Equity and Efficiency in Technology Adoption: Evidence from Digital Health*

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Abstract: Digital technologies are bringing vast changes to modern society and are proving increasingly promising in improving population health. Digital Health, which encompasses digital technologies in the medical sphere, is a fast-growing market that represents a leading segment of transformative digital and medical innovation. But new technologies also carry the risk of exacerbating existing disparities when adopted at lower rates by vulnerable communities. We study this efficiency-equity tradeoff in the context of a new technological advancement in digital health. In a diverse patient population of a major academic healthcare system in Southern California (UC San Diego Health), we study the adoption patterns and health effects of a remote patient monitoring program, designed to improve outcomes for patients with hypertension by enabling transmission of real-time blood pressure data to their healthcare provider for timely treatment. On the efficiency side, we find significant and persistent health improvements of reduction in blood pressure and cardiovascular risk, which were notable across all subgroups of gender, age, race/ethnicity, and geographic affluence. But on the equity side, we find that the new technology is systematically adopted at lower rates by black/Hispanic patients and by patients from economically vulnerable communities. These patient groups, who already face health inequities at baseline, are less likely to either take up or to adhere to the program. Our analysis highlights the simultaneous promise and hazards of digital technologies, as it places across-the-board improvements in health outcomes against the drawback of uneven adoption of new technologies that deepens health disparities. Evidence suggests that physicians can have a role in promoting more equitable adoption of new technologies of digital health.

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1. Introduction

Technology is a key driver of growth and improvements in economic well-being, and it is particularly important in advancing population health (Cutler and Miller 2005; Cutler, Deaton, and Lleras-Muney 2006). Powered by mobile internet, recent technological advances in digital health—such as remote monitoring devices, digital wearables, and telemedicine services—are becoming increasingly promising in the efforts to promote population health (Mathews et al. 2019; WHO 2022). By reducing transaction costs that could hinder the utilization of traditional care (e.g., accessibility, distance, and time), these technologies aim to improve patient health by providing solutions that promote adherence to healthy behaviors and real-time continuous care.

But with the widespread geographic and socioeconomic disparities in health in the U.S. (Cutler, Lleras-Muney, and Vogl 2011; Chetty et al. 2016), new health technologies can bring both opportunities and challenges in the equity-efficiency tradeoff. While they can improve patient health and healthcare delivery, the degree to which new technologies are adopted by vulnerable households would determine the equity implications of a technological innovation. Along with their great promise to improve population health, a key concern with the introduction of digital health technologies has been that unequal adoption could deepen existing inequities in health or the delivery of care (Lyles et al. 2021). Such concerns are also at the heart of the WHO's Global Strategy on Digital Health on how to steer the digital revolution in the provision of health (WHO 2022).

A recent technological innovation in digital health, with fast growing popularity among researchers and policymakers, is the integration of remote patient monitoring devices to the provision of care (Burke et al. 2015). Monitoring devices, such as digital cuffs for blood pressure measurement, facilitate ongoing electronic transmission of patient health data to enable timely medical advice and provision of care. This paper studies the equity-efficiency consequences of offering this new technology to a wide and diverse population of households.

We analyze an original remote patient monitoring program designed within our home institution, at UC San Diego Health. The program targeted at reducing cardiovascular risk due to its prominence as a leading cause of death in the U.S. (Ahmad and Anderson 2021). Our intervention was motivated by recent trials that provided, within clinical settings, promising

results of the effectiveness of digital devices. Building on these studies, we designed a field intervention that offered a digital health program to patients with hypertension with the following features. First, our study's population displays a diverse representation reflective of UC San Diego Health's patient population, as well as health disparities across location and race/ethnicity reflective of nationwide patterns. Second, the setting provides us with an opportunity to investigate both the effectiveness and the adoption patterns of this new digital health technology, within a real-world health system of busy clinical practice and the intersection of primary care and population health team. Therefore, our work lends itself to a real-world study of the equity-efficiency consequences of a new digital health technology, with the aim to establish stronger external validity for future integration of innovative health solutions.

In this program, known as "Project 1000," primary care physicians (PCPs) within the UC San Diego Health network were asked to refer their patients with hypertension, whose blood pressures had been poorly managed by traditional means of care, to the digital health team in the Population Health Services in the health system. The team would offer the referred patients a digital program within which they receive electronic Bluetooth-enabled digital cuffs, which automatically transmit their blood pressure information to the clinical team upon measurement. Population Health clinical staff would monitor these patients' data daily on a dashboard in the Electronic Health Record (EHR) in order to manage patients' blood pressure levels based on standard treat-to-target guidelines (i.e., protocols that provide treatment to reach a target of a clinically desirable outcome such as a blood pressure level). The patient population in this study is comprised of the 2,512 patients who were referred to the program by their PCP between October 2020 and July 2022.

Our analysis of the equity-efficiency consequences of this technological intervention begins with the efficiency side, by assessing the effect of the program on patients' health outcomes measured by systolic ("upper") blood pressure. We analyze the program's impact based on an event study design. Specifically, in high-frequency analysis, we study the evolution of patients' blood pressure levels over the course of the year before and the year after they were referred to the program by their primary care physician. Identification relies on how outcomes

right after the intervention deviate from the baseline trend prior to the intervention. We also accompany the main design with a matched control group as robustness.

We find clear evidence of improvements in health outcomes following referral to the program. The reductions in blood pressure amount to 10 mmHg (millimeters of mercury) on a baseline of 134 mmHg. Patients display a 16 percentage points (pp) increase in the propensity to reach healthy blood pressure levels below 120 on a baseline of 24 pp. Furthermore, we study an aggregate measure of the health value of the technological change using the common ASCVD scoring of cardiovascular risk, which indicates a patient's ten-year risk of having a serious cardiovascular event such as a heart attack or stroke (Goff et al. 2014). We find that after one year, the intervention leads to a decline of 2 percent in cardiovascular risk (on a baseline of 18 percent). These health improvements are large in magnitude as they compare with the efficacy of blood pressure medication in clinical trials (Paz et al. 2016, Bennett et al. 2017, Canoy et al. 2022). Exploiting our demographic data, we find across-the-board health improvements over the subpopulations of patients of different levels of geographic affluence, ages, gender, race, and ethnicity.

On the equity side, we study the adoption rate of the program and how it may vary across patient groups and communities. In our setting of California and reflective of nationwide phenomena, large disparities have been documented across race/ethnicity and families from differentially affluent communities, which we also illustrate in our population based on cardiovascular health. We therefore investigate potential disparities in the delivery of care that could arise from the introduction of the new technology by studying gaps in adoption across these subpopulations. A common metric in our study's region for a community's affluence is the "Healthy Places Index" (HPI), which has been developed in the State of California for the design of policies to fight disparities (Maizlish et al. 2019).

The effective adoption rate combines the initial takeup decision and the follow-on adherence to the program. In the overall sample, the initial takeup rate was 0.53. Following signup, the conditional mean adherence rate averaged to 0.49 over the year from referral. This translates to an overall average adoption rate of 0.28. Comparing across subpopulations, we find that black and Hispanic patients are 13 percent less likely to adopt the program, which is driven

by lower adherence rates after the initial takeup. Disparities across geographic communities display even larger gaps, on the order of 25 percent, in the ability or willingness to adopt the digital technology. The geographic disparities already arise in the initial takeup stage, suggesting patients from less affluent communities face additional upfront frictions. Since HPI is largely based on local economic indicators, this pattern is in-line with policymakers' concerns that lower-income households could face greater challenges in engaging with digital health due to financial or logistical constraints (Lyles et al. 2021; WHO 2022).

Our overall findings of health outcome improvements along with only partial adoption imply meaningful frictional costs in households' technological adoption, as they are leaving meaningful health gains on the table. These frictional costs reflect both logistical costs (such as limited access to internet connection) and psychological costs (such as aversion to new technologies). To identify pathways that could reduce these frictions, we study the potential role of physicians in inducing adoption. We first find a strong relationship between adoption and a PCP's performance, as measured either by rate of reaching objective clinical goals or by Net Promoter Score (NPS) on a routinely collected metric of patients' subjective experience based on their "likelihood to recommend the PCP to friends and family." Moreover, we find that patients are much more likely (by 7 pp) to adopt the program when the PCP-patient relationship is longer, which could proxy for stronger trust. These patterns prevail across households from differentially affluent communities and from traditionally underserved minorities, which points to the physician-patient relationship as a promising pathway to promote more equitable adoption of digital technologies.

Finally, we conclude with an illustrative investigation of the potential financial value generated by the program in the medium run. We use internal data on healthcare costs attributed to professional services, which include primary care and specialists. These data cover a subpopulation of patients in UC San Diego Health's managed care value-based contracts with payers (for whom UC San Diego Health bears professional risk through capitation payments). We find that the digital program generates financial returns already in our analysis horizon of one year. The reduction in costs is notable in the second half of the year following the referral, amounting to an average decline of 40 percent relative to counterfactual levels.

Related Literature. Our study contributes to several literatures. First, our work was motivated by recent trials in clinical settings on the promise of digital health devices in reducing cardiovascular risk (as reviewed in, e.g., Burke et al. 2015). Building on their evidence, our intervention was designed to study the consequences of introducing a new digital technology to a wide patient pool in a working healthcare environment. It therefore allows a novel analysis of the real-world efficiency and equity tradeoffs of digital technological innovation in population health, analysis whose absence has been highlighted in the literature (Tinetti and Studenski 2011; Lyles et al. 2021). We study both the decision of household technology adoption (which is outside the scope of clinical trials by their voluntary nature) and the degree of possible health improvements in a scalable way that involves daily and routine hurdles (which can burden engagement in digital health in practice from both the provider and patient sides). When studying health effects, we use a high-frequency dynamic event study design to recover estimates of the intent-to-treat. This stands in contrast to the American Heart Association's critique that previous larger scale observational studies suffer from making before and after comparisons of patients who self-select to participate in a program (Burke et al. 2015), which also applies to more recent work (e.g., Blood et al. 2022). Finally, we harness the diversity of our sample to analyze health efficacy among traditionally underserved communities, addressing the need for their representation in health research as recently emphasized by the medical and economic professions (Bruke et al. 2015, Lyles et al. 2021, Alsan et al. 2022).

