GAMMs (**Supplementary Table S1)**. Daily locations visited between January and April 2020, 2021, and 2022 were all significantly below mean levels observed between January and April 2019 (standardized β= [-0.24 – -0.10], all $P<.001$). Similarly, mean daily distance travelled remained below January–April 2019 levels in January–April 2020 and 2021 (standardized β=[-0.13 – 0.07], all $P<.001$) though they were not significantly different from 2019 levels in January–April 2022 (standardized $\beta=-0.03$, $P= .29$). Mean positive affect remained significantly below early 2019 levels in January–April 2020, 2021, and 2022 (standardized $\beta=[-0.20 – -0.16]$, all $P<.001$). Relative to early 2019 levels, mean negative affect was not significantly different in January–April 2020 or 2021 (standardized $\beta=[0.00;0.09]$, P=[$.99;.07$]) but was significantly higher in January–April 2022 (standardized $\beta=0.14$, P=0.04).

Figure 1. Pandemic Onset Effects on Affect and Mobility Measures Over Time.

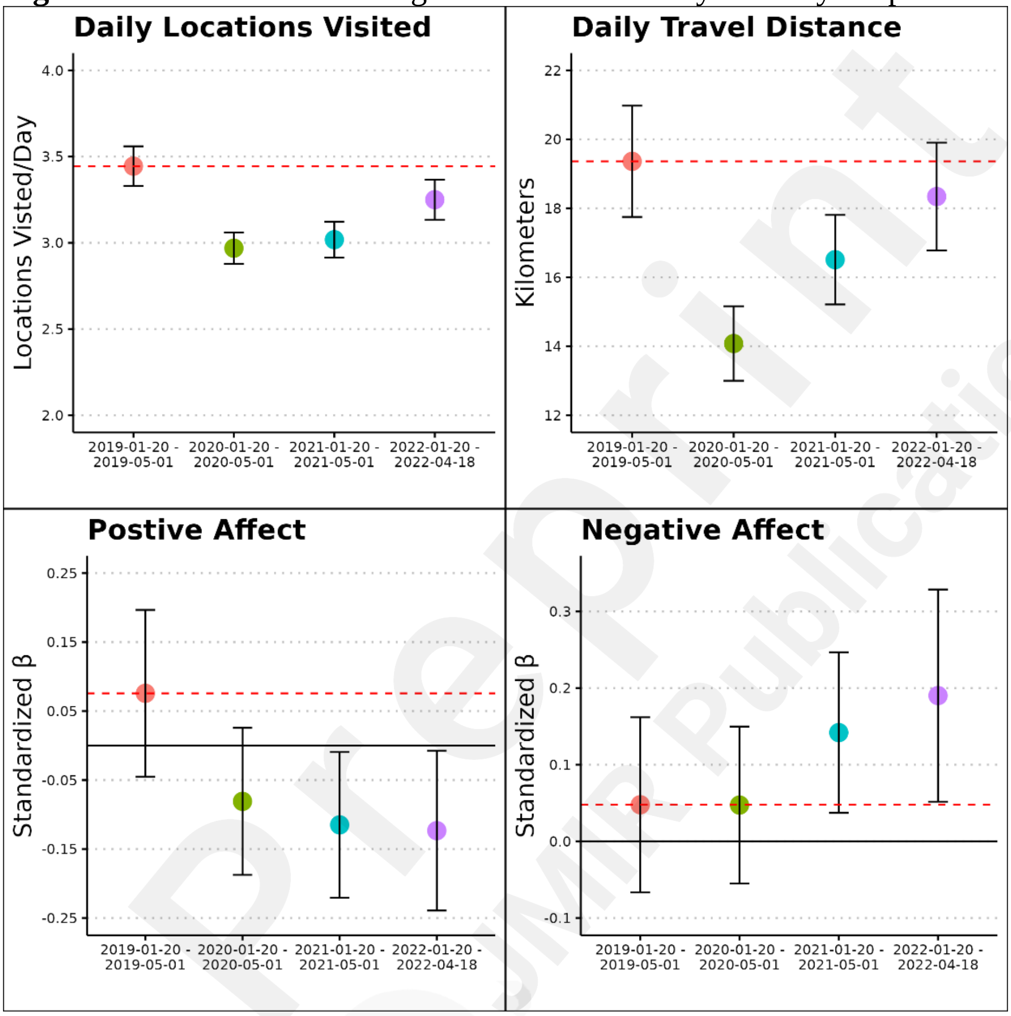


Affect and mobility measures regressed onto a smooth date term (fit via penalized spline regression). Colored bands indicated 95% confidence intervals. Blue segments of the curve indicate areas where the derivative of the curve is significantly greater than 0 ($P < .01$) while red segments indicate areas where the derivative is significantly less than 0 ($P<.01$). For reference, the number of daily national COVID-19 cases is presented in dark gray behind each curve.

