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

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Abstract: Digital technologies are bringing vast improvements to modern society but also carry the risk of perpetuating disparities if adopted at lower rates by underserved communities. We investigate the efficiency and equity aspects of technological advancement in digital health by studying an intervention of "remote patient monitoring" that enabled patients to transmit real-time clinical data for timely treatment. The program was deployed at the Academic Medical Center UC San Diego Health among a diverse population of patients and targeted hypertension management to reduce the risk of cardiovascular disease. From an efficiency standpoint, we find significant and persistent reductions in cardiovascular risk, which are notable across all subgroups of gender, age, race/ethnicity, and geographic affluence. Evidence suggests both reduced frictions in the provision of care and improved health behaviors as mechanisms. The program also led to significant reductions in healthcare utilization costs from improved hypertension control. From an equity standpoint, however, we find that the longer-run health gains from the program fell short among underserved patient subpopulations, inducing inequities in the reductions in cardiovascular risk. The new technology was systematically adopted at lower rates by Black/Hispanic patients and by patients from disadvantaged geographic communities, who were less likely to either take up or adhere to the program. Overall, our analysis highlights the simultaneous promise and hazards of digital health technologies. We further provide evidence that primary care physicians and the nature of their relationship with patients can have a promising role in promoting greater and more equitable adoption 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 et al. 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. Along with their promise to improve population health, however, a general concern with the introduction of new technologies is that they could perpetuate inequities. Such concerns have become central in the context of digital health with the challenge that lower adoption rates among underserved communities (e.g., due to non-inclusive product design and uneven implementation) would lead to biased health improvements and deepen disparities (Lyles et al. 2021, WHO 2022). Still, while investment in the digital health sector is enormous and growing (with nearly $6 billion in funding in 2017), evidence of solutions that provide real value in the production of population health and of their implications for health equity is notably limited (Mathews et al. 2019, Lyles et al. 2021).

In this paper, we provide novel analysis of both the equity and efficiency consequences of a digital "remote patient monitoring" program, which was deployed in a real-world healthcare setting at the Academic Medical Center UC San Diego Health (UCSDH). The program targeted cardiovascular risk—due to its prominence as a leading cause of death in the U.S. (Ahmad and Anderson 2021)—and was offered to a wide and diverse population of individuals. The program operated as follows. Primary care physicians at UCSDH were asked to offer the new program to their patients with poorly managed hypertension on a rolling basis. The program provided participating patients with electronic Bluetooth-enabled digital blood pressure devices. When patients used the device, it automatically transmitted blood pressure data via Bluetooth to the patient portal of the electronic health record at UCSDH. A team of clinical staff would then monitor the data daily and manage patients' blood pressure levels based on standardized medical protocols. The program was designed to maximize access and health equity by ensuring no out-of-pocket costs regardless of patients' insurance. The patient population of our study is comprised of the 2,512 patients who were referred to the program by their primary care physicians between

October 2020 and July 2022, with representation across race/ethnicity, geographic affluence, gender, and age.

We first focus on efficiency aspects by assessing the effect of the program on patients' health outcomes. We analyze the program's impact using a high-frequency event study design. Specifically, at a monthly frequency, we study the evolution of referred patients' blood pressure levels over the course of the year before and the year after they were referred to the program by their physician. Identification relies on how outcomes immediately after the referral event deviate from the baseline trend prior to it. We also accompany this research design with matched control groups using exact matching as a robustness check with virtually similar findings.

We find clear evidence of meaningful improvements in health outcomes following the referral to the program. Patients display a 15 percentage points (pp) increase in the propensity to reach healthy systolic blood pressure levels on a baseline of 22 pp.[1] We further study an aggregate measure of the health value of the intervention by using the Atherosclerotic Cardiovascular Disease (ASCVD) score, which indicates a patient's ten-year risk of experiencing a serious cardiovascular event such as a heart attack or stroke (Goff et al. 2014). We find that after one year, the intervention led to a decline of 4.4 pp in exhibiting high cardiovascular risk (defined as 20 percent or higher by the American College of Cardiology) on a baseline of 35.5 pp. Additional analysis provides suggestive evidence of reduced frictions in the provision of care via enhanced treatment tailoring as well as patients' adherence to healthier behaviors as potential mediating channels in the health gains from the remote monitoring program.

We also investigate the financial implications of the digital health program using internal administrative data on healthcare utilization and costs. We find that within our analysis horizon of one year, the program and its effects of improved hypertension management led to a decline of 40 percent in utilization costs ($385 quarterly on a counterfactual of $1,004). Our results thus offer a promising pathway for curbing healthcare expenditures.

We then turn our focus to equity. Exploiting our patient demographic data, we first find that the large health improvements were experienced across-the-board, along the dimensions of

[1] Blood pressure is measured as two numbers in millimeters of mercury (mmHg) units: (1) systolic blood pressure (the first and higher number) measures the pressure inside the arteries when the heart beats; (2) diastolic blood pressure (the second and lower number) measures the pressure inside the arteries when the heart rests between beats. We follow the medical literature and focus on systolic blood pressure in the context of hypertension management (The SPRINT Research Group 2021).

age, gender, race/ethnicity, and geographic affluence. That said, we find that in the longer run, the reduced-form intent-to-treat estimates (which incorporate the program adoption margin) display large gaps in health gains. Health improvements for Black/Hispanic patients fall short to about half of those for White patients (for whom improvements keep growing), with similar patterns of unequal gains across geographic economic affluence. We show that the disparities induced by the introduction of the digital health program are large when benchmarked against nationwide inequities in cardiovascular health.

This leads us to analyze the program's adoption behavior and how it varied across social subgroups. As reference, the initial takeup rate of the program (or the enrollment rate) across the analysis sample was 0.53; and, conditional on takeup, adherence to the program (defined by the likelihood of digitally transmitting blood pressure data in a given month) averaged to a monthly rate of 0.47 over the subsequent 1.5 years. The product of these two likelihoods translates to an aggregate adoption rate over the 1.5-year horizon, which averaged to 0.27 in the full sample.

Comparing across subpopulations, we find that Black and Hispanic patients were 15 percent less likely to adopt the program over this period (4.04 pp on a baseline of 27.7 pp), driven by lower adherence rates after the initial takeup. Adoption rates across geographic communities display even larger gaps, on the order of 28 percent (8.24 pp on a baseline of 29 pp). Geographic disparities already arise in the initial takeup stage, which are then further exacerbated by lower adherence rates. These patterns affirm policymakers' concerns that households from underserved communities could face greater challenges in engaging with new digital health technologies as those are integrated into traditional care (Lyles et al. 2021, WHO 2022), and the findings further suggest that policy efforts should target both takeup and adherence in the adoption of digital health.

Our findings of significant improvements in health outcomes along with only partial and differential participation across subgroups suggest the presence of frictions in the adoption of the digital program. To identify pathways that could reduce these frictions, we study the potential role of primary care physicians in inducing greater and more equitable adoption. We find a strong relationship between patients' program adoption and their physician's baseline performance, as measured either by objective clinical outcomes or by average ratings of subjective patient experience. We also find that patients are much more likely to adopt the program when the physician-patient relationship is longer, which could reflect greater trust that has been emphasized

as an important factor in recent work on health inequities.[2] Notably, these patterns prevail across race/ethnicity and across geographic communities, pointing to the physician-patient relationship as a potentially promising pathway to promote more equitable adoption of digital health.

Contribution to Literature. Our study contributes to three main strands of the literature. First, our work was motivated by recent small trials in *clinical settings* on the promise of digital health monitoring in reducing cardiovascular risk (Burke et al. 2015). In this domain, prior work has highlighted the clear absence of research on real-world digital health implementations at scale (Tinetti and Studenski 2011, Lyles et al. 2021). In turn, our intervention was designed to provide an original setting for studying the consequences of introducing a digital health program in a *real-world* healthcare environment with novel evidence of scalability.[3] Our setting—population health services within a busy academic health system—offers exactly the type of healthcare environments in which digital health programs would be rolled out. Moreover, integration of remote patient monitoring into the provision of care—the context that we study here—is particularly relevant in the efforts to improve population health and multiple reimbursement government policies via Medicaid and Medicare have been recently implemented (Burke et al. 2015; Hayes et al. 2023). Overall, we are able to study both the real-life technology adoption decision (which is outside the scope of clinical trials by nature) and the potential for health improvements at scale (as our program was offered to a broad patient population and built into the workflow of the busy health system).[4]

Second, we contribute to the active and pressing work addressing geographic, racial, and ethnic disparities in health in the U.S. (e.g., Chandra and Skinner 2003, Bolen et al. 2010, Cutler et al. 2011, 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 in the provision of traditional care, including physical inaccessibility

[2] See Greenwood et al. (2018), Alsan et al. (2019), Frakes and Gruber (2022).

[3] Our intervention includes aspects of both stages III and IV of the NIH Stage Model for Behavioral Intervention Development as it advances existing work from pure efficacy to real-world efficacy and wider-scale effectiveness (https://www.nia.nih.gov/research/dbsr/nih-stage-model-behavioral-intervention-development).

[4] An additional advantage of our setting is that it allows us to harness the diversity of our patient population to analyze the digital program's efficacy among traditionally underserved communities; thus addressing the pressing need for their representation in health research as recently emphasized by both the medical and economic professions (Bruke et al. 2015, Lyles et al. 2021, Alsan et al. 2024). We also note that, when analyzing health effects, we use an event study design to recover estimates based on the intent-to-treat (ITT), which stands in contrast to the American Heart Association's critique of existing studies that make before and after comparisons of patients who self-select to participate in a program (Burke et al. 2015, Blood et al. 2022).

and time constraints of financially disadvantaged households. But concerns have been raised that digital health can harm equity due to, e.g., product design and evaluation that lack representation as well as implementation hurdles from lack of training, support, or trust (Lyles et al. 2021). Our work provides a novel setting to evaluate and quantify these various considerations of efficiency and equity. In our setting, we find both improvements in health across all subpopulations and inequities that arise in health gains from unequal adoption of the new technology. Our findings imply that policies should target both takeup and adherence in the adoption of digital health (e.g., via community outreach) and we moreover find that physicians could have an important role in overcoming adoption gaps.

Finally, we contribute to work on the economics and value of medical innovation (e.g., Cutler et al. 2006, Miller and Tucker 2011, Williams 2013, Budish et al. 2015, Sampat and Williams 2019, Bauer, Lakdawalla, and Reif 2022, Chandra et al. 2022), here in the digital health sphere. Digital health represents a large and growing market in medical innovation, with global estimates on the order of $350 billion in value and an annual expected growth of 8 percent.[5] Still. economic research is in its infancy of assessing the value of digital health, with new insightful studies such as the work by Dahlstrand (2021) in Sweden and Zeltzer et al. (2024) in Israel on the availability of remote visits for primary care. We provide a timely assessment of innovation in remote patient monitoring, which represents a key segment of the growing digital health market (see, e.g., Vegesna et al. 2017, Thomas et al. 2021). We are in the unique position of assessing the economic value of the new technology in several dimensions. In terms of health outcomes, we are able to directly study high-frequency clinical measures (particularly blood pressure). Direct clinical measures of health status are typically absent in observational economic studies, in which health status is imputed from claims data or by healthcare utilization that has been shown to be affected by financial incentives. In addition, we can directly assess changes in the financial burden on the healthcare system by studying administrative data on medical costs. Overall, our remote patient monitoring intervention shows large and scalable economic returns from the introduction of the digital health innovation.

The remainder of the paper proceeds as follows. Section 2 describes the digital health program. Section 3 introduces the data, patient population, and analysis sample. Section 4

[5] 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.

describes the empirical framework. We then analyze the consequences of the intervention: Section 5 studies efficiency gains in health outcomes and reductions in costs, and Section 6 studies inequities in health gains and in the technology adoption decision. Section 7 concludes.

2. Program Overview

High blood pressure, or hypertension, is a major health problem that is affecting nearly half of all American adults and can lead to severe cardiovascular disease, such as heart attacks and strokes. In turn, hypertension management has been a top priority for UCSDH and across healthcare systems nationwide. Hypertension can be effectively controlled with healthy lifestyle changes (not smoking, eating a healthy diet, being physically active) and medication (Whelton et al. 2018, Muntner et al. 2022). As such, hypertension management requires continuous monitoring to guarantee that patients remain within blood pressure targets and that timely medical care is provided when cardiovascular risk escalates.

