Ostrobothnia Digital Clinic Experiment: Statistical Analysis Plan for a Randomized Controlled Trial

Tapio Haaga, Mika Kortelainen, Oskari Nokso-Koivisto, Tanja Saxell, Meeri Seppä, Lauri Sääksvuori*

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Abstract

This randomized controlled trial (RCT) examines the impacts of a publicly provided digital clinic that offers primary care services through digital channels. Our intervention grants access to a public digital clinic that provides chat-based primary care consultations via a mobile phone application and website, including triage, diagnoses, prescriptions, and follow-up care recommendations. The digital clinic is designed to supplement traditional public primary care services, including in-person visits and phone consultations. The trial takes place in Ostrobothnia, Finland, a healthcare district serving a population of 179,000 residents. We randomize access to the digital clinic at the household level, providing access to 50% of the households. In doing so, our objective is to evaluate whether digital services can substitute, complement, or increase the utilization of traditional primary care, particularly in-person visits or calls to traditional clinics. At the end of the nine-month trial, access to the digital clinic will be expanded to the entire population.

Keywords: digital healthcare, telemedicine, digital clinic, primary care, healthcare utilization, randomized controlled trial

*Haaga: Finnish Institute for Health and Welfare (THL) and University of Turku (UTU). **Kortelainen:** UTU and THL. **Nokso-Koivisto:** Aalto University (Aalto). **Saxell:** Aalto and VATT Institute for Economic Research. **Seppä:** Aalto. **Sääksvuori:** THL.

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Contents

1 Introduction

This document outlines our statistical analysis plan for a randomized controlled trial (RCT) entitled *Ostrobothnia Digital Clinic Experiment*. Our complete analysis plan and experimental protocol consist of three separate documents written and made public in the following order:

1. A general-level pre-analysis plan (PAP) describing the main idea, study design, data sources, primary and secondary outcomes, and our statistical approach. The PAP was registered *before* initiating the trial. See our registration in the AEA RCT Registry (https://doi.org/10.1257/rct.15587-2.0) and on ClinicalTrials.gov (NCT06904469).

2. A statistical analysis plan (SAP), which maps the idea into code based on blinded/placebo data. This is the document you are currently reading. Statistical codes are included at this step of the registration, illustrating in detail how we plan to construct our variables and analysis data. We registered the SAP *after* initiating the trial and observing aggregate statistics on the utilization of digital services, but *before* linking the treatment assignment and outcome data. This process can be verified by a third party. In the SAP, we include some additional analyses compared to the PAP.

3. A populated SAP, which replaces the tables and figures in the SAP with real data after the trial has ended. At this stage, no deviations from the SAP will be made.

Finally, we will produce a research paper or series of papers, intended for publication in scholarly journals. The final research papers are distinct from the populated SAP as they may contain not only confirmatory analyses registered in the PAP and SAP but also post-blind and exploratory analyses conducted after linking the treatment indicator and outcome data. In our research papers, we will clearly differentiate between pre-registered analyses and post-blind analyses.

The structure of this SAP is as follows. Section 1 discusses the key motivation for our experiment and describes our key research questions. Section 2 describes the institutional context. Section 3 describes the intervention. Section 4 provides details on the extraction of the study population, our inclusion and exclusion criteria, and the randomization process. Section 5 presents our data sources and specifies our outcomes of interest. Section 6 presents our main statistical approach and planned key tables and figures. Section 7 outlines potential extensions to the pre-registered analyses. Appendix A discusses the likelihood of interference in the context of our experiment and presents a back-of-the-envelope model to assess the Stable Unit Treatment Value Assumption (SUTVA) in our experimental context.

1.1 Study motivation

Digital services leverage technological solutions to deliver online services to consumers through digital platforms, such as mobile applications, websites, and marketplaces. As in other digital service industries, digital platforms in healthcare offer consumers fast and easy access to services, potentially shifting demand from in-person visits and phone hold queues to online platforms. This trend is largely driven by increased convenience and lower costs of online services (Dorsey & Topol, 2020). While there is a growing body of literature examining the effects of health information technologies (Goldfarb & Tucker, 2019), the impacts of digital services remains much less well understood. Importantly, digital healthcare services may not only substitute for traditional health care but also induce new demand and utilization that would not have occurred without the digital channel (Dahlgren et al., 2023; Ellegård et al., 2022). The convenience of digital care (no time spent traveling, shorter waiting times, extended opening hours, and access from any geographical location) can lower the barriers to access, potentially reducing underdiagnosis and undertreatment, or, conversely, exacerbating the utilization of medically low-value services.

Through random assignment of patients to a digital clinic, our objective is to contribute to a better understanding of the impacts of digital healthcare services. We conduct a large, region-wide RCT in Finland, where we randomly grant access to digital primary care services. Our intervention is implemented at the household level and provides digital medical services during a nine-month period to 50% of households in an administrative region with approximately 179,000 individuals.

The digital clinic provides chat-based primary care consultations through a mobile app and website, offering consumers fast access to healthcare professionals. Services include care needs assessments, diagnoses, follow-up recommendations, and prescriptions. Thus, the digital clinic supplements traditional primary care services, including in-person visits and telephone consultations. Consequently, a key question of scientific and policy relevance is whether and how digital clinics affect the utilization of primary care services.

1.2 Research questions

Our main research questions are the following:

A. What is the impact of having *access* to the digital clinic on the use of digital clinic services (*i.e.*, take-up)?

B. What is the impact of having *access* to the digital clinic on the utilization of traditional primary care services (intent-to-treat effect, ITT)?

C. **What is the impact of *using* the digital clinic on the utilization of traditional primary care services (average causal response, ACR)?**

D. What is the impact of having *access* to the public digital clinic on the overall utilization of public primary care services, including both the digital clinic and traditional primary care services (ITT)?

In our research, we prioritize the importance of research question C. Beyond its policy relevance, the ACR estimate accounts for expected non-compliance in using the digital clinic.[1] However, we list our research questions here in a sequential order from A to D, as we are unlikely to detect the impact of using the digital clinic on any downstream outcomes if the take-up of the digital clinic during the trial period is not large enough.

[1]See Angrist and Hull (2023) for an illustration for the importance of accounting for non-compliance in pragmatic randomized trials.

