

Trends in mental health care and telehealth use across area deprivation: An analysis of electronic health records from 2016 to 2024

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Abstract

While telehealth may improve access to healthcare for some, it may also widen gaps in access across different economic groups. Using electronic health records for outpatient mental health care of patients with depression in a large US academic health system, we assessed changes in mental health care utilization from 2016 to 2024 (primary care: $n = 42,640$ patients, 270,754 visits; psychiatry: $n = 12,846$ patients, 336,918 visits) and odds of using telehealth relative to in-person care from 2020 to 2024, across national area deprivation index (ADI) percentiles. We found that over 3 years prepandemic (July 2016–June 2019), the volume of mental health care delivered to patients from low-deprivation areas (1st–25th national ADI percentile) was increasing at a steeper rate than for high-deprivation areas (76th–100th national ADI percentile). Visit volume changed rapidly at the onset of the COVID-19 pandemic, and by July 2021 it was increased relative to prepandemic levels. From July 2021 to June 2024, volume of care declined for all deprivation groups, but at a more rapid rate for the high-deprivation group than the low-deprivation group. Further, on average from July 2020 to June 2024, the odds of receiving telehealth relative to in-person care were significantly higher for patients living in low deprivation rather than high-deprivation areas in both primary care and psychiatry. We did not find evidence of telehealth improving access to care for patients in high-deprivation areas. Differences in telehealth use may contribute to sustained disparities in access to mental health care across economic groups.

Keywords: Telehealth, electronic medical records, health services research, socioeconomic status, mental health

Significance Statement

It is unknown how changes in mental health care utilization from prepandemic to postpandemic varied for patients across deprivation areas and whether differences in the use of telehealth could contribute to disparities in utilization. We found that after rapid changes in utilization at the start of the pandemic, volume of mental health care delivered to patients from high-deprivation areas dropped off more steeply than for patients from low-deprivation areas. Patients in lower deprivation areas were also more likely than patients in more deprived areas to use telehealth than in-person care. Action is needed to ensure that differences in use of telehealth across socioeconomic groups do not contribute to differences in care.

Competing Interest: Dr. Mojtabei reports having received royalties from UpToDate, MindMed, and Medscape and providing expert consultation regarding social media litigation on behalf of the plaintiffs. The other authors report no financial relationships with commercial interests.

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Introduction

The US healthcare system's approaches to mental health have evolved over the past two decades. However, despite these advances, inequalities in access to treatment prevail, particularly across economic status. Receipt of health care, including for mental health, has long been unequal across socioeconomic groups (1). Historical differences in access to economic resources contribute to differences in receipt of mental health care and shape modern engagement with the health system across groups (2, 3). While there has been an awareness for multiple decades of differences in receipt of health care across socioeconomic groups, they remain a stubborn feature of health and of mental health care. Depression, which affects more than 21 million people in the United States (4), and costs over \$326 billion annually (5), is vulnerable to stressors and can be responsive to treatment among those who are able to receive care.

Features of the places where patients live can inform population access to financial, physical, and social assets (6), which can shape access to mental health services and mental health (7, 8). Neighborhoods, beyond a summary of the individuals who live there, contribute to the health outcomes of residents (9–11). Patients who live in more deprived areas are exposed to more stressors, have worse hospital outcomes (12), and may face greater challenges in accessing mental health care. Moreover, such patients experience a higher severity of symptoms of depression after hospitalization due to COVID-19 (13). The area deprivation index (ADI) is a composite measure that captures a neighborhood's aggregate income, education, and poverty, among other economic factors (14, 15). People who live in areas with worse area deprivation may face greater barriers to accessing in-person mental health care. For example, areas with greater deprivation may have fewer resources that could facilitate care such as reliable public transportation, safe streets, and access to high quality medical facilities. People who live in areas with greater deprivation likely have fewer resources, on average, than people who live in areas with less deprivation. Therefore, it is possible that their economic circumstance may prevent them from accessing mental health care, either through underinsurance or uninsurance, high out-of-pocket costs, lack of transportation, or the need to take off work to visit a mental health provider's office in person. In this way, lower rates of mental health care system engagement may reflect the inverse care law, whereby populations with the most need are the least likely to receive health care (16). Area deprivation can, therefore, be a helpful measure to identify and understand inequities in access to mental health care.

The rapid rise of telehealth (receipt of medical care via synchronous video or phone calls) following the COVID-19 pandemic created a paradigm shift in the delivery of mental health care. At the start of the COVID-19 pandemic, regulations were temporarily eased to ensure continuity of care: many state Medicaid programs and private insurers required payment parity between telehealth and in-person care (17), location restrictions were relaxed by Medicare and some state Medicaid programs (18, 19), some state licensure stipulations were lifted so that therapists could provide care to patients living in different states (17), state Medicaid programs expanded the kinds of care that could be offered virtually (19), in-person requirements for prescribing were relaxed by the Drug Enforcement Administration (19), and the Health Insurance Portability and Accountability Act (HIPAA) rules on compliant communication software were not enforced (17, 19). These regulations, alongside difficulties receiving in-person care, caused a rapid rise of telehealth (20). In-person care rebounded in later stages

of the pandemic (21, 22), although telehealth use remained elevated (especially in behavioral health) and some of the public health emergency rules on telehealth use became permanent (18, 19, 21, 22). Around 22.5% of Americans surveyed between April 2021 and August 2022 had used telehealth care for any kind of treatment in the last month (23), and 16% of telehealth visits had a primary purpose of addressing mental/behavioral health (24). Before the COVID-19 pandemic, 60.6% of mental health facilities offered only in-person care, which decreased to 11.9% by 2022 (25). The height of the pandemic saw more than 10 times as much use of telehealth appointments for mental health care compared to the period prior to the pandemic (22). The COVID-19 pandemic illustrates the role of area-level assets in differences in health outcomes (26), and potentially differences in health care seeking behaviors.

Telehealth has been proposed as a potential solution to reduce barriers in access to mental health care for populations with fewer resources. Telehealth may transform delivery of care, particularly for mental health care, which may be more feasible to facilitate via virtual engagement than for physical health conditions. Digital technologies, including telehealth, have been recommended as opportunities to reduce barriers to care and increase access for groups who have historically been marginalized (27). Telehealth may be particularly effective for depression, which can be managed through therapy and medication, as opposed to more severe forms of mental illness, which may be more appropriate to treat in person. For instance, telehealth-based cognitive behavioral therapy (CBT) has been shown to be an effective method of treating major depressive disorder, on par with in-person CBT (28). However, few studies to our knowledge have examined whether telehealth is being used by patients who face greater barriers to mental health care and whether telehealth is improving access to mental health care for patients who live in high-deprivation areas.

It is possible that differences in the use of telehealth across socioeconomic groups could fuel differences in access to care (29). While telehealth may reduce some barriers to care, such as needing to travel physically to attend appointments, some people are more able to take advantage of the benefits of telehealth than others. Specifically, using telehealth requires adequate technology, internet access, private space, and technical literacy. Early evidence suggests that there are differences in telehealth use related to social constructs of racial and ethnic groups (24, 30–32), sex (24, 30), education (33), age (24), marital status (24), insurance (31, 34), community socioeconomic status (31, 34), and access to a reliable transportation method and internet connection (24). Certain populations may face additional barriers to accessing telehealth, including rural populations (35–37) and older patients (35, 38). In sum, to the extent that telehealth use remains a commonly used feature of the health system, these new requirements for accessing care, if unaddressed, could become sources of inequality in mental health service utilization.

