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# Changes in healthcare costs following engagement with a virtual mental health system: a matched cohort study of healthcare claims data

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**Abstract**

The COVID-19 pandemic has exacerbated the pressing need for mental health services. Digital mental health interventions could increase access to care and be an effective approach to reducing anxiety and depression at scale; however, research on their impact on healthcare expenditure is in the nascent stage and requires further investigation. The current study used claims data to examine the associations between use  of an on-demand digital mental health platform and healthcare utilization costs compared to a matched control cohort. The study found that there were no significant differences between cohorts in total healthcare costs and pharmacy costs. There was a 16.8% reduction in outpatient costs (p=.08). On-demand digital mental health interventions can serve as a scalable approach to addressing the current mental health demands and potentially lower outpatient costs.



*Keywords:* Teletherapy; mental health; healthcare claims

## 1. Introduction

Even prior to the COVID-19 pandemic, anxiety and depression were the leading causes of disability globally and resulted in significant societal costs. In fact, anxiety and depression cost an estimated $1 trillion global economic cost in lost productivity, absenteeism, and medical costs, and this figure is expected to rise to $6 trillion by 2030.

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[1]–[3] Furthermore, a recent commissioned report found that average annual costs for those with a behavioral health condition was 2.8 to 6.2 times higher than those without a behavioral health condition.[4] The economic benefit for investment in scaled-up treatment for depression and anxiety is convincing, with a $4 return in better health and productivity for every $1 invested.[3] The pandemic has only exacerbated a pressing need for mental health services, making access to timely and quality care imperative.[5] In January 2019, 8.1% and 6.5% of adults reported symptoms of anxiety or depression, respectively, and there was over a four-fold increase in reported symptoms by July 2020 during the pandemic (36.1% and 29.6% for anxiety and depression, respectively).[6] These numbers only continued to increase in the midst of the pandemic and current reported rates remain high (26.7% and 22.0% for anxiety and depression, respectively, as of April 2022).[6] Unfortunately, the demand for mental health services has outpaced the workforce capacity and available resources.[7] Coupled with other encumbered barriers to treatment (e.g., transportation issues, long-waitlists, high out-of-pocket expenses), a lack of access to services remains a critical issue and many with depression or anxiety remain undiagnosed and untreated.[8-9]

There has been a dramatic shift toward teletherapy and other virtual interventions as a scalable approach to increasing access to mental health care services and delivering evidence-supported therapy.[10] As face-to-face visits were restricted as a result of the pandemic, the full potential of these tools were now being realized by both providers and patients alike.[11] Even as the pandemic wanes, telehealth use has remained strong for mental health and substance use treatment, representing 36% of these outpatient visits.[12] Within the virtual care models, a variety of treatment modalities such as self-guided content, coaching, and teletherapy are now available to individuals seeking support for anxiety and/or depression. The strong efficacy and evidence-base of these telehealth interventions has been established, demonstrating similar outcomes as face-to-face therapy and greater efficacy than usual care or placebo.[10,13–16]

As telehealth interventions are seeing a surge in adoption, including teletherapy, there has been a growing interest in examining the association between these interventions and both direct and indirect health care spending. While a small number of reviews on the economic value of specific digital mental health interventions exist,[17-18] some have reported that there is no conclusive evidence regarding their cost-effectiveness.[19] The authors also noted that most economic evaluations of digital mental health interventions were conducted alongside clinical trials, and failed to capture the relevant available evidence and comparators, as well as the long-term impact of mental health disorders.[19] A different systematic review found that 81% of internet-based interventions for anxiety and depression were cost-effective.[20] However, the authors mention that varying methodologies made making conclusions about cost-effectiveness difficult and that many studies failed to provide cost definitions or differentiate between patient versus system-level costs.