Second, we contribute to the active and pressing work on geographic, racial, and ethnic health disparities in the United States (e.g., Chandra and Skinner 2003, Institute of Medicine 2003, Bolen et al. 2010, Chetty et al. 2016, Eberly et al. 2018, Schwandt et al. 2021, Couillard et al. 2021, Finkelstein et al. 2021). Digital health solutions have been rising in attractiveness due to their promise to shatter barriers of provision of traditional care, including physical inaccessibility and time constraints of financially disadvantaged households. But concerns were raised that digital health can harm equity due to gaps in accessibility to digital infrastructure, design and evaluation that lack representation, and implementation hurdles from lack of training, support, or trust (Lyles et al. 2021). Our work exactly evaluates and quantifies these multiple considerations. We show both improvements in health across all subpopulations and a

deepening of the disparities in the delivery of care due to unequal adoption of the new technology, which we estimate to be a concern of practical relevance.

Finally, we contribute to work on the economics and value of medical innovation (e.g., Cutler et al. 2006, Williams 2013, Budish et al. 2015, Sampat and Williams 2019, Bauer, Lakdawalla, and Reif 2022, Chandra et al. 2022). Digital health represents a large and growing market in medical innovation, with global estimates on the order of $350 billion in value and annual expected growth of 8 percent.[1] Economic research is at its infancy of assessing the social value of digital health, with new insightful studies such as the work by Zeltzer et al. (2021) in Israel and Dahlstrand (2021) in Sweden on the availability of remote visits for primary care. We provide a timely assessment of an implementation of innovation in digital remote patient monitoring, which represents a key segment of the growing telemedicine market. Our setting also uniquely allows an assessment of the value of the new technology in terms of direct health outcome improvements, by studying high-frequency clinical health measures. Such measures are usually absent in observational economic studies, in which health is imputed from claims data by low incidence events with lower precision to detect meaningful effects or by healthcare utilization that has been shown to be affected by financial incentives. In addition, we can assess changes in costs, by studying administrative data on the medical costs involved in professional services provided by the primary care physician of a specialist for a subsample of patients. Overall, we find large social returns from the introduction of the digital technology.

The remainder of the paper proceeds as follows. In Section 2 we describe the digital health program. Section 3 introduces the data, patient population, and analysis sample. In Section 4 we lay out a simple conceptual framework to fix ideas. Section 5 describes the empirical framework. Section 6 provides our main analysis of the consequences of the intervention: Section 6.1 studies efficiency in health and Section 6.2 studies equity in adoption. Section 7 investigates the role of physician in inducing patients' program adoption. Section 8 assesses changes in professional medical costs. Section 9 concludes.

[1] See a 2019 report by McKinsey & Company at https://www.mckinsey.com/industries/life-sciences/our-insights/healthtech-in-the-fast-lane-what-is-fueling-investor-excitement.

2. Program Overview

Appendix Figure B.1 provides a diagram that illustrates the main steps of the workflow, from PCP referral to patient outreach, to onboarding, and to integration of remote monitoring data into the dashboard in the EHR managed by clinical staff.

Specifically, we provided iHealth Ease, a Bluetooth-enabled digital blood pressure device, to patients referred by their PCPs, reached by digital health program staff, and chose to participate in the program. See a picture of the device in Appendix B. Technical support for device setup and app downloading was provided telephonically. For patients experiencing difficulties that could not be successfully addressed over the phone, a digital health specialist would make a home visit to set up the device and teach the patient how to use it to transmit blood pressure measures.

After a successful setup, the patients were advised to take blood pressure measures a minimum of twice daily and transmit the data using an app in their smartphone to the patient portal of the Epic Electronic Health Record (EHR) system (Verona, WI) which automatically records the blood pressures data and populates a dashboard. The dashboard stratifies the incoming blood pressure measures into 3 risk groups: normal, high and priority, and critical. A team of care managers, including a pharmacist and two registered nurses, reviews the EHR dashboard daily, and makes treat-to-target medication adjustments as needed per established protocol as well as recommendations for behavioral adjustments. Example snapshot pictures of the dashboard, as well as additional program details, are provided in Appendix B.

Patients were advised to continue their participation for at least six months and technical support was provided throughout patient participation.

3. Data, Population, and Analysis Sample

3.1. Data

Data on health outcomes come from the administrative patient electronic health records. The data include all readings of blood pressure measures, taken in office or transmitted electronically from remote monitoring devices. The EHR also has patients' atherosclerotic cardiovascular disease (ASCVD) risk scores, a standard risk measurement which indicates a

patient's risk of having a heart attack or stroke in the next ten years. It is calculated with data on a patient's age, gender, race, HDL cholesterol, total cholesterol, systolic blood pressure, diastolic blood pressure, whether the patient has diabetes, whether the patient is being treated for high blood pressure, and whether the patient is a current tobacco smoker (Goff et al. 2014). The score applies to patients between the ages of 40 and 79 years who have not had a prior ASCVD event.

We merge these data with patient birthyear and gender, as well as with self-reported demographic information that comes from the standard health survey that new patients must fill out when becoming new UC San Diego Health patients. This includes race, ethnicity, and place of residence. We characterize differentially affluent communities by using the "Healthy Places Index" (HPI), which was constructed by the Public Health Alliance of Southern California (Maizlish et al. 2019). The HPI combines neighborhood-level data on social conditions which include measures of income, education, employment, and housing quality, and can be used to inform health delivery and policy, especially for the most disadvantaged communities. This index was created to advance health equity in the region and is currently used by researchers, health system leaders, and government agencies toward that effort (Tai-Seale et al. 2022).

Our analysis of costs attributed to professional services relies on healthcare costs data, which are available for patients for whom UC San Diego Health receives capitation payments from payers for the provision of medical professional services, i.e., an advanced amount per patient per month. Capitation payments put UC San Diego Health financially responsible for professional services provided to these patients. The UC San Diego Health Physician Practice Group receives payments for professional services provided by its physician members. Therefore, we have access to information on the healthcare costs associated with these patients' utilization of physician services at UC San Diego Health. We focus on these patients in the cost analysis since for them we know that lack of claims means no professional costs, whereas otherwise it could also be a result of patients no longer receiving care at UC San Diego Health. The data provide detailed information of claim entries per patient, which we aggregate within patients at a monthly level.[2]

[2] The internal pricing used for healthcare costs of Managed Care patients is at 100 percent of Medicare reimbursement rates for capitated patients on Medicare Advantage HMO Plans and about a third of that for capitated patients on Commercial HMO Plans.

3.2. Patient Population: Baseline Disparities

To provide the context of our study, we characterize baseline health in our setting of cardiovascular risk using the ASCVD risk score. We specifically analyze the prevalence of low cardiovascular risk, which the American College of Cardiology defines as lower than 5 percent in ASCVD risk (Arps et al. 2018). We focus on geographic disparities and racial/ethnic disparities to reflect the work on disparities in health in the U.S.

Among UC San Diego Health patients, 58,789 individuals are included in the hypertension registry which requires an I10 code of hypertension diagnosis using the ICD10 classification. This baseline pool is comprised of 39,820 patients younger than 65 and 18,969 patients 65 or older; 0.55 share female patients; and 36,863 non-Hispanic white patients and 9,580 black and Hispanic patients.

Using data from this registry, we illustrate baseline disparities in health in our setting. Panel A of Figure 1 focuses on geographic disparities. It illustrates how the prevalence of low cardiovascular risk sharply declines among less financially affluent communities of lower HPI quartile. Panel B of Figure 1 shows the racial/ethnic gap. It shows that black and Hispanic patients are 8 pp less likely to display low risk, compared to white patients whose prevalence rate of low risk is 0.32. These patterns are overall reflective of the broader nationwide phenomena.

3.3. Analysis Sample: Patients and their Physicians

Our analysis sample is comprised of the 2,512 patients who were referred to the digital health program by their UC San Diego Health PCP from October 2020 to July 2022. The program is currently still ongoing for both enrolled and potentially new patients. Only patients with an assigned UC San Diego Health PCP could participate, so that patients are those continuously treated by UC San Diego Health. Appendix Table 1 provides characteristics of the analysis sample in terms of age, gender, race/ethnicity, and HPI of residence. An advantageous feature of our setting is that the sample has broad representation of different demographic subgroups. It allows us to study both heterogeneity in clinical health impacts and heterogeneity in technology adoption, thereby relating to work on health disparities in both medical and economic research.

For our analysis of costs, we study the subsample of patients for whom UC San Diego Health receives capitation payments. It involves 1,792 patients, comprising 71% of our subject pool.

It is also useful to describe the primary care physicians who referred our subjects to the program. A total of 274 primary care physicians referred patients, where the number of referred patients per physician had a median of 26 and a mean of 70. On average, patients have been treated by their PCP for 2.2 years, with a median physician-patient relationship length of 0.8 years. We later use two proxies to characterize physician "quality" in terms of performance. Our first measure relies on objective health benchmarks. We use a measure of the incentive rewards a physician received as part of ongoing performance-pay incentive schemes undertaken by UC San Diego Health for quality promotion. Each program sets target rates and compensates physicians with respect to how well they perform relative to that target, which places them on a reward tier represented in percent. We take the mean tier for each physician based on rewards for 2021 across all programs that are not directly related to management of cardiovascular health (to avoid mechanical correlations). Our second proxy relies on subjective patient evaluations. We use a physician's current ranking in the Net Promoter Score (NPS). It is a physician's rate of approval based on their patients' reported likelihood to recommend their PCP to friends and family, which is a patient experience metric from routinely administered patient surveys. This metric is also tied to financial incentives to physicians. The mean and median NPS in 2022 of physicians in our sample were at 87 percent with a standard deviation of 8 percent.

4. Conceptual Framework

To fix ideas, we postulate a simple model of a household's decision to adopt a new health technology. Consider the potential gains from technological adoption to be the gap between the value of adopting the new technology, V^1, and the value of the counterfactual of no adoption, V^0, that is: $\Delta V = V^1 - V^0$. We think of these as values that are normalized to reflect cardiovascular health (e.g., ASCVD risk), so that ΔV represents changes in cardiovascular risk. As these gains are in physical health, we assume they are similar across households of similar baseline health risk captured by an array of potential risk modifiers.

Household i faces adoption costs, δ_i, drawn from a distribution $F(\delta_i)$. These costs can include logistical costs, such as limited access to internet connection, and psychological costs, such as aversion to use of new technologies. Adoption costs may be attenuated by PCPs and their practice styles. The literature has shown large effects of PCPs on patient utilization for a variety of services (Fadlon and Van Parys 2020) and likewise how their characteristics (such as race and gender concordance) can alter patients' willingness to utilize medical care and undertake a range of procedures (Greenwood et al. 2018; Alsan et al. 2019; Frakes and Gruber 2022). We therefore denote by $p_{j(i)}$ a measurable characteristic of PCP j to whom patient i is assigned, and we allow adoption costs to vary by this characteristic. We also allow costs to vary by demographic characteristics, denote by d_i (and assumed continuous for simplicity), which can reflect differential affluence of a patient's community or self-association with an under-represented minority. Variation in d_i can reflect, for example, differential access to logistical requirements that are necessary for continuous engagement in the program, including smartphones, reliable internet connection, as well as time, which lower-income households might have limited access to because of financial constraints. Formally, we let the cost of adoption vary along these dimensions by denoting $\delta_i\left(d_i, p_{j(i)}\right)$, and we normalize it to reflect the same units as ΔV.