While many articles have been written about the potential of telehealth to transform mental health care (39, 40), few empirical studies have documented in a large health system the evolution of telehealth services during and after the COVID-19 emergency declarations that lifted regulations on telehealth use and changed reimbursement for telehealth care relative to in-person care (41). We utilized eight years of patient data (July 1, 2016–June 30, 2024) from the electronic health records (EHR) of patients with depression at a large, academic, urban health system to investigate trends in the utilization of mental health services in primary care, where more than 30% of mental health care takes place (42), and

in the department of psychiatry of the same academic health system. Our research questions were how did trends in mental health care utilization change from 2016 to 2024 across levels of area deprivation (Research question 1) and how did trends in telehealth use for mental health care differ from 2020 to 2024 across levels of area deprivation (Research question 2)?

Results

Research question 1: trends in mental health care utilization from 2016 to 2024

Table 1 shows characteristics of our two cohorts of patients with depression who received mental health care in primary care ($n = 42,640$ patients, 270,754 visits) and/or in the department of psychiatry ($n = 12,846$ patients, 336,918 visits) between July 1, 2016, and June 30, 2024, overall and stratified by time period (pre- and postpandemic). Both cohorts were largely female (71.1% in primary care, 64.7% in psychiatry) and white (68.5% in primary care, 59.8% in psychiatry). The primary care cohort had a higher percentage of middle aged, married, employed full-time, and privately insured patients than the psychiatry cohort and were generally seen fewer times during the study time frame, with a median of 4 vs. 6 visits per patient in primary care and in psychiatry, respectively. The primary care cohort consisted of 44.2% of patients from low-deprivation areas (1st–25th national percentile), 51.2% of patients from medium-deprivation areas (26th–75th national percentile) and 4.6% from high-deprivation areas (76th–100th national percentile); the psychiatry cohort consisted of 36.4, 50.8, and 12.8% of patients from low-, medium-, and high-deprivation areas, respectively. See Table S1 for descriptives by area deprivation levels. Higher area deprivation correlates with multiple other indicators of adversity including minority racial group, employment, and substance use disorders. Sample construction is illustrated in Fig. S1.

Figure 1 shows the change in daily number of telehealth-eligible outpatient mental health care visits (“visits-per-day”, on weekdays from 7 AM to 7 PM, aggregated to the monthly average) relative to the average in July 2018–June 2019 for each ADI group. The volume of mental health care postpandemic was higher than prepandemic levels for the low-deprivation group while it was relatively consistent with prepandemic levels for the high-deprivation group. In primary care, there was an initial drop in visits-per-day at the start of the pandemic (March 2020) followed by an increase in visit volume over the first year of the pandemic. In psychiatry, we documented a sharp increase at the start of the pandemic and elevated visit volume over the first year of the pandemic.

Negative binomial generalized linear models (controlling for seasonal and day-of-week trends via fixed effects for month and weekday) were used to test for differences in trends of daily number of mental health-related visits between 3 years “prepandemic” (July 1, 2016–June 30, 2019) and 3 years after the start of the COVID-19 pandemic (“postpandemic”: July 1, 2021–June 30, 2024), for the low- and medium-deprivation group relative to the high-deprivation group (Table S2). The estimated slopes for each ADI group and time period were computed using linear combinations of the model coefficients (Table S3).

In primary care settings, the daily volume of mental health care delivered did not change significantly for patients from high-deprivation area ($P = 0.30$) over the prepandemic period but did increase over time for the low-deprivation group, by 7.7% (6.0–9.4%, $P < 0.01$) per year, a significant difference from the high-deprivation group by a factor of 1.06 (1.02–1.10, $P < 0.01$). In

psychiatry, both low- and high-deprivation groups saw yearly increases in visits-per-day prepandemic: by 12.6% per year (10.8–14.5%, $P < 0.01$) and 2.0% (0.3–3.8%, $P = 0.02$), respectively. The yearly increase for the low-deprivation group was significantly greater than for the high-deprivation group, by a factor of 1.10 (1.08–1.13, $P < 0.01$).

Over the postpandemic period, the number of visits-per-day decreased for all groups, in both primary care and psychiatry. In primary care, visits-per-day from the high-deprivation group decreased by 6.2% per year (3.1–9.3%, $P < 0.01$), with a change in slope from prepandemic by a factor of 0.92 (0.88–0.96, $P < 0.01$). For the low-deprivation group, visits per day decreased by 1.6% (0.2–3.0%, $P = 0.03$) per year, a similar rate to the high-deprivation group ($P = 0.72$). In psychiatry, there was a 2.6% (0.9–4.3%, $P < 0.01$) yearly decrease for the high-deprivation group, changing from the prepandemic by a factor of 0.95 (0.93–0.98, $P < 0.01$), and a yearly decrease of 2.2% (0.7–3.6%, $P < 0.01$) for the low-deprivation group, a factor of 0.91 (0.88–0.94, $P < 0.01$) significant difference from the change in the high-deprivation group.

Thus, the number of appointments remained consistently higher for patients living in low-deprivation areas than patients living in high-deprivation areas in the postpandemic period relative to the prepandemic period for mental health appointments received in primary care and psychiatry. In additional analyses shown in the [Supplemental materials](#) providing context for these results, we found that the average volume of mental health care was higher for the low deprivation group and lower for the high deprivation group in the postpandemic period relative to the prepandemic period.

Research question 2: Trends in utilization of telehealth for mental health care from 2020 to 2024

To understand the role of telehealth in access to mental health care, we used EHR from patients with depression seen between July 1, 2020, and June 30, 2024. Overall characteristics and over time characteristics are reported in Table S4 (patient level) and Table S5 (visit level). Figure S2 shows sample construction. There were $n = 29,608$ patients in the 2020–2024 primary care cohort and $n = 7,577$ patients in the 2020–2024 psychiatry cohort. In the primary care cohort, 36,633 of the 132,275 (27.7%) mental health-related visits were conducted over telehealth, while in the psychiatry cohort, 130,405 of 172,080 visits (75.8%) were conducted over telehealth. Figure 2 shows the percentage of visits conducted over telehealth by month from July 1, 2020, to June 30, 2024, in primary care and psychiatry by low-, medium-, and high-area deprivation groups.

We estimated the odds ratios (OR) of telehealth use by area deprivation level for each time period, via generalized estimating equation (GEE) models at the visit level, which accounted for multiple visits per patient. The models adjusted for patient characteristics (age, race, ethnicity, gender, marital status, employment status, patient’s modal insurance type, urbanicity, and indicators of comorbid anxiety disorder or substance use disorder), visit characteristics (time of day, day of week), and temporal features (an indicator of time period, interacted with calendar time, and the weekly number of COVID-19 related hospitalizations in Maryland). The time frame is divided into 4-year-long time periods: T1 (July 2020–June 30, 2021), T2 (July 1, 2021–June 30, 2022), T3 (July 1, 2022–June 30, 2023), and T4 (July 1, 2023–June 30, 2024). We modeled primary care and psychiatry separately. Over the full 2020–2024 period, the visits of patients who lived in low-

Table 1. Characteristics of the 2016–2024 primary care and psychiatry cohorts across time.