Ginger is an on-demand platform that provides members with access to a variety of virtual treatment support services, including text-based behavioral health coaching, teletherapy, telepsychiatry and self-guided content and assessments. Members generally have access to Ginger as part of their employee or health plan benefits. After downloading the mobile app, members can begin chatting with a behavioral health coach through text-messaging. Some members will engage solely with coaches, whereas other members will request clinical care (teletherapy or telepsychiatry), and some will require treatment escalation if coaches identified a clinical need. When members are escalated to teletherapy or telepsychiatry, they may continue working with a coach concurrently, which can continue to support them in addressing day-to-day goals and challenges and serve as an adjunct to the care plan from the therapist and/or psychiatrist. While the impact of Ginger on anxiety and depression outcomes, as well as user engagement has been examined,[21], [22] there is additional interest in better understanding its impact on healthcare expenditure. Thus, the current study examines the association between Ginger and healthcare costs of its members compared to a matched control cohort.

## 2. Data

The principal data source for this study was a patient-month panel dataset constructed from the IQVIA New Data Warehouse (NDW). IQVIA is a leading multinational form that provides analytics, technology solutions, and clinical research services to the life sciences industry. The underlying NDW is a warehouse that sources de-identified healthcare cost and utilization data from all healthcare channels in the US, including medical, pharmacy and provider claims. The NDW is comprised of three datasets. First, the hospital charge data master (CDM) contains records from over 450 hospital CDM files, service order records and other hospital reference sources. This covers 7 million annual inpatient stays and 60 million annual outpatient visits. Underlying data elements include all inpatient and outpatient encounters with detailed drug, procedure, diagnosis and charge data for each encounter. Second, the prescription claims include records on more than 1.6 billion retail and mail-order prescriptions, covering approximately 85% of pharmacies in the US. Third, professional fee claims include approximately 1 billion claims per year, covering over 870,000 providers per month. These claims represent 60-70% of physician activity in the US.

From the underlying NDW, a patient-month panel dataset was constructed that includes the following data: patient demographics, total healthcare costs and costs by type of care (outpatient and pharmacy costs), 3-digit ZIP code, pre-period mental health diagnoses, pre-period Charlson comorbidity index and plan type (cash, Medicare, Medicaid, third party/commercial, and other/unknown). Given the low frequency of hospital admissions in our sample, inpatient costs were not included in the panel dataset.

The first step in constructing the analysis sample is to match Ginger members to the NDW. We restricted analysis to members who signed up between Jan 1, 2018 and June 30, 2020. The current study examined all member sign-ups regardless of specific treatment modality utilized. For each member, 12 months of claims data were used encompassing the 6 months before a member joined Ginger and the 6 months after (including the month that they joined). Thus, claims from July 1, 2017 to Dec 31, 2020 were included in the analysis. For this study, 8464 Ginger members matched to the NDW.

Because the NDW is an open claims warehouse where insurance eligibility files are not confirmed for members,the universe of utilization during the entire 12-month period is not guaranteed for each member. Thus, observing no utilization in a given month could reflect missing data for that month, for example, if a member switched insurance plans during the study period. Given missing eligibility files, we cannot confirm which members have complete data and which have missing data. To reduce the likelihood that members in our study sample have missing data for their entire pre- or post-period, we restrict analysis to members with at least one claim in both the pre- and post-period. Of the 8464 members who matched, 2148 (25.3%) satisfied this inclusion criteria. Importantly, this inclusion criteria excludes patients with consistently low healthcare utilization, which restricts the external validity of this study.

To construct the matched control cohort sample, a direct matching methodology was used. Members were matched based on the following pre-period characteristics: age, gender, Charlson comorbidity index, diagnosis with largest total pre-period cost and total pre-period cost quintile. Of the 2148 Ginger members, 2142 (99.7%) matched. This results in a Ginger cohort and control cohort of equal size, totaling 4284 individuals.