Household i chooses to adopt the new technology whenever:

$$\Delta V = V^1 - V^0 > \delta_i.$$

The adoption rate is captured by $F(\Delta V)$. Our empirical analysis will accordingly estimate the following expressions. First, we will study the impact of the program on key health outcomes, which maps to ΔV. Second, we will study adoption rates, $F(\Delta V)$, and how they may vary across households from different communities, $\frac{\partial F(\Delta V)}{\partial d_i}$, which will allow us to explore disparities. We will also assess the degree to which physicians may attenuate adoption costs by studying how one's adoption propensity may vary by PCP characteristics, $\frac{\partial F(\Delta V)}{\partial p_j}$.

5. Empirical Framework

We use a semi-parametric event study design to assess the program's impact, closely in line with specifications from Dobkin et al. (2018). In the first step, we residualize the raw outcome based on pre-period observations (from months -12 to -2 relative to referral where month -1 will

be used as the baseline year). In the second step, we run a non-parametric event study of the residualized outcome for the year before and the year after the referral at a monthly frequency. The idea behind the first step is to allow for potential underlying trends that led a PCP to refer the patient to the program. By design and the instructions communicated to physicians, a referral typically occurs after a patient's blood pressure has been poorly managed by traditional care practices, which could follow a period of a trending trajectory. Appendix Figure A.2 displays the evolution of the raw data for our main health outcome of systolic blood pressure around the event.

The exact equations we run are as follows. In the first step, we estimate:

$$y_{i,t} = x_{i,t}\lambda + \epsilon_{i,t},$$

where $y_{i,t}$ is an outcome for patient i in month t, and $x_{i,t}$ includes a linear trend in months relative to referral and a vector of age fixed effects. This equation is estimated using months -12 to -2 relative to the PCP referral. We then project this equation onto the entire time horizon of 12 months before and 12 months after the referral, and we take the residual value of the outcome variable (i.e., the difference between the actual value and the predicted value). We denote the residual by $\tilde{y}_{i,t}$. In the second step, we estimate:

$$\tilde{y}_{i,t} = \sum_{r \neq -1} \beta_r \times I_r + \alpha_i + \varepsilon_{i,t}, \quad (1)$$

where r is the time period relative to the event, I_r is a set of indicators, and α_i are household fixed effects. Robust standard errors are clustered at the patient level. We plot β_r, which traces the evolution of patients' health around the referral event relative to the baseline period -1. Appendix Figure 1 displays the distribution of time of referral in terms of calendar year/month. Our identification relies on the rollout of referrals across the different periods within the intervention's time horizon. It estimates impacts based on how outcomes right after the intervention deviate from the baseline trend in the pre-intervention period. We later also augment the design with a matched control group as a robustness check.

For analyses of heterogeneity and subpopulations, we will also look at average effects by running regressions of the form:

$$\tilde{y}_{i,t} = \beta \times after + \alpha_i + \varepsilon_{i,t}, \quad (2)$$

where $after$ is an indicator for whether the observation comes from periods before or after the intervention, and β captures the average effect.

6. Empirical Evidence: Equity-Efficiency Tradeoff in Technology Adoption

We now turn to our main empirical analysis. First, we assess the program's impact on patient health. Then, we study potential healthcare disparities that may arise through uneven adoption rates.

6.1. Efficiency: Health Impacts

As a main outcome to assess the program's impact on patient cardiovascular health, we resort to the medical literature and study systolic blood pressure. Panel A of Figure 2 plots the event study coefficients from equation (1) for all patients who were referred by PCPs at a monthly frequency. We include all referred patients, who are either adopters or non-adopters, as the adoption decision itself is endogenous to the household. That is, we focus on estimating the intent-to-treat. This is in contrast to observational medical research that often rely on pre and post average outcomes of self-selected patients for causal identification (Burke et al. 2015).

The reductions in blood pressure are visually apparent right after the intervention, as patients begin to actively engage with the program and its health-management goals. By the end of the one-year analysis period, we find that the intervention reduced patients' blood pressure by an average of 10 mmHg (millimeters of mercury) on a baseline of 134 at $t = -1$.

As an important robustness analysis, we assess threats from potential selection in observations that remain in our sample (though we already include patient fixed effects). In panel B of Figure 2, we replicate the analysis using observations of patients for whom we have repeated blood pressure readings within our analysis period of a year before and a year after the referral. Specifically, we include patients with at least one data point in the pre-period (day -365 up to day -10 to provide sufficient distance from the day of referral) and at least one data point in the latter part of the post-period (up to day 365). In this figure, we include all patients who have at least one reading at or after day 150 as a threshold. Appendix Figure A.3 studies the sensitivity to the choice of threshold (for value 50, 100, 150, 200, 250) at a quarterly frequency for increased precision. Overall, all samples provide results that are virtually uniform.

As an additional robustness check we complement the event study design with a matched control group. We use exact matching of patients on birthyear, gender, race, ethnicity, quartile of HPI, and the bin of patients' average level of systolic blood pressure in a baseline year 2019 (where we split this average into twenty equal bins). To each matched control patient, we assign the referral date of the treated unit they were matched with as a placebo referral date. We include patients with repeated measures, resulting in a sample of 583 treated units and 2,362 control units. We then repeat our two-stage event study analysis for each experimental group and test the differential across them. Appendix Figure A.4 shows the robustness of our results to this augmented design.

To benchmark effect magnitudes, we note that the effects we find are on the same order of magnitude as estimates from clinical trials for the effect of antihypertensive drugs, which are perceived to be highly effective and are widely recommended and used (Paz et al. 2016, Bennett et al. 2017, Canoy et al. 2022). Importantly, the health improvements that we find show remarkable persistence over our analysis horizon of up to one year. In fact, pushing the data further (and cautioning against the reliance on an increasingly small sample), the evidence suggests these reductions persist even longer. Panel C of Figure 2 shows that after 20 months following the referral, the decline in blood pressure is on the order of 14 mmHg. Having seen the effects in high frequency, the rest of the analysis is aggregated at the quarterly level and include the sample of patients with repeated readings. Appendix Figure A.3 replicates Figure 2 at the quarterly level.

As an intuitive indicator of health outcome improvements, we also study the probability of reaching normal blood pressure levels as defined by medical professional organizations. The American College of Cardiology and the American Heart Association define blood pressures below 120/80 mmHg as normal; blood pressures at or above 130/80 mmHg as stage 1 hypertension; and high blood pressures at or above 140/90 mmHg as stage 2 hypertension (Whelton et al. 2018). Panel A of Figure 3 plots the event study coefficients of the probability that a patient's systolic blood pressure drops below the 140 mark of high blood pressure and below the 120 mark of normal blood pressure. We find clear improvements across the two categories. Within one year of referral to the program, patients display a 24 pp increase in the propensity to

fall below high hypertension levels (on a baseline of 63 pp) and a 16 pp increase in the propensity to reach healthy blood pressure of normal levels (on a baseline of 22 pp).

Finally, we translate all these effects to reductions in overall cardiovascular risk using the ASCVD risk score. In panel B of Figure 3, we find that by one year after the intervention, referred patients' long-run risk to experience major cardiovascular conditions declines by 2 percent on a baseline of 18 percent. Overall, we find visual evidence of large health improvements following the intervention.

Next, we study how these effects reflect improvements in health across different subpopulations. Table 1 reports estimates of the effect on systolic blood pressure based on equation (2). In defining the variable $after$, we include in the pre-period observations from months -6 to -1 and in the post-period observations from months 7 to 12. As a benchmark, we first provide the estimate for the overall sample with repeated readings, which amounts to a decline of -7.66 mmHg.

We find meaningful reductions in blood pressure across all heterogeneity dimensions: age (over or under age 65), gender, the affluence of a patient's community (across different HPI percentiles), and race and ethnicity (black/Hispanic patients or white patients). The relative representativeness of our sample allows us to draw these conclusions of implications for improvements in health across under-served communities and economically vulnerable families, who tend to be very narrowly represented in clinical studies (Alsan et al. 2022). We also find improvements among patients with the comorbidities of diabetes and ischemic heart disease. This appeals to the medical profession where studies often lack representation of such patients although they account for more than 80 percent of Medicare costs and are overrepresented in Medicaid and private insurance plans (Tinetti and Studenski 2011).

6.2. Equity: Disparities in Adoption Rates

The adoption of the program is determined by both its initial takeup and the follow-on adherence to it conditional on takeup. We define the initial takeup of the program, denoted by T_i, as the event that the patient transmits data at least once after the referral. This approach guarantees the patient has successfully engaged with the program. We let T_i assume the value 1 if the patient takes up the program and assume the value 0 otherwise. We define patient's i

adherence to the program at time period t (in months relative to referral), denoted by A_{it}, based on the event that the patient transmits data in period t. The probability of adherence conditional on takeup, $Pr(A_{it}|T_i = 1)$, will characterize the patient's "survival" on the program, with its average over time periods providing us with mean adherence probabilities. The implied mean adoption rate over our analysis horizon of one year following referral will be defined based on the interaction of the two variables ($T_i \times A_{it}$) averaged over months in the follow-up year.

Figure 4 characterizes adoption among the entire sample. The initial takeup rate among all referred patients was 0.53, and the average adherence rate conditional on takeup was 0.49 with clear declining pattern in the one year horizon. Overall, the adoption rate of the program among the entire subject pool averaged to 0.28.

To investigate potential gaps in adoption, we next compare these behaviors across subpopulations of interest (in panel A of Table 2). We first compare black and Hispanic patients to white patients. We see that that black and Hispanic patients display a lower overall adoption rate. The racial/ethnic gap in the adoption of the digital health program amounts to 13 percent (-3.82 pp relative to rate of 29 pp among white patients). The gap is driven by lower adherence rates, that is, differential rates of "survival" on the program.