Besides our main analysis on the impacts of the use of the public digital clinic on the use of *traditional public primary care*, we register two other families of outcomes in this SAP.

First, we are interested in whether improved access to and the utilization of the public digital clinic can reduce reliance on more expensive *specialized healthcare at hospitals, such as referrals to hospitals, emergency department (ED) visits – either telemedicine or in-person – or outpatient hospital visits*. This could happen, for example, if the improved access to the public digital clinic enhances health by enabling earlier medical intervention and preventive care. We note that the power to detect differences in some of these outcomes is expected be lower than for our pre-registered outcomes restricting to primary care. These analyses will be informative about the digital clinic's role in optimizing the delivery and utilization of healthcare services.

Second, we will examine whether the use of the public digital clinic reduces *telemedicine contacts or in-person visits with private clinics or occupational healthcare*. In other words, we examine whether the use of the public digital clinic has impacts on other sectors that complement public primary care.

2 Institutional background

2.1 Primary care in Finland

Finland has a decentralized, universal healthcare system that primarily relies on the public provision of health services. By law, the wellbeing service counties (21 in total) are responsible for organizing public health and social care services, including public primary care (PPC), for their residents. PPC services are characterized by gatekeeping, varying and sometimes long waiting times, and moderate copayments.[2] Primary care services provided by employer-sponsored occupational healthcare and the private sector complement the services provided by PPC, which is disproportionally important for low-income individuals, unemployed, and pensioners. Fast access

[2] There are no co-payments for nurse visits. The maximum co-payment for general practitioner visits is 23€ for the first three visits annually.

and no copayments make occupational healthcare an attractive alternative to PPC for those who have access to it. There are also private clinics with fast access and no gatekeeping (even for specialists), albeit with fees much higher than in PPC.

2.2 Traditional public primary care

Traditionally, patients first contact a nurse by phone (hold queue or a call-back service) or by visiting a traditional PPC clinic. The nurse then conducts a care needs assessment, provides potential self-care guidance, and, acting as a gatekeeper, books a phone consultation or an in-person appointment for a physician or other professionals if needed. Team-based models, based on collaboration and consultative interactions between physicians and nurses, are common in PPC, with the goal of optimizing healthcare delivery and addressing issues even during the first contact, reducing the need for follow-ups.

2.3 Public digital clinic

We study the launch of a public digital clinic by a wellbeing services county. Following the widespread adoption and use of digital clinics in occupational healthcare and the private sector, several wellbeing service counties (PPC providers) have launched their own digital clinics in 2020s as a remote, chat-based access channel to complement their traditional clinic-based service provision.[3] Digital clinics aim to provide patients fast access to healthcare professionals (here: nurses and physicians) through chat, available through a mobile application or website, with extended opening hours and waiting times measured in minutes. Compared with traditional clinics, digital clinics can reduce barriers to healthcare access through extended opening hours, shorter waiting times, and reduced travel time to a health clinic for an in-person visit. While digital clinic services are not suitable for all patients and health conditions, these services offer many patients fast, easy, and user-friendly access to primary care. The most common medical issues treated

[3]Patients can choose to contact a public or private clinic (traditional or digital). In the private sector, patients can access digital clinic services through occupational healthcare (employed working-age population), voluntary private health insurance, or by paying the full out-of-pocket cost.

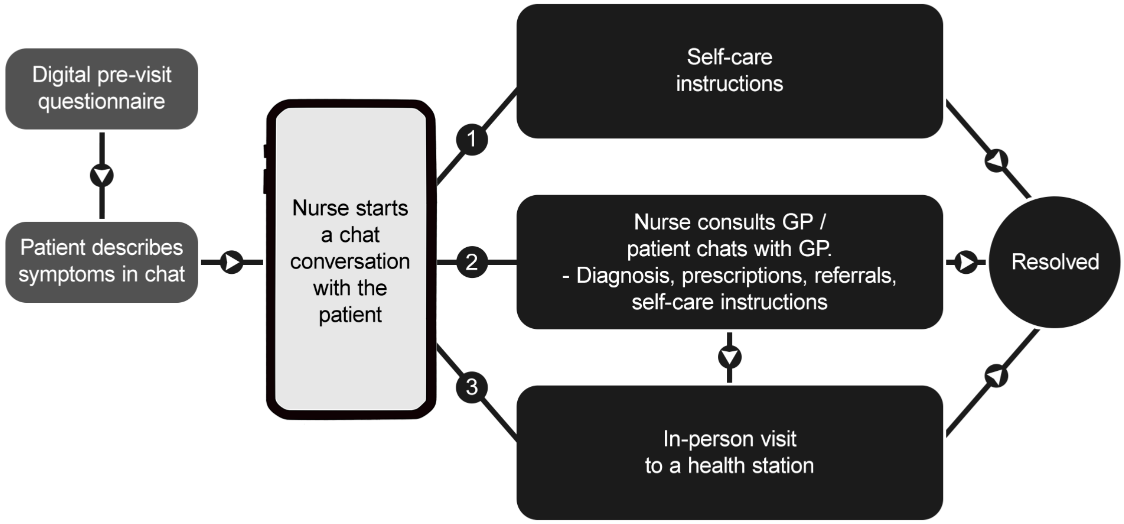

Figure 1: Potential care paths for a patient who experiences a care need and chooses to contact the public digital clinic instead of traditional public primary care by phone or by visiting a traditional PPC clinic in person.

in digital clinics are cold symptoms, stomach problems (e.g., diarrhea, vomiting), gynecological problems, skin problems, allergies, eye infections, and mental health problems.

Figure 1 illustrates the use of a public digital clinic from the patient's perspective and the potential care paths after the digital clinic contact. Logging into the digital clinic via a mobile application or website requires verifying a person's identity through online banking credentials or a national authentication service for public services. Thereafter, the patient fills out a digital pre-visit questionnaire before a healthcare professional, often a nurse, performs a care needs assessment, asking follow-up questions via chat. In broad terms, the patient may i) receive instructions from the nurse for self-care and health monitoring, ii) be directed to a physician at the digital clinic (nurse-physician consultation or patient-physician chat), for diagnoses, prescriptions, or referrals (for lab tests or specialist visits), or iii) be directed to an in-person visit to an appropriate professional at the traditional PPC clinic.