Local Case Count Effects on Affect and Mobility

Results of GAMMs of affect and mobility measures regressed on a smooth effect of local past-week COVID-19 cases per 100,000, fixed effects covariates, and random intercepts of individuals nested in families are presented in **Supplementary Table S3.** Fixed effects covariates showed largely the same relationships to affect and mobility measures as in the smooth date GAMMs (**Supplementary Table S1**). Case count smooths were significantly non-linear for all outcome variables (*edf* =5.77–8.55, F=23.04–338.9, *ps*<.001). K-basis tests were significant for negative affect (k-index=0.93, P<.001) and daily travel distance (k-index=0.97, P=.03), suggesting possible underfitting, though these models' effective degrees of freedom, 6.54 and 5.77 respectively, were deemed sufficiently different from *k'*, 9.00, that it was not necessary to refit these models with additional basis dimmensions (Wood, 2017).

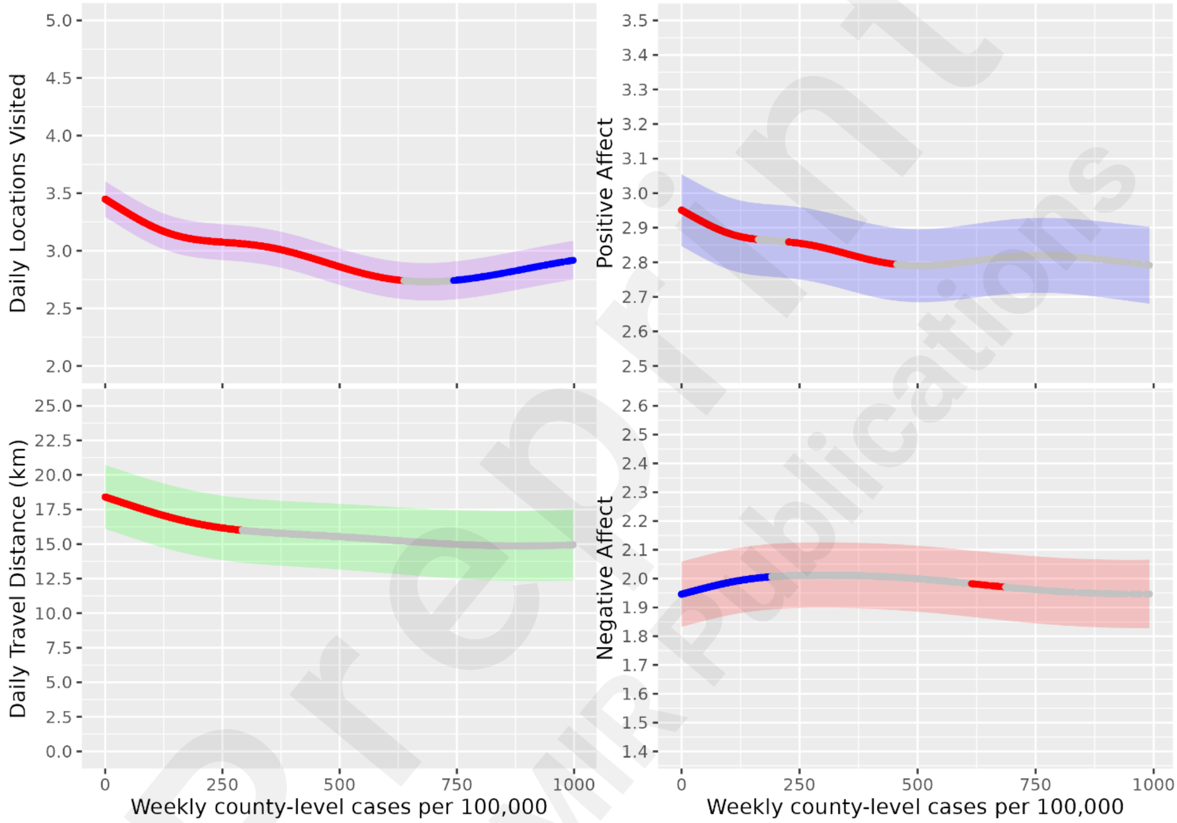
Figure 2. Differences in Average Affect and Mobility: January – April 2019-2022



Predicted affect and mobility values from January 20th – May 1st 2019 – 2022 according to linear mixed effects models. Affect values are represented in standard-deviation units for interpretability.