To look at disparities across geographic communities, we compare patients from the lowest affluent communities (in the first HPI quartile) to patients from the highest affluent communities (in the fourth HPI quartile). The technological adoption gap across households from differentially affluent communities amounts to 27 percent (a gap of -8.4 pp relative to a baseline of 30.5 pp). The geographic disparities already arise in the initial takeup decision, suggesting patients from less affluent communities face additional upfront frictions. Since HPI is based mostly on local economic indicators, the findings are consistent with broad concerns that lower income households could face more barriers to engage with digital health from financial and logistical constraints (Lyles et al. 2021; WHO 2022).

7. Role of Physicians in Adoption of Digital Health

Overall, we find significant health improvements along with partial participation, suggesting meaningful frictions in the adoption of the digital technology. This raises the important question of whether the adoption decision is a margin that can be influenced and, if

so, how. The primary care physicians, who are the point of contact between the patient and the program, are an obvious candidate to investigate. More generally, primary care physicians have shown to have fundamental effects on their patients' healthcare utilization and willingness to undertake medical procedures (Alsan et al. 2019, Fadlon and Van Parys 2020, Frakes and Gruber 2022).

7.1. Baseline Variation

We first characterize the distribution of patient adoption rates at the physician level. We limit the sample to primary care physicians with more than one referred patient, totaling to 186 physicians. Across them, the physician level adoption rate has a mean of .24 and a standard deviation of .15, so that there is substantial variation. We then calculate physician-level patient adoption rates residualized of clinic fixed effects, including only clinics with more than one referring PCP, which totals to 18 clinics and 178 physicians. For these physicians and clinics, we plot in panel A of Figure 5 the physician-level patient adoption rate residualized of clinic fixed effects against the baseline physician-level patient adoption rates, where both measures are normalized to have zero means. The plot shows that both measures follow each other tightly, so that most of the variation is coming from within-clinic variation across physicians. The variation of the residualized measure amounts to .14. This suggests that the variation across physicians cannot be explained by differences across clinics' locations and the population they serve, lending evidence that the physicians drive this variation.

Next, we use these rates to assess correlations at the PCP level. We construct for each patient the leave-out mean adoption rate of the PCP's other patients. We then study a patient's propensity to adopt as a function of this intensity measure. That is, we ask whether patients whose physicians maintain higher adoption rates are more likely to adopt the new technology themselves. Panel B of Table 2 summarizes the results. We see that among physicians who maintain higher rates of adoption (relative to the median), at-risk patients would be 11 pp more likely to accept the program. This pattern prevails across all patient subgroups.

7.2. Physician Characterization

What can characterize physicians that induce higher adoption of digital health? That is, can the variation patterns we see be harnessed in a predictable way in policy design? We assess

whether we can identify physician "types" that are more successful in having their patients engage with new digital solutions.

We begin by asking whether higher "quality" physicians, who exhibit better performance, also induce higher adoption rates. We use our two proxy measures for performance, where we split physicians into three equal-sized bins within each performance measure assigned to categories high, medium, and low. The first measure that is based on objective medical goals is taken to be the average performance-pay tier the physician scored in the incentive schemes administered by UC San Diego Health. Recall that this calculation, based on year 2021 performance, excludes management of cardiovascular health to avoid mechanical correlations. Panel B of Figure 5 plots the relationship between average patient adoption rates and physician performance, reporting differentials relative to the lowest performing physicians. We see a clear gradient such that higher performing physicians see their patients adopting the program at a rate that is 10 pp higher relative to 24 pp among low performing physicians.

This gradient likewise persists when we use our subjective measure of physician performance as perceived by their patients. Recall that patients rate their experience in routine surveys where they are asked about the "likelihood to recommend the PCP to friends and family," which is combined across patients into a physician's Net Promoter Score (NPS). Panel C of Figure 5 plots average patient adoption rates against physician NPS. We find that physicians' who rank higher in this metric induce a higher adoption rate of 6.3 pp relative to the lowest ranking physicians whose mean patient adoption rate is 28 pp. Overall, we see that higher adoption of the program is highly associated with measures of physician quality and performance.

Finally, we characterize the physician-patient relationship. Specifically, we investigate a proxy for stronger relationships or trust, which are factors that could induce higher willingness to accept a new form of medical care. Within our data we can observe the length of the physician-patient relationship, which we use as our proxy. Panel B of Table 2 provides these results. Indeed, we find that patients are 7 pp more likely to adopt the digital health technology in longer physician-patient relationship, defined relative to the median of 0.80 years. As this is a low threshold for the length of relationship with primary care providers (with a sample mean of 2.2 years), it suggests continuity of care is a feasible margin to leverage in health technology

adoption. Importantly, the patterns prevail across all subgroups over geographical affluence and race/ethnicity. Hence, stronger provider-physician relationships could be a promising pathway to promote equitable adoption of digital health.

8. Financial Effects: Provider Services Costs

The total societal value of the digital health program includes households' utility value of the health improvements as well as the overall financial implications of these improvements. Both these aspects should be integrated over the short run and long run. We quantified the long run implications for improvements in health using the ten-year ASCVD score. We have found a decline of 2 percent in the ten-year predicted probability of patients experiencing a heart attack or stroke (on a baseline of 18 percent). Common money metrics in this context of reduction in health risks are the value of statistical life (VSL) for the mortality implications and quality adjusted life years (QALYs) for integration of the morbidity implications (e.g., Viscusi 2014, Bauer et al. 2022). For example, the current VSL estimate used by the US Department of Health and Human Services is $11.4 million (HHS 2021). On the financial side of the reduction in longer run risk, the AHA estimated using data from MEPS (2016-2017) that the annual direct and indirect cost of CVD in the United States is $363.4 billion (Virani et al. 2021). This estimate includes $216 billion in direct healthcare expenditures and $147.4 billion in lost future productivity attributed to premature CVD mortality. The reduction in productivity due to the morbidity involved in CVD should also be considered, as hospitalization in the U.S. induces average earnings declines among non-elderly insured adults on the order $9,000 (Dobkin et al. 2018).

In the short to medium run, we can assess potential changes in direct healthcare costs from our estimated reduction in hypertension. Americans with high blood pressure have been estimated to face nearly $2,000 higher annual healthcare expenditure with an estimated total associated costs of about $131 billion (Kirkland et al. 2018), so that hypertension prevention and management could also induce earlier financial returns beyond their longer run implications.

We provide such an analysis of healthcare costs attributable to professional medical services within our setting, as a proof-of-concept exercise that offers a glimpse into direct medium-run changes in healthcare costs from reductions in hypertension. We analyze our sample of patients with capitation payments which includes approximately 71 percent of our

study's population. In Table 3 we report the event study estimates at the quarterly level for the evolution of professional costs paid to primary care physicians and specialists around the referral. We also report estimations when the outcome is winsorized from the top to study robustness to extreme value of cost.

We find that already by the third quarter following the referral, patients exhibit meaningful reductions in average costs. The reduction in quarterly costs per referred patient average to $385 in the second half of the year after referral on a counterfactual predicted level of $1,004, which amounts to a meaningful decline on the order of 40 percent.

9. Conclusion

We study the equity-efficiency consequences of offering households a new digital health technology that monitors cardiovascular health in real time. We find that the program led to meaningful health improvements across a diverse population of patients. Nonetheless, the program was initially adopted by only half of households who also exhibited notable dynamics of declines in adherence, where we found substantial gaps in overall adoption rates across households from subpopulations who face significant existing disparities in health and medical care. Evidence suggests that physicians and the nature of their relationship with patients can be instrumental in inducing higher and more equitable adoption of innovations in digital health.

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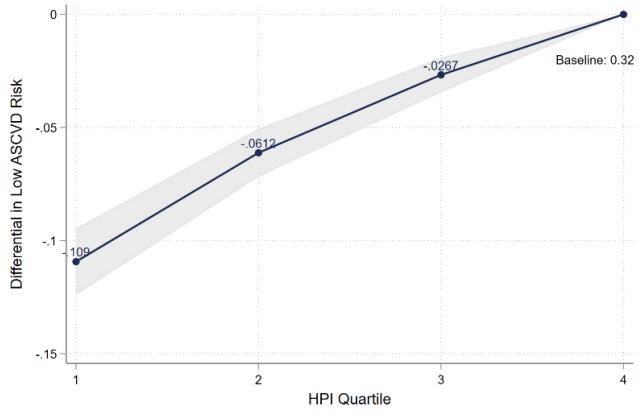
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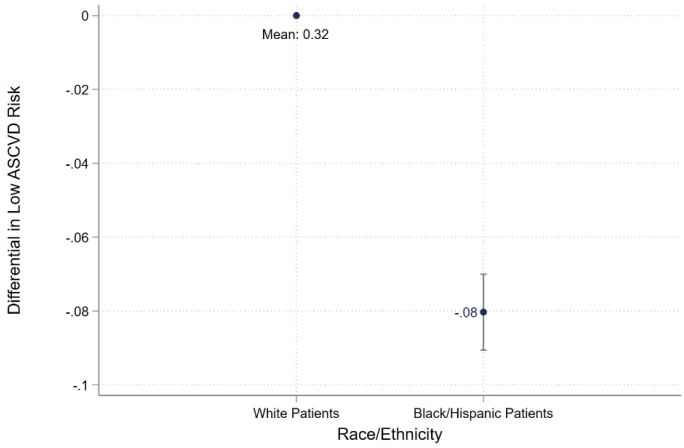
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Figure 1: Baseline Disparities in Cardiovascular Risk

Panel A: Prevalence of Low ASCVD Risk by HPI of Residence



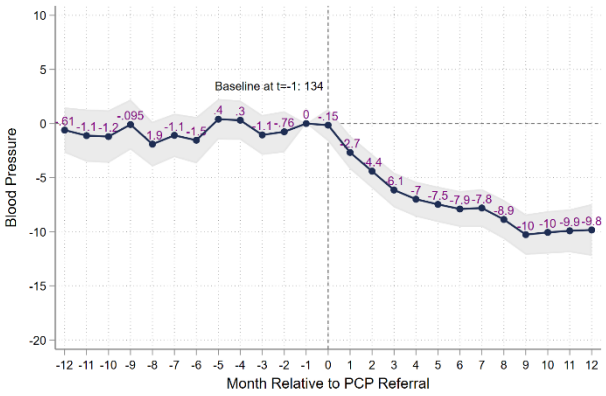
Panel B: Prevalence of Low ASCVD Risk by Patient Race/Ethnicity



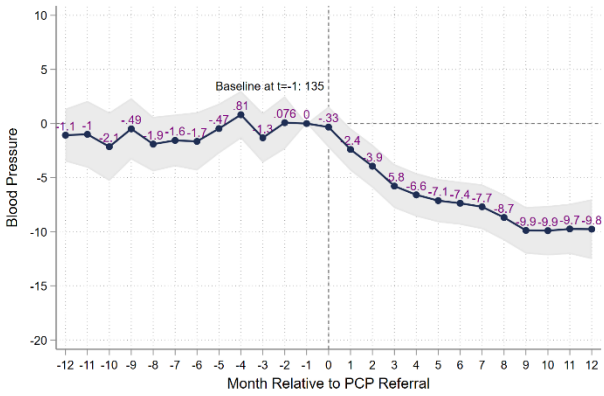
Notes: This figure plots baseline disparities in health outcomes among our population pool. It plots the prevalence of low cardiovascular risk, which the medical guidelines define as having lower than 5 percent in ASCVD risk score. Panel A displays the prevalence of low risk by HPI quartile of patients' residence. It displays group differentials relative to patients in the 4th HPI quartile (most affluent) whose prevalence is marked as "baseline" on the figure. Panel B displays the prevalence of low risk by a patient's race/ethnicity. It displays group differentials relative to white patients among whom the prevalence of low risk is marked as "baseline" on the figure. All differentials adjust for a quadratic in age since age is a direct input into ASCVD risk scoring calculations.