Time frame ^d	Mental health care ^a in primary care ^b					Mental health care ^a in psychiatry ^c				
	Full sample	Prepandemic	Emerging pandemic	Early pandemic	Postpandemic	Full sample	Prepandemic	Emerging pandemic	Early pandemic	Postpandemic
Start date	July 1, 2016	July 1, 2016	July 1, 2019	July 1, 2020	July 1, 2021	July 1, 2016	July 1, 2016	July 1, 2019	July 1, 2020	July 1, 2021
End date	June 30, 2024	June 30, 2019	June 30, 2020	June 30, 2021	June 30, 2024	June 30, 2024	June 30, 2019	June 30, 2020	June 30, 2021	June 30, 2024
Visit characteristics	n (%)	n (%)	n (%)	n (%)	n (%)	n (%)	n (%)	n (%)	n (%)	n (%)
Mental health care visits	270,754	92,403	35,982	38,093	104,276	336,918	112,296	41,574	51,628	131,420
Telehealth visits	47,793 (17.7%)	9 (0.0%)	8,189 (22.8%)	14,477 (38.0%)	25,118 (24.1%)	145,239 (43.1%)	23 (0.0%)	14,119 (34.0%)	45,124 (87.4%)	85,973 (65.4%)
Patient characteristics	n (%)	n (%)	n (%)	n (%)	n (%)	n (%)	n (%)	n (%)	n (%)	n (%)
Patients seen for mental health care	42,640	25,402	17,111	18,459	28,869	12,846	6,987	4,135	4,022	6,697
Area deprivation index group ^e										
Low deprivation	18,836 (44.2%)	10,636 (41.9%)	6,961 (40.7%)	7,846 (42.5%)	12,803 (44.3%)	4,675 (36.4%)	2,333 (33.4%)	1,389 (33.6%)	1,393 (34.6%)	2,558 (38.2%)
Medium deprivation	21,838 (51.2%)	13,462 (53.0%)	9,298 (54.3%)	9,755 (52.8%)	14,840 (51.4%)	6,526 (50.8%)	3,623 (51.9%)	2,120 (51.3%)	2,055 (51.1%)	3,348 (50.0%)
High deprivation	1,966 (4.6%)	1,304 (5.1%)	852 (5.0%)	858 (4.6%)	1,226 (4.2%)	1,645 (12.8%)	1,031 (14.8%)	626 (15.1%)	574 (14.3%)	791 (11.8%)
Gender										
Female	30,334 (71.1%)	18,400 (72.4%)	12,475 (72.9%)	13,421 (72.7%)	20,789 (72.0%)	8,317 (64.7%)	4,531 (64.8%)	2,681 (64.8%)	2,614 (65.0%)	4,321 (64.5%)
Male	12,286 (28.8%)	7,000 (27.6%)	4,632 (27.1%)	5,035 (27.3%)	8,062 (27.9%)	4,523 (35.2%)	2,456 (35.2%)	1,454 (35.2%)	1,408 (35.0%)	2,370 (35.4%)
Other	20 (0.0%)	2 (0.0%)	4 (0.0%)	3 (0.0%)	18 (0.1%)	6 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	6 (0.1%)
Age										
18–39	15,794 (37.0%)	8,014 (31.5%)	5,147 (30.1%)	5,960 (32.3%)	10,398 (36.0%)	5,312 (41.4%)	2,649 (37.9%)	1,654 (40.0%)	1,631 (40.6%)	2,713 (40.5%)
40–64	17,647 (41.4%)	11,569 (45.5%)	7,802 (45.6%)	8,084 (43.8%)	12,408 (43.0%)	4,505 (35.1%)	2,697 (38.6%)	1,546 (37.4%)	1,539 (38.3%)	2,377 (35.5%)
65+	9,199 (21.6%)	5,819 (22.9%)	4,162 (24.3%)	4,415 (23.9%)	6,063 (21.0%)	3,029 (23.6%)	1,641 (23.5%)	935 (22.6%)	852 (21.2%)	1,607 (24.0%)
Race										
Black	8,943 (21.0%)	5,000 (19.7%)	3,304 (19.3%)	3,597 (19.5%)	5,899 (20.4%)	3,798 (29.6%)	2,172 (31.1%)	1,281 (31.0%)	1,226 (30.5%)	1,965 (29.3%)
White	29,197 (68.5%)	18,111 (71.3%)	12,313 (72.0%)	13,140 (71.2%)	20,027 (69.4%)	7,681 (59.8%)	4,177 (59.8%)	2,420 (58.5%)	2,386 (59.3%)	3,979 (59.4%)
Other/unknown	4,500 (10.6%)	2,291 (9.0%)	1,494 (8.7%)	1,722 (9.3%)	2,943 (10.2%)	1,367 (10.6%)	638 (9.1%)	434 (10.5%)	410 (10.2%)	753 (11.2%)
Ethnicity										
Not Hispanic	38,698 (90.8%)	23,654 (93.1%)	15,985 (93.4%)	17,183 (93.1%)	26,047 (90.2%)	11,631 (90.5%)	6,531 (93.5%)	3,841 (92.9%)	3,718 (92.4%)	5,916 (88.3%)
Hispanic	2,018 (4.7%)	1,098 (4.3%)	697 (4.1%)	770 (4.2%)	1,238 (4.3%)	625 (4.9%)	304 (4.4%)	190 (4.6%)	207 (5.1%)	337 (5.0%)
Other/unknown	1,924 (4.5%)	650 (2.6%)	429 (2.5%)	506 (2.7%)	1,584 (5.5%)	590 (4.6%)	152 (2.2%)	104 (2.5%)	97 (2.4%)	444 (6.6%)
Marital status										
Divorced/legally separated/widowed	7,869 (18.5%)	5,465 (21.5%)	3,775 (22.1%)	3,856 (20.9%)	5,179 (17.9%)	2,118 (16.5%)	1,287 (18.4%)	741 (17.9%)	686 (17.1%)	1,061 (15.8%)
Married	20,706 (48.6%)	12,571 (49.5%)	8,590 (50.2%)	9,212 (49.9%)	14,496 (50.2%)	4,569 (35.6%)	2,478 (35.5%)	1,438 (34.8%)	1,409 (35.0%)	2,456 (36.7%)
Single/unknown/other	14,065 (33.0%)	7,366 (29.0%)	4,746 (27.7%)	5,391 (29.2%)	9,194 (31.8%)	6,159 (47.9%)	3,222 (46.1%)	1,956 (47.3%)	1,927 (47.9%)	3,180 (47.5%)
Employment										
Disabled	1,655 (3.9%)	1,283 (5.1%)	917 (5.4%)	886 (4.8%)	1,062 (3.7%)	992 (7.7%)	716 (10.2%)	437 (10.6%)	407 (10.1%)	512 (7.6%)
Full-time	20,217 (47.4%)	11,585 (45.6%)	7,630 (44.6%)	8,382 (45.4%)	14,092 (48.8%)	3,833 (29.8%)	1,923 (27.5%)	1,167 (28.2%)	1,135 (28.2%)	2,070 (30.9%)
Not employed	6,561 (15.4%)	4,032 (15.9%)	2,593 (15.2%)	2,749 (14.9%)	4,209 (14.6%)	3,246 (25.3%)	1,841 (26.3%)	1,050 (25.4%)	1,032 (25.7%)	1,573 (23.5%)
Other/missing	1,467 (3.4%)	754 (3.0%)	486 (2.8%)	561 (3.0%)	978 (3.4%)	640 (5.0%)	240 (3.4%)	162 (3.9%)	176 (4.4%)	386 (5.8%)

(continued)