## 3. **Methods**

To estimate the association between use of Ginger services and healthcare costs, we employed an event study design with a control cohort to net out sample construction effects. The event study is a common econometric methodology first applied in the field of finance and has since been leveraged to study the impact of events on healthcare utilization.[23-25] Event study designs are an extension of the familiar difference in differences approach with the following deviations. First, the event in our setting is the date a member joins Ginger, which varies from member to member. We defined the pre-period as the 6 months prior to a member joining and the post-period as the 6 months after joining Ginger (including the month a member joins). Second, our setting allowed us to leverage the member-month panel data structure to estimate time trends based on pre-period costs and use the post-period costs that would have arisen if pre-trends had continued as the counterfactual. Third, given the cohort-specific pre-period trends observed in the data, we relaxed the typical parallel trends assumption on which the typical difference in differences methodology relies. Because the Ginger and control cohort had different pre-trends, each cohort's pre-trend and corresponding counterfactual were estimated separately. Fourth, the sample inclusion criteria that members must have at least one claim in both the pre- and post-periods may bias the pre- and post-period trends. Differencing out the control cohort's trends can help account for this potential bias associated with sample composition.

Empirically, we estimate the following model:

$$y_{it} = \alpha^C + \beta_1 t^C + \alpha^G + \beta_2 t^G + \sum_{t=0}^{5} \tau_t + \sum_{t=0}^{5} \tau_t{}^G + X'_t\beta_3 + \varepsilon_{it} \quad (1)$$

In Equation 1, $i$ indexes members, and $t$ indexes months relative to the index event, which is when a member joins Ginger (or a control cohort member's matched counterpart joins Ginger). The index event is defined as $t$=0. In this way, months -6 to -1 are the six months prior to the index event, and months 0 to 5 are the six months including and following the index event. Patient-month healthcare costs are $y_{it}$, $\alpha^C + \beta_1 t^C$ captures the control cohort's linear pre-trend, $\alpha^G + \beta_2 t^G$ captures the Ginger cohort's linear pre-trend, $\tau_t$ are monthly deviations in the post-period between the control cohort's actual spending and the predicted counterfactual based on the control cohort's linear pre-trend, $\tau_t{}^G$ are the monthly deviations above and beyond $\tau_t$ that fill the gap between the Ginger cohort's post-period costs and the counterfactual based on the Ginger cohort's linear pre-trend, $X'_t\beta_3$ capture the relationship between costs and member characteristics, including age, gender, 3-digit ZIP code, Charlson comorbidity index, pre-period mental health diagnoses, and plan type, and $\varepsilon_{it}$ are the unexplained error terms. This model was estimated as an OLS regression with heteroskedasticity-robust standard errors.

The coefficients of interest were the six $\tau_t{}^G$ terms. These captured the difference between actual post-period costs for the Ginger cohort and what that cohort's linear pre-trend would have predicted, netting out the same difference computed for the control cohort. To compute the average treatment effect on monthly costs, an estimate of the linear combination of the $\tau_t{}^G$ for t in [0,5] terms was computed. Statistical significance of this estimate wass based on the two-sided Wald test with the null hypothesis that the average treatment effect is 0. All estimation was done using Stata 17.

This model was estimated separately for overall healthcare costs and costs by subtype of care. Subtypes included outpatient care and pharmacy care. All cost measures are in terms of allowed amounts. An inverse hyperbolic sine transformation was used to account for the extreme right skew of the underlying distribution of patient-month costs, which is typical in this setting. This transformation is similar to a log transformation; however, it is advantageous because it is defined at 0. See Zhang et al. for an exposition of this methodology and an example application in the domain of health services literature.[26]

## 4. **Results**

Table 1 presents descriptive statistics for both the Ginger and control cohort. For continuous variables, the mean, median and standard deviation are shown. For categorical variables, the number of individuals and percent of the sample included in each category is shown. For age, the p-value corresponds to a Wald test whose null hypothesis was that the means for the two cohorts are the same. For categorical variables, the $p$-value shown corresponds to an F-test whose null hypothesis was that the distributions across categories within category type for the two cohorts are the same. For all matching variables included in this table (i.e. age, gender, index year and Charlson comorbidity index) the p-value is 1, demonstrating that the two cohorts are similar by construction. The mean age was 37 and 36.1 for the Ginger and control cohorts, respectively. The majority (75%, n=1606) of both cohorts are female and the most common index year is 2020 (76.7%, n=1642). The Ginger cohort was more likely to live in the West and Northeast than the control cohort. While the payer type for both cohorts was predominantly third party (94-98.6%, Ginger cohort n=2112, control cohort n=2013), the control cohort was more likely to contain Medicare and Medicaid members. Members were matched on Charlson Comorbidity Index, so the distribution across CCI values was the same across both cohorts. The vast majority of members (90.4%, n=1937) had a CCI of 0, indicating no chronic conditions in the pre-period.