Figure 2: Program's Impact on Patient Blood Pressure

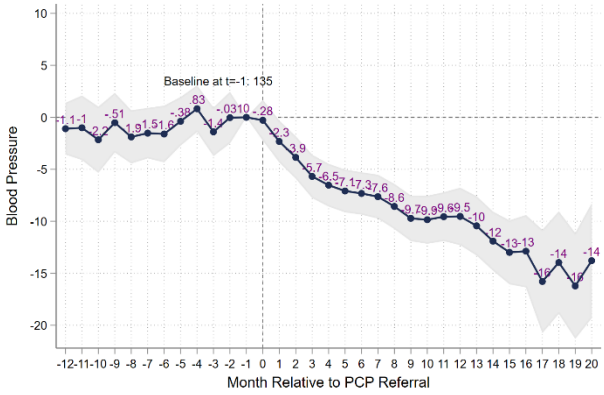
A. All Patients



B. Patients with Repeated Measures



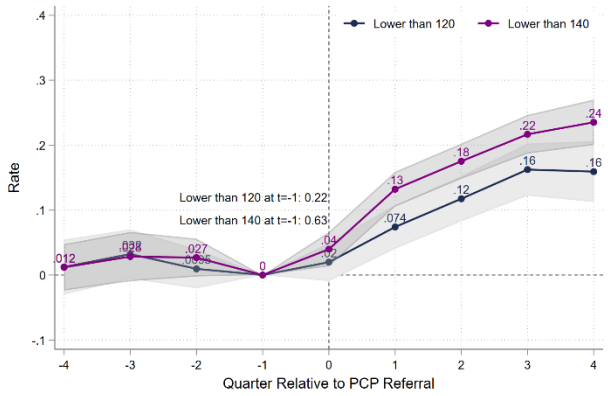
C. Longer Horizon



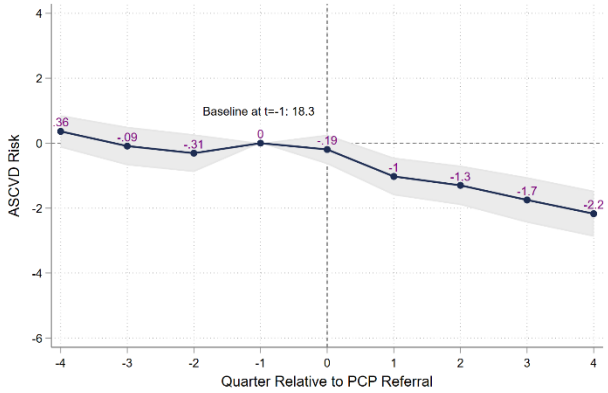
Notes: This figure evaluates the program's impact on systolic blood pressure among patients referred to the program. We use a semi-parametric event study design that is conducted in two steps. In the first step, we residualize the outcome based on observations from pre-periods (months -12 to -2) using a linear term in time relative to the intervention and age fixed effects. In the second step, we run the non-parametric event study for the residualized outcome. The plots display the event study coefficients from equation (1) along with their 95-percent confidence intervals. Panel A displays the event study estimates for the entire sample of referred patients. Panel B displays the event study estimates for the subsample of patients with repeated measures in the analysis horizon of a year before and a year after the referral. We define this subsample as patients with at least one data point in the pre-period, taken as days -365 to -10 to provide sufficient distance from the day of referral, and at least one data point in the post-period, taken here to be days 150 to 365. Robustness to this threshold of day 150 is provided in Appendix Figure 3. Panel C extends the analysis in panel B up to 20 months after the referral. Robust standard errors are clustered at the patient level.

Figure 3: Program's Impact on Cardiovascular Risk

A. Desirable Levels of Blood Pressure

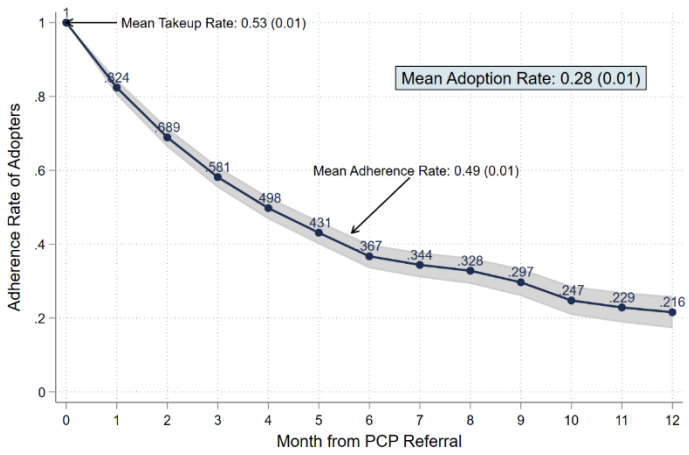


B. ASCVD Score of Cardiovascular Risk



Notes: This figure evaluates the program's impact on cardiovascular risk. In panel A, we study the probability of reaching favorable blood pressure levels, based on the probability that a patient's systolic blood pressure drops below 140 (Stage 2 hypertension) and below 120 (normal blood pressure). In panel B, we study the ASCVD risk score which indicates a patient's risk of having a serious cardiovascular event in the next ten years. We display event study coefficients from a specification of equation (1) at a quarterly frequency (along with their 95-percent confidence intervals) estimated using the sample of patients with repeated measures. Robust standard errors are clustered at the patient level.

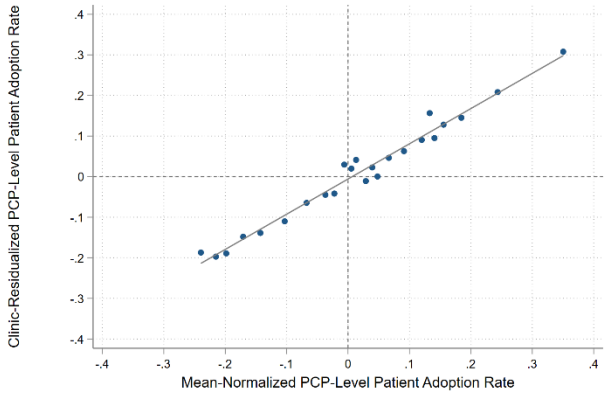
Figure 4: Adoption Rate—Initial Takeup and Follow-on Adherence



Notes: This figure displays the overall adoption rate of the program. Adoption is a composition of the initial takeup decision and the follow-on adherence to the program. As displayed, the mean takeup rate of the program was 0.53 (s.e.: 0.01). The plot then displays the adherence to the program conditional on takeup. It is measured as the rate of electronically transmitting data in each follow-up month in the year after referral. The mean adherence rate during that period is reported on the figure to be 0.49 (s.e.: 0.01). The combination of these two behaviors translates to an overall average adoption rate of the program of 0.28 (0.01) in the year following the referral, as displayed on the figure.

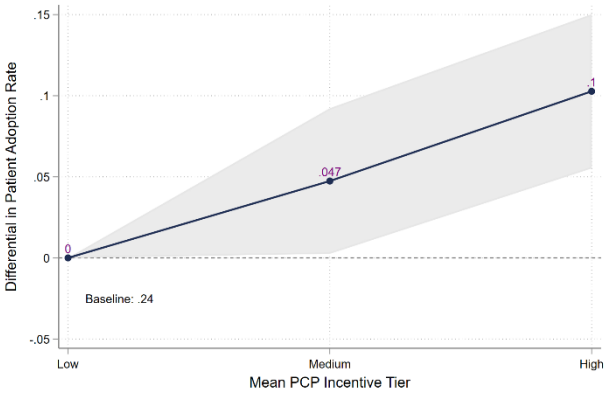
Figure 5: Role of Physicians in Patients' Program Adoption

A. Physician-Level Patient Adoption Rates—Total and Within-Clinic

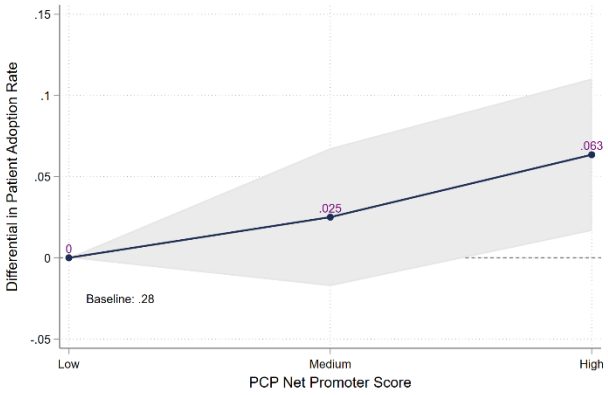


B. Physician-Level Adoption Rates and Performance

Extent of Incentive Rewards



Net Promoter Score



Notes: This figure analyzes patient adoption rates across primary care physicians who referred patients to the program. In panel A, we display physician-level patient adoption rates. We first calculate the mean of patient adoption at the physician level, limiting the sample to primary care physicians with more than one referred patient, which totals to 186 physicians. We then estimate physician-level patient adoption rates residualized of clinic fixed effects, including only clinics with more than one referring PCP, which totals to 18 clinics and 178 physicians. For these physicians and clinics, we plot the physician-level patient adoption rate residualized of clinic fixed effects against the baseline physician-level patient adoption rates, where both measures are normalized to have zero means. In panel B, we study how the physician-level patient adoption rates correlate with proxies for physician performance. Our first proxy is a measure of the incentive rewards a physician received as part of ongoing performance-pay incentive schemes undertaken by UC San Diego Health for quality promotion. Each program sets target rates and compensates physicians with respect to how well they perform relative to that target, which places them on a reward tier represented in percent. We take the mean tier for each physician from 2021 across all programs that are not directly related to management of cardiovascular health (to avoid mechanical correlations). The second proxy is "Net Promoter Score" for the year 2022. It is a physician's rate of approval based on their patients' reported likelihood to recommend their PCP to family and friends as answered in quality promotion surveys.