Table 1. Continued

Time frame ^d	Mental health care ^a in primary care ^b				Mental health care ^a in psychiatry ^c					
	Full sample	Prepandemic	Emerging pandemic	Early pandemic	Postpandemic	Full sample	Prepandemic	Emerging pandemic	Early pandemic	Postpandemic
Part time	1,703 (4.0%)	958 (3.8%)	665 (3.9%)	725 (3.9%)	1,156 (4.0%)	496 (3.9%)	264 (3.8%)	158 (3.8%)	165 (4.1%)	262 (3.9%)
Retired	8,626 (20.2%)	5,908 (23.3%)	4,214 (24.6%)	4,362 (23.6%)	5,720 (19.8%)	2,914 (22.7%)	1,714 (24.5%)	960 (23.2%)	890 (22.1%)	1,495 (22.3%)
Student—full-time	2,411 (5.7%)	882 (3.5%)	606 (3.5%)	794 (4.3%)	1,652 (5.7%)	725 (5.6%)	289 (4.1%)	201 (4.9%)	217 (5.4%)	399 (6.0%)
Insurance										
Medicaid	2,413 (5.7%)	1,645 (6.5%)	983 (5.7%)	1,034 (5.6%)	1,503 (5.2%)	2,810 (21.9%)	1,515 (21.7%)	895 (21.6%)	851 (21.2%)	1,392 (20.8%)
Medicare	8,860 (20.8%)	6,170 (24.3%)	4,308 (25.2%)	4,462 (24.2%)	5,899 (20.4%)	3,161 (24.6%)	2,000 (28.6%)	1,226 (29.6%)	1,166 (29.0%)	1,703 (25.4%)
Medicare advantage	2,192 (5.1%)	1,425 (5.6%)	1,187 (6.9%)	1,223 (6.6%)	1,572 (5.4%)	454 (3.5%)	209 (3.0%)	152 (3.7%)	166 (4.1%)	287 (4.3%)
Other	7,923 (18.6%)	4,692 (18.5%)	3,084 (18.0%)	3,414 (18.5%)	5,437 (18.8%)	849 (6.6%)	383 (5.5%)	254 (6.1%)	278 (6.9%)	494 (7.4%)
Private	19,720 (46.2%)	10,599 (41.7%)	7,032 (41.1%)	7,792 (42.2%)	13,646 (47.3%)	3,118 (24.3%)	1,474 (21.1%)	1,010 (24.4%)	1,002 (24.9%)	1,812 (27.1%)
Self-pay	1,532 (3.6%)	871 (3.4%)	517 (3.0%)	534 (2.9%)	812 (2.8%)	2,454 (19.1%)	1,406 (20.1%)	598 (14.5%)	559 (13.9%)	1,009 (15.1%)
Urbanicity										
Urban	37,863 (88.8%)	22,566 (88.8%)	15,094 (88.2%)	16,222 (87.9%)	25,382 (87.9%)	11,838 (92.2%)	6,484 (92.8%)	3,852 (93.2%)	3,753 (93.3%)	6,147 (91.8%)
Rural	4,777 (11.2%)	2,836 (11.2%)	2,017 (11.8%)	2,237 (12.1%)	3,487 (12.1%)	1,008 (7.8%)	503 (7.2%)	283 (6.8%)	269 (6.7%)	550 (8.2%)
Comorbid anxiety	27,517 (64.5%)	17,137 (67.5%)	12,602 (73.6%)	13,616 (73.8%)	20,151 (69.8%)	9,065 (70.6%)	4,922 (70.4%)	3,180 (76.9%)	3,145 (78.2%)	4,971 (74.2%)
Comorbid substance use disorder	8,786 (20.6%)	6,422 (25.3%)	4,575 (26.7%)	4,628 (25.1%)	6,082 (21.1%)	4,470 (34.8%)	2,710 (38.8%)	1,518 (36.7%)	1,495 (37.2%)	2,160 (32.3%)
County ^f										
Anne Arundel	6,585 (15.4%)	3,896 (15.3%)	2,525 (14.8%)	2,785 (15.1%)	4,530 (15.7%)	934 (7.3%)	454 (6.5%)	300 (7.3%)	296 (7.4%)	494 (7.4%)
Baltimore County	8,669 (20.3%)	5,731 (22.6%)	3,961 (23.1%)	3,994 (21.6%)	5,842 (20.2%)	3,545 (27.6%)	2,058 (29.5%)	1,202 (29.1%)	1,158 (28.8%)	1,838 (27.4%)
Baltimore City	5,569 (13.1%)	3,108 (12.2%)	2,020 (11.8%)	2,156 (11.7%)	3,613 (12.5%)	4,327 (33.7%)	2,495 (35.7%)	1,545 (37.4%)	1,505 (37.4%)	2,272 (33.9%)
Howard County	3,140 (7.4%)	1,602 (6.3%)	1,065 (6.2%)	1,212 (6.6%)	2,162 (7.5%)	914 (7.1%)	402 (5.8%)	268 (6.5%)	268 (6.7%)	509 (7.6%)
Montgomery County	5,673 (13.3%)	3,343 (13.2%)	1,932 (11.3%)	2,230 (12.1%)	3,477 (12.0%)	1,145 (8.9%)	582 (8.3%)	288 (7.0%)	281 (7.0%)	569 (8.5%)
Other counties	13,004 (30.5%)	7,722 (30.4%)	5,608 (32.8%)	6,082 (32.9%)	9,245 (32.0%)	1,981 (15.4%)	996 (14.3%)	532 (12.9%)	514 (12.8%)	1,015 (15.2%)
Patients seen in multiple time periods										
Patient seen during prepandemic	25,402 (59.6%)	25,402 (100.0%)	12,922 (75.5%)	12,071 (65.4%)	14,516 (50.3%)	6,987 (54.4%)	6,987 (100.0%)	2,784 (67.3%)	2,236 (55.6%)	2,152 (32.1%)
Patient seen during emerging pandemic	17,111 (40.1%)	12,922 (50.9%)	17,111 (100.0%)	11,103 (60.1%)	12,369 (42.8%)	4,135 (32.2%)	2,784 (39.8%)	4,135 (100.0%)	2,682 (66.7%)	2,325 (34.7%)
Patient seen during early pandemic	18,459 (43.3%)	12,071 (47.5%)	11,103 (64.9%)	18,459 (100.0%)	14,590 (50.5%)	4,022 (31.3%)	2,236 (32.0%)	2,682 (64.9%)	4,022 (100.0%)	2,844 (43.1%)
Patient seen during postpandemic	28,869 (67.7%)	14,516 (57.1%)	12,369 (72.3%)	14,590 (79.0%)	28,869 (100.0%)	6,697 (52.1%)	2,152 (30.8%)	2,325 (56.2%)	2,884 (71.7%)	6,697 (100.0%)
Patient seen both pre- and postpandemic	14,516 (34.0%)	14,516 (57.1%)	9,789 (57.2%)	10,013 (54.2%)	14,516 (50.3%)	2,152 (16.8%)	2,152 (30.8%)	1,801 (43.6%)	1,805 (44.9%)	2,152 (32.1%)
Median		Median (IQR)	Median (IQR)	Median (IQR)	Median (IQR)	Median (IQR)	Median (IQR)	Median (IQR)	Median (IQR)	Median (IQR)
(IQR) ^g										
Number of visits per patient ^h	4 (2, 8)	3 (1, 5)	2 (1, 3)	2 (1, 2)	3 (1, 5)	6 (2, 24)	6 (2, 17)	5 (2, 12)	6 (2, 12)	6 (2, 22)

^aMental health care visits are completed appointments that were assigned an ICD-10 diagnostic code in the "Mental, Behavioral, and Neurodevelopmental disorders" category (F01–F99) or a code related to suicidal ideation or attempt.

^bThe mental health care in primary care sample consists of completed telehealth-eligible mental health care outpatient visits that took place in primary care departments in the Johns Hopkins Health System network.

^cThe mental health care in psychiatry sample consists of completed telehealth-eligible mental health care outpatient visits that took place in the department of psychiatry.

^dData come from the EHR of patients with depression in the Johns Hopkins Health System between July 1, 2016 and June 30, 2024. The numbers of patients seen in each time period do not add up to the full-time frame number of patients because some patients were seen in multiple time periods.

^eArea deprivation index (ADI) uses national percentiles from 2020 at the census block-group level.

^fPercentage are shown for the five counties containing the most patients (Anne Arundel County, Baltimore City, Baltimore County, Howard County, and Montgomery County), pooled across the primary care and psychiatry samples. The percentage in all other counties is included in the "Other" category.

^gThe median and interquartile range (IQR) (first quartile Q1, third quartile Q3) of number of visits per patient seen in each time period is presented. Note that while the length of time for the prepandemic and postpandemic are both 3 years, the emerging pandemic (July 1, 2019–June 30, 2020) and early pandemic (July 1, 2020–June 30, 2021) are each 1 year in length.