The effects of local case count smooths, corrected for fixed effects covariates, on affect and mobility measures are presented in **Figure 3.** Increased county-level COVID-19 transmission was associated with small or moderate declines in positive affect and both measures of mobility, though increases above several hundred past-week county-level cases per 100,000 were generally not significantly related to either positive affect or mobility. Correspondingly, negative affect exhibited a small but statistically significant increase of 0.06 standard deviations as local COVID-19 incidence increased from 0 to 190 past-week local cases per 100,000, though further increases in local COVID-19 transmission generally exhibited non-significant relationships with negative affect.

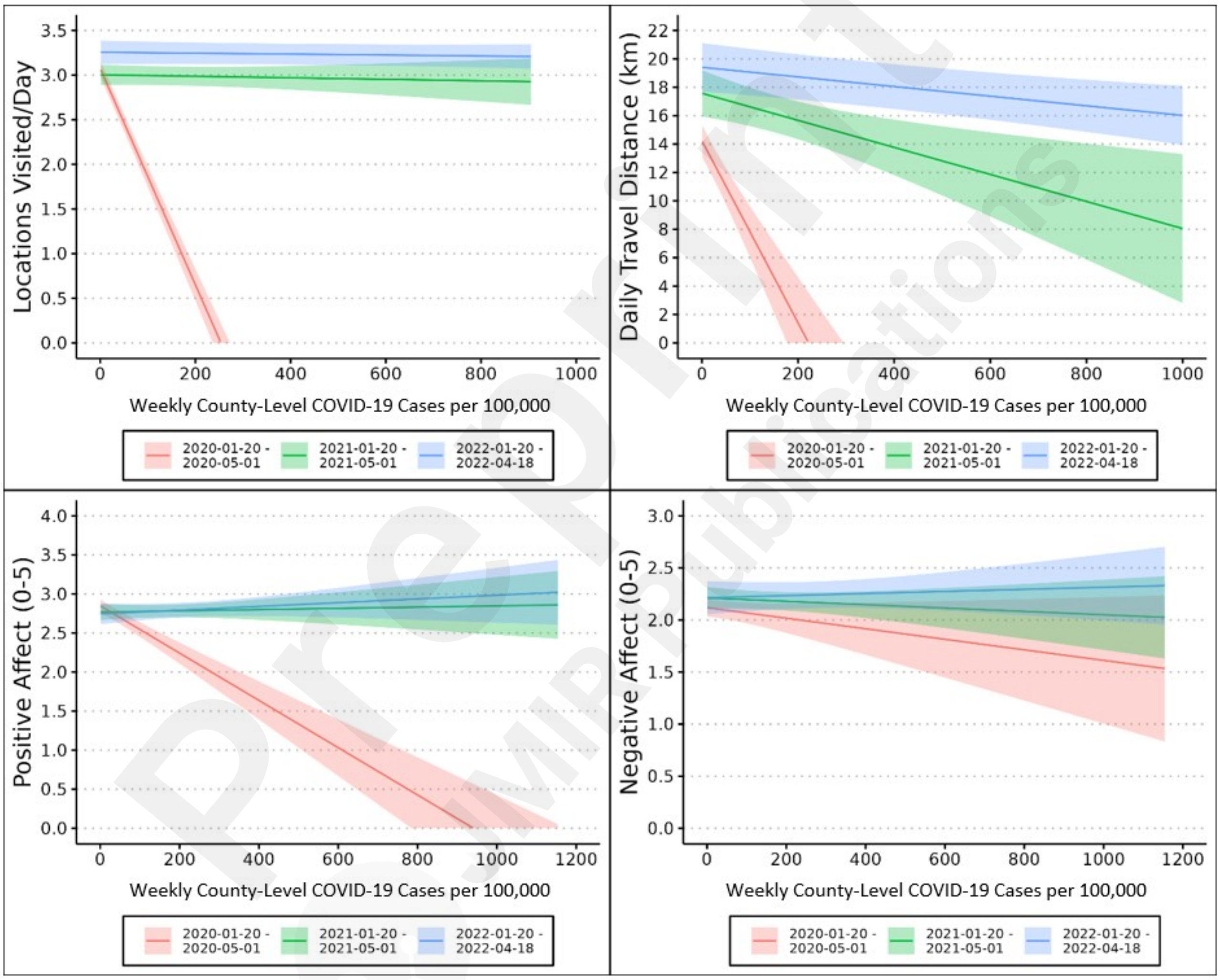
Figure 3. Local Case Count effects on Affect and Mobility Measures



Affect and mobility measures regressed onto smooth past week county-level COVID-19 cases per 100,000 people. Colored bands indicated 95% confidence intervals. Blue segments of the curve indicate areas where the derivative of the curve is significantly greater than 0 (P < .01) while red segments indicate areas where the derivative is significantly less than 0 (P<.01).