Table 1: Program's Impact on Blood Pressure—Patient Subpopulations

	All	Age Group		Gender	
		Below 65	Above 65	Male	Female
Treatment Effect	-7.66***	-6.12***	-8.30***	-8.65***	-6.94***
	(0.64)	(1.08)	(0.78)	(0.94)	(0.89)
Baseline	134	132	135	134	134
Number of Individuals	1,300	457	843	588	712

	HPI Percentile					
	Below 50	Above 50	Quartile 1	Quartile 2	Quartile 3	Quartile 4
Treatment Effect	-7.06***	-7.93***	-8.72***	-6.18***	-7.37***	-8.42***
	(1.28)	(0.73)	(2.28)	(1.51)	(1.25)	(0.84)
Baseline	133	134	132	133	134	134
Number of Individuals	405	890	136	269	386	504

	Race/Ethnicity	
	Black/Hispanic	White
Treatment Effect	-6.81***	-7.59***
	(1.19)	(0.85)
Baseline	135	134
Number of Individuals	316	782

	Comorbidities	
	Diabetes	Ischemic Heart Disease
Treatment Effect	-6.65***	-5.39***
	(1.00)	(1.60)
Baseline	134	131
Number of Individuals	470	188

Notes: This table studies the effect of the program on systolic blood pressure among different patient subpopulations. We estimate equation (2) using the sample of patients with repeated measures. Observations from before the referral come from months -6 to -1 and observations from after the referral come from months 7 to 12. Robust standard errors are clustered at the patient level. Baselines are reported as subpopulation means of the outcome variable in month -1 relative to referral. *** p<0.01, ** p<0.05, * p<0.1

Table 2: Heterogeneity in Adoption Rates

Panel A: Disparities across Patient Subpopulations

	Race/Ethnicity			HPI		
	Takeup	Adherence	Adoption	Takeup	Adherence	Adoption
Differential between Patient Groups:						
Black/Hispanic and White	0.0024	-0.0603***	-0.0382**			
	(0.0246)	(0.0216)	(0.0173)			
HPI Quartile 1 and Quartile 4				-0.0796***	-0.0807***	-0.0838***
				(0.0219)	(0.0195)	(0.0149)
Baseline Group	0.5272***	0.5083***	0.2903***	0.5510***	0.5126***	0.3050***
	(0.0135)	(0.0120)	(0.0100)	(0.0118)	(0.0102)	(0.0089)
Number of Individuals	1,970	1,040	1,970	2,500	1,319	2,500

Panel B: The Role of PCP in Inducing Adoption

	All	HPI<50	HPI>50	White Patients	Black/Hispanic Patients
B.1 PCP-Level Leave-Out Adoption Rate					
Higher than Median (0.55)	0.1148***	0.0997***	0.1118***	0.1103***	0.0932***
	(0.0145)	(0.0250)	(0.0178)	(0.0192)	(0.0294)
Number of Individuals	2,426	707	1,707	1,425	564
B.2 Length of Relationship					
Higher than Median (0.80 Years)	0.0708***	0.0681***	0.0641***	0.0642***	0.0997***
	(0.0150)	(0.0253)	(0.0185)	(0.0200)	(0.0297)
Number of Individuals	2,316	691	1,613	1,335	557

Notes: This table studies heterogeneity in technology adoption rates. Panel A studies disparities in adoption across subpopulations. It displays initial takeup rates, follow-on adherence rates, and the resulting overall adoption rate. Panel B studies the potential role of the PCP in inducing higher rates of adoption. First, we assess within PCP correlations. For each patient, we construct the leave-out mean adoption rate of the PCP's other patients. We then study whether patients whose physicians have a high patient adoption rate are more likely to adopt the new technology themselves. We include only PCPs with at least 2 referred patients and define high acceptance rate relative to the sample median 0.55. Second, we assess the role of the length of the PCP-patient relationship in the adoption behavior. We study whether patients with relationships longer than the sample median of 0.80 years are more likely to adopt the technology. *** p<0.01, ** p<0.05, * p<0.1

Table 3: Event Study of Professional Healthcare Costs

	(1)	(2)
Quarter Relative to Referral		
-4	67.86	66.95
	(174.3)	(168.1)
-3	-95.88	-89.20
	(144.2)	(143.6)
-2	48.39	44.82
	(155.9)	(152.7)
-1	0	0
	(0)	(0)
0	-62.07	-63.01
	(128.3)	(128.2)
1	132.1	112.3
	(173.5)	(169.6)
2	-124.6	-143.6
	(170.2)	(163.9)
3	-431.8***	-444.5***
	(148.1)	(147.9)
4	-338.6**	-354.8**
	(172.5)	(172.3)
Medium Run Effect:	-385.2***	-399.7***
	(149.2)	(149.1)
Baseline Level	887	886
Medium Run Counterfactual	1,004	1,012
Costs Top Winsorized		X
Number of Individuals	1,651	1,651

Notes: This table evaluates the program's impact on provider services costs which include healthcare costs attributed to primary care or specialists. We display event study coefficients from a specification of equation (1) at a quarterly frequency along with their 95-percent confidence intervals. We include observations of patients for whom UC San Diego Health receives capitation payments. We also report estimations when the outcome is winsorized from the top at the 0.01 percent. The medium run effect averages the impact on costs in the last half of the year following the referral (quarters 3 and 4). We report baseline levels (from quarter -1) and the counterfactual level in the medium run (average effects over quarters 3 and 4). Robust standard errors are clustered at the patient level. *** p<0.01, ** p<0.05, * p<0.1

Appendix

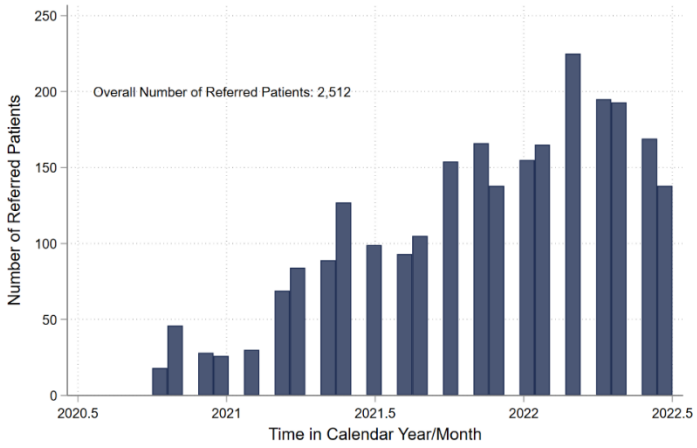
Appendix A: Figures and Tables

Appendix Table A.1: Sample Characteristics

	Statistic
Number of Individuals	2,512
Age:	
Average Age	65.34
Share 65 and Older	0.595
Location:	
Average HPI Percentile	63
Share in Quartile:	
1st	0.10
2nd	0.19
3rd	0.31
4th	0.40
Gender:	
Female	1,369
% Female	54.5
Race/Ethnicity:	
Non-Hispanic White	1,379
Black/Hispanic	591
Year of Referral:	
2020	92
2021	1,180
2022	1,240
Number of Individuals	2,512

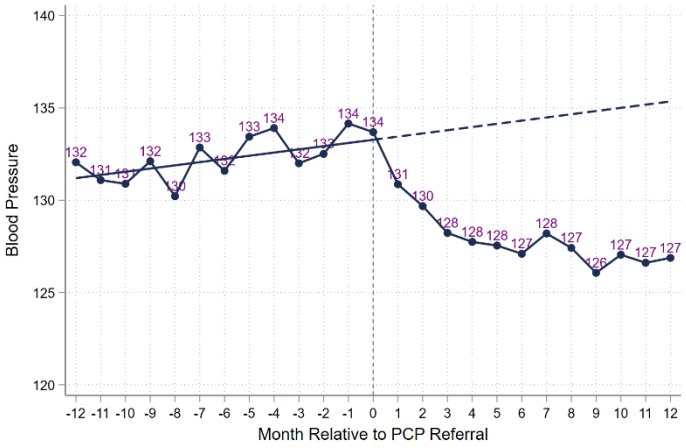
Notes: This table provides average characteristics for our study's population in terms of age, gender, race/ethnicity, and HPI of residence. Our sample is comprised of the 2,512 patients who were referred to the digital health program by their PCP from October 2020 to July 2022.

Appendix Figure A.1: Distribution of Calendar Time of Referral



Notes: This figure plots the distribution time of referral in terms of calendar year/month.

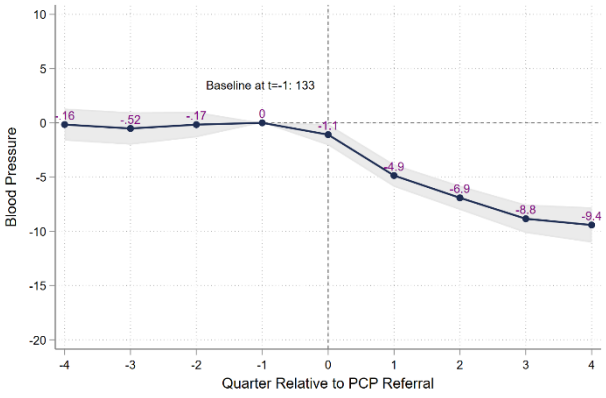
Appendix Figure A.2: Raw Data of Systolic Blood Pressure around PCP Referral



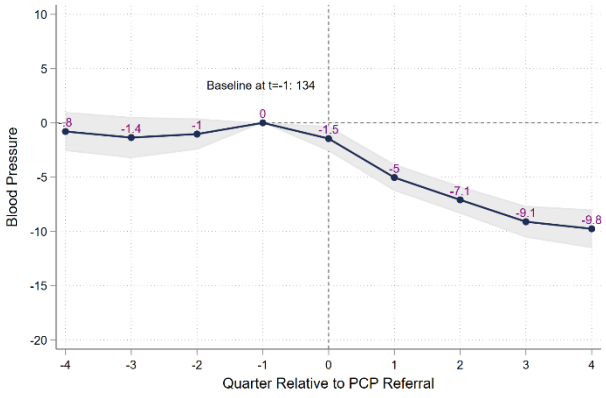
Notes: This figure plots the raw data of systolic blood pressure among patients referred to the program. We also display the linear fit for the pre-period months to assess patterns prior to the intervention.