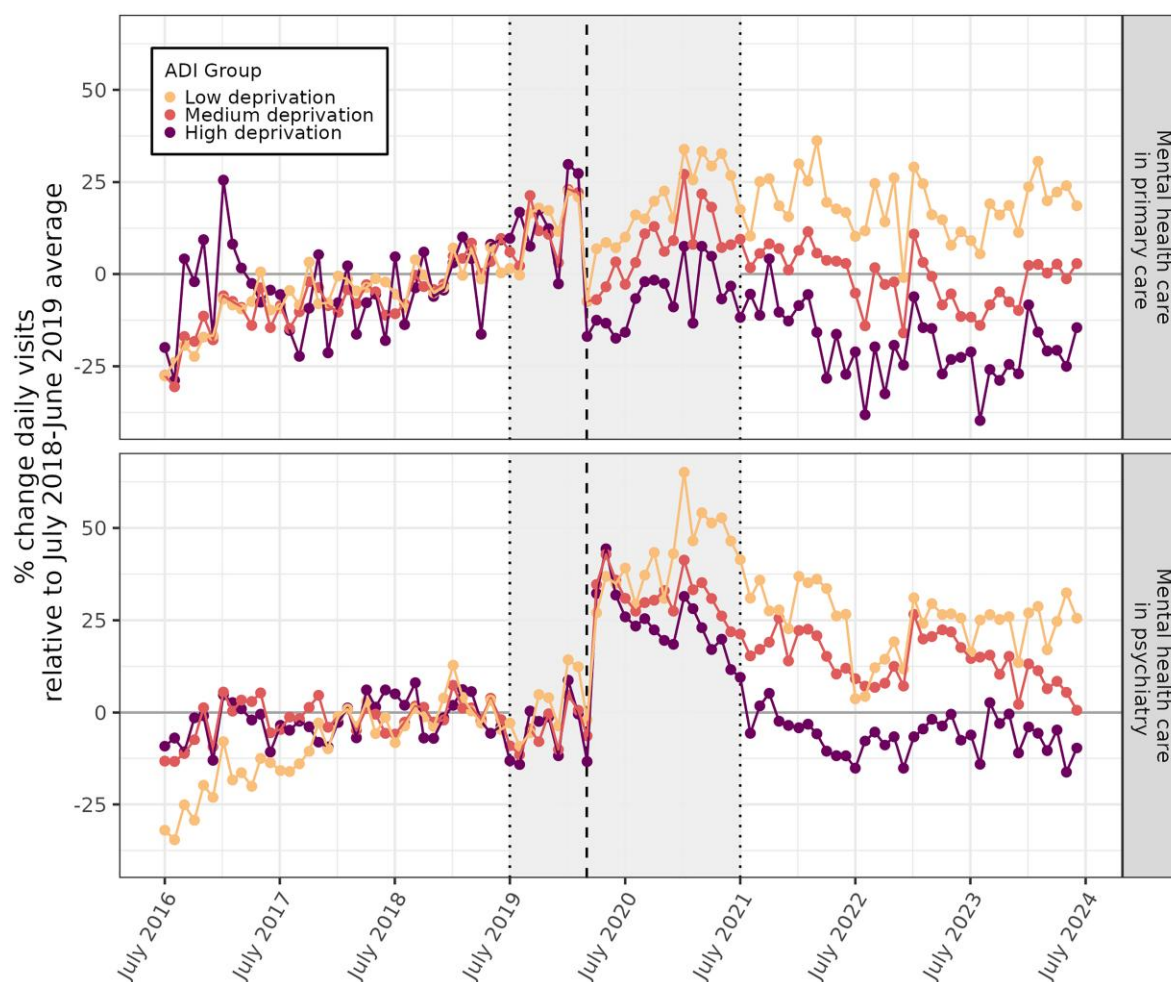


Fig. 1. Changes in the daily number of mental health care visits from each deprivation group relative to July 2018–June 2019 separately for primary care (top) and psychiatry (bottom), the percent change in daily visits for month i and ADI group j is computed as the difference in average number of daily visits coming from group j during month i , minus the average number of daily visits in July 2016 from group j , divided by the average number of daily visits in July 2016 from group j . The dashed line at March 2020 indicates the start of the COVID-19 pandemic. The gray region, July 2019–June 2021, is not included in the analysis of how trends in utilization by ADI group changed from the pre- to postpandemic. ADI national percentiles from 2020 at the census block-group level were used to define three groups: low-deprivation areas (1st–25th national percentile), medium-deprivation areas (26th–75th national percentile), and high-deprivation areas (76th–100th national percentile). Mental health care visits are completed appointments that were assigned an ICD-10 diagnostic code in the “Mental, Behavioral, and Neurodevelopmental disorders” category (F01–F99) or a code related to suicidal ideation or attempt. Data come from the EHR of patients with depression in the Johns Hopkins Health System.

deprivation areas had 1.62 (95% CI: 1.45–1.82, $P < 0.01$) and 1.67 (1.33–2.10, $P < 0.01$) times the odds of being conducted over telehealth relative to the visits of persons in high-deprivation areas for primary care related to mental health and in psychiatry, respectively (Table S6).

Figure 3 shows the average OR of telehealth vs. in-person visits over 4 years of the COVID-19 pandemic for medium- and low-deprivation areas relative to high-deprivation areas (also reported in Table S7). We tested for changes over time in the OR for deprivation groups using GEE models as previously described, with the addition of interactions between area deprivation group and time period, and obtained average OR for each period using these models. In T1 (July 1, 2020–June 30, 2021), mental health primary care visits from persons who lived in low-deprivation areas had 1.52 (1.31–1.75, $P < 0.01$) times the odds of using telehealth relative to persons in high-deprivation areas. The OR of telehealth use for the low-deprivation group relative to the high group in T2, T3, and T4 were 1.86 (1.55–2.22, $P < 0.01$), 1.65 (1.35–2.02, $P < 0.01$), and 1.53 (1.22–1.91, $P < 0.01$); however, the difference between these OR

and the OR in T1 was only significant in T2 (by a factor of 1.22, 1.00–1.49, P -value = 0.05) and was not significant in T3 ($P = 0.54$) or T4 ($P = 0.97$).

In psychiatry, the odds of telehealth use were lower for the low-deprivation group than the high-deprivation group during T1, with an OR of 0.64 (0.49–0.93, $P < 0.01$). In T2, the OR changed significantly (by a factor of 1.59, 1.32–1.91, $P < 0.01$), such that the difference in odds of telehealth use between the low- and high-deprivation groups was no longer significant ($P = 0.97$). However, in T3 and T4, the odds of telehealth were significantly higher for the low-deprivation group relative to the high-deprivation group, with estimated OR of 1.40 (1.13–1.75, $P < 0.01$) and 1.72 (1.36–2.17, $P < 0.01$) in T3 and T4, respectively, corresponding to 2.28 (1.76–2.94, $P < 0.01$) and 2.81 (2.10–3.78, $P < 0.01$) factor increases relative to the OR for the low- vs. high-deprivation group in T1. Additional sensitivity analyses were conducted and are described in the Materials and methods and presented in the Supplemental material. Sensitivity analyses support the conclusions of the main results.