In our intervention, primary care physicians (PCPs) were encouraged to refer their patients with poorly managed hypertension to the digital health program in the Population Health Services Organization at UCSDH. PCPs first learned of the program from their clinic's primary care leaders, to whom the new program was announced and described in a routine operation meeting. Our analysis includes PCP referrals from as early as October 2020. In addition, later on in June 2021, a presentation on the program was delivered to PCPs at a primary care retreat. The descriptions of the program that were disseminated included content of hypertension management guidelines and details of local workflow for how to refer eligible patients—those with blood pressure trend over 140/90 mmHg—to the digital remote monitoring program.

For research design considerations, it is important to emphasize that the intervention was designed to provide a real-world healthcare setting that can offer novel insights about scalability of digital monitoring for population health. As a Population Health Services Organization in an academic health system, we were ethically obligated to offer all medically eligible patients the same high-quality treatment when anticipated risk is minimal and in the absence of capacity constraints. As such, we had to refrain from experimental designs that include randomization, which would have effectively deprived some eligible patients of access to new modes of care. This makes causal analysis more complex (for internal validity); but it allows us to analyze a real-life setting of a busy healthcare system (for external validity), which is where evidence is lacking. Our

research design therefore utilizes quasi-experimental techniques (high-frequency event studies along with matched placebo control groups), as we describe in detail in Section 4.

The program operated as follows. After the referral from their PCP, referred patients were contacted by the digital health team and invited to participate in the program. Patients who chose to participate in the program were provided with iHealth Ease, Bluetooth-enabled digital cuffs for blood pressure measurement (see a picture of the device in Appendix B.1). Blood pressure measurements taken by this device were automatically transmitted via an app in patients' smartphones to the patient portal in the Electronic Health Records (EHR) system. Technical support for setting up the device and downloading the accompanying app was provided in a telephone conversation. 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. The digital health program was set up such that, upon data transmission, the EHR system would stratify the incoming blood pressure measures into three risk groups: normal, high/priority, and critical.

A team of care managers, including a pharmacist and registered nurses, would monitor and review the transmitted data in the EHR daily during the work week. The team would then make medication adjustments as needed per established medical protocols, as well as recommendations for behavioral adjustments based on the patient's blood pressure levels. Example snapshot pictures of the EHR dashboard and details on the program's care protocol are provided in Appendix B.

After a successful setup, participating patients were advised to take blood pressure measures daily and were contacted if they did not transmit measures at least once every 30 days. Patients were advised to continue their participation in the program for at least six months and technical support was provided throughout a patient's participation.

Overall, the program was designed with the objectives to: 1) reduce the burden of patients managing their health and incentivize adherence, by providing a service that seamlessly gathers data with little effort on the patient's part and delivers remote ongoing engagement; 2) minimize clinician burden, by integrating the monitoring and alerting systems into existing clinical workflows; and 3) maximize inclusion for health equity. To address the latter, the device and team-based continuous support were free of charge to patients regardless of their health insurance plan.

Appendix Figure B.1 provides a schematic diagram that illustrates the main steps of the program's workflow. These steps flow from the PCP referral to patient outreach by the digital

program staff, to active participation of the patient in the program, and to integration of remote data into the EHR system.

3. Data, Population, and Analysis Sample

3.1. Data Sources

Our baseline data include information on the overall patient population of UCSDH. Data on *clinical health outcomes* come from the Electronic Health Records (EHR) including all readings of blood pressure measures, either taken in-clinic or transmitted electronically via the remote monitoring devices. The EHR also has patients' atherosclerotic cardiovascular disease (ASCVD) risk scores, a standard risk measurement that indicates a patient's risk of having a heart attack or a stroke in the next ten years for patients between ages 40-79. Predictors of ASCVD risk include age, high-density lipoprotein (HDL) cholesterol, total cholesterol, systolic blood pressure, diastolic blood pressure, whether the patient has diabetes, whether the patient is being treated with medication for high blood pressure, and whether the patient is currently, formerly, or has never been a tobacco smoker (Goff et al. 2014).

The EHR data include patients' self-reported *demographic information*, collected from a standard survey that new patients fill out when becoming UCSDH patients. These demographics include birth year, gender, race, ethnicity, and place of residence. The EHR also includes a measure that maps a patient's residential address onto the "Healthy Places Index" (Maizlish et al. 2019), which we use as our measure of geographic affluence. The Healthy Places Index (HPI) combines neighborhood-level data on economic and social conditions, including income, education, employment, and housing. The index was created to advance health equity in California and is used in practice to characterize differentially affluent communities by researchers, health systems, and government agencies (see, e.g., Tai-Seale et al. 2022).[6] The HPI is highly correlated with CDC's Social Vulnerability index (SVI), both at the Census tract level, with a correlation of -0.87 ($p<0.0001$).[7]

[6] For more information see https://www.phi.org/our-work/programs/healthy-places-index-hpi and https://www.healthyplacesindex.org.

[7] CDC's SVI ranks the relative vulnerability of a Census tract based on social factors, including unemployment, racial and ethnic minority status, and disability (see: https://www.atsdr.cdc.gov/placeandhealth/svi/documentation/SVI_documentation_2020.html).

For our analysis sample of patients who were referred to the program, we have administrative *claims data* (with healthcare costs) at the monthly level. When analyzing costs, we focus on Managed Care patients, for whom UCSDH receives capitation payments from payers (i.e., an advanced amount per patient per month) for providing these patients with medical care. As UCSDH is fully financially responsible for capitated patients, we know that for them the lack of claims in a given month implies no costs (whereas, otherwise, it could also be a result of patients receiving care elsewhere in that month).[8]

Our data also include the linking of all patients to their *primary care physicians*, for whom we have two measures that can characterize provider performance. The first measure relies on objective health benchmarks. Specifically, we exploit internal information on incentive payments a physician received as part of value-based performance incentives that are determined by health outcomes of patients. Target rates (e.g., a cutoff share of a physician's patients whose specific medical condition is within healthy levels) are set relative to national or regional performance goals. The incentive programs gather information on how effectively each PCP manages the health of their patients relative to the set targets and accordingly places them on a reward tier represented in percent of the maximum performance incentive. We take the mean tier for each physician based on rewards for performance in 2021 across all target medical conditions that are not directly related to management of cardiovascular health (to avoid mechanical correlations with our program). The second proxy for physician performance relies on subjective patient evaluations. We use a physician's current ranking within the "Net Promoter Score" (NPS) (Adams et al. 2022), which is based on routinely gathered patient experience surveys on the likelihood of recommending the PCP to friends and family. NPS is a prevailing metric used by many health systems and is also tied to performance incentives within UCSDH.

3.2. Patient Population and Analysis Sample

The overall population of UCSDH patients who have an assigned primary care physician and for whom we have information on year of birth, gender, race/ethnicity, and health outcomes consists of 55,624 patients. Among these patients, 26,804 have a hypertension diagnosis (based on code I10 of the ICD-10 classification); 37,375 are younger than 65; the share of female patients is

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

0.55; 34,942 are non-Hispanic White and 8,987 are Black and Hispanic. This large and diverse pool of patients enables us to provide a complementary matching design that uses exact matching on a wide range of observables (birth year, gender, race, ethnicity, quartile of HPI, and baseline systolic blood pressure) with sufficient matches and precision.

Our analysis 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. The program is still ongoing for both enrolled and potential new patients and we note that only patients with an assigned UCSDH PCP are eligible to participate in the program. Appendix Table A.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 intervention's analysis sample has a diverse representation of different demographic subgroups, specifically across race/ethnicity. This is in light of the recent work that emphasizes the pressing need for representation of underserved communities in health research (Bruke et al. 2015, Lyles et al. 2021, Alsan et al. 2024). For cost analysis, the subsample of capitation patients includes 1,792 patients, comprising 71 percent of all referred patients in our studied period.

A total of 274 physicians referred the patients in our analysis sample to the digital health program. On average, referred patients have been treated by their physicians for 2.3 years, with a median physician-patient relationship length of 1 year. The mean and median of these physicians' Net Promoter Score (NPS) rate in 2022 were 87 percent with a standard deviation of 8 percent.

4. Empirical Framework

We use a semi-parametric event study design to assess the program's impact, closely in line with specifications from Dobkin, Finkelstein, Kluender, and Notowidigdo (2018). In the first step, we residualize the raw outcome based on pre-period observations. Physicians were encouraged to refer patients with hypertension whose blood pressures averaged above 140/90 mmHg, so the first step allows for potential underlying trends that may have led a PCP to refer their patient to our program. We use data from months -12 to -2 relative to the referral, where month -1 will serve as the baseline period. In the second step, we run a non-parametric event study of the residualized outcome for the horizon of a year before and a year after the referral at a monthly frequency; that is, using data from month -12 to month +12 relative to the referral. We will accordingly identify effects based on high-frequency breaks in trends following the referral event.

Appendix Figure A.2 illustrates the evolution of the raw data for our main health outcome of systolic blood pressure around the month of referral to the program.

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

$$y_{i,t} = x_{i,t}\lambda + \epsilon_{i,t}, \quad (1)$$

where $y_{i,t}$ is an outcome for referred 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 residualized outcome by $\tilde{y}_{i,t}$; that is, $\tilde{y}_{i,t} \equiv y_{i,t} - x_{i,t}\hat{\lambda}$, where $\hat{\lambda}$ represents coefficient estimates from the estimation in the first step. In the second step, we estimate:

$$\tilde{y}_{i,t} = \sum_{r \neq -1} \beta_r \times I_r + \alpha_i + \varepsilon_{i,t}, \quad (2)$$

where r is the time period relative to the referral event, I_r denotes indicators of time relative to the event, and α_i are patient fixed effects. Robust standard errors clustered at the patient level are calculated from the estimation of equation (2). In Appendix Figure A.3, we calculate standard errors via bootstrap, which also accounts for error from the first-step estimation of equation (1).

Our parameter vector of interest is β_r, which traces the evolution of patients' health outcomes around the referral event relative to the baseline period -1. We identify the program's impacts, β_r for $r > 0$, based on how outcomes right after the intervention deviate from the baseline trend in the pre-intervention period.[9]

As a robustness analysis to our main design, we provide an important complementary strategy. Specifically, we augment the design with a matched control group to address some key potential threats to identification (exact details are described when we discuss estimation results in Section 5.1).

For analyses of heterogeneous effects across subpopulations, we will study average effects by running pooled regressions of the form:

$$\tilde{y}_{i,t} = \beta \times after_t + \alpha_i + \varepsilon_{i,t}, \quad (3)$$

[9] The distribution of the time of referral in terms of calendar year/month is displayed in Appendix Figure A.1. Our research design implicitly takes advantage of the fact that the rollout of referrals spanned different calendar times, so that dynamics around referrals is not governed by particular calendar times.

where $after_t$ is an indicator for whether the observation comes from periods before or after the intervention, and β captures the average effect of the dynamic specification in equation (2). Technically, when estimating specification (3), we weight each observation by the inverse of the frequency of observations from the same period for a given subgroup (in terms of months relative to referral). This allows the mean estimates from specification (3) to preserve their dynamics that show up in the estimation of specification (2) without being affected by data censoring (since those referred later have shorter follow-up panels). We now turn to our empirical analysis.

5. Efficiency: Health Effects of the Digital Health Program

In this section, we assess the program's impact on patient health, its potential underlying mechanisms, as well as the associated changes in healthcare costs.

5.1. Health Impacts

Dynamic Effects on Blood Pressure. As a main outcome to assess the program's impact on patient cardiovascular health, we follow the medical literature and focus on systolic blood pressure (The SPRINT Research Group 2021). Panel A of Figure 1 plots the event study coefficients from equation (2) at a monthly frequency for all patients who were referred to the program. We estimate the intent-to-treat (ITT) by including all referred patients, as the takeup decision itself is endogenous. Recall that we use all data on blood pressure measurements (taken either at home or in-office).

Clear 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 9.8 mmHg on a baseline of 134 mmHg at $t = -1$. To focus on the effect on enrollees who take up the program, we scale the reduced-form intent-to-treat by the enrollment rate. Out of our 2,512 referred patients, 1,327 patients took up the program. The enrollment rate is therefore 0.53, which we use as the scaling factor. Our findings accordingly imply that program enrollment led to an average reduction of 18.5 mmHg (=9.8/0.53) in systolic blood pressure.