From the provider's perspective, digital clinics allow healthcare professionals to manage several patients at the same time via chat, unlike in traditional clinics, where they manage one patient at a time in person or by phone. Consequently, compared with traditional clinics, digital clinics can save professionals' time as no time is wasted waiting for the next patient. The model also allows professionals to specialize in telemedicine and in the chat-based user interface. The task of asking routine questions is automated in the digital clinic via a pre-visit questionnaire. Having a large customer base with enough contacts outside typical office hours makes extended opening hours possible.

3 Intervention

The Wellbeing Services County of Ostrobothnia, a mid-sized administrative region in Western Finland (Figure 2), launched its *digital clinic platform*, a website and app for its digital services, on April 15, 2025. Over time, the digital clinic platform will include several different chat channels for various services. The main channel, the *digital clinic*, is a chat channel to contact primary care professionals. The initial contact will be with a nurse, after which the nurse has the opportunity to consult with a physician. Primary care patients with new health issues who choose to contact the digital clinic are expected to log in with strong identification for a care needs assessment and treatment. At the time of writing, the digital clinic is open from 8 AM to 2 PM on Monday through Thursday and from 8 AM to 1 PM on Fridays,[4] but Ostrobothnia is considering an extension to these opening times. Other chat channels that Ostrobothnia has launched, such as a chat for social services, a chat for rehabilitation, and a chat for customer service, do not require strong identification, and are not intended to serve as a substitute for the digital clinic.

3.1 Access to the digital clinic

Our intervention randomized access to the digital clinic for a nine-month period, starting on April 15. The randomization assigned households to two groups that either have access (*the treatment group*) or do not have access (*the control group*) to the newly launched digital clinic. Individuals

[4]The telephone service, a potential substitute, is is open from 8 AM to 3 PM on Monday through Thursday and from 8 AM to 2 PM on Fridays.

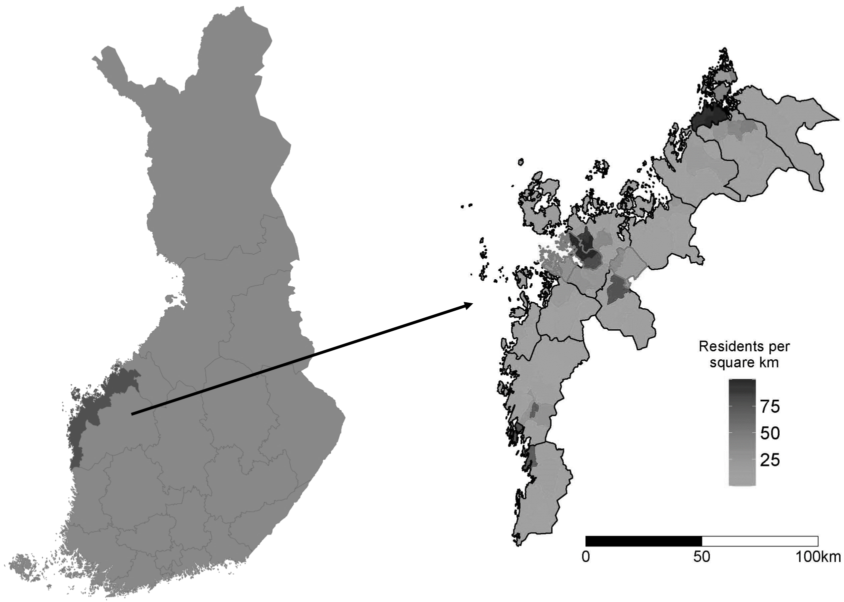

Figure 2: The Wellbeing Services County of Ostrobothnia is located in Western Finland.

Notes: By law, the Wellbeing Services County of Ostrobothnia is responsible for organizing public health, social, and rescue services, including public primary care (PPC), for its residents. Ostrobothnia has the highest share of Swedish speakers in Finland, with a Swedish-speaking majority in many municipalities. Unlike most of Finland, which is Finnish-dominated, Ostrobothnia has a strong bilingual culture. Unlike the heavily urbanized capital region, Ostrobothnia has a balanced mix of urban centers and strong rural communities. The region also has strong religious traditions, which have contributed to socially conservative values in some areas.

in the treatment group had access to the digital clinic immediately after its opening. The entire population residing in the region will have access to the digital clinic after the nine-month trial period. The trial does not affect access to other available alternatives for contacting primary care, such as traditional PPC, occupational healthcare, or private clinics.

Individuals in the treatment group can access the digital clinic by logging into the clinic via a mobile application or website, using strong identification and personal identity number. We expect that some individuals belonging to the control group may try to log in to the digital clinic. In this case, their access will be automatically denied based on their identity number. Moreover, the digital clinic platform will display a short message notifying them that their access to the platform is currently blocked because the digital clinic is being tested with a subset of the population, but that they will ultimately get access to the digital clinic after the test period.

3.2 Communication with the treatment group

The intervention (access to the digital clinic) was accompanied by an information campaign targeting all households in the treatment group. The primary communication channel with the treatment group was through mailed letters. These letters informed recipients about their option to use the digital clinic during the trial period and provided instructions on what the digital clinic is, and how to use it, as well as the rationale for granting access initially only to a randomly-selected subgroup of the population. These letters were sent on the first week of May, 2025.

These information letters were sent to all households belonging to the treatment group. We sent one letter per household and randomized the recipient within the household so that all household members over the age of eighteen had the same probability of receiving the letter. In a small sample of households consisting only of minors, all individuals aged 15 to 18 had an equal probability of receiving the letter. There were no information letters addressed to individuals under the age of fifteen.

3.3 Population-wide information during the study period

The scale of the digital clinic launch and the significant changes in available healthcare services were expected to generate public discussion and interest in the reform. In response, the Wellbeing Services County of Ostrobothnia issued a press release about the digital clinic launch, its staggered implementation, and the associated informational letters to the treatment group on April 11, 2025, shortly before the launch of the digital clinic.