Mixed effects models testing for interactions between local case count and the year in which the observation was reported are presented in **Supplementary Table S4** and visualized in **Figure 4.** Covariate effects were largely consistent with those observed in previous models. An increase of 100 additional weekly cases per 100,000 was associated with significantly greater reductions in daily locations visited, daily travel distance, and positive affect during 2020 than during 2021 or 2022 (standardized *β= [0.096 – 1.527]*, all *P<.001)* and with significantly attenuated reductions in negative affect during 2022 than during 2020 (standardized *β=0.184*, *P<.001).*

Figure 4. Effects of Local Case Count on Affect and Mobility Measures Moderated by Date.



The linear effect of COVID-19 case counts on affect and mobility between 01/20 and 05/01 in 2020, 2021, and 2022 obtained via linear mixed effects models. Shaded regions indicate 95% confidence intervals.

Discussion

This study investigated changes in affect and mobility patterns in American youth throughout the COVID-19 pandemic. As a nearly six-year intensive longitudinal design, this study represents a lengthy and longitudinally rich investigation into the pandemic's psychological impact on youth.

Consistent with expectations, during the first pandemic months in 2020 we observed large decreases in participants' average locations visited per day and daily travel distance, a moderate decrease in mean positive affect, and a modest increase in mean negative affect. These changes are consistent with prior research conducted in adults (Blasco-Belled et al., 2022; Bonaccorsi et al., 2020; Carstensen et al., 2020; Hu et al., 2021; Lades et al., 2020; Santana et al., 2023) suggesting youths exhibited behavioral and emotional changes similar to adults. However, we found that mean changes in affect during the first months of the pandemic were quite small; the average positive and negative affect between Jan 20 and May 1 2020 differed by less than 0.2 standard deviations from average levels over the same period in 2019. These youth were, on average, resilient in the face of the pandemic's dramatic uncertainties.

Contrary to expectation, daily locations visited and positive affect remained significantly below and negative affect significantly above early 2019 levels through at least April 2022. This incomplete return to mean pre-pandemic levels more than two years after the pandemic's onset is more consistent with trauma-based theories on the psychology of disasters (Goldmann & Galea, 2014; Norris & Wind, 2009), which predict lasting emotional impacts following traumatic experiences like natural disasters. That said, effect sizes are minimal if significant, and the lasting scar of the pandemic of uncertain significance in the lives of these youth, at least on average.

These persistent differences – years after the pandemic onset – may reflect psychological scarring, or may represent the ongoing spread of COVID-19 in April 2022. Yet we found that the relationship between affect and case count greatly attenuated with time, showing almost no relationship with affect by 2022. Another explanation is that these differences represent developmental effects associated with participants transitioning from adolescence to early adulthood. However, existing research indicates that the transition from adolescence to emerging adulthood is associated with *increases* in positive affect (Furlong, 2016) and daily mobility (Alexander et al., 2022) and *decreases* in negative affect (Bailen et al., 2019; Furlong, 2016), opposite of our findings. Identifying the causes of these persistent affect and mobility differences two years after the pandemic's onset is likely beyond the scope of any single study yet, speculatively, a combination of sociocultural changes, ongoing pandemic-related stressors, and lasting psychological impacts in the aftermath of the pandemic represent reasonable initial hypotheses for contributing factors.

Our hypothesis that local case count would be associated with reduced mobility and positive affect and increased negative affect was partially supported. These effects were strong earlier in the pandemic and decayed later that year and in the months surrounding the availability of vaccines. The reasons for this change could be myriad, including vaccine availability, loosening of COVID-19 restrictions, better understanding of the limited effects of infection on youth, or more simply changing attitudes toward the pandemic.