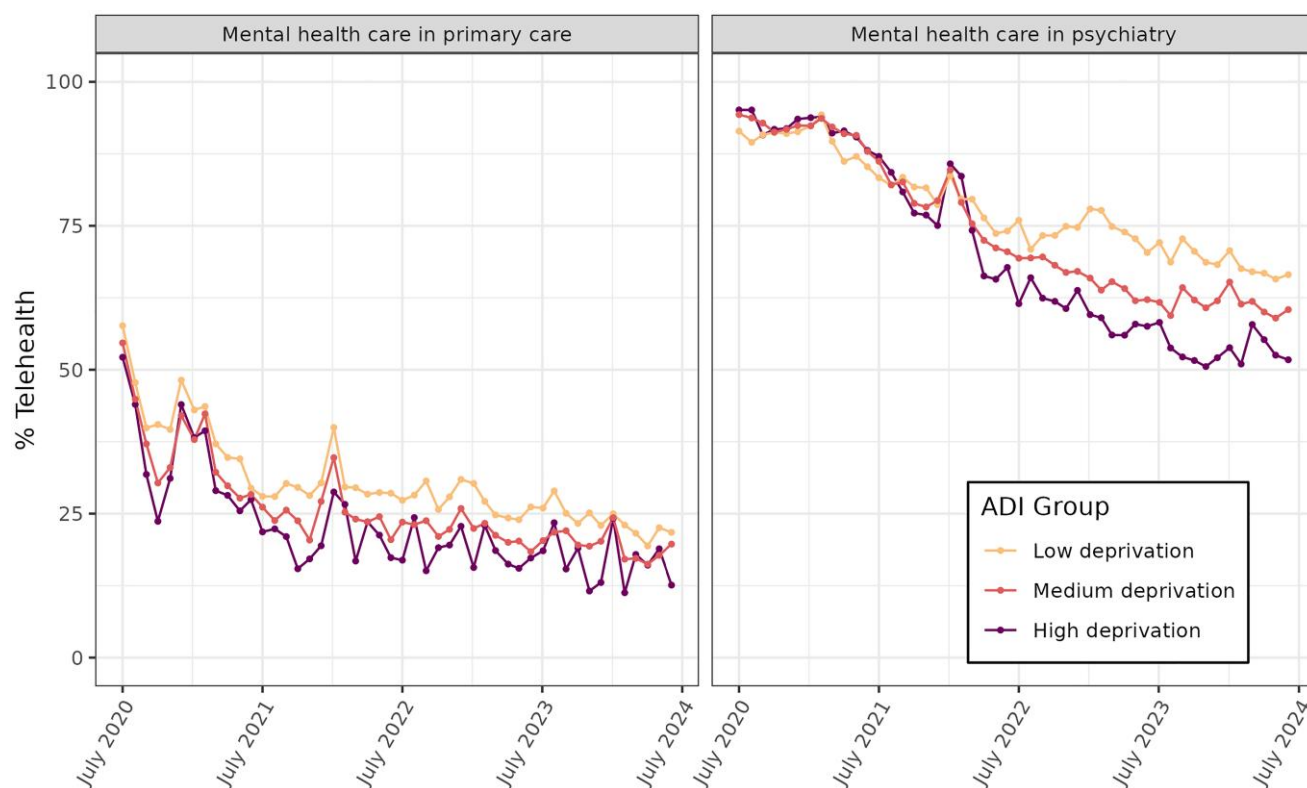


Fig. 2. Percentage of mental health care received via telehealth by level of area deprivation. Each dot connected by solid lines shows the percentage of visits per month conducted over telehealth, among outpatient, telehealth-eligible visits for mental health care in the primary care and psychiatry samples. ADI national percentiles from 2020 at the census block-group level were used to define three groups: low-deprivation areas (1st–25th percentile), medium-deprivation areas (26th–75th percentile), and high-deprivation areas (76th–100th national percentile). Mental health care visits are completed appointments that were assigned an ICD-10 diagnostic code in the “Mental, Behavioral, and Neurodevelopmental disorders” category (F01–F99) or a code related to suicidal ideation or attempt. Data come from the EHR of patients with depression in the Johns Hopkins Health System. ADI, area deprivation index.

Discussion

Using data from EHR from two cohorts of adult patients with depression receiving mental health care in primary care and psychiatry settings in a large academic health center, we found differences in the trends in mental health care utilization among patients by levels of area deprivation: following the initial increases over the start of COVID-19 pandemic, volume of care delivered to patients from low-deprivation areas declined more slowly than for high-deprivation groups, and remained elevated above prepandemic levels. We also found that the percentage of appointments conducted by telehealth was higher among patients living in low-deprivation areas than high-deprivation areas. These findings together suggest that telehealth use could be contributing unequally to expansions in health care utilization between patients living in low relative to high-deprivation areas.

Our first finding, which showed that mental health care visits were increasing more rapidly for patients in higher socioeconomic areas while staying relatively constant for patients in lower socioeconomic areas in primary care and slightly increasing in psychiatry, is consistent with evidence that patients with greater resources are more likely to receive health care (43). Such a finding would be appropriate if higher resourced patients had greater health care needs; however, social stress theory would suggest that patients living in areas with greater deprivation would have more stressors and (44), therefore, worse mental health, than patients living in areas with less deprivation, requiring more health care, consistent with the Inverse Care Law (16). This paper is also consistent with studies

that find differential use in mental health services across socioeconomic indicators (45–47), as well as differential use of health services in general across area-level indicators (48, 49).

These findings are consistent with other trends identified leading up to and at the start of the COVID-19 pandemic. In the years leading up to the COVID-19 pandemic, we identified an increase in the number of primary care appointments related to mental health over time for low- and medium-deprivation groups; this trend is consistent with the findings of Rotenstein et al. (50). The initial drop in mental health care utilization in primary care at the start of the pandemic followed by an increase over the first year of the pandemic is consistent with the trends reported McBain et al. (51). Increased use of health care to address mental health is also consistent with higher reporting of symptoms of depression at the start of the pandemic relative to before it (52).

Given the rapid expansion of telehealth use that characterized health care delivery at the start of the COVID-19 pandemic, it is necessary to consider how telehealth might be utilized differently across deprivation groups to understand differences in health care utilization by deprivation groups. In our analyses, we found differences in telehealth use by area deprivation within primary care in the first year of the pandemic, which persisted in the following 3 years. In psychiatry, while there was no significant difference in the odds of telehealth vs. in-person care across areas with different levels of deprivation in 2021–2022 and high-deprivation groups were more likely to use telehealth in 2020–2021 (the initial year of the COVID-19 pandemic) in psychiatry, differences emerged in 2022–2023 and 2023–2024. Given that the start of the