The launch of the trial received moderate media attention. YLE, one of the largest media outlets in Finland, wrote a brief article about it on April 11. In May 2025, the trial was mentioned in a local news paper *Vaasa-Pohjanmaa* (May 27th) and in the Finnish doctors' association's own publication *Lääkärilehti* (May 27th). In addition, the Ministry of Social Affairs and Health published an article on the trial on their website (May 28th). In June, a local newspaper *Vasabladet* reported about the launch of the trial (June 2nd).

At the time of writing, Ostrobothnia has conducted or plans to conduct the following information campaings: 1) Paid advertisement on social media on their digital platform (the app) and the digital clinic (the chat). 2) Digital messages to parents of schoolchildren informing about the digital platform and the digital clinic. 3) An information letter to all households in early October 2025, advertising seasonal influenza vaccinations, and informing about the services of the wellbeing services county, as well as the digital platform and the digital clinic. 4) A press release on the early experiences with the digital clinic: the utilization rates and experiences of patients and healthcare professionals.

4 Study design

4.1 Target and study population

We extracted individuals whose municipality of residence was within the Ostrobothnia region on March 14, 2025 (target population). Our inclusion criteria required individuals to be alive at the time of extraction and to have a registered permanent address.[5] We additionally excluded individuals residing in the city of Kristinestad, as PPC services in this municipality are outsourced to a private provider. Finally, we aimed to exclude individuals residing in institutional care homes. We defined institutional care homes as residences where more than two individuals aged over 80 years lived or where more than four individuals over 60 years lived. We identified no other scientific or ethical reasons to exclude any other individuals who met the inclusion criteria from randomization. See Figure 3 for our target population and sample sizes.

[5] The permanent address was missing for 1% of the population. Age, gender, or language did not appear to be correlated with the address being missing. The permanent address is not recorded for individuals with a protection order (approximately 0.2% of the population nationally). The protection order is a legal measure in Finland that restricts the disclosure of an individual's address and other personal information in official registries to protect their safety and privacy.

However, in our analyses, we will restrict the sample to individuals aged 0 to 70 to have more statistical power. Moreover, we exclude from the analysis, but not from the randomization, those individuals who are observed in the Finnish Population Information System (study population) but not in the Statistics Finland datasets (background covariates used in analysis) – see Section 5. The number of such individuals is expected to be small. We can report the number only after linking the treatment indicators with the relevant administrative datasets.

4.2 Randomization

We randomized treatment at the household level based on permanent addresses, ensuring that all members of a household were assigned to the same treatment group. Households were stratified by size to maintain balance across different household compositions. Within each stratum, we randomly assigned 50% of the households to the treatment group (a 1:1 ratio). Specifically, for each household ID cluster, we generated a random floating-point number and sorted the clusters by this value within each household size group. Households in the top 50% of these sorted values were assigned to the treatment group.[6]

Moreover, we randomized one recipient of the information letter (see Section 3.2) per treated household as follows: All household members over the age of eighteen had the same probability of receiving the letter. In a small sample of households consisting only of minors, all individuals aged 15 to 18 had an equal probability of receiving the letter. The randomization code, like all other code, is available in the Github repository of this project.[7]

[6]The actual proportion of treated households and individuals may not be exactly 50%. If the remainder when dividing the stratum size by 2 was not zero, we randomly varied between using the floor and ceiling function within each stratum to select the number of treated units. This approach ensures that approximately half of the units are in the treatment group.

[7]https://github.com/SoteDataLab/ostrobothnia_digi_rct

5 Data and outcomes

5.1 Data sources

This study uses multiple Finnish administrative data sources containing individual-level data. The datasets are merged via pseudonymized person identifiers (IDs). Figure 3 summarizes different steps in our research design, including target population construction, randomization, and the construction of the analysis data and study population. We use the following data sources:

- Finnish Population Information System maintained by the Digital and Population Data Services Agency. This dataset was used to extract the target population on March 14, 2025.

- Register of Primary Care Visits maintained by the Finnish Institute for Health and Welfare. This dataset contains contacts with public primary care, private outpatient care, and occupational healthcare. We use data from 4/2024–1/2026. ***Note: we use data from 4/2022–1/2024 in the SAP.***

- Full population data on the socioeconomic and sociodemographic characteristics of Finnish residents, maintained by Statistics Finland (FOLK population data and INFRA location data) from 2024. *Note: At the time of writing, the latest data is available for year 2023. Data for the year 2024 is expected to be released in spring 2026. Due to this release lag, we use the data for year 2023 for the populated SAP, and the data for the year 2024 for the final research paper(s). The choice of the FOLK statistical data year affects the sample sizes of the analysis data. For example, restricting the analysis to the year 2023 data excludes from the analysis sample individuals born between January 1, 2024, and March 14, 2025.*

- Hospitalizations and contacts with specialized health care from the Care Register for Health Care, maintained by the Finnish Institute for Health and Welfare. We use these data from 4/2024 to 1/2026. ***Note: we use data from 4/2022–1/2024 in the SAP.***

- Reimbursements for private doctor visits from the Finnish Social Insurance Institution. We use these data from 4/2024 to 1/2026. ***Note: we use data from 4/2022–1/2024 in the SAP.***

- Entitlements to prescription drug reimbursements at a higher rate of special reimbursement from the Finnish Social Insurance Institution from 2024.

- Moreover, our data set includes self-collected data on the location (address) of traditional PPC clinics in September 2023 from the websites of PPC providers.

Access to the data. The research data are governed by their owners listed above. Access to the healthcare data can be obtained by sending a request to the Finnish Social and Health Data Permit Authority, Findata (https://findata.fi/en/). Access to demographic administrative data can be obtained by sending a request to Statistics Finland (https://www.stat.fi/en).

5.2 Data cleaning and preparation

This SAP is accompanied by detailed R code on the construction of our variables, analysis data, and the study population (link: https://github.com/SoteDataLab/ostrobothnia_digi_rct). The SAP code defines how variables are constructed, missing data are handled, and transformations or aggregations are conducted. Note that:

- If an individual from the target population, extracted from the Population Information System, is not observed in Statistics Finland datasets, which is defined as not having a municipality of residence (missing data) at the end of 2024, we will not use that individual in the study population in the analyses because we do not have covariates for the individual.

- Some analyses in the final research paper will be post-blind, *i.e.*, implemented after unblinding the data by linking treatment indicators and outcomes. In these cases, the data construction choices will also be post-blind.