Some limitations of this study are of note. Participants were adolescents/young adults and tended to be wealthy, educated, and white, albeit 16% of Hispanic ethnicity, largely consistent with ethnic diversity of Colorado. Generalization to other socioeconomic or ethnic contexts may not be straightforward. Indeed, generalizability may be particularly challenging for studies of pandemic-related behavior, as experiences of the pandemic varied considerably across geographic and sociodemographic contexts (Bonaccorsi et al., 2020; Pullano et al., 2020; Showalter et al., 2021). Twin participants are necessarily more similar to one another in their behaviors, personalities, and life circumstances than unrelated individuals. Hence the effective sample size of the study is likely smaller than suggested by the study *N* of 887. As expected in lengthy intensive-longitudinal studies, both affect surveys and mobility data were subject to substantial missing data (Bolger & Laurenceau, 2013; Lydon-Staley & Bassett, 2018). Efforts to characterize and limit this impact included covarying for the proportion of missing data in all models and reporting and investigating relationships between attrition, demographics, and model outcomes and covariates. We identified several significant relationships between attrition and demographics, affect, and mobility, suggesting that, though we partially account for missingness via a fixed effects covariate, this strategy may not have fully accounted for missingness effects, especially if missingness was influenced by unanticipated, unmeasured, confounds (Dong & Peng, 2013).

In summary, we found substantial reductions in daily mobility and modest changes in positive and negative affect following the onset of the COVID-19 pandemic in early 2020, with reductions in daily locations visited and positive affect and increases in negative affect relative to early 2019 levels persisting through at least mid-2022. We further found that increases in local COVID-19 case counts were associated with reduced mobility and positive affect, as well as increased negative affect, though with diminishing effects above several hundred cases per 100,000 and weaker effects in 2021 or 2022 relative to 2020. Lasting changes in affect and mobility do not appear to be well explained by the ongoing spread of COVID-19 during mid-2022, and instead may reflect lasting pandemic-related harms, sociocultural changes, or disruptions to normative trajectories in social, emotional, professional, or educational development.

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Conflicts of Interest:
None of the study's authors have any conflicts of interest to disclose.