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 relying

on an increasingly smaller sample[10]), the evidence suggests these reductions persist even longer. Panel C of Figure 2 shows that 1.5 years following the referral, the decline in blood pressure is on the order of 14 mmHg; or an average reduction of 26.4 mmHg (=14/0.53) among enrollees.

Robustness I: Dynamic Selection. We further assess threats of potential dynamic selection from observations that remain in our sample, although we already include patient fixed effects in all specifications which in principal capture such selection on systematic differences. Still, we replicate the analysis using observations of patients for whom we have repeated blood pressure readings within our main 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, from 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, from a chosen time threshold and up to day 365. In panel B of Figure 1, we include all patients who have at least one post-period reading after day 150 as the chosen time threshold. Appendix Figure A.4 (panel D) studies the sensitivity to the choice of this threshold for the values of 50, 100, 150, 200, and 250 days at a quarterly frequency for increased precision. Overall, all exercises provide results that are virtually the same. The rest of the analysis accordingly includes the sample of patients with repeated readings (based on the day 150 threshold) and is aggregated at the quarterly level. Panels A-C of Appendix Figure A.4 replicate panels A-C of Figure 1 at the quarterly level for completeness.

Robustness II: Matching Design. We provide an important complementary identification strategy that augments the event study design with a matched control group. This design is helpful for gauging general concerns of threats to identification. Such threats could include mean reversion in our dynamic context as well as confounding factors that may come from patient interactions with their physicians irrespective of the program, as we elaborate on below.

We use *exact* matching of patients on birth year, gender, race, ethnicity, quartile of HPI, and the bin of patients' average systolic blood pressure level in the baseline year of 2019 (where we split this average into twenty equal bins).[11] Matched control (non-referred) patients were then

[10] The sample becomes smaller for later periods since the number of referred patients who can be followed in the data up to later periods becomes smaller (as determined by their referral date and our data range over calendar time), and it is not due to enrollees' declining engagement with the program in our ITT framework.

[11] Our ability to construct a sample of matched control (non-referred) patients who are closely observationally and clinically comparable to our treatment (referred) patients stems from the nature of the rollout of the program and the process of dissemination of information about it as described in Section 2. Recall that the digital health program was first introduced to clinical primary care leaders, who were then responsible to disseminate the information to PCPs in

assigned the referral date of the treated patient they were matched with. This assigned date serves as a placebo referral date for control patients. In both the treatment and the control groups, we include patients with repeated measures, resulting in a sample of 583 treated units and 2,362 control units. In panel A of Figure 2, we repeat our two-step event study analysis of equations (1) and (2) for each experimental group separately (in the plot on the left), and we then plot the differentials across the two groups as our estimates for the treatment effects (in the plot on the right). The plots clearly show the robustness of our results to this augmented design.

We further note that referrals by PCPs typically occurred in routine primary care office visits as suggested by program design. While the program targeted patients with a poorly managed hypertension *condition* who had already been under the care of their PCP for this condition, the office visit in itself might still represent a confounding factor, e.g., from patient receiving general counseling again on ways to reduce blood pressure. To alleviate such concerns, we limit the analysis sample of both experimental groups in the matching design to include only patients who have had a PCP visit around the "referral event" (the actual referral event for treatment units and the placebo referral event for control units). The results remain practically the same in panel B of Figure 2.

Robustness III: Measurement. Finally, it is useful to note that referred patients who took up the program (i.e., the program's enrollees) could have blood pressure measured either at home or in-clinic. Appendix Figure A.5 plots the dynamics of the share of blood pressure readings that were taken at home versus in-clinic over our analysis period, for the entire sample of referred patients (in panel A) and for the subsample of patients who took up the program (in panel B). In this regard, practitioners consider the "white coat effect" (e.g., Gerin et al. 2006, Manios et al. 2008), which refers to potential transient blood pressure rises during clinical visits. This issue could potentially confound our estimated effects, as transmitted measures taken at home could be

their clinics, and PCPs were those who later made the referrals. This created variation in referral rates over time across PCPs during the program's rollout period. When we look at the distribution of the total number of patients referred by PCPs we see that control units come from the pool of patients with PCPs who engaged with our digital health program to a lesser degree in the studied period. Specifically, among included patients, control units come from physicians whose 5th, 25th, 50th, 75th, and 95th percentiles are 0, 3, 9, 25, and 67 referred patients, and treatment units come from physicians whose 5th, 25th, 50th, 75th, and 95th percentiles are 3, 13, 31, 67, and 121 referred patients.

artificially lower. In practice, however, two important observations mitigate such concerns that measurement issues could govern our results.[12]

First, we later show (in Figure 5 and as reflected in panel B of Appendix Figure A.5) that due to declining engagement with the program following initial takeup, the highest rate of electronic data transmission from home occurs in months 0 to 1 following the referral. Therefore, the high-frequency dynamics of declining adoption (in Figure 5) and the high-frequency dynamics of increasing improvements in blood pressure in the ITT estimates (in Figure 1) together imply the following: these types of mechanical measurement concerns could explain, *at most*, a decrease of -2.4 mmHg (i.e., the ITT coefficient on month 1) out of the total long-run effect of -14 mmHg.[13] Second, since enrollees still have occasional in-clinic measures (as shown in panel B of Appendix Figure A.5), we can narrow the analysis to include only blood pressure measurements taken *in-clinic*. This covers 1,246 of the referred patients among whom 60 percent took up the program, and we include in the analysis only measures taken in-clinic whether the referred patient enrolled or not. While this is a selected subsample (for whom, for example, post-referral office visits might have been due to an illness), the patterns of their blood pressure are all consistent with minimal potential measurement issues and with similar-magnitude impacts of reductions at the end of the one-year analysis horizon (see Appendix Figure A.6 as compared to Appendix Figure A.4).

5.2. Cardiovascular Risk Outcomes

We also examine the probability of reaching healthy blood pressure levels as defined by established guidelines. 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 (of stage 2 hypertension) as well as below the 120 mark of normal blood pressure. We find clear

[12] In this regard, we should mention that, in part due to the white coat effect and since patients sometimes rush to a clinic visit, the blood pressure measurement standard workflow in UCSDH clinics is to retake blood pressure measures if the initial readings are high compared to clinical benchmarks. Blood pressure is taken again after patients are more settled in. Accordingly, we use the minimal value among all potential readings in a given day (whether at home or in-clinic).

[13] Beyond the clear dynamics in systolic blood pressure effects, our analysis of healthcare costs in Section 5.4 further mitigates related concerns as it is not prone to such potential measurement issues.

significant improvements in both categories. Within one year of referral to the program, patients display a 25 pp increase in the propensity to fall below stage 2 hypertension levels and a 15 pp increase in the propensity to reach healthy blood pressure of normal levels.

Finally, we quantify the predicted long-run effects on severe cardiovascular events using the ASCVD risk score. The ASCVD score essentially maps the causal reductions in blood pressure over our one-year analysis period to a ten-year surrogate index analysis for the long-run risk of experiencing a severe cardiovascular event (Athey et al. 2019). As our analysis sample is composed of patients with higher cardiovascular risk, we analyze changes in the share of patients who exhibit high ASCVD risk, defined relative to the 20 percent benchmark by the American College of Cardiology (Arps et al. 2018). In panel B of Figure 3, we find that the intervention led to a decline of 4.4 pp in the share of patients who exhibit a high long-run probability of experiencing a severe cardiovascular event on a baseline of 35.5 pp. This translates to an average decline of 8.3 pp (=4.4/0.53) among program enrollees. Overall, across health and risk outcomes that we study in this section, our results provide clear visual evidence of large improvements in health following the intervention.

5.3. Mechanisms of Change

There are two basic approaches to lowering high blood pressure which are usually combined (see, e.g., Goff et al. 2014, Smith, Lennon, and Carlsgaard 2020, WHO 2021, Mayo Clinic 2024). The first is adoption of healthy lifestyle habits, such as weight control, physical activity, healthier diets, and reduced tobacco smoking. The second is taking antihypertensive medication. There is a wide variety of medication regimens (in terms of drug combinations and dosages), whose efficacy varies widely across patients due to patient tolerance, presence of multiple chronic conditions, etc. Patient-tailoring of effective medication regimens requires a series of adjustments and experimentations, which necessitate recurring feedback between the prescribed regimen and its health consequences until patients reach their health goals.[14] This process can be delayed in traditional office-based care, where measurements are taken only upon in-person visits. Remote monitoring lets patients provide continuous measurements from the comfort of their own home in their own time with minimal hassle, which could reduce frictions

[14] As one example, WHO guidelines suggest a monthly follow-up after initiation or a change in antihypertensive medications until patients reach target (WHO 2021).

and delays in the process of tailoring care. Accordingly, the team-based remote patient monitoring program was designed such that transmission of real-time health indicators triggers timely healthcare provider involvement by the clinical team (of pharmacists and registered nurses), who monitors the data daily and makes medication adjustments and recommendations for behavioral changes. By program design, there are therefore two key channels that we hypothesize could underlie the estimated health improvements in blood pressure and ASCVD risk: 1) more efficient provision of tailored care, and 2) patient behavioral changes. With limitations that we describe below, our rich data offer empirical ways to explore aspects of both channels.

Efficiency in the Provision of Tailored Care. We merge administrative information on all prescription orders for antihypertensive medication made from 2016-2022 by physicians at UCSDH to patients in our analysis sample. We note that 87 percent of our referred patients (2,185 out of 2,512) were ever prescribed such medication within the data horizon. As a proxy measure of medication experimentation, we study the time gap between sequential distinct medication orders, as defined by the pair of medication/s and dosage. In this way, we can capture different variations, specifically along the dimensions of the single medication prescribed ("monotherapy"), multiple medication classes ("combination therapy"), and dosage changes of any medication involved ("titration"). We note that when multiple medication classes are prescribed it comes in the form of a "combination blood pressure medication," which is a pill that contains more than one class of antihypertensive drugs.

Panel A of Figure 4 plots the event study of time between unique medication orders in days (where the pre-treatment mean is 121 days, reflecting that medication for chronic use is often prescribed in bulk for several months). The pattern is closely consistent with enhanced experimentation of patient-tailored medication regimens. There is a clear increase in the frequency of unique prescription orders following the referral with the highest effect in the first quarter. The frequency of experimentation then declines and converges to baseline, which is closely in line with the intervention uncovering the regimen that is effective for a given enrolled patient in achieving successful hypertension management.

Health Behaviors. We merge information from the EHR on patient's tobacco smoking behavior. Patients are asked about their smoking habits in the standard new patient survey as well as in recurring office visits, where patients can report the categories: never smoker, former smoker, light smoker, some days, every day/heavy smoker. We study an indicator for heavy smoking (every

day/heavy smoker), as 58 percent of our sample are heavy smokers at baseline. It is important to raise an important caveat here about data quality: beyond being self-reported, smoking information is also poorly populated since it is not a mandatory field in the EHR. This both decreases the number of observations substantially, and brings on concerns that the intervention itself may induce differential reporting. To limit concerns of the latter form, we accordingly limit the analysis only to patients for whom we have at least one data point in the pre-period and one data point in the post-period on smoking. As such, we think the findings on smoking should be interpreted with caution and viewed as suggestive.

Still, while the sample reduces to only 204 patients (with 4,697 patient-month observations) and standard errors become less precise, the effects sizes are large enough to be statistically detectable. Panel B of Figure 4 shows a clear pattern of reduction in smoking intensity, which begins following the intervention and is then persistent at least throughout our analysis horizon. Whereas suggestive, this finding is important nonetheless, as health-related behaviors are well-known to be sticky and hard to change (see discussion in, e.g., Fadlon and Nielsen 2019).

5.4. Healthcare Costs

In our final exercise of analyzing efficiency aspects of the program, we directly study the potential reductions in healthcare costs from the improvements in prevention and management of hypertension that our intervention induced. As a rough benchmark for cost reductions per program enrollee, we note that Americans with high blood pressure have been estimated to face nearly $2,000 higher annual healthcare expenditure for treating their hypertension condition, with an estimated total associated costs of about $131 billion nationwide (Kirkland et al. 2018).

In Table 1, we analyze healthcare costs among capitated patients, who comprise 71 percent of our study's sample. We provide the event study estimates at the quarterly level for the evolution of patients' costs from professional medical services around the referral event (in column 1). We also report estimations for when costs are capped from above at the top 0.01 percent to investigate robustness to extreme cost values (in column 2).