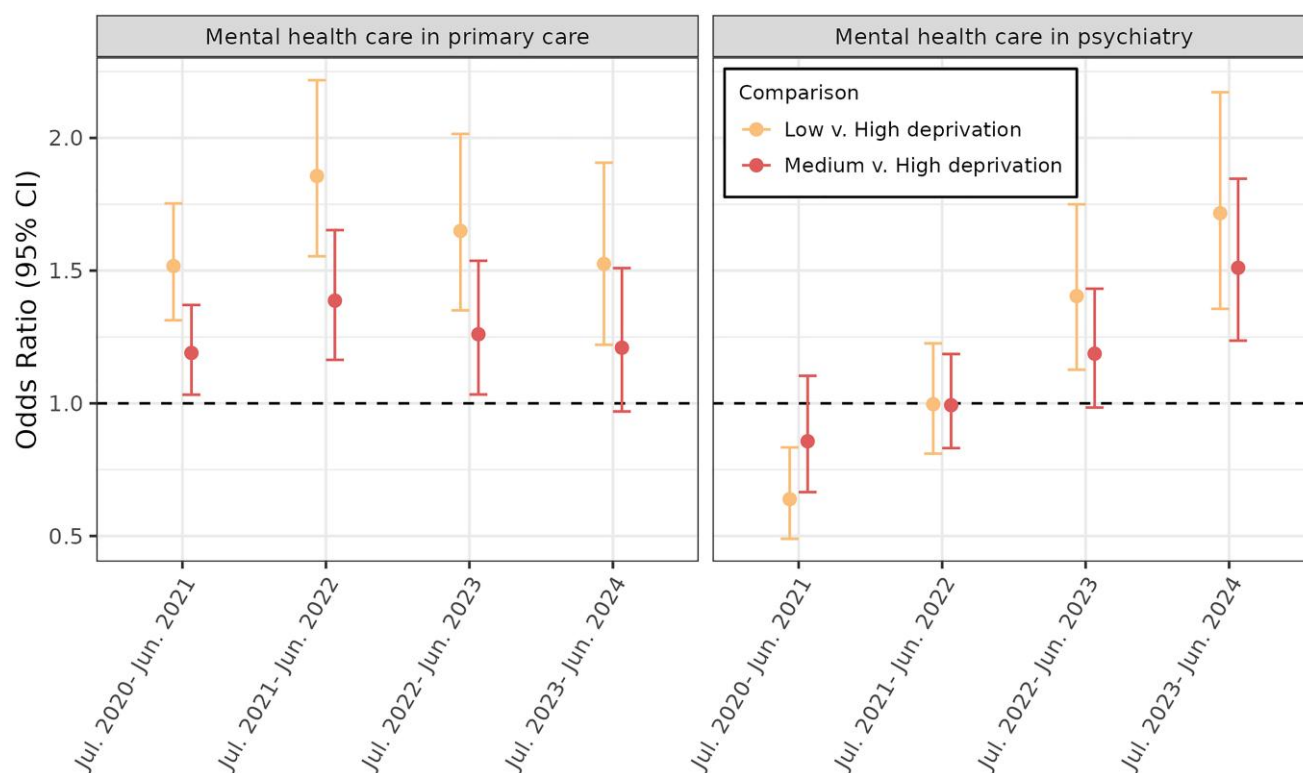


Fig. 3. OR of use of telehealth vs. in-person visits by area deprivation, by time period the average OR with 95% CI for telehealth use in the low- and medium-deprivation groups relative to the high-deprivation groups are plotted for 4-year-long periods. The OR for each time period are obtained using an exponentiated linear combination of coefficients, with CI obtained using the delta method. These estimates come from separate GEE models (with exchangeable correlation structure) analyzing the odds of telehealth among the outpatient, telehealth-eligible mental health care visits of two cohorts of patients with depression (primary care and psychiatry). Models adjust for patient and visit-level covariates. ADI national percentiles for 2020 at the census block-group level were used to define three groups: low-deprivation areas (1st–25th percentile), medium-deprivation areas (26th–75th percentile), and high-deprivation areas (76th–100th national percentile). Mental health care visits are completed appointments that were assigned an ICD-10 diagnostic code in the “Mental, Behavioral, and Neurodevelopmental disorders” category (F01–F99) or a code related to suicidal ideation or attempt. Data come from the EHR of patients with depression in the Johns Hopkins Health System.

pandemic also corresponded with many other fundamental changes (worsening of mental health, economic hardship, job loss) we cannot disentangle the impact of the telehealth expansion from other changes that may have influenced mental health care utilization (53–55). However, as we found both that patients from high-deprivation areas were generally less likely to use telehealth than patients from low-deprivation areas and that mental health care utilization returned approximately to prepandemic levels by 2024 for the high-deprivation group, our findings suggest that telehealth was not expanding access equally for different groups of patients.

These findings are consistent with a body of literature suggesting that contextual factors, including area-level assets, may influence patients' ability to access more flexible forms of healthcare delivery and should therefore be considered in health services research (6, 56). People who live in neighborhoods with worse deprivation are more likely to use emergency care in ways that may have been avoidable (48, 49). In a study of veterans receiving mental health care before and after the start of the COVID-19 pandemic, O'Shea et al. (57) found that veterans who lived in areas with faster broadband download and upload speeds had more telehealth visits and fewer in-person visits following the start of the pandemic, relative to veterans who lived in areas with lower broadband speed. It is possible that people living in high-deprivation areas were capable of using telehealth during the COVID-19 pandemic but preferred to move back to in-person care when it became available. Multiple factors related to area-

level assets could cause this behavior. For example, persons living in high-deprivation areas may not have had privacy at home or at work to take telehealth appointments. Finally, these results are consistent with the few prior studies looking at the relationship between area deprivation and telehealth for mental health care specifically (58, 59). Our results also bolster studies that assessed the relationship between telehealth use and area deprivation (60–63), although some studies disagreed (64–67) or found nuances in the telehealth vs. in-person relationship across area deprivation according to whether video or telephone calls were used (68), which our study did not explore.

This study should be considered in light of several limitations. First, while mental health is increasingly addressed in primary care settings (50), the characteristics of patients and the types of visits in primary care differ from those in psychiatry. Therefore, it is difficult to interpret differences in trends between the two groups. Second, while we used a relatively large sample of EHR in an urban, academic health setting, with over 2.8 million patients each year in an outpatient setting (69), the results may not be representative of other health systems. However, the health system, which is based in Baltimore, serves a high proportion of patients of color, who have faced systematic challenges to accessing resources (70), making it an important case study for other health systems. It is possible that these patterns may be relevant for other urban areas with similar demographics. Third, we are unable to ascertain whether differences in use of telehealth across area deprivation are the result of patient preference

or other forces such as provider preferences for telehealth or systemic barriers leading to new or different challenges for accessing mental health care among low resourced populations. Thus, we are unable in the present analysis to distinguish between differences and disparities in use of mental health care across patient groups (2). The present study suggests that there are differences in the use of telehealth vs. in-person care across area deprivation; however, if the preference for patients living greater deprivation areas was for in-person relative to telehealth care, then a lower percentage of appointments via telehealth across high-deprivation relative to low-deprivation groups could be clinically appropriate. On the other hand, if the lower percentage of care being received via telehealth by high-deprivation groups was due to structural barriers, upstream factors, or system-level practices that contributed to fewer appointments, then the lower use of telehealth in patients with greater deprivation could be problematic from a health systems operations perspective. Future research should consider the preferences of patients and the clinical judgement of providers that could inform quality of care.

This study identifies divergence in volume of mental health care over time and a lower use of telehealth relative to in-person care postpandemic for patients living in high-deprivation relative to low-deprivation areas. While telehealth has the potential to shift engagement with mental health services, health systems and policy makers should monitor trends in the use of novel digital technologies to ensure that differences in use do not lead to disparities in care.

Materials and methods

Sample

To investigate how trends in the volume of mental health care by area deprivation group changed across time for Research question 1 (RQ-1) and how trends in telehealth use differed across area deprivation for mental health-related care among patients with depression for Research question 2 (RQ-2), we utilized the EHR of patient encounters in the Johns Hopkins Health System over an 8-year period from July 1, 2016 to June 30, 2024. We defined two cohorts of patients with depression: patients seen in primary care departments for mental health care ($n = 42,640$ patients) and patients seen in psychiatry departments for mental health care ($n = 12,846$), referred to respectively as the “primary care” and “psychiatry” cohorts. There were 2,650 patients who were in both cohorts, meaning they were seen at least once for visits related to mental health care in both primary care and psychiatry. Both cohorts consisted of adults (aged 18 or older at the time of the visit) with a diagnosis of depression (determined by an International Classification of Diseases, Tenth Revision (ICD-10) code of F32 or F33) in at least one encounter between July 1, 2016, and June 30, 2024. In the primary care cohort, the diagnosis of depression could be from an encounter in either primary care or psychiatry, while in the psychiatry cohort, the diagnosis must have been at an encounter in psychiatry. We exclude patients with bipolar disorder (determined by an ICD-10 code diagnosis of an F31 for an encounter in any department during the study time frame) to reduce potential misclassification of depressive episodes prior to bipolar diagnosis. Given differences in reimbursement policies in telehealth across state lines during the pandemic, we included only patients living in the state of Maryland, as indicated by the census block group associated with their billing address.

Our analyses use visit-level data. For each cohort of patients with depression, the corresponding analytic sample consisted of visits (completed appointments) that related to mental or

behavioral health care, defined as having an ICD-10 diagnostic code in the “Mental, Behavioral, and Neurodevelopmental disorders” category (F01–F99) or a code related to suicidal ideation or attempt (71, 72). The samples only included visits that were eligible for telehealth (determined using encounter and visit type information available in the EHR data). For example, inpatient visits, procedures such as methadone treatment or electroconvulsive therapy, or encounters such as MyChart patient portal messages and historical documentation were not considered to be eligible for telehealth. Additionally, we focused our analyses on regular operating conditions. Therefore, we excluded the small number of visits that took place on weekends or outside of a 7 AM–7 PM time frame. For the same reason, we also excluded visits conducted on “low volume days” (which we defined as having fewer than 75 visits in either primary care or psychiatry) which corresponded entirely to holidays or days immediately adjacent to holidays (e.g. July 3–5, 2020). Because we were interested in understanding differences in patient access to (or preference for) telehealth, we excluded group visits, for which the modality of care may be predetermined.