Table 1: Cohort characteristics

| | **Study Main Cohorts** | | |
|---|---|---|---|
| | **Ginger Subscribers** | **Control Cohort** | |
| | **N=2,142** | **N=2,142** | ***p*-value** |
| **Age (years)** | | | |

| | | | | | |
|---|---|---|---|---|---|
| Mean | 37 | | 36.1 | | 0.0074 |
| SD | 10.6 | | 12.2 | | |
| Median | 34 | | 34 | | 1 |
| **Gender (n, %)** | | | | | |
| Female | 1,606 | 75.00% | 1,606 | 75.00% | 1 |
| Male | 536 | 25.00% | 536 | 25.00% | |
| **Geographic region (n, %)** | | | | | |
| Northeast | 548 | 25.60% | 430 | 20.10% | <.0001 |
| Midwest | 241 | 11.30% | 475 | 22.20% | |
| South | 739 | 34.50% | 832 | 38.80% | |
| West | 614 | 28.70% | 403 | 18.80% | |
| Unknown | 0 | 0.00% | 2 | 0.10% | |
| **Payer type (n, %)** | | | | | |
| Cash | 0 | 0.00% | 0 | 0.00% | <.0001 |
| Medicaid | 9 | 0.40% | 68 | 3.20% | |
| Medicare | 21 | 1.00% | 61 | 2.80% | |
| Third party | 2,112 | 98.60% | 2,013 | 94.00% | |
| **Charlson Comorbidity Index (CCI) score (n,%)** | | | | | 1 |
| 0 | 1937 | 90.40% | 1937 | 90.40% | |
| 1 to 2 | 178 | 8.30% | 178 | 8.30% | |
| 3+ | 27 | 1.30% | 27 | 1.30% | |
| **Index year (n, %)** | | | | | |
| 2018 | 124 | 5.80% | 124 | 5.80% | 1 |
| 2019 | 376 | 17.60% | 376 | 17.60% | |
| 2020 | 1,642 | 76.70% | 1,642 | 76.70% | |

Table 2 presents the mean, standard deviation and median of pre-period overall healthcare costs, outpatient costs and pharmacy costs for both the Ginger and control cohorts. There was no statistical difference in mean costs between the two cohorts. The mean (SD) overall healthcare costs in the pre-period was $1739.46 ($5874.55) for the Ginger cohort and $1835.01 ($5999.95) for the control cohort. The mean (SD) outpatient costs in the pre-period was $514.21 ($930.11) for the Ginger cohort and $584.44 ($1866.86) for the control cohort. The mean (SD) pharmacy costs in the pre-period was $1133.97 ($5367.63) for the Ginger cohort and $1107.78 ($5083.89) for the control cohort.

Table 2: Healthcare costs

| | Ginger subscribers N=2,142 | | | Control Cohort N=2,142 | | | *p*-value |
|---|---|---|---|---|---|---|---|
| **All-cause Costs** | **Mean** | **SD** | **Median** | **Mean** | **SD** | **Median** | |
| Total healthcare costs per patient | 1739 | 5874 | 426 | 1835 | 6000 | 420 | 0.598 |
| Total pharmacy costs per patient | 1134 | 5368 | 62 | 1108 | 5084 | 56 | 0.869 |
| Total outpatient medical costs per patient | 514 | 930 | 223 | 584 | 1867 | 210 | 0.120 |

Figures 1 and 2 show the trajectory of total monthly healthcare costs for the Ginger and control cohorts, respectively. Each figure plots the mean percent change in monthly costs relative to the month before the index event with the 95% confidence interval around the mean. These are computed after controlling for the covariates listed above. The month prior to the index event was the leave-out reference group. In addition to the percent change in costs, the cohort-specific linear trend is represented by the dashed line. For both cohorts, there was a clear upward pre-trend in costs followed by either a leveling off of costs, or a reduction in costs relative to the month before the index event.