We find that, by the third quarter after the referral, patients begin showing meaningful reductions in average costs. The reduction in quarterly costs per referred patient averages to $385 in the second half of the year following the referral on a counterfactual predicted level of $1,004, amounting to a decline on the order of 40 percent. The overall one-year reduction in costs (captured by the sum of the statistically significant effects from quarters 3-4) is about $770. The enrollment

rate among this subsample of capitated patients was 0.52 (=928/1,792), closely similar to that in the overall sample. Correspondingly, scaling the reduced-form effect by the takeup rate implies that the program led to an average reduction of $1,488 (=770.4/0.5178) in annual cost per enrollee. This analysis offers novel promising findings about the potential of digital monitoring to reduce healthcare costs in the context of a leading cause of death.

6. Equity: Disparities in Health Outcomes and Program Adoption

Next, we analyze patient subpopulations in order to study potential inequities in the gains from the program. As we show in the tables that we report below, given that referrals were based on medical criteria, all patient subpopulations have similar average health outcomes at baseline. As such, our intervention provides an opportune setting, in which we can study whether the introduction of digital health itself can lead to disparities even when the initial departure point displays parity in health outcomes across social subgroups.

6.1. Disparities in Health Gains

We study how the reductions in cardiovascular risk reflect improvements in health across different subpopulations. Table 2 reports estimates of the effect on systolic blood pressure based on equation (3). In defining the variable $after_t$, we include observations from quarter -1 as baseline in the pre-referral period. Given the dynamics in treatment effects that we found in Figure 1, we offer specifications that include in the post-referral observations quarters 1-2 for the "short run," quarters 3-4 for the "medium run," and quarters 5-6 for the "longer run." As a benchmark, we provide the corresponding estimates for the overall sample with a long run reduction of 12.15 mmHg in systolic blood pressure.

Given the focus of the recent health disparities studies, we are particularly interested in comparing the findings for Black/Hispanic patients to those for White patients and across differentially affluent geographic communities.[15] It is first worth noting the meaningful reductions in blood pressure across race and ethnicity (Black/Hispanic patients or White patients) and the affluence of a patient's community (below and above the median HPI). Notably, the representation of our sample allows us to draw these conclusions for improvements in health outcomes across

[15] Appendix Table A.3 additionally considers differences across gender and age.

underserved communities and economically vulnerable families, who are typically very narrowly represented in clinical studies (Alsan et al. 2024).

Table 2 then additionally provides tests for the gaps in health improvements across these patient subgroups. We find that the estimates for the reduced-form intent-to-treat, which also incorporate differentials in the program adoption decision, start displaying meaningful gaps in the longer run both economically and statistically. In particular, as improvements in health outcomes among White patients continue to grow larger, improvements among Black/Hispanic patients fall short to about half (8.74 compared to 15.81). We find similarly differential improvements across a community's economic affluence, comparing patients from below-median HPI locations and above-median HPI locations (who display reductions of 8.62 compared to 14.85). We note that as referred patients across subgroups have similar average baselines (see bottom of Table 2, reflecting the uniform clinical criteria for referrals), differences in absolute magnitudes also reflect differences in percent changes.

To put these disparate gains from the digital innovation in context, we compare them to nationwide estimates of inequities in cardiovascular health. Aggarwal et al. (2021) use the National Health and Nutrition Examination Survey (NHANES) to study blood pressure management among U.S. adults with hypertension across race/ethnicity.[16] They find that, when compared with blood pressure control rates for White adults (0.49), control rates are lower among Black adults (0.392) and Hispanic (0.40) adults. That is, there is an overall racial/ethnic gap of about 10 pp. To convert the gaps in our program's gains in blood pressure to a metric comparable to that in Aggarwal et al. (2021), we analyze the differential in the program's impact on reaching controlled levels of systolic blood pressure as defined relative to the 140 mmHg mark. Using equation (3), Appendix Table A.2 (panel A) summarizes the longer-run effects of the program on the probability of reaching controlled blood pressure levels by race/ethnicity. We find that the program itself led to a gap on the order of 13 pp in health outcomes across race/ethnicity, highlighting the magnitude of disparities that could result from uneven gains from a technological innovation.

[16] The National Health and Nutrition Examination Survey (NHANES) is a cross-sectional population-based survey conducted by the U.S. Centers for Disease Control and Prevention with in-person biannual physical examinations.

These findings of inequities in the reduced-form health gains depend on the degree to which the different subpopulations take up and adhere to the program. This leads us to analyze next the program's adoption behavior and how it varies across social subgroup.

6.2. Disparities in Adoption Rates

Definitions. The *adoption* of the digital program is determined both by the initial *takeup* of the program (i.e., enrollment) and by the follow-on *adherence* to the program conditional on takeup.

We define a patient's initial *takeup* of the program as the event that the patient transmits data at least once after the referral. This approach guarantees the patient has successfully integrated into the system and has engaged with the program. We denote an indicator for takeup by T_i, which assumes the value 1 if the referred patient takes up the program and assumes the value 0 otherwise.

We define patient i's *adherence* to the program in time period r in months relative to referral, denoted by the indicator A_{ir}, based on the event that the patient transmits data in period r. The probability of adherence in period r conditional on initial takeup, $Pr(A_{ir}|T_i = 1)$, will characterize patients' "survival" on the program. The average of this probability over time periods will provide us with mean adherence probabilities.

The implied mean adoption rate over the analysis horizon for a specific subgroup will be defined based on the interaction of the two variables. Specifically, we will take averages of $T_i \times A_{ir}$ for a given patient subgroup over the months in the follow-up period. We provide estimates for the 6-months, 1-year, and 1.5-year horizons, bearing in mind that enrollees were all advised to adhere to the program for at least 6 months.

Results. Figure 5 first characterizes adoption among the entire sample on a monthly basis for the 1.5-year horizon following the referral. The initial takeup rate among all referred patients was 0.53. The average adherence rate conditional on takeup was 0.47 over the 1.5-year horizon with a clear declining pattern across months. Overall, the adoption rate of the program over the entire follow-up horizon averaged to 0.265.[17]

Next, we compare these behaviors across subpopulations of interest in Table 3. We first compare Black and Hispanic patients to White patients in panel A. We find consistently lower

[17] For the 6-months horizon, the average adherence rate conditional on takeup was 0.57 (s.e.: 0.01) and the overall adoption rate averaged to 0.32 (s.e.: 0.01); for the 1-year horizon, the average adherence rate conditional on takeup was 0.49 (s.e.: 0.01) and the overall adoption rate averaged to 0.28 (s.e.: 0.01).

adoption rates among Black and Hispanic patients compared to White patients. By the end of our analysis period, the racial/ethnic gap in the adoption of the digital health program amounts to 15 percent, a 4.04 pp lower rate relative to 27.67 pp among White patients. We find that this gap is driven by lower adherence rates (that is, lower rates of "survival" on the program), suggesting that Black/Hispanic patients may face greater difficulties in continuously engaging with the program.[18]

To look at disparities across geographic communities, we compare patients from low-affluence communities (with below-median HPI) to patients from high-affluence communities (with above-median HPI). The adoption gap across households from differentially affluent communities amounts to 28 percent, a gap of -8.24 pp relative to a baseline of 29.06 pp among the most affluent (see panel B of Table 2). Geographic disparities already arise in the initial takeup decision and are then exacerbated by lower adherence rates among enrollees.

6.3. Role of Physicians in Adoption of Digital Health

We have found that the program leads to significant improvements in health outcomes along with only partial and differential participation across subgroups. The combination of these findings suggests the presence of frictions in the adoption of the digital program, which raises the question of whether the adoption decision is a margin that can be influenced and, if so, how. Primary care physicians, who are the point of contact between the patient and the program, are obvious candidates to investigate. More generally, primary care physicians have been 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). In this final analysis, we assess whether we can identify practice styles and characteristics that predict a physician's success in inducing higher patient engagement with digital health.

We begin by asking whether higher performing physicians induce higher adoption rates by utilizing our two performance proxies. We split physicians into three equal-sized bins within each performance measure, accordingly assigning them to the categories high, medium, and low.

[18] Interestingly, the results suggest that active enrollment in the program provides similar health gains for Black/Hipanic and White patients. To see this, let us focus on the short run of quarters 1-2 when gaps are smallest, and consider the treatment effect "per enrollee" (defined by the reduced-form effect divided by takeup rate) and the treatment effect "per active enrollee" (defined by the reduced-form effect divided by adoption rate). Appendix Table A.2 (panel B) shows that these estimates are closely similar across Black/Hispanic patients and White patients.

The first measure, based on objective medical goals, is represented by the average performance-pay tier the physician achieved within the incentive program. Recall that this calculation, based on performance in the year 2021, excludes management of patient cardiovascular health to avoid mechanical correlations. Panel A of Figure 6 plots the relationship between 1.5-year patient adoption rates and physician performance, reporting differentials relative to the lowest performing physicians. We see a clear gradient such that the highest performing PCPs see their patients adopting the program at a rate that is 10.5 pp higher relative to 25 pp among the lowest performing PCPs.

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." This rating is combined across patients into a physician's Net Promoter Score (NPS). Panel B of Figure 6 plots 1.5-year patient adoption rates against physician NPS category. We find that physicians who rank higher in this metric, i.e., those who induce improved patient experience, also foster a higher program adoption rate of 6.2 pp among their patients, relative to the lowest ranking physicians whose mean patient adoption rate is 27 pp. Overall, we see that higher adoption of the program is highly associated with measures of physician performance.

Lastly, we characterize the physician-patient relationship and its association with technology adoption. Specifically, we investigate the length of the relationship, which could either reflect or engender trust that may induce a higher willingness to take up a new program.[19] Table 4 provides these results. We find that patients are 7.7 pp more likely to adopt the digital health program in longer physician-patient relationships, defined relative to the sample median of 1 year at baseline. Importantly, the patterns prevail across all subgroups over race/ethnicity and geographic affluence. The findings therefore suggest that stronger provider-physician relationships via continuity of care could be a promising pathway to promote higher and more equitable adoption of digital health programs.

7. Conclusion

In this paper, we study the efficiency and equity consequences of offering individuals with high cardiovascular risk a digital health program of remote patient monitoring that enabled them

[19] The EHR provides information on the date a physician-patient match started.

to transmit real-time clinical data for timely treatment. We find that the real-world digital health program led to meaningful and persistent health improvements across a diverse population of patients, providing novel empirical evidence of the great promise of digital solutions in medical care. Further bolstering its benefits, we find that the program resulted in meaningful cost reductions, offering a promising pathway for curbing healthcare costs more broadly. Nonetheless, the intervention induced meaningfully lower health gains among patients from traditionally underserved communities, whose adoption of the program was substantially lower. As such, our findings also simultaneously highlight the challenges that could hinder equity in gains from the introduction of new technologies within the growing digital health sector.

Our results underscore the importance of well-targeted policy designs in the efforts to achieve equity in digital health. Effective policies could include, for example, community outreach involving digital training and information campaigns, as well as the design of inclusive, culturally adapted products that are suitable for adoption by lower-income households. In fact, the Digital Equity Act of 2021 will allocate $2.75 billion in federal grant funding for digital equity over a five year period to support initiatives such as training programs for digital literacy for underserved communities to promote digital inclusion.[20] In our context of health, the evidence suggests that physicians and the nature of their relationship with patients can be instrumental in inducing greater and more inclusive adoption of digital innovations in the provision of care.

[20] See https://www.congress.gov/117/plaws/publ58/PLAW-117publ58.pdf#page=781 for details.