To investigate changes in mental health care utilization over time (RQ-1), we used data from the full-time period (July 1, 2016–June 30, 2024). To examine telehealth use by area deprivation level across stages of the COVID-19 pandemic (RQ-2), we restricted our analytic sample to visits that occurred between July 1, 2020, and June 30, 2024, for patients with a depression diagnosis in at least one visit and no bipolar diagnosis in any visits during that time frame. Additionally, for RQ-2, we did not include clinical units within primary care or psychiatry known to only conduct visits in-person since the start of the pandemic (more details in the Supplementary material).

The Supplementary material contains additional information about the inclusion criteria, including a flow chart illustrating sample selection for the 2016–2024 cohorts and the 2020–2024 subsets, Figs. S1 and S2, respectively.

Measures

Temporal variables

For RQ-1, we divided the study period into two periods for analysis: prepandemic (July 1, 2016–June 30, 2019) and postpandemic (July 1, 2020–June 30, 2024). While the average number of visits per day in the time between these periods (July 1, 2019–June 30, 2020) is plotted in Fig. 1, this time period is not included in the regression models of the pre- and postpandemic. For research question 2, we focus on the postpandemic period, dividing it into 4-year-long periods: T1 (from July 1, 2020 to June 30, 2021), T2 (July 1, 2021 to June 30, 2022), T3 (July 1, 2022 to June 30, 2023), and T4 (July 1, 2023 to June 30, 2024). The end of T1 corresponds to the end of the COVID-19 state of emergency in Maryland. Additionally, for both RQ-1 and RQ-2, we included a “years” variable measuring calendar time computed as the number of weeks from the start of the study period to the visit date divided by 52. In RQ-1, we include indicators of month and day of the week (Monday–Friday). In RQ-2, we include day of week, time of day (morning: 7:00 AM–11:59 AM and afternoon/evening: 12:00 PM–7:00 PM), and the log of the weekly average of the Maryland daily COVID-19 related hospital bed occupancy in thousands (plotted in Fig. S5) (73).

Area deprivation

To assess area deprivation, we used the ADI (74, 75). The ADI aims to quantify area-level disadvantage, combining measures of

employment, income, housing quality, and more from the American Community Survey. A low value of ADI corresponds to areas of higher socioeconomic status. We used national ADI percentiles for census blocks in 2020 to create three groupings: low (1st–25th percentile), medium (25th–75th percentile), and high (76th–100th percentile) deprivation. Given the small number of patients living in census block groups without a defined ADI, we excluded these patients from the analysis (see Figs. S1 and S2). The distribution of ADI in the 2016–2024 sample is shown in Fig. S3. Figure S4 shows a map of ADI groups in Maryland and Baltimore. Table S1 provides characteristics of the cohorts by low, medium, and high ADI group.

Patient characteristics

We included the following patient-level characteristics in our models of telehealth use (RQ-2): age (18–39, 40–64, and 65+), racial groups (White, Black, Other/Unknown), ethnic group (Hispanic, Non-Hispanic, other/unknown), gender (male or female), marital status (married, divorced/legally separated/widowed, and single/unknown/other), employment (full time, not employed, part time, retired, disabled, full-time student, or other/unknown), urbanicity (urban, rural), and patient's modal insurance type within their visits during the study time frame (Medicare, Medicare advantage, Medicaid, private insurance, self-pay, or other). Urbanicity of each census block group is derived from the Census Bureau 2020 list of census blocks within urban areas (76, 77). Additionally, we included indicators of comorbid anxiety disorder and substance use disorder defined as the presence of ICD-10 codes for any visit for that patient within the study period. Given the small number of patients with a gender other than male or female we did not include this subgroup of patients in the analysis for RQ-2. These patients were included in the analytic sample for RQ-1, for which the small size of the subgroup was not a concern as gender was not a covariate in the models. See Supplementary material for details.

Analysis

Research question 1: Trends in mental health care utilization from 2016 to 2024

First, we presented descriptives of the 2016–2024 primary care and psychiatry cohorts at the patient level in the full sample and by time period (Table 1) and stratified by ADI group (Table S1). Second, we plotted the temporal trends in mental health care utilization before and across the pandemic, for each month in the full-time period, as a percentage change in average number of mental health care visits per day, relative to July 1, 2016, for each ADI group (Fig. 1).

Third, we use negative binomial generalized linear models to estimate trends in the number of mental health care visits per day in each ADI group, in separate models for primary care and psychiatry. We allowed for levels and slopes (percentage change in daily number of visits per year) to differ between ADI group and between time periods (pre- and postpandemic) using a three-way interaction in the model. Table S2 contains model coefficients with 95% CI and P-values. Fourth, we used these models to obtain the average percentage change per year in each deprivation group and time period, presented in Table S3. The *marginalEffects* package in R was used to compute these estimates as linear combinations of coefficients with confidence intervals obtained via the delta method (78). All statistical analyses were conducted in R 4.3.1.

Research question 2: Trends in utilization of telehealth for mental health care from 2020 to 2024

Fifth, we shifted our focus to telehealth use in 2020–2024 and presented the patient-level characteristics of this sample in Table S4 and at the visit level in Table S5. Sixth, we plotted the percentage of visits conducted by telehealth each month for each ADI group, to produce a plot of the unadjusted averages over time (Fig. 2).

Seventh, we estimated the average OR for telehealth use among the visits of patients living in low- and medium-deprivation areas, relative to high-deprivation areas, over the full study period, using GEE models (79, 80). GEE models were fit using the *geepack* R package, using an exchangeable correlation to account for multiple visits per patient, with standard errors accounting for patient-level clustering computed using the robust “sandwich” estimator (81). Models were run stratified by department (primary care and psychiatry) and were conducted at the visit level, adjusting for patient and visit-level characteristics and calendar time in years interacted with time period. Table S6 contains all exponentiated coefficients from the pooled-time period models. Ninth, we added interactions between time period and ADI group, to investigate whether there were differences in the OR over time. In Fig. 3 (Table S7), we present the average OR (for the odds of telehealth use in the low and medium groups compared to the high-deprivation group) for each time period, computed using the *marginalEffects* R package (Fig. 3, Table S7). The exponentiated coefficients for interaction terms for each area deprivation group are also included in Table S7, indicating whether changes in OR from the first year (July 2020–June 2021) to subsequent years were significant. The exponentiated coefficients for all covariates are included in Table S8. As supplemental analyses, we fit analogous models that did not control for patient and visit-level characteristics (Table S9), as well as models that interact all patient and visit-level characteristics with time period and present the results in Table S10. Figure S7 shows the average OR in each time period for the supplemental models for comparison with the estimates from the main model (as in Fig. 3).

Table S11 shows the average daily volume of mental health care across area deprivation groups using negative binomial models pooled over time. Additional details on modeling choices, equations for the models, and discussion of the interpretation of coefficients can be found in the [Supplementary material](#).

This study was approved by the Institutional Review Board at the Johns Hopkins University School of Medicine. Consent was waived for use of the EHR data for research purposes.

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Supplementary Material

[Supplementary material](#) is available at PNAS Nexus online.

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Author Contributions

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Data Availability

Electronic health records from the Johns Hopkins Health System are not publicly available as the data contains personal and potentially identifiable data about patients and cannot be shared outside of the IRB approved team. Available data supporting the findings of this study are available within the article and its [supplementary materials](#) and the code used for the main analyses is openly available at https://github.com/gringle1/telehealth_ADI_trends at [http://doi.org/\[doi\]](http://doi.org/[doi]).

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