- There may be outliers, *e.g.*, individuals with suspiciously high health care utilization, leading to suspicion about duplicate values in the data (one underlying contact could be linked to several rows in the data). By defining health care contacts as the number of days with any contact (see Section 5.3) should partially alleviate the risk that outliers pose to the estimates. Our plan is

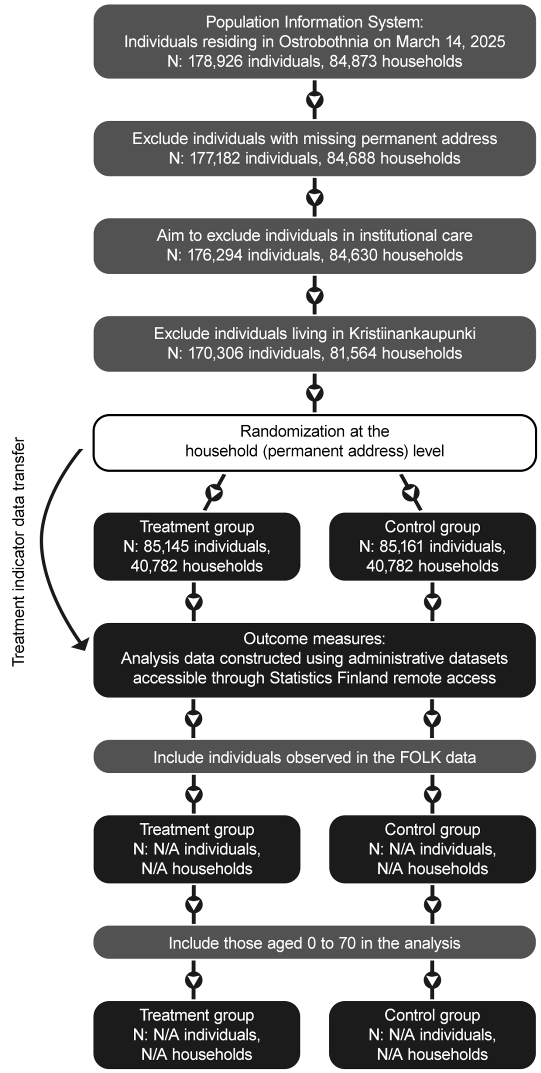

Figure 3: Target Population, Randomization, and Data Construction

Notes: At the time of writing, we cannot report the exact sample sizes of the analysis data, only the sample sizes of the randomization data. This is mainly because the exact sample sizes of the final research paper will be observed only after merging Statistics Finland full population data (FOLK) of 2024 with the treatment indicator data (or the FOLK data for 2023 for the statistical analysis plan, SAP, see Section 5). At the time of writing, the latest statistical year fully available is 2023. The year 2024 is expected to become fully available in spring 2026. For example, restricting the analysis to the FOLK statistical year 2023 would exclude from the analysis sample individuals born between January 1, 2024, and March 14, 2025, as they are not observed in the FOLK data for 2023. The second reason is that our plan is to bring the treatment indicator data into the remote access computer (*i.e.*, unblind the data) only after registering this SAP. This is done to create a credible and verifiable firewall between planning the SAP and observing any results.

to include potential outliers in the main analysis, but we may conduct a robustness check to examine whether the estimates change as a result when excluding individuals with suspiciously high health care utilization from the analysis.

5.3 Outcomes Y1.X and D.X: the utilization of public primary care

In this subsection, we list the outcomes registered earlier in the PAP. They were restricted to curative outpatient contacts in the public primary care.[8] The definitions of outcome variables are based on three additional variables: health care provision unit's identifier, contact type (telemedicine or traditional), and the profession (nurse or physician) of the provider.

As stated in Section 1, our main interest is in estimating the impact of *using* the public digital clinic on the use of traditional PPC services. Accordingly, we need to estimate impacts not only on the utilization of traditional PPC (ultimate outcome of interest) but also on the utilization of the digital clinic (take-up). We measure the annualized number of digital clinic contacts in PPC (D. digital clinic utilization; take-up) and the annualized number of contacts to traditional PPC clinics (Y. traditional PPC utilization; reduced form).[9] We count all contacts received during the same day as one contact or visit.

Our primary outcomes include the following types of contacts:

- **in-person visits in PPC (Y1.1)**. Our main research question is whether the use of digital clinics can reduce contacts with traditional PPC, including in-person visits and phone contacts. Of these contacts, we chose in-person visits as our primary outcome. In-person visits are more expensive to provide than phone contacts and require face-to-face interaction. At the same time, we expect that other contacts with traditional PPC, involving telemedicine (mainly phone calls) and professional-to-professional interactions, are a closer substitute for digital clinic contacts than

[8]Restricting to curative contacts should exclude preventive contacts, such as seasonal influenza vaccinations. Restricting service type to outpatient care should exclude visits to other service types, such as school and student healthcare, dental care, or occupational healthcare.

[9]We compute the annualized number of contacts during our 9-month follow-up period by dividing the total number of contacts by 9 and multiplying it by 12.

in-person visits. *This outcome includes in-person visits to nurses and physicians in traditional PPC clinics.*

- **the number of public digital clinic contacts (D.1)**. This outcome is required for estimating the impact of *using* the public digital clinic on the utilization of traditional PPC. *This outcome includes care needs assessments, remote appointments to nurses and physicians (via chat), and professional-to-professional interactions between nurses and physicians in digital PPC clinics.*

Our secondary outcome can help provide a more nuanced picture of whether the use of the digital clinic can reduce pressure on traditional PPC as compared to focusing strictly on in-person visits, which represent only a minority of contacts in traditional PPC. It includes all traditional PPC contacts except in-person visits:

- **other contacts with traditional PPC (Y1.2)**. We expect that the substitution rate between digital clinics and traditional PPC is higher with respect to this outcome, compared to in-person visits (Y1.1). Other traditional PPC contacts involve remote contacts (*e.g.*, phone calls between professionals and patients and professional-to-professional interactions) and are likely to be a closer substitute for digital clinic contacts than in-person visits. *This outcome includes care needs assessments, remote appointments to nurses and physicians, and professional-to-professional interactions between nurses and physicians in traditional PPC clinics.*[10]

Finally, we have two tertiary outcomes:

- **the total number of PPC contacts (Y1.3)**. We expect that the digital clinic access will increase the total number of contacts to PPC, including the digital clinic and the traditional PPC. The question is: by how much? *This outcome includes in-person visits to nurses and physicians, care needs assessments, remote appointments to nurses and physicians,*

[10]While our institutional knowledge suggests that nurses' care needs assessments and professional-to-professional interactions in traditional PPC are often done remotely on rather than in-person with the patient being present, our data does not distinguish between these contact types for these outcomes.

and professional-to-professional interactions between nurses and physicians in digital and traditional PPC clinics.