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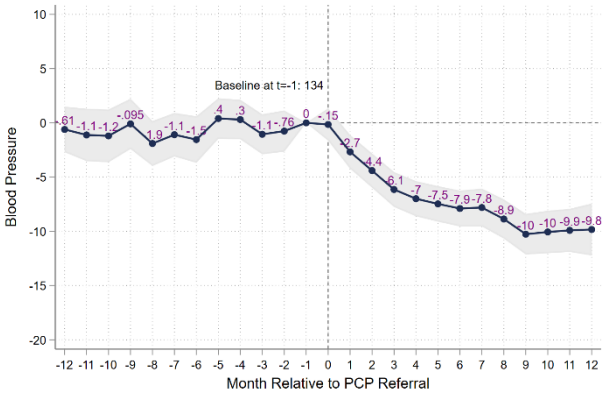
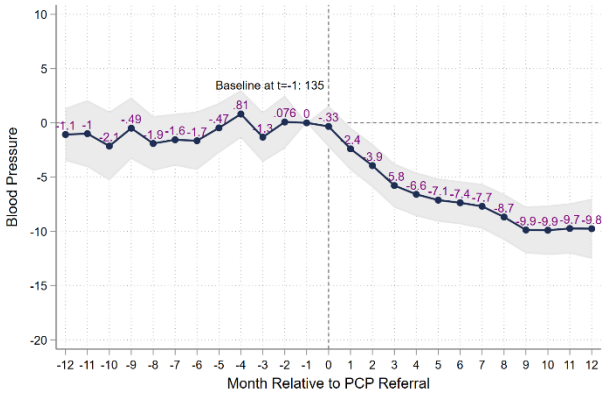
Figure 1: Program's Impact on Patient Blood Pressure

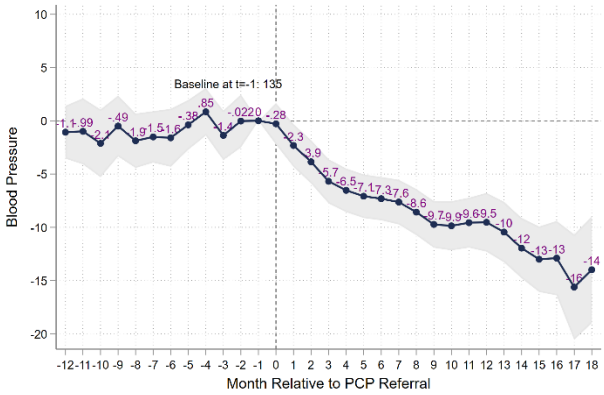
A. All Patients



B. Patients with Repeated Measures



C. Longer Horizon

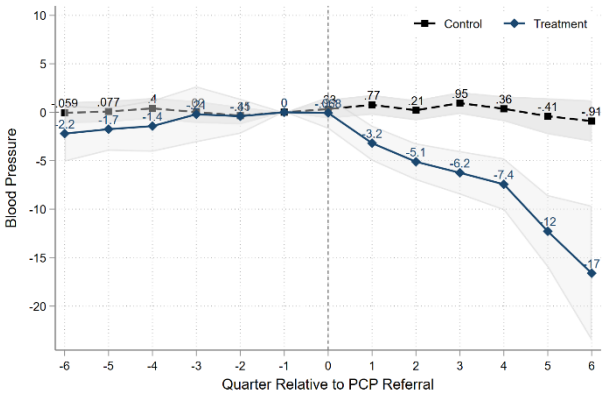


Notes: This figure evaluates the program's impact on systolic blood pressure among patients who were referred to the program. We use a semi-parametric event study design that is conducted in two steps. In the first step, we residualize the outcome based on observations from pre-periods (months -12 to -2) using a linear term in time relative to the intervention and age fixed effects. In the second step, we run a non-parametric event study for the residualized outcome. The plots display the event study coefficients from equation (2) along with their 95-percent confidence intervals, where robust standard errors are clustered at the patient level. 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 A.4. Panel C extends the analysis of panel B up to 1.5 years after the referral.

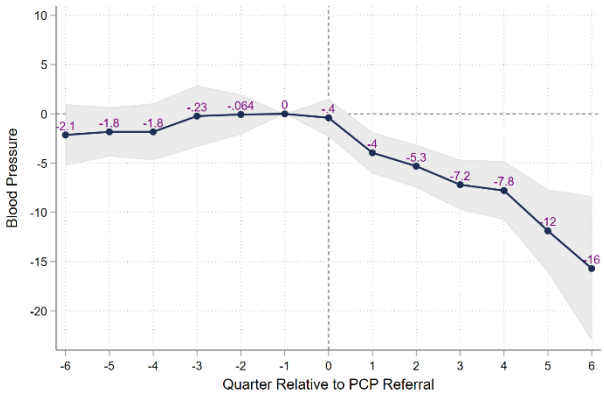
Figure 2: Program's Impact on Patient Blood Pressure—Matched Control Group

A. All Matches

Referred Patients vs. Matched Control Patients

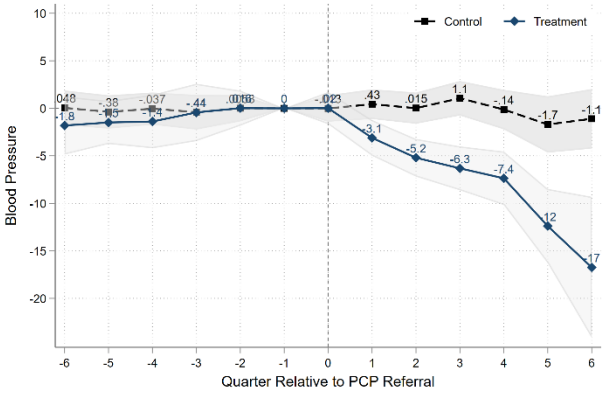


Differential

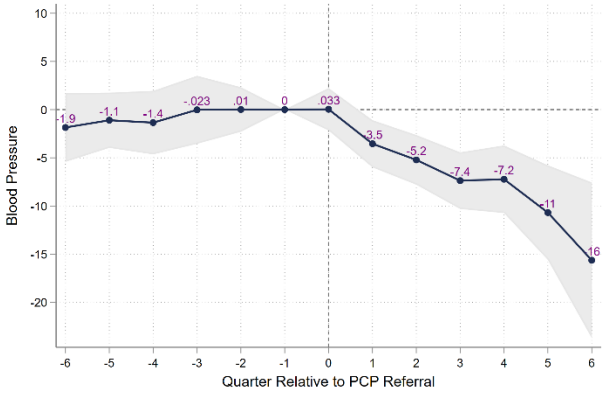


B. Matches with PCP Visits

Referred Patients vs. Matched Control Patients



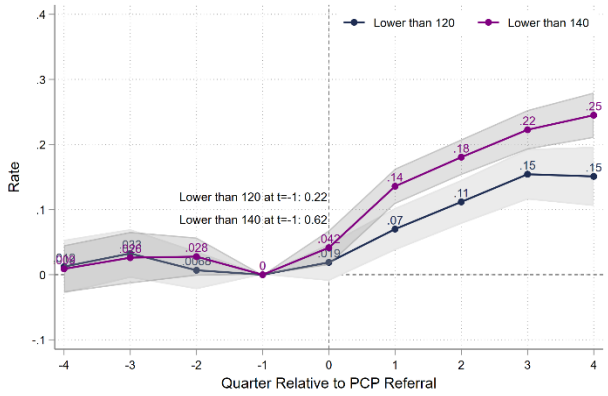
Differential



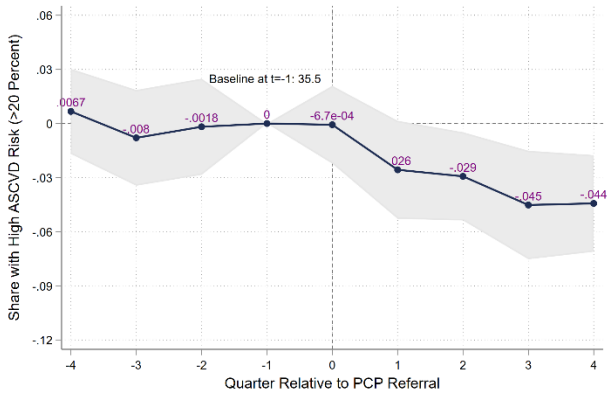
Notes: This figure evaluates the program's impact on systolic blood pressure based on a matched control group design. We create exact matches of patients based on birth year, gender, race, ethnicity, quartile of HPI, and the bin of their average level of systolic blood pressure in the baseline year of 2019, where we split this average into twenty equal bins. In cells with matches of control and treatment patients, the 75th percentile of the number of matched treatment (referred) patients is one, so we keep only cells with exactly one referred patient for simplicity. We assign to matched control (non-referred) patients the referral date of the treated patient they were matched with as a placebo referral date. We then include only patients with repeated measures. For each experimental group, we separately perform our two-stage analysis of residualizing the outcome and then running an event study. We display both the event study coefficients from the specifications of equation (2) at a quarterly frequency (along with their 95-percent confidence intervals) for each experimental group and the differentials between the two groups (along with their 95-percent confidence intervals), which provide the matching design estimates of treatment effects. Panel A includes the entire matched sample that is comprised of 583 treated units and 2,362 control units. Panel B limits the analysis to the subsample of units that have had a PCP visit around the event (specifically, within days -10 to +10) that is comprised of 526 treated units and 711 control units. Robust standard errors are clustered at the patient level.

Figure 3: Program's Impact on Cardiovascular Risk

A. Desirable Blood Pressure Levels



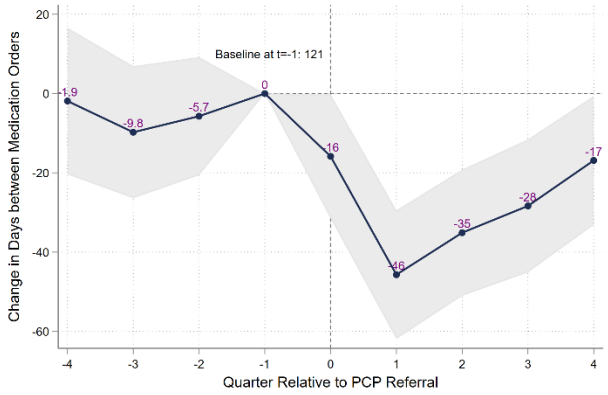
B. Prevalence of High ASCVD Risk Score



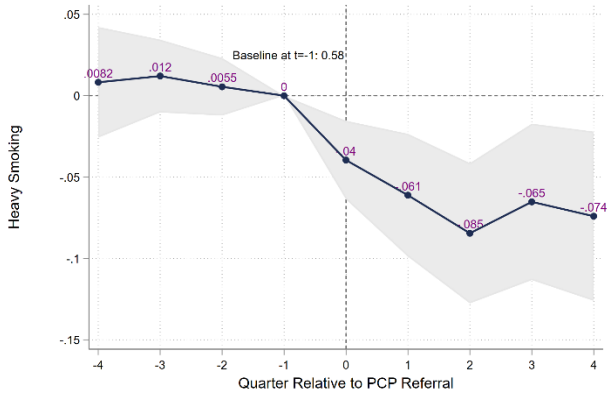
Notes: This figure evaluates the program's impact on cardiovascular risk. In panel A, we study the probability of reaching favorable blood pressure levels based on the probability that a patient's systolic blood pressure drops below 140 (stage 2 hypertension) and below 120 (normal blood pressure). In panel B, we analyze changes in the share of patients who exhibit high ASCVD risk of 20 percent or above as defined by the American College of Cardiology. We display event study coefficients from a specification of equation (2) at a quarterly frequency along with their 95-percent confidence intervals, where robust standard errors are clustered at the patient level. Estimations include the sample of patients with repeated blood pressure measures.

Figure 4: Channels of Change

A. Time between Orders of Antihypertensive Prescriptions

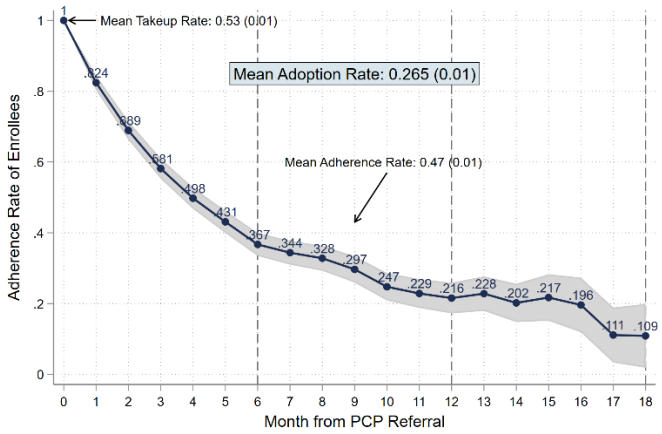


B. Prevalence of Heavy Tobacco Smoking



Notes: This figure provides tests for potential mediating mechanisms of the improvements in health outcomes. In panel A, we study a proxy for more efficient provision of tailored care. We plot the event study of time between unique medication orders to study the degree to which the frequency of unique prescriptions orders are consistent with enhanced experimentation in medication regimens following the referral. We use administrative information on all prescription orders for antihypertensive medication made from 2016-2022 by physicians at UCSDH to patients in our analysis sample. In panel B, we study patient behavioral changes. Specifically, we plot the evolution of heavy smoking using information from the EHR on a patient's self-reported tobacco smoking behavior. The plots display event study coefficients from a specification of equation (2) at a quarterly frequency along with their 95-percent confidence intervals, where robust standard errors are clustered at the patient level.