Appendix Figure A.3: Program's Impact on Patient Blood Pressure—Quarterly Frequency

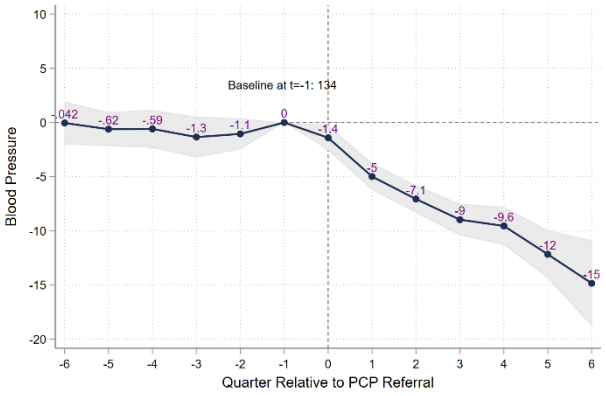
A. All Patients



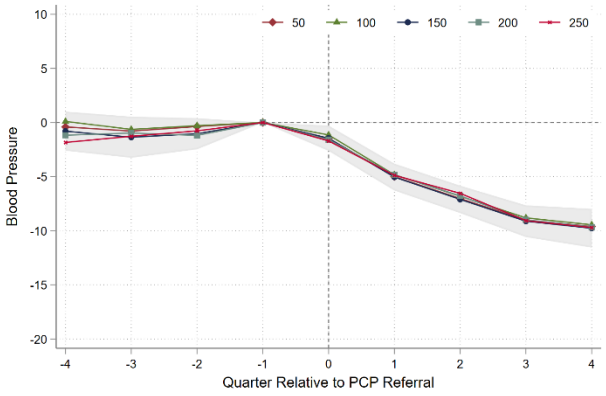
B. Patients with Repeated Measures



C. Longer Horizon



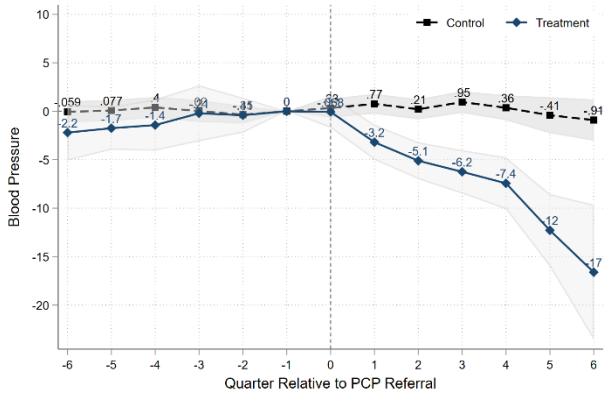
D. Patients with Repeated Measures—Robustness



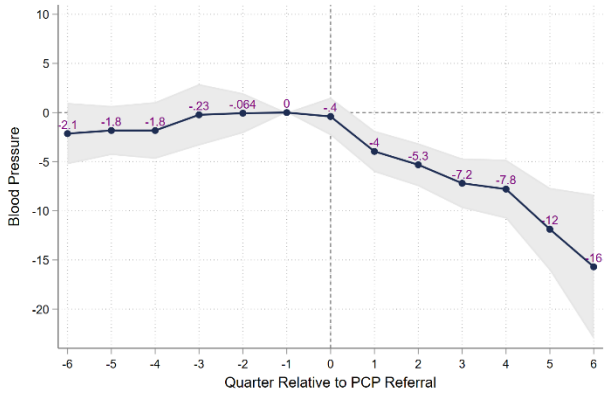
Notes: This figure evaluates the program's impact on systolic blood pressure among patients referred to the program. In panel A-C we replicate panels A-C from Figure 2 at a quarterly frequency. Panel D displays the event study coefficients for different subsamples of patients with repeated blood pressure readings in the analysis horizon of a year before and a year after the referral. We define this subsample as patients with at least one data point in the pre-period, taken as days -365 to -10 to provide sufficient distance from the day of referral, and at least one data point in the post-period, from a chosen threshold date up to day 365. We present plots for the threshold dates 50, 100, 150, 200, and 250 days after the referral.

Appendix Figure A.4: Program's Impact on Patient Blood Pressure—Matched Control

A. Referred Patients Compared to Matched Control Patients



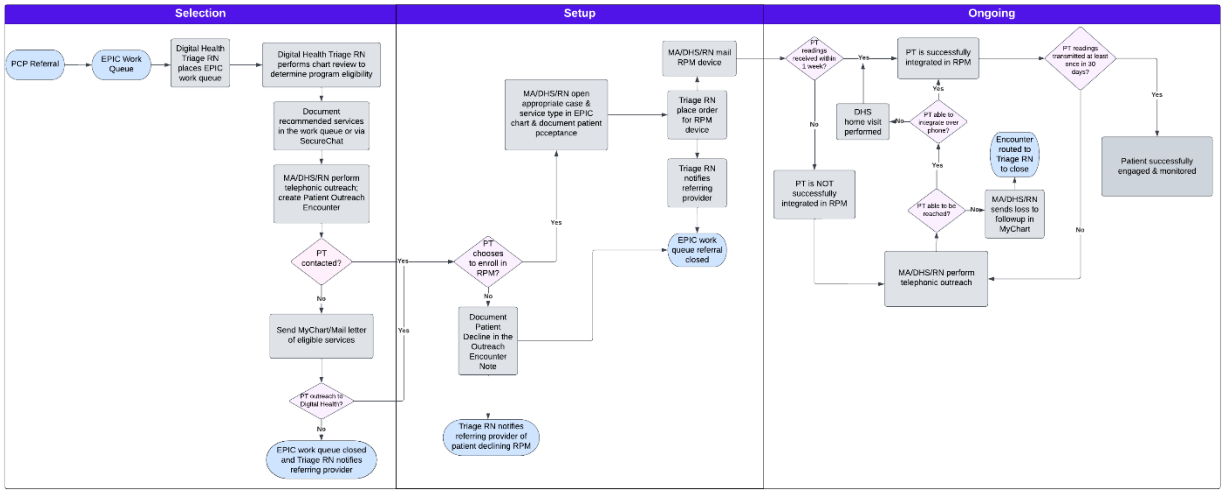
B. Differential between Referred Patients and Matched Control Patients



Notes: This figure evaluates the program's impact on systolic blood pressure based on a matched control group. We create exact matches of patients based on birthyear, gender, race, ethnicity, quartile of HPI, and the bin of their average level of systolic blood pressure in a baseline year 2019 (where we split this average into twenty equal bins). In cells with matches, the 75th percentile of the number of referred patients is one, so we keep only cells with exactly one referred patient for simplicity. To each matched control patient, we assign the referral date of the treated unit they were matched with as a placebo referral date. We include only patients with repeated measures. The resulting sample is composed of 583 treated units and 2,362 control units. For each group, we separately perform our two-stage analysis of residualizing the outcome and then running the event study. Panel A displays the event study coefficients from a specification of equation (1) at a quarterly frequency (along with their 95-percent confidence intervals) for each experimental group. Panel B displays the differential between the two groups (along with their 95-percent confidence intervals), providing the matching design estimates of treatment effects. Robust standard errors are clustered at the patient level.

Appendix B: Program Details

Appendix Figure B.1: Program Stages from Referral to Active Participation



Notes: This figure provides a schematic flowchart that illustrates the stages from physician referral of a patient to the program until successful engagement with the program. Blue rounded boxes indicate start and end points of a workflow, pink diamond boxes indicate decision points, and gray rectangular boxes indicate actions taken.

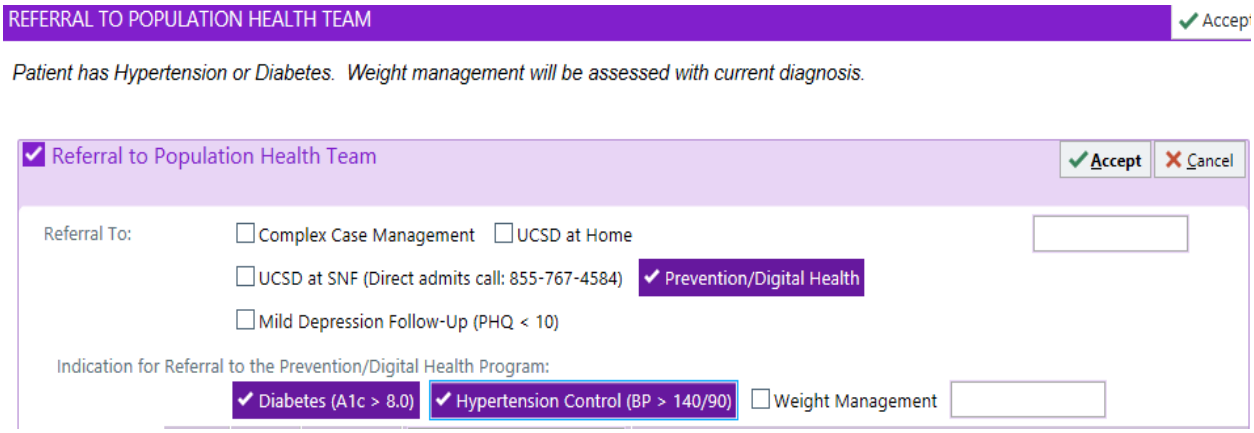
Appendix B.1: Logistical Details—Remote Patient Monitoring Device and Clinical Chart

The remote patient monitoring device is an iHealth Ease, which a Bluetooth-enabled digital blood pressure device. It appears in the following picture:



To be eligible to participate in the program, a patient must have compatible smartphone and comfort using apps to be able to turn on devices and synchronize data from home independently.

To place a referral to the Population Health Team, a provider checks the box for "Prevention/Digital Health" and indicate "Hypertension Control."