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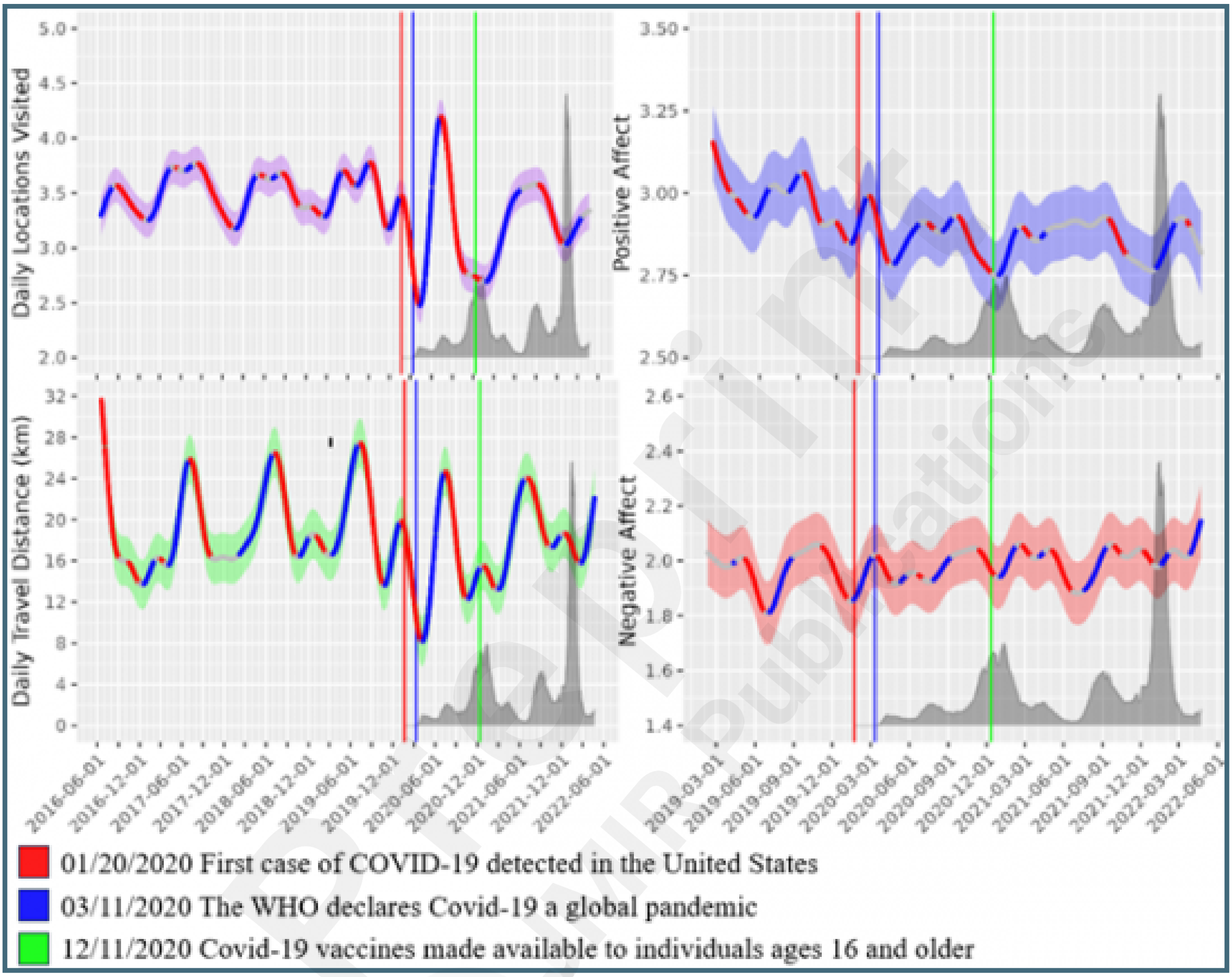