- **an indicator for having any public digital clinic contact during the follow-up (D.2)**. The purpose of adding this outcomes is to allow interested readers to construct the Local Average Treatment Effect (LATE) parameter by dividing reduced-form estimates on Y1.1 and Y1.2 by D.2. In other words, this outcome is an alternative approach for estimating the impact of *using* the public digital clinic on the utilization of traditional PPC. *This outcome includes care needs assessments, remote appointments to nurses and physicians (via chat), and professional-to-professional interactions between nurses and physicians in digital PPC clinics.*

5.4 Outcomes Y2.X: the utilization of specialized healthcare at hospitals

Our second family of outcomes includes variables related to hospital utilization. There are four outcomes in this domain.

- **The number of referrals to hospitals (Y2.1)** *This outcome includes the total number of referrals from public primary care to hospitals*.
- **The number of in-person ED contacts (Y2.2)** If the digital clinic access has an effect on the number of emergency department visits, we would expect it to be stronger for telemedicine contacts. Therefore we divide emergency department visits into two outcomes: in-person and other. *This outcome includes all in-person emergency department visits.*
- **The number of other ED contacts (Y2.3)** *This outcome includes all remote contact to emergency department as well as professional-to-professional interactions at the emergency departments.*
- **The number of outpatient hospital visits (Y2.4)** We focus on out-patient visits, as we do not expect to see any effect on longer hospital stays. *This variable includes all in-person out-patient contacts to hospitals in public sector.*

5.5 Outcomes Y3.X: impacts on the utilization of private clinics and occupational healthcare

Our third family of outcomes focuses on the potential impacts of the use of the public digital clinic on the use of other sectors, namely private clinics and occupational healthcare. We have four outcomes in this domain:

- **in-person visits in occupational healthcare (Y3.1)**. *This outcome includes in-person visits to nurses and physicians in occupational health care.*

- **other contacts with occupational healthcare (Y3.2)**. Occupational clinics are free-of-charge for patients at the point of use. For this reason, we assume that the public digital clinic utilization is hardly a substitute for telemedicine in occupational health care. *This outcome includes telemedicine contacts (chat, video, and calls) to nurses and physicians in occupational health care.* Due to data limitations, we cannot separate digital contacts from other telemedicine contacts.

- **in-person visits in private healthcare (Y3.3)**. *This outcome includes in-person visits to physicians in private clinics that are reimbursed by the Finnish Social Insurance Institution.*

- **other contacts with private healthcare (Y3.4)**. This outcome includes, among others, contacts with private digital clinics that are reimbursed by the Finnish Social Insurance Institution, which we think are the closest substitute for the public digital clinic. For instance, parents who earlier contacted a private digital clinic for their ill children may start to use the public digital clinic (lower out-of-pocket costs) once it is launched. *This outcome includes reimbursed telemedicine contacts (chat, video, and calls) to physicians in private clinics.* Due to data limitations, we cannot separate digital contacts from other telemedicine contacts.

6 Statistical analysis

6.1 Estimation and inference

To answer our research questions specified in Section 1.2, we estimate two statistical models. Our first model uses Ordinary Least Squares (OLS) to estimate the impacts of *access* to the public digital clinic. We estimates the impacts of digital clinic *access* on outcomes related to i) the utilization of the public digital clinic (D.1 and D.2; *take-up*), ii) the utilization of traditional PPC services (Y1.1 and Y1.2), and iii) the total utilization of PPC (Y1.3), including traditional and digital services. We estimate the following model for individual *i*:

$$Y_i = \beta_0 + \beta_1 1(Treatment)_i + \beta_2 X_i + \varepsilon_i, \tag{1}$$

where Y_i is the outcome of interest and $1(Treatment)_i$ is an indicator variable equal to one if the individual belongs to a household randomly assigned to the treatment group and zero if the individual belongs to a household randomized to the control group. X_i is a vector of control variables, defined at the end of this subsection. β_0 is an intercept, and ε_i is the error term. Our parameter of interest is β_1, which measures the causal effect of *access* to the public digital clinic on the corresponding outcome (D.1–D.2, Y1.1–Y1.3).

Our primary objective is to estimate the impact of *using* the public digital clinic on downstream outcomes. For this purpose, we account for non-compliance in the RCT, unlike in the estimation of ITT effects using Model 1. This non-compliance occurs because not all individuals in the treatment group are expected to use the digital clinic.[11] Due to this non-compliance, the impact of *using* the digital clinic can be expected to be different from the impact of *having access to* the clinic (ITT).

[11]Our experiment has one-sided non-compliance. All individuals in the treatment group cannot be expected to use digital health care services during the follow-up period, but none of the individuals in the control group are by construction able to use the digital clinic during the follow-up period.

Our second model estimates the impacts of *using* the public digital clinic (D.1) on the utilization of traditional PPC services (Y1.1 and Y1.2), using Two-Stage Least Squares (2SLS) and the random assignment into the treatment group as an instrumental variable for the utilization of the public digital clinic.[12] Specifically, our parameter of interest is *the average causal response (ACR)*, which is defined as a generalization of the Local Average Treatment Effect (LATE) to settings where the treatment variable is multi-valued rather than binary (Angrist & Imbens, 1995). It represents the expected causal effect of a unit increase in the treatment variable (the number of digital clinic contacts) for individuals whose treatment status (digital clinic use) is influenced by the instrument (randomization).[13]

We estimate for individual i the following model using 2SLS:

$$\begin{aligned} D_i &= \alpha_0 + \alpha_1 1(Treatment)_i + \alpha_2 X_i + \varepsilon_i, \\ Y_i &= \pi_0 + \pi_1 \widehat{D}_i + \pi_2 X_i + \zeta_i, \end{aligned} \tag{2}$$

where $1(Treatment)_i$ is an indicator variable equal to one if the individual belongs to a household randomly assigned to the treatment group and zero if the individual belongs to a household randomized to the control group; D_i is the number of public digital clinic contacts (D.1) and $\widehat{D}$ is its predicted value based on the first equation, and Y_i is the outcome of interest (Y1.1–Y1.2). Moreover, X_i is a vector of control variables, defined at the end of this subsection. α_0 and π_0 are intercepts, and ε_i and ζ_i are the error terms. The parameter of interest, π_1, is the estimated average causal response (ACR).We use outcome D.1 as the take-up outcome in the 2SLS regressions.