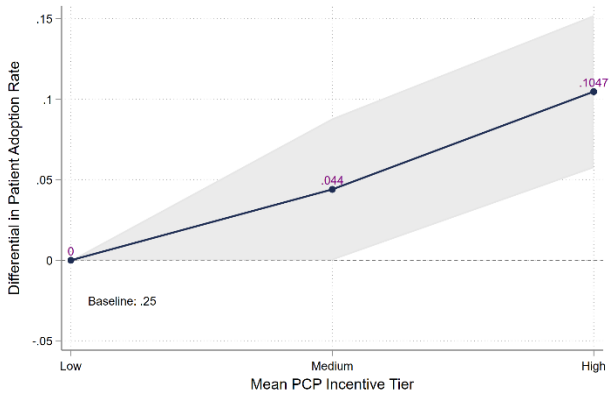
Figure 5: Adoption Rate—Initial Takeup and Follow-on Adherence



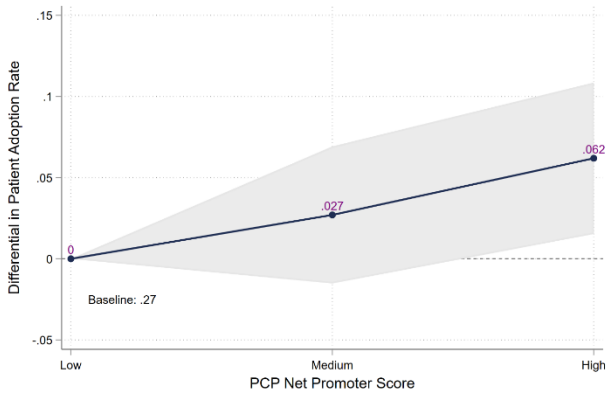
Notes: This figure displays the overall adoption rate of the program. Adoption is a composition of the initial takeup decision and the follow-on adherence to the program. As reported on the figure, the mean initial takeup rate of the program was 0.53 (s.e.: 0.01). The plot then displays the adherence to the program conditional on takeup. It is measured as the rate of electronically transmitting data in each follow-up month over a 1.5-year horizon after the referral. The mean adherence rate during this period is reported on the figure to be 0.47 (s.e.: 0.01). The combination of these two behaviors translates to an average program adoption rate of 0.265 (s.e.: 0.01) over the 1.5-year horizon following the referral, as reported on the figure.

Figure 6: Physician-Level Adoption Rates and Performance

A. Extent of Incentive Rewards



B. Net Promoter Score



Notes: This figure studies how physician-level patient adoption rates correlate with proxies for physician performance. Our first proxy in panel A 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 the year 2021 across all programs that are not directly related to management of cardiovascular health (to avoid mechanical correlations). The second proxy in panel B is "Net Promoter Score" for the year 2022. It is physicians' rate of approval based on their patients' reported likelihood to recommend them to family and friends, as answered in routine quality promotion surveys.

Table 1: Event Study of Healthcare Costs

	Costs (1)	Capped Costs (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***
(Average of Quarters 3-4)	(149.2)	(149.1)
Annual Effect	-770.4***	-799.3***
(Sum of Quarters 3-4)	(298.5)	(298.1)
Baseline Level	887	886
Medium Run Counterfactual	1,004	1,012
Number of Individuals	1,651	1,651

Notes: This table evaluates the program's impact on healthcare costs. We provide event study coefficients from a specification of equation (2) at a quarterly frequency along with their 95-percent confidence intervals, where robust standard errors are clustered at the patient level. We include observations of patients for whom UC San Diego Health receives capitation payments. Column 1 uses raw data of costs, and column 2 caps costs from above at the top 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), and the annual effect is the sum over this period. We report baseline levels (from quarter -1) and the counterfactual level in the medium run. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 2: Program's Impact on Blood Pressure by Patient Subpopulations

	All	Race/Ethnicity		HPI	
		Black/Hispanic	White	Below Median	Above Median
	(1)	(2)	(3)	(4)	(5)
Short Run (quarters 1-2)					
Treatment Effect	-6.72***	-6.18***	-6.67***	-5.85***	-7.10***
	(0.59)	(1.04)	(0.81)	(1.02)	(0.73)
Difference		0.49		1.252	
		(1.32)		(1.246)	
Number of Individuals	1,312	317	745	407	899
Medium Run (quarters 3-4)					
Treatment Effect	-9.42***	-7.13***	-9.61***	-9.76***	-9.20***
	(0.92)	(1.53)	(1.25)	(1.50)	(1.14)
Difference		2.48		-0.56	
		(1.97)		(1.88)	
Number of Individuals	1,186	285	671	370	811
Longer Run (quarters 5-6)					
Treatment Effect	-12.15***	-8.74***	-15.81***	-8.62***	-14.85***
	(1.60)	(2.90)	(2.01)	(2.35)	(2.04)
Difference		7.06**		6.23**	
		(3.52)		(3.11)	
Number of Individuals	1,019	248	583	321	693
Baseline (quarter -1)	134.06	135.13	134.05	134.17	133.97
	(0.85)	(1.73)	(1.07)	(1.47)	(1.04)
Difference		1.08		0.20	
		(2.03)		(1.80)	

Notes: This table studies the program's effect on systolic blood pressure among patient subpopulations. We estimate equation (2) using the sample of patients with repeated measures. Observations from before the referral come from quarter -1. Observations from after the referral correspond to quarters 1-2 for the "short run," quarters 3-4 for the "medium run," and quarters 5-6 for the "longer run." Observations in a given month relative to referral are weighted by the inverse of the frequency of same-period observations within a subpopulation. Baseline levels are subpopulation means of the outcome in quarter -1. Robust standard errors are clustered at the patient level. *** p<0.01, ** p<0.05, * p<0.1

Table 3: Disparities in Adoption Rates

Panel A: Disparities across Race/Ethnicity

	Initial	6-Month Horizon		1-Year Horizon		1.5-Year Horizon	
	Takeup	Adherence	Adoption	Adherence	Adoption	Adherence	Adoption
Rates among White patients	0.5272***	0.5898***	0.3304***	0.5083***	0.2903***	0.4885***	0.2767***
	(0.0135)	(0.0115)	(0.0105)	(0.0120)	(0.0100)	(0.0122)	(0.0099)
Black/Hispanic patients relative to White patients	0.0024	-0.0597***	-0.0342*	-0.0603***	-0.0382**	-0.0656***	-0.0404**
	(0.0246)	(0.0214)	(0.0183)	(0.0216)	(0.0173)	(0.0216)	(0.0169)
Number of Individuals	1,970	1,040	1,970	1,040	1,970	1,040	1,970

Panel B: Disparities across Geography

	Initial	6-Month Horizon		1-Year Horizon		1.5-Year Horizon	
	Takeup	Adherence	Adoption	Adherence	Adoption	Adherence	Adoption
Rates among patients with above-median HPI	0.5510***	0.5930***	0.3474***	0.5126***	0.3050***	0.4932***	0.2906***
	(0.0118)	(0.0099)	(0.0093)	(0.0102)	(0.0089)	(0.0104)	(0.0089)
Below-median relative to above-median HPI	-0.0796***	-0.0716***	-0.0839***	-0.0807***	-0.0838***	-0.0845***	-0.0824***
	(0.0219)	(0.0195)	(0.0160)	(0.0195)	(0.0149)	(0.0193)	(0.0146)
Number of Individuals	2,500	1,319	2,500	1,319	2,500	1,319	2,500

Notes: This table studies disparities in adoption rates across patient subpopulations. It displays initial takeup rates, follow-on adherence rates conditional on takeup, and the resulting overall adoption rate. Panel A compares Black/Hispanic patients to White patients, and panel B compares patients from lower HPI communities to patients from higher HPI communities. *** p<0.01, ** p<0.05, * p<0.1

Table 4: Adoption Rates and Length of PCP-Patient Relationship

	All	Below-Median HPI	Above-Median HPI	White Patients	Black/Hispanic Patients
Relationship Longer than Median	0.0774***	0.0736***	0.0711***	0.0749***	0.0934***
	(0.0150)	(0.0248)	(0.0184)	(0.0204)	(0.0294)
Number of Individuals	2,316	691	1,613	1,253	557

Notes: This table assesses the role of the length of the PCP-patient relationship in patient adoption behavior. We study whether patients with relationships longer than the sample median of 1 year are more likely to adopt the technology over the 1.5-year horizon after the referral. *** p<0.01, ** p<0.05, * p<0.1

Online Appendix

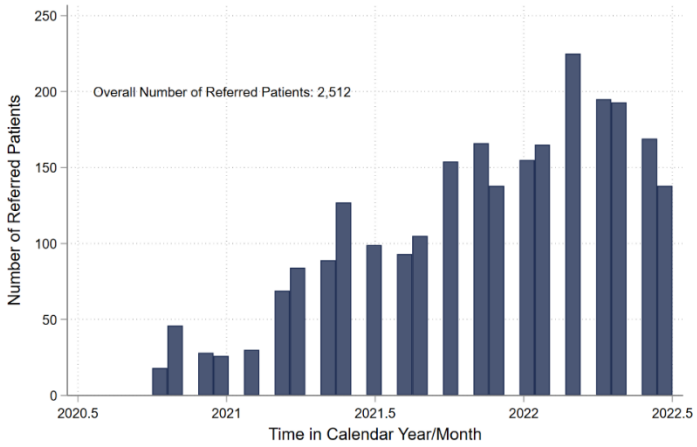
Appendix A: Figures and Tables

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

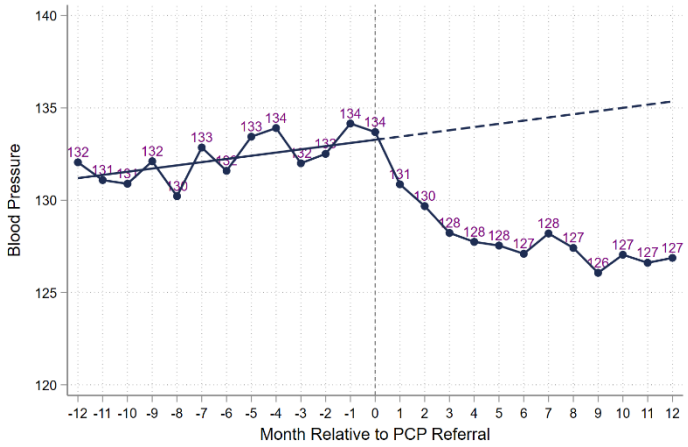
Notes: This table provides average characteristics for our analysis sample in terms of age, gender, race/ethnicity, and HPI of residence. Our sample includes 2,512 patients who were referred to the digital health program by their physicians from October 2020 to July 2022.

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



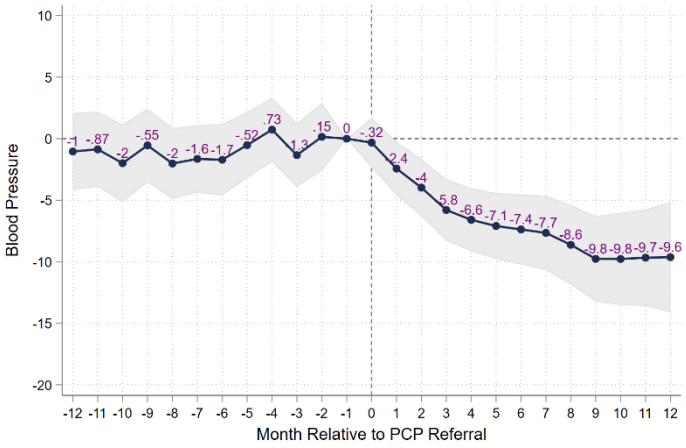
Notes: This figure plots the distribution of time of referral in terms of calendar year/month.

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 who were referred to the program. We also display a linear fit for the pre-period months to assess patterns prior to the intervention (solid linear line), which we extrapolate to the post-period months (dashed linear line).