Figure 1. Trajectory of total monthly cost for Ginger

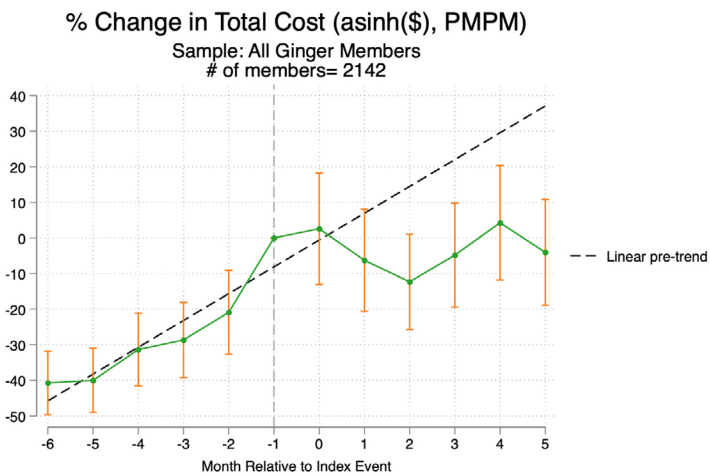


Figure 2. Trajectory of total monthly cost for control cohort

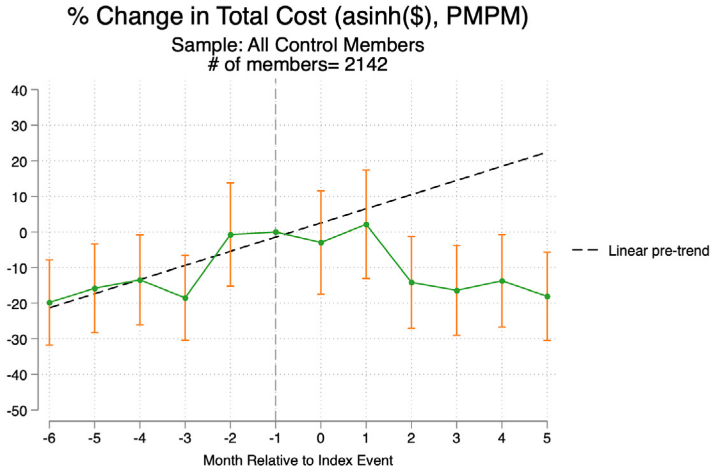


Figure 3 superimposes versions of Figures 1 and 2 that have subtracted the estimated linear pre-trend for each cohort. This yields trajectories that have an average slope of 0 centered on 0 in the pre-period and fall in the post-period. Each cohort's deviation from 0 in the post period illustrates that cohort's deviation from their pre-period linear trend. Here, the Ginger cohort's trajectory fell below the control cohort's trajectory in months 1 through 5; however, the confidence intervals for each cohort overlap.

Figure 3. Mean log costs, subtracting the estimated linear pre-trend for each cohort