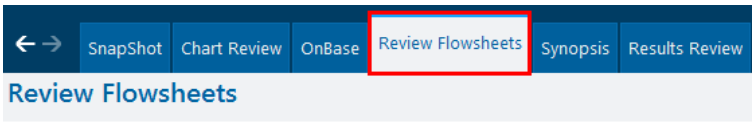


When patients measure their blood pressure, the data is synchronized through MyChart (the patient portal) and flows into the patient chart for easy review by clinicians. There are 2 methods to review these home measurements:

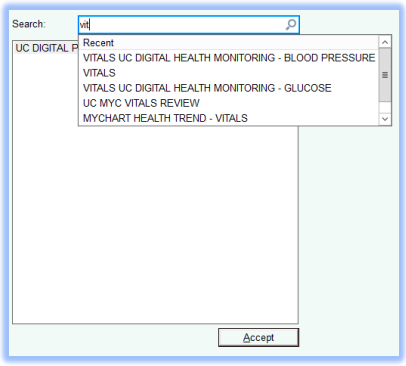
Method 1: Review Results via Flowsheets

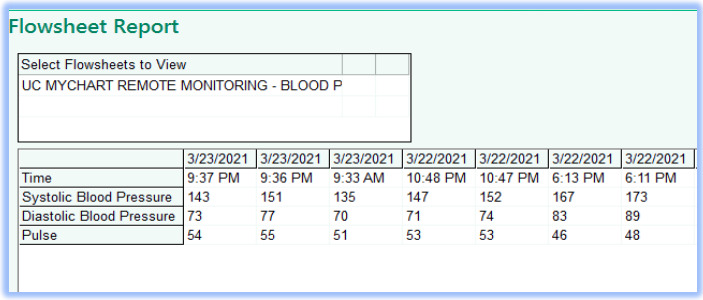
1. Open patient's chart within Epic

2. Click the Review Flowsheets activity tab.



3. Search for "VITALS UC DIGITAL HEALTH MONITORING - BLOOD PRESSURE" to review blood pressure data.





Flowsheet Report

Select Flowsheets to View

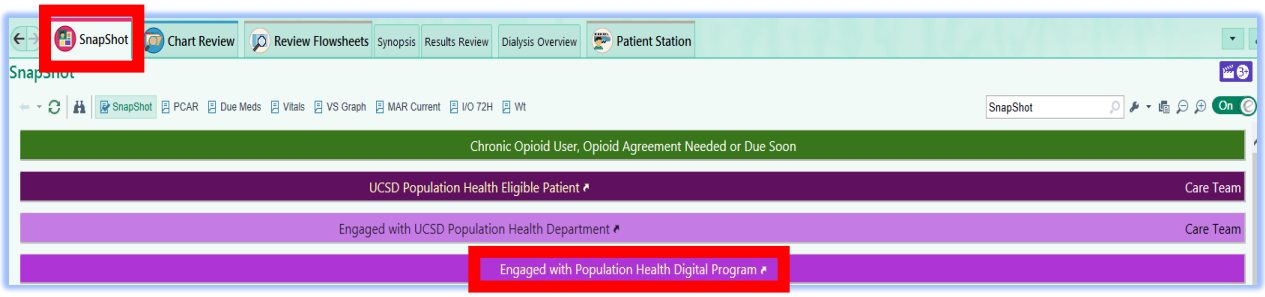
UC MYCHART REMOTE MONITORING - BLOOD P

	3/23/2021	3/23/2021	3/23/2021	3/22/2021	3/22/2021	3/22/2021	3/22/2021
Time	9:37 PM	9:36 PM	9:33 AM	10:48 PM	10:47 PM	6:13 PM	6:11 PM
Systolic Blood Pressure	143	151	135	147	152	167	173
Diastolic Blood Pressure	73	77	70	71	74	83	89
Pulse	54	55	51	53	53	46	48

Method 2: Review Results via Synopsis

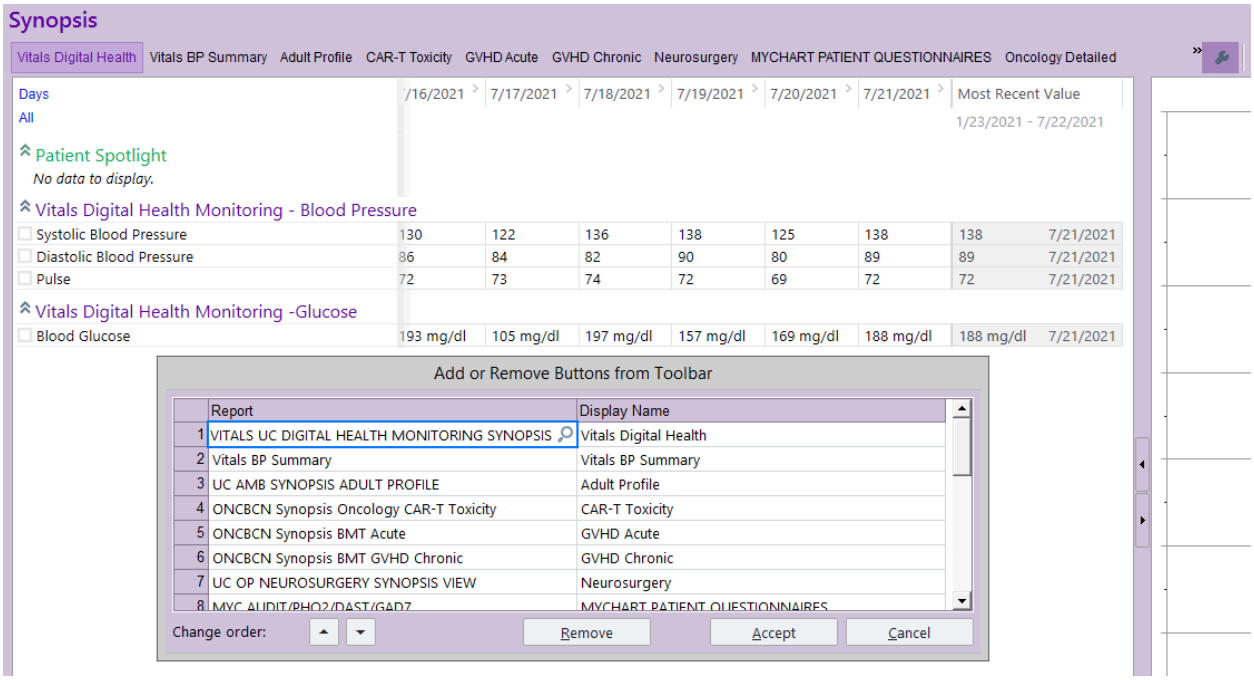
1. Once enrolled, the patient will have a “Engaged with Population Health Digital Program” purple banner on their Snapshot view

2. Click on this banner to access remote patient monitoring data “Synopsis” which displays blood pressure data.



3. Wrench in the flowsheet subtab "Vitals Digital Health“

4. Use arrows to move flowsheet subtab access if desired


Synopsis
Vitals Digital Health
Vitals BP Summary
Adult Profile
CAR-T Toxicity
GVHD Acute
GVHD Chronic
Neurosurgery
MYCHART PATIENT QUESTIONNAIRES
Oncology Detailed
Days
All
/16/2021
7/17/2021
7/18/2021
7/19/2021
7/20/2021
7/21/2021
Most Recent Value
1/23/2021 - 7/22/2021
Patient Spotlight
No data to display.
Vitals Digital Health Monitoring - Blood Pressure
Systolic Blood Pressure 130 122 136 138 125 138 138 7/21/2021
Diastolic Blood Pressure 86 84 82 90 80 89 89 7/21/2021
Pulse 72 73 74 72 69 72 72 7/21/2021
Vitals Digital Health Monitoring -Glucose
Blood Glucose 193 mg/dl 105 mg/dl 197 mg/dl 157 mg/dl 169 mg/dl 188 mg/dl 188 mg/dl 7/21/2021
Add or Remove Buttons from Toolbar
Report
Display Name
1 VITALS UC DIGITAL HEALTH MONITORING SYNOPSIS Vitals Digital Health
2 Vitals BP Summary Vitals BP Summary
3 UC AMB SYNOPSIS ADULT PROFILE Adult Profile
4 ONCBCN Synopsis Oncology CAR-T Toxicity CAR-T Toxicity
5 ONCBCN Synopsis BMT Acute GVHD Acute
6 ONCBCN Synopsis BMT GVHD Chronic GVHD Chronic
7 UC OP NEUROSURGERY SYNOPSIS VIEW Neurosurgery
8 MYC AUDIT/PHQ2/DAST/GAD7 MYCHART PATIENT QUESTIONNAIRES
Change order:
Remove
Accept
Cancel

Appendix B.1: Population Health Team Digital Health Protocol for Outreach and Ongoing Care

This appendix describes the digital health team outreach protocol. It is designed based on the Milliman Care Guidelines (more details can be found at https://www.mcg.com/)

Subjective
@NAME@ is a @AGE@ @SEX@ who I have contacted regarding: {phtoutreach:33397} related to the Digital Health Program for {rpmtask:32434} Monitoring. Was able to establish telephonic contact with the patient and verified patient's identity with full name and date of birth.

Patient's most recent Remote Patient Monitoring (RPM) {rpmtask:32434} reading of: *** with the following device(s): {digitalequipment:29472}

Contact outcome: {phtoutcome:33398}

Service Type Updated: {rpmyesnona:32440}

Motivational interviewing and positive affirmation techniques deployed with an emphasis on health coaching:

Blood Pressure Discussion:
-How to take BP Accurately (AHA guidelines): Patient well rested, arm at heart level, confirm cuff placement/fit; both feet flat on ground; bladder empty, prior to caffeine or activity. For any unusual readings / asymptomatic, rest/reposition/recheck - {rpmyesnona:32440}
-Frequency (at least x1/week, consistent times or as otherwise directed by MD):{rpmyesnona:32440}
-Patient is taking BP medications as prescribed? {rpmyesnona:32440}
-Patient has questions regarding BP management / medication (routing for potential f/u) {phtrns:33399}

Diet:
-HTN Patient following DASH diet: {rpmyesnona:32440}
-DM Patient following low glycemic diet: {rpmyesnona:32440}
-Patient requires additional dietary support {rpmrefer:32437}

Exercise:
-Patient regularly exercises: {rpmyesnona:32440}
-Patient requires additional exercise support {rpmrefer:32437}

RPM Disclaimer:
Reiterated that RPM f/u is available M-F 8:30a-4:30p (with the exception of National/University Holidays), does not replace emergent care, as there may be a delay in the upload/analysis of your blood pressure/blood sugar readings.

In the event of a Hypertensive Crisis (BP > 180 + symptoms of CP, Severe HA/Blurred Vision, SOB) or Hyperglycemic Medical Emergency (Blood Sugar > 300 + symptoms of Frequent Urination, N/V Increased Thirst and/or Hunger) please contact 911 or go to your nearest ED.

Plan:
Direct contact information provided and patient encouraged to reach out with further questions or concerns. DH Team to continue to monitor peripherally via Digital Health Dashboard or Self-Report outreach. Routing to {phtrns:33399} as FYI.