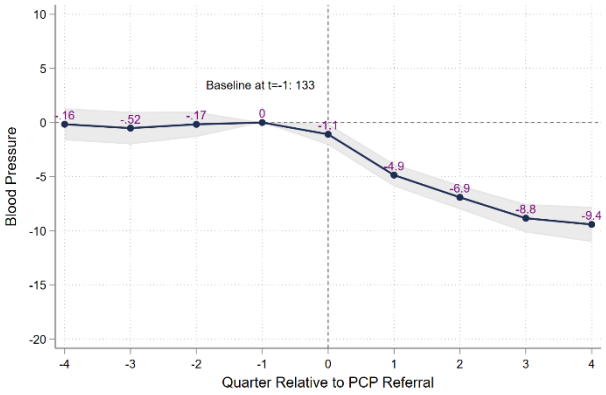
Appendix Figure A.3: Program's Impact on Patient Blood Pressure—
Bootstrapping Standard Errors



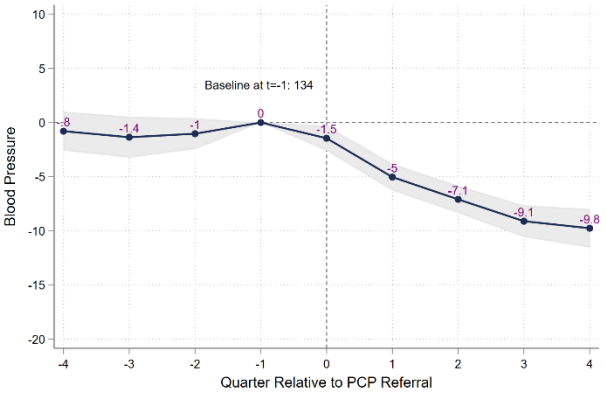
Notes: This figure evaluates the program's impact on systolic blood pressure, where we compute confidence intervals via bootstrapping. Specifically, we repeat our estimation procedure for 100 replications of 2,000 patient draws (sampled with replacement). For each replication, we perform our semi-parametric event study on the subsample of patients with repeated measures. The plot displays the event study coefficients averaged across iterations, along with their 95-percent confidence intervals based on the standard deviation of coefficient estimates across replications.

Appendix Figure A.4: Program's Impact on Patient Blood Pressure—Quarterly Frequency

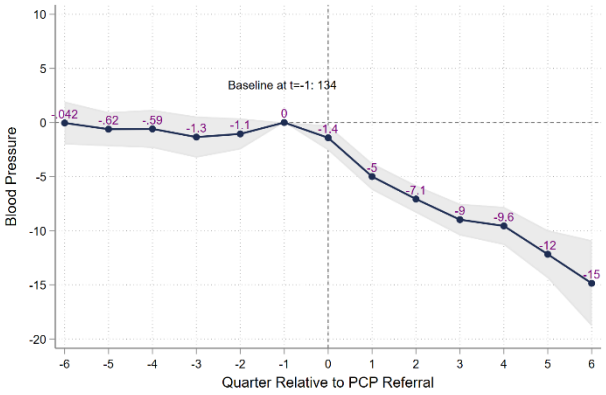
A. All Patients



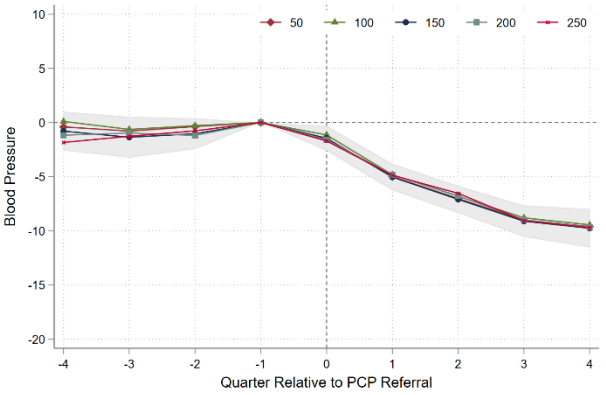
B. Patients with Repeated Measures



C. Longer Horizon



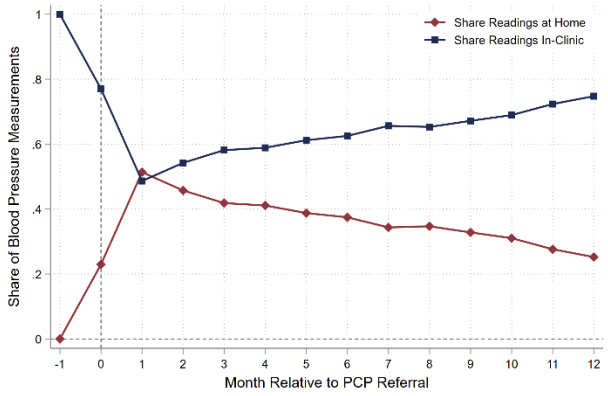
D. Patients with Repeated Measures—Robustness



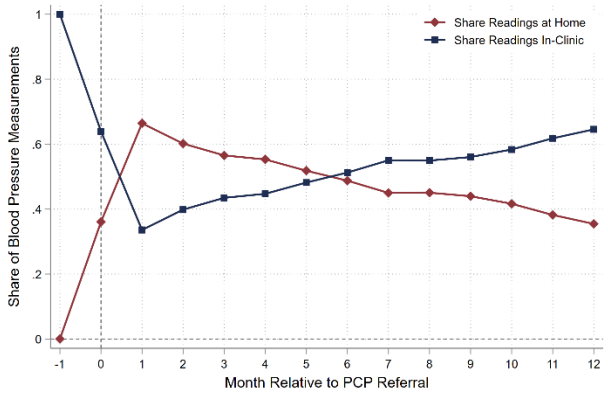
Notes: This figure evaluates the program's impact on systolic blood pressure among patients who were referred to the program. In panels A-C, we replicate panels A-C from Figure 1 at a quarterly frequency. Panel D displays the event study coefficients for different subsamples of patients with repeated 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 day up to day 365. We present plots for the threshold values of 50, 100, 150, 200, and 250 days after the referral (along with the 95-percent confidence intervals for estimates from the day 150 threshold).

Appendix Figure A.5: Method of Blood Pressure Measurement—At Home versus In-Clinic

A. All Referred Patients



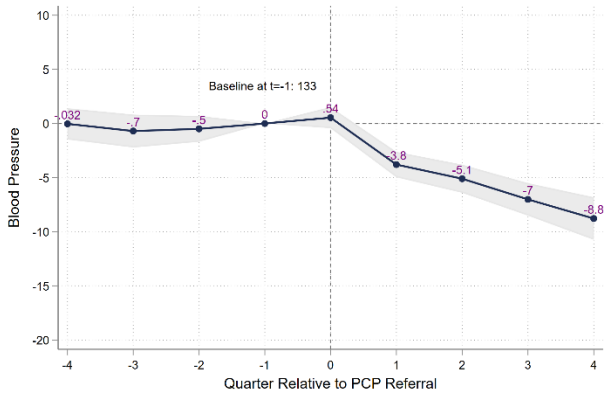
B. Referred Patients who Took Up the Program



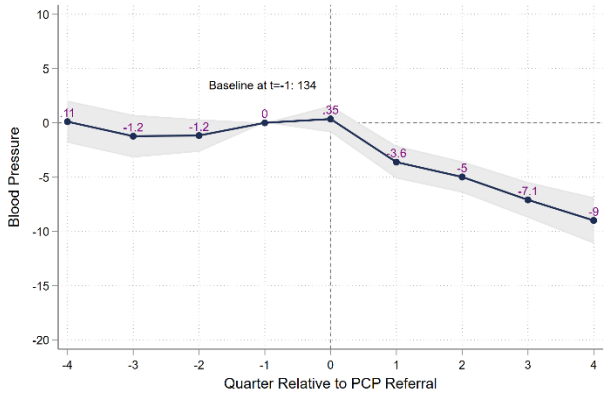
Notes: This figure displays the breakdown of blood pressures measurements by whether they were taken at home or in-clinic over the one-year horizon following the referral event. Panel A includes blood pressure readings for the entire sample of referred patients, and panel B includes blood pressure readings of only referred patients who took up the program.

Appendix Figure A.6: Program's Impact on Patients' In-Clinic Blood Pressure Measures—Quarterly Frequency

A. All In-Clinic Readings



B. In-Clinic Readings for Patients with Repeated In-Clinic Measurements



Notes: This figure evaluates the program's impact on systolic blood pressure among patients who were referred to the program using only measures taken in-clinic. This includes 1,246 referred patients among whom 60 percent were initial adopters. The plots display the quarterly-level event study coefficients from a specification of equation (2) along with their 95-percent confidence intervals, where robust standard errors are clustered at the patient level. Panel A displays the event study estimates using in-clinic readings for the entire sample. Panel B displays the event study estimates for a narrower set of in-clinic readings for patients with repeated in-clinic measurements. The latter group is comprised of patients with at least one in-clinic 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 in-clinic data point in the post-period of days 150 to 365.

Appendix Table A.2: Program's Impacts by Race/Ethnicity

Panel A: Controlled Blood Pressure Rates

	Black/Hispanic	White
Treatment Effect in Quarters 5-6	0.2234***	0.3518***
	(0.0482)	(0.0388)
Difference	-0.1284**	
	(0.0618)	
Number of Individuals	248	583
Baseline in Quarter -1	0.5968***	0.6251***
	(0.0303)	(0.0256)
Difference	-0.0283	
	(0.0397)	

Panel B: Effects on Enrollees and Active Enrollees

	Black/Hispanic	White
Treatment Effect in Quarters 1-2	-6.18	-6.67
Takeup Rate	0.5296	0.5272
Effect per Enrollee	-11.6692	-12.6517
Adoption Rate in Quarters 1-2	0.2962	0.3304
Effect per Active Enrollee	-20.8643	-20.1877

Notes: Panel A provides estimates using equation (3) for the longer-run effects of the program on the probability that a patient's systolic blood pressure drops below the 140 mark by race/ethnicity. Panel B focuses on the short run of quarters 1-2 and considers the treatment effect "per enrollee" (defined by the reduced-form effect divided by take-up rate) and the treatment effect "per active enrollee" (defined by the reduced-form effect divided by adoption rate).

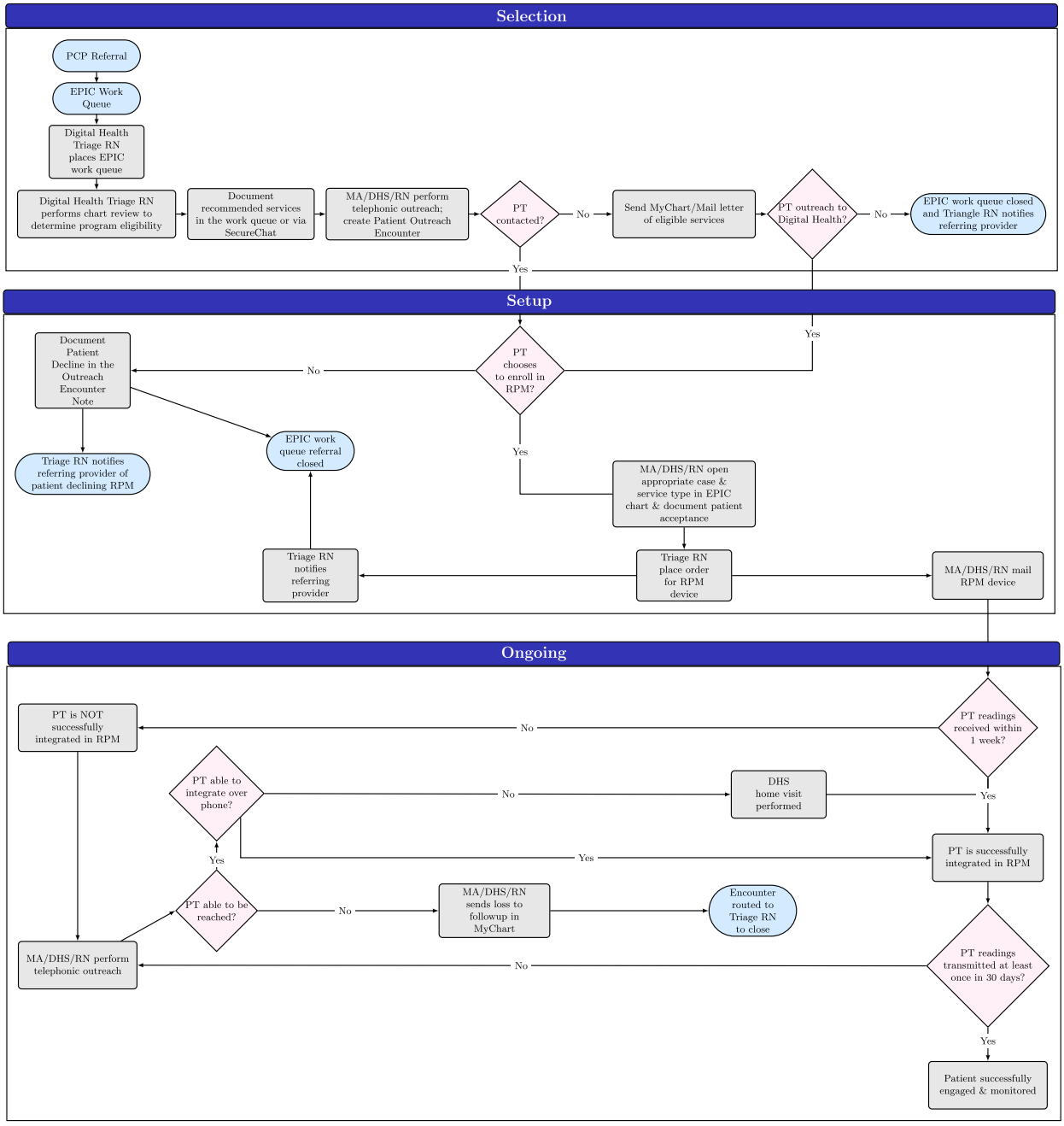
Appendix Table A.3: Program's Impact on Blood Pressure by Patient Subpopulations