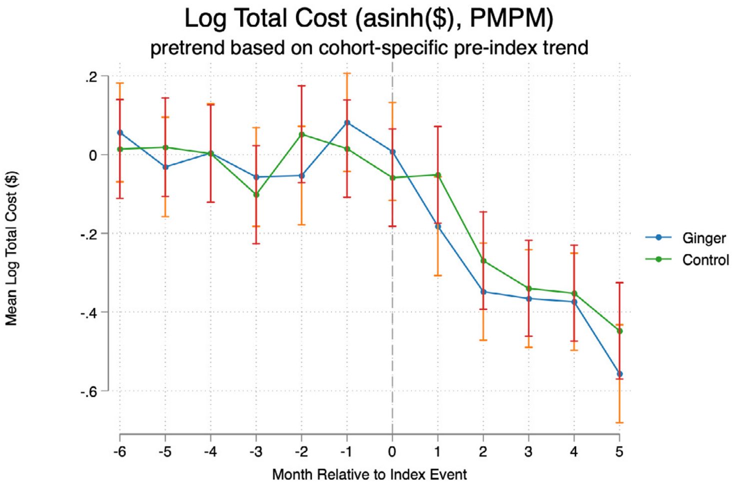


Table 3 presents the estimated treatment effect and p-values for overall healthcare costs, outpatient costs and pharmacy costs. Overall healthcare costs fell by 4.65 percent, which is not statistically significant. Outpatient costs fell by 16.79 percent (p=.08). Pharmacy costs rose by 0.45 percent, which was not statistically significant.

Table 3: Estimated treatment effects

| | TE (% change) | p-value |
|---|---|---|
| Total Healthcare Costs | -4.65% | 0.68 |
| Outpatient costs | -16.79% | 0.08 |

| | | |
|---|---|---|
| Pharmacy costs | +0.45% | 0.96 |

## 5. Limitations and Future Directions

There are several challenges with claims data studies in the area of digital mental health, including a) needing data-sharing agreements between providers and employers/health plans; b) complex data-matching requirements to respect member privacy; and c) the inherent noise and ambiguity in standard claims datasets. Consistent with previous claims analysis studies, there are limitations in the current study. First, the matched cohort used in the current study was done with limited refinement (e.g., not matched on mental health diagnosis or zip code). Even with improved matching, there likely exist unobservables (and thus could never be used for matching) that can explain why an individual decides to join Ginger. The impact of Ginger on cost-utilization could vary by care modality as well as severity of mental health symptoms at baseline. Furthermore, changes in cost could be driven by Ginger members joining the virtual on-demand care platform around the same time as starting a new job. The external validity of the current study is limited, as members were required to have at least 1 claim data in both pre- and post-periods, which ignores patterns driven by members who either do not seek care before or after joining the platform. A more detailed and granular claims data could provide additional insight into the nuanced patterns of healthcare utilization between and within the two groups. Despite the focus on members with at least some healthcare utilization, the vast majority of members included in this study had no chronic conditions prior to joining Ginger. While this sample may be representative of individuals seeking support from virtual mental health platforms, like Ginger; it may not be representative of the population of Americans with a mental health need, which is correlated with physical chronic conditions. Future studies will require more rigorous demonstration of the cost-effectiveness of digital mental health interventions vis-a-vis the type of service provided, the target population, and the current standard of care.[27] In addition, there has been limited comparisons of virtual mental health interventions with medication therapy,[16] and should be included in future analyses.

The temporary waiving of numerous rules and regulations around telehealth during the pandemic has resulted in an expansion in digital mental health interventions.[11] These virtual care options offer the potential to increase access to care in the overstretched and resource limited mental healthcare system.[19] With this expansion, there becomes increased importance on understanding the impact of these virtual interventions on overall healthcare costs, including both direct costs of the interventions as we as second-order costs of other healthcare utilization. Focusing on the latter, the current study demonstrated that virtual care interventions do not significantly increase total health care costs. In fact, results show that engaging in Ginger is associated with a reduction in outpatient costs, suggesting that novel behavioral health interventions can shift the modality of care without increasing overall health care spending.

## 6. Conclusions

Demonstrating the clinical and cost impact of virtual interventions for anxiety and depression and other mental health disorders, as well as its delivery at scale and translation into real-world benefits, has been slow.[3] To fill this gap, the current study looked at the association between use of an on-demand virtual care platform and overall costs. For Ginger members, the impact of Ginger overall healthcare and pharmacy costs was not significant; however, outpatient costs were reduced by 16.8% (p=.08). Because the majority of the sample (76.7%) joined Ginger in 2020, these results contribute to our understanding of the impact of digital mental health interventions on healthcare costs during the pandemic.

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