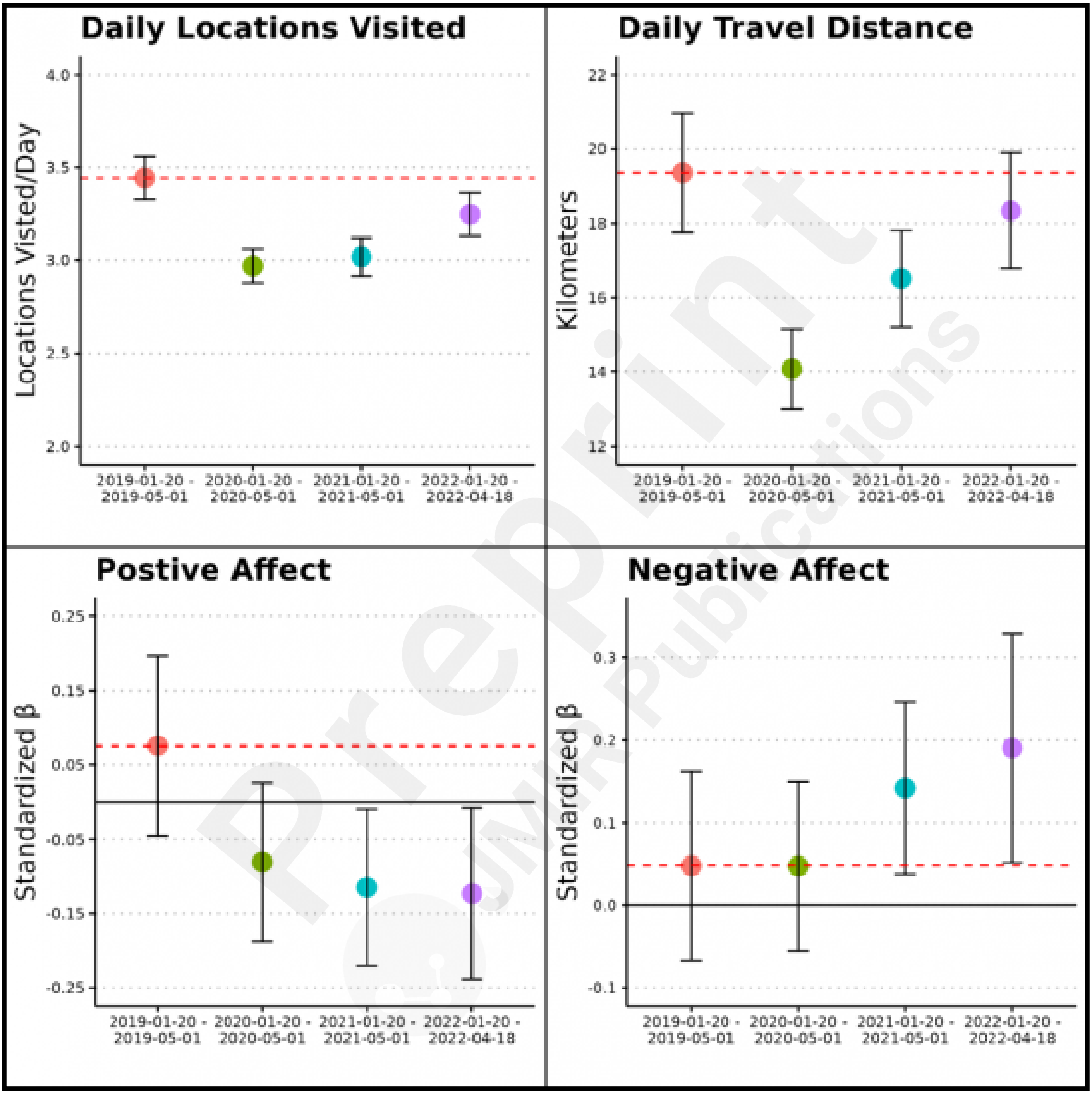
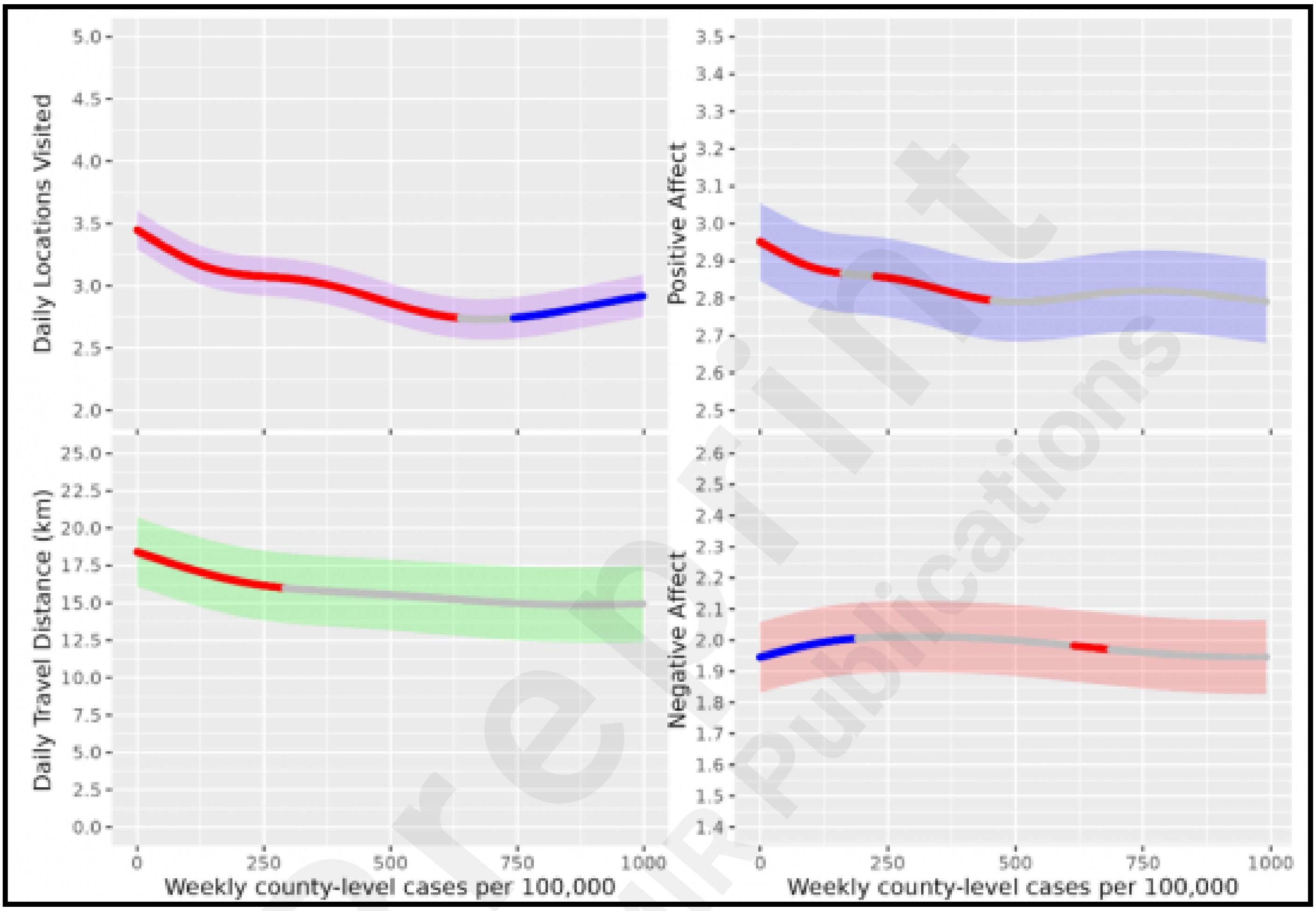
Supplementary Files