	All	Age Group		Gender	
		Below 65	Above 65	Male	Female
Short Run (quarters 1-2)					
Treatment Effect	-6.72***	-6.06***	-7.03***	-7.93***	-5.67***
	(0.59)	(0.91)	(0.74)	(0.83)	(0.84)
Difference		0.98		-2.27*	
		(1.17)		(1.18)	
Number of Individuals	1,312	454	858	591	721
Medium Run (quarters 3-4)					
Treatment Effect	-9.42***	-8.09***	-9.98***	-10.48***	-8.54***
	(0.92)	(1.71)	(1.08)	(1.13)	(1.38)
Difference		1.89		-1.95	
		(2.01)		(1.79)	
Number of Individuals	1,186	410	776	544	642
Longer Run (quarters 5-6)					
Treatment Effect	-12.15***	-11.28***	-12.32***	-14.88***	-9.06***
	(1.60)	(2.96)	(1.91)	(2.28)	(2.20)
Difference		1.04		-5.82*	
		(3.51)		(3.17)	
Number of Individuals	1,019	328	691	463	556
Baseline (quarter -1)	134.06	131.36	135.32	133.79	134.27
	(0.85)	(1.67)	(0.94)	(1.41)	(1.09)
Difference		-3.96**		-0.48	
		(1.92)		(1.75)	

Notes: This table studies the program's effect on systolic blood pressure among patient subpopulations. We estimate equation (2) using the sample of patients with repeated measures. Observations from before the referral come from quarter -1. Observations from after the referral correspond to quarters 1-2 for the "short run," quarters 3-4 for the "medium run," and quarters 5-6 for the "longer run." Observations in a given month relative to referral are weighted by the inverse of the frequency of same-period observations within a subpopulation. Baseline levels are subpopulation means of the outcome in quarter -1. Robust standard errors are clustered at the patient level. *** p<0.01, ** p<0.05, * p<0.1

Appendix B: Program Details

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



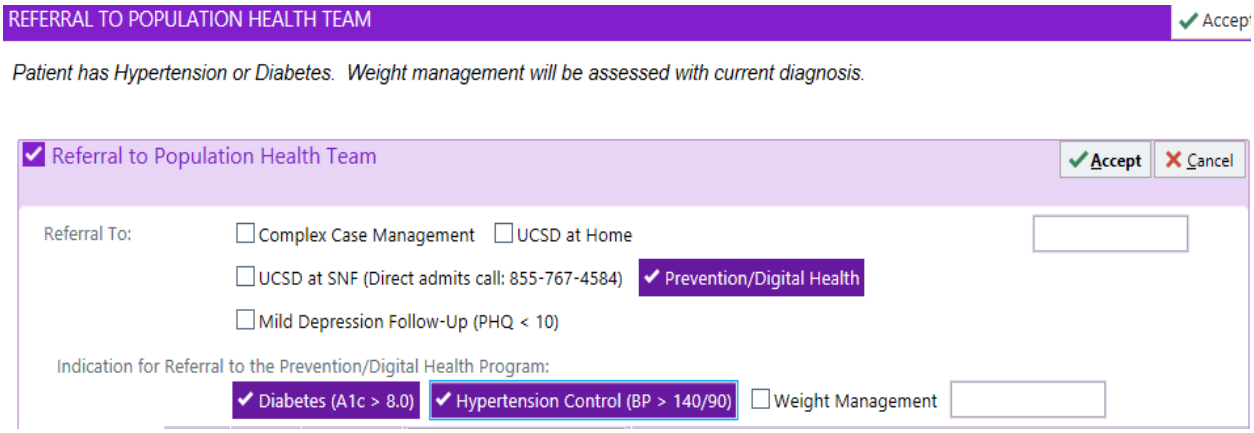
Notes: This figure provides a schematic flowchart that illustrates the stages of the program from a physician's referral of a patient to the patient's successful engagement with the program. Blue rounded boxes indicate the start and end points of a workflow, pink diamond boxes indicate decision points, 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 device, which is a Bluetooth-enabled digital blood pressure cuff. It appears in the following picture:

To be eligible to participate in the program, a patient must have a 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 indicates "Hypertension Control":

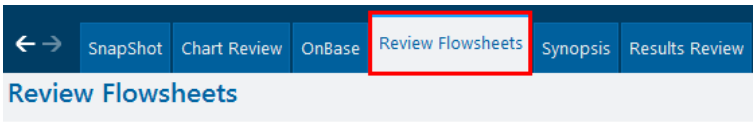


When patients measure their blood pressure, the information is synchronized through MyChart (the patient portal) and flows into the patient chart for easy review by clinicians. There are 2 methods to review these home measurements:

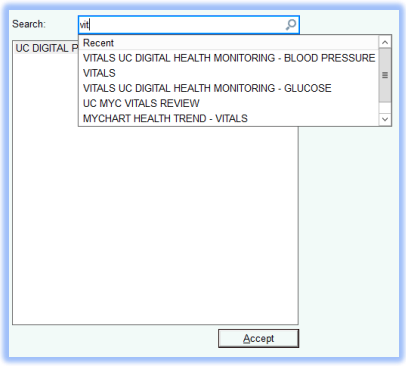
Method 1: Review Results via Flowsheets

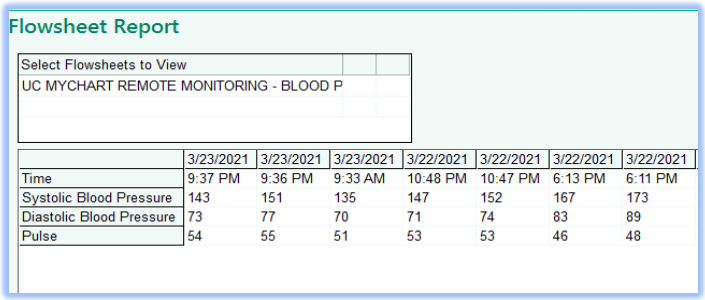
1. Open patient's chart within Epic.

2. Click the Review Flowsheets activity tab.



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



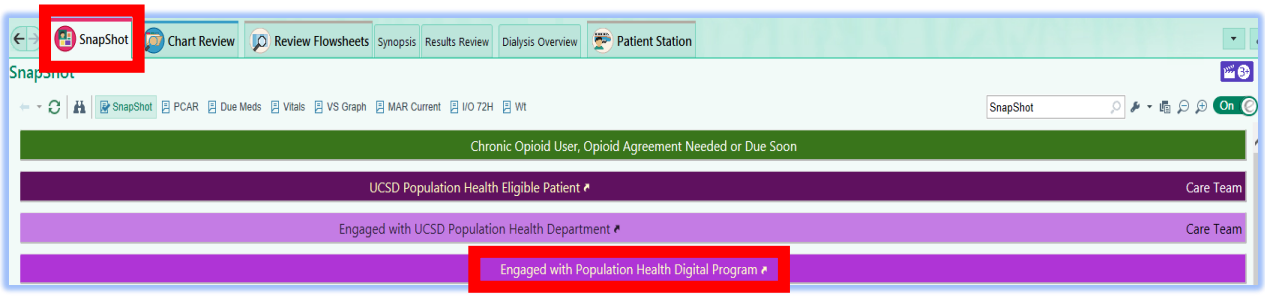


	3/23/2021	3/23/2021	3/23/2021	3/22/2021	3/22/2021	3/22/2021	3/22/2021
Time	9:37 PM	9:36 PM	9:33 AM	10:48 PM	10:47 PM	6:13 PM	6:11 PM
Systolic Blood Pressure	143	151	135	147	152	167	173
Diastolic Blood Pressure	73	77	70	71	74	83	89
Pulse	54	55	51	53	53	46	48

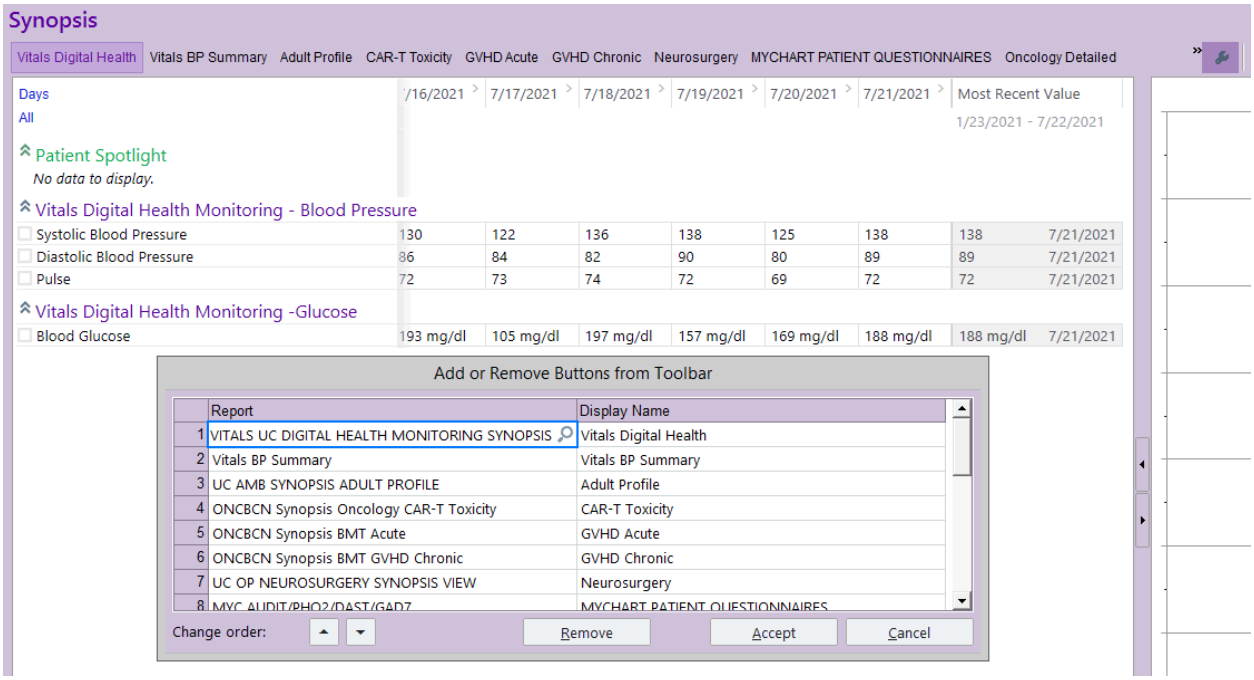
Method 2: Review Results via Synopsis

1. Once enrolled, the patient will have an “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”:


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.2: Population Health Team Digital Health Protocol for Outreach and Ongoing Care

This appendix provides the exact 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.