Covariates: We include the following fixed effects as covariates (X_i) in all regressions (OLS and 2SLS): the previous number of in-person visits in PPC (Y1.1), an indicator variable for having

[12]See Angrist and Imbens (1995), Angrist et al. (1996), and Imbens and Angrist (1994) for the econometric and statistical background of using 2SLS estimation in randomized controlled trials.

[13]Formally, the ACR is a weighted average, over all values of d (potential intensity of the treatment), of the effect of increasing treatment from $d-1$ to d among switchers whose treatment status goes from strictly below to above d over time (Angrist & Imbens, 1995). In our application, we interpret it to measure the degree of substitution between the public digital clinic and traditional PPC for compliers who consult the digital clinic more only because they were offered access to it.

at least one previous contact with occupational healthcare during 12 months preceding the trial, age (in years), gender, municipality, income percentile, language, distance quartile to the nearest traditional PPC clinic, and indicators for having a common chronic disease and multimorbidity.[14] These covariates are expected to be uncorrelated with the treatment indicator, but can substantially improve the precision of our estimates.

Standard errors: Standard errors are clustered at the permanent address level, which corresponds to the level of randomization.

Multiple hypothesis testing: In the PAP and in this SAP, we do not pre-specify a plan to adjust for multiple comparisons in our main results table, Table 3, but we specify a hierarchy of outcomes (primary, secondary, tertiary) in Section 5.3. Consequently, we report p-values only for the primary outcome (the ACR and ITT effects on the number of in-person visits in PPC, Y1.1) and report 95% confidence intervals without p-values for all secondary and tertiary outcomes. The confidence intervals for secondary and tertiary outcomes will not be adjusted for multiple comparisons, suggesting that inferences drawn from these outcomes may therefore not be reproducible. However, for the other results tables registered in this SAP (Table 4 and Table 5), instead of p-values, we report sharpened q-values proposed by Benjamini and Yekutieli (2001) within each family of outcomes (Y2.X and Y3.X). The confidence intervals remain unadjusted.

6.2 Planned tables

We describe here our key pre-registered analyses to be included in our research paper intended for publication in a scholarly journal.

Table 1: Characteristics of the Residents at Baseline. This table presents the means, standard deviations (SD), percentage differences in means (difference %), and standardized mean

[14]The common diseases covered here include special reimbursement rights for cardiovascular diseases, diabetes, respiratory diseases, rheumatic diseases, cancer, neurological diseases, and severe mental health disorders. Multimorbid individuals are defined as those with special reimbursement rights for at least two out of three: cardiovascular diseases, respiratory diseases, and diabetes.

differences (SMD) of several baseline covariates for the treated and control individuals, as well as means for the populations of Ostrobothnia and Finland.

Table 2: Characteristics of Public Digital Clinic Users vs. Traditional PPC Clinic Users in the Treatment Group in Ostrobothnia. This table presents the means, standard deviations (SD), percentage differences in means (difference %), and standardized mean differences (SMD) of several baseline covariates for the users of public digital clinics and for the users of traditional PPC services among treated individuals, as well as means and SDs for the total population of Ostrobothnia. The hypothesis is that the digital clinic users differ noticeably from the general population and from the population that use traditional PPC services.

Table 3: Effects of Access and Utilization of Public Digital Clinic on the Utilization of Traditional Public Primary Care. This table illustrates how we plan to report the results of our pre-registered confirmatory analyses. In Panel A, we report the impact of having *access* to the public digital clinic on the use of the public digital clinic (take-up). In Panel B, we report the impact of having *access* to the public digital clinic on the use of traditional PPC services and the total use of PPC (intent-to-treat effect, ITT). In Panel C, we report the impact of *using* the public digital clinic on the use of traditional public primary care services (average causal response, ACR). Here, we use outcome D.1 (the total utilization of the digital clinic in PPC) as the take-up outcome in the 2SLS regressions (see Section 5.3).

Table 4: Effects of Access and Utilization of Public Digital Clinic on the Utilization of Hospital Visits. This table illustrates how we plan to report the results on the use of specialized healthcare at hospitals. In Panel A, we report the impact of having *access* to the public digital clinic on the utilization of hospital visits, while Panel B presents the impact of *using* the public digital clinic on the use of hospital visits. Similarly as in Table 3, we use outcome D.1 (the total utilization of the digital clinic in PPC) as the take-up outcome in the 2SLS regressions (see Section 5.3).

Table 5: Effects of Access and Utilization of Public Digital Clinic on the Utilization of Other Healthcare Sectors. This table presents the potential effects of the use of the public digital clinic on the use of other sectors, namely private clinics and occupational healthcare. Panel A shows the impact of having *access* to the public digital clinic on the use of other sectors. Panel B presents the impact of *using* the public digital clinic on the use of other sectors. As previously, we use outcome D.1 (the total utilization of the digital clinic in PPC) as the take-up outcome in the 2SLS regressions (see Section 5.3).

Table 1: Characteristics and Means Comparisons of Residents at Baseline.