Figures

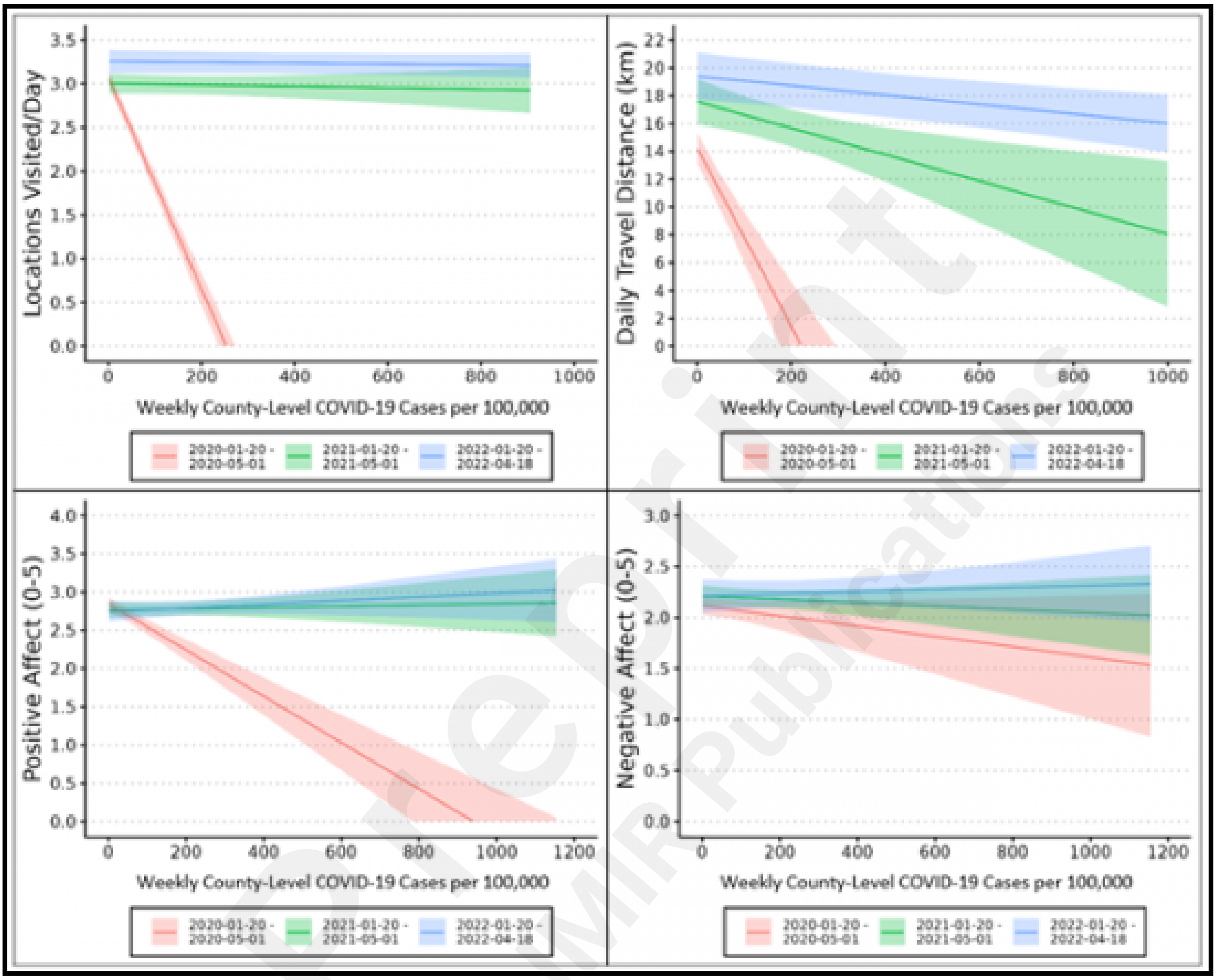

Daily Locations Visited
Positive Affect
Daily Travel Distance (km)
Negative Affect
01/20/2020 First case of COVID-19 detected in the United States
03/11/2020 The WHO declares Covid-19 a global pandemic
12/11/2020 Covid-19 vaccines made available to individuals ages 16 and older

Differences in Average Affect and Mobility: January – April 2019-2022. Predicted affect and mobility values from January 20th – May 1st 2019 – 2022 according to linear mixed effects models. Affect values are represented in standard-deviation units for interpretability.




Daily Locations Visited
Positive Affect
Daily Travel Distance (km)
Negative Affect
Weekly county-level cases per 100,000
Weekly county-level cases per 100,000
0
250
500
750
1000

Effects of Local Case Count on Affect and Mobility Measures Moderated by Date. The linear effect of COVID-19 case counts on affect and mobility between 01/20 and 05/01 in 2020, 2021, and 2022 obtained via linear mixed effects models. Shaded regions indicate 95% confidence intervals.



Multimedia Appendixes

Supplementary Tables S1. - S4.

URL: http://asset.jmir.pub/assets/58c7a68e22717fa93902c2b6849a4a18.docx