	Treated N:	Control N:	Treated - Control	Ostrobothnia N:	Finland N:
	Mean [SD]	Mean [SD]	Diff. (%) [SMD]	Mean	Mean
A. Prior health care use					
PPC: in-person visits (days)					
PPC: other contacts (days)					
Private HC: in-person visits (days)					
Private HC: other contacts (days)					
Occup. HC: in-person visits (days)					
Occup. HC: other contacts (days)					
B. Sociodemographic covariates					
Age (in years)					
Is female (share)					
Language: Finnish (share)					
Language: Swedish (share)					
Relationship or widowed (share)					
Living in a city (share)					
Dist. to nearest trad. PPC clinic (km)					
Tertiary education (share)					
Pensioner (share)					
Employed (share)					
Income (thousands of euros)					
C. Morbidities					
Common chronic disease (share)					
Has multimorbidity (share)					
Observations					

Notes: The table presents the means, standard deviations (SD), percentage differences in means (difference %), and standardized mean differences (SMD) of several covariates for the treated and control individuals, as well as means and SDs for the total population of Ostrobothnia and Finland. The analysis sample is restricted to those aged 0–70. In Panel A, health care use is measured in 12 months preceding the trial and represent annualized health care utilization. Health care contacts are here defined in terms of contact dates: individuals get value 1 if they have any relevant contact on the given day. For occupational health care, we include curative contacts conducted by nurses or doctors. For private clinics, we include reimbursed physician contacts. Covariates in Panel B are measured at the end of 2024. Living in a city is defined based on the city–countryside classification. Income is defined as the equivalent family disposable income. Distance to the neareast traditional PPC clinic is a straight-line distance. The list of traditional PPC clinics was collected in late 2023. In Panel C, morbidity is defined based on special reimbursement rights in 2024. The common diseases covered here include special reimbursement rights for cardiovascular diseases, diabetes, respiratory diseases, rheumatic diseases, cancer, neurological diseases, and severe mental health disorders. Multimorbid individuals are defined as those with special reimbursement rights for at least two out of three: cardiovascular diseases, respiratory diseases, and diabetes.

Table 2: Characteristics of Public Digital Clinic Users vs. Traditional PPC Clinic Users in the Treatment Group in Ostrobothnia.

Clients of:	digital clinics N:		trad. PPC clinics N:		Digi - trad. clinics		Ostrobothnia N:	
	Mean	[SD]	Mean	[SD]	Diff. (%)	SMD	Mean	[SD]
A. Prior health care use								
PPC: in-person visits (days)								
PPC: other trad. contacts (days)								
Private HC: in-person visits (days)								
Private HC: other contacts (days)								
Occup. HC: in-person visits (days)								
Occup. HC: other contacts (days)								
B. Sociodemographic covariates								
Age (in years)								
Is female (share)								
Language: Finnish (share)								
Language: Swedish (share)								
Relationship or widowed (share)								
Living in a city (share)								
Dist. to nearest trad. PPC clinic (km)								
Tertiary education (share)								
Pensioner (share)								
In labor market (share)								
Income (thousands of euros)								
C. Morbidities								
Common chronic disease (share)								
Has multimorbidity (share)								
Observations								

Notes: The table presents the means, standard deviations (SD), percentage differences in means (difference %), and standardized mean differences (SMD) of several covariates for the users of public digital clinics versus the users of traditional PPC clinics among the treated individuals. The two groups are constructed as follows: 1) those in the treatment group with at least one digital clinic contact in PPC are defined as users of the digital clinic, and 2) those in the treatment group with at least one contact in traditional PPC but zero digital clinic contacts are defined as the users of traditional PPC clinics. The table also contains means and SDs for the total population in Ostrobothnia. The analysis sample is restricted to those aged 0–70. In Panel A, health care use is measured in 12 months preceding the trial, representing annualized utilization. Health care contacts are defined in terms of contact dates: individuals get value 1 if they have any eligible contact on the given day. For occupational health care, we include curative contacts conducted by nurses or doctors. For private clinics, we include reimbursed physician contacts. Covariates in Panel B are measured at the end of 2024. Living in a city is defined based on the city–countryside classification. Income is defined as the equivalized family disposable income. Distance to the neareast traditional PPC clinic is a straigth-line distance. The list of traditional PPC clinics was collected in late 2023. In Panel C, morbidity is defined based on special reimbursement rights in 2024. The common diseases covered here include special reimbursement rights for cardiovascular diseases, diabetes, respiratory diseases, rheumatic diseases, cancer, neurological diseases, and severe mental health disorders. Multimorbid individuals are defined as those with special reimbursement rights for at least two out of three: cardiovascular diseases, respiratory diseases, and diabetes.

Table 3: Effects of Access and Use of Public Digital Clinic on Use of Traditional Public Primary Care.

	Digital clinic contacts (D.1)	Any digital clinic contact (D.2)	
A. Impact of *access* on the use of the digital clinics			
Effect			
Control group mean			
SE			
CI	[,]	[,]	
	In-person visits (Y1.1)	**Other traditional contacts (Y1.2)**	**Primary care contacts in total (Y1.3)**
B. Impact of *access* on the use of traditional primary care and primary care in total			
Effect			
Control group mean			
SE			
CI	[,]	[,]	[,]
Relative effect (%)			
Relative CI (%)	[,]	[,]	[,]
	In-person visits (Y1.1)	**Other traditional contacts (Y1.2)**	
C. Impact of *using* digital clinic (D.1) on the use of traditional primary care			
Effect			
SE			
CI	[,]	[,]	
N			

Notes: The table contains our baseline intention-to-treat (ITT) results for the impact of access to the digital clinic and our baseline average causal response (ACR) results for the impact of the use of the digital clinic, using a 9-month follow-up. The analysis sample is restricted to those aged 0–70. We estimate the impacts on both the annualized number of digital clinic contacts (DCT utilization; take-up) in Panel A and the annualized number of contacts to traditional PPC (traditional PPC utilization; reduced form) or the annualized number of total contacts to PPC (ITT) in Panel B. Estimators: OLS with Model 1 in Panel A (take-up) and in Panel B (reduced-form), and 2SLS with Model 2 in Panel C (ACR). Covariates: fixed effects as listed in Section 6. Standard errors are clustered at the permanent address level (the level of randomization). Relative effects are calculated by dividing effect estimates by control group means and multiplying by 100. Outcome D.1 (the total utilization of the digital clinic in PPC) is used as the take-up outcome in the 2SLS estimation. The p-values for the primary outcome Y1.1: ACR N/A, ITT N/A.

Table 4: Effects of Access and Utilization of Public Digital Clinic on Utilization of Hospitals.

	Referrals to hospitals (Y2.1)	ED contacts		Outpatient hospital visits (Y2.4)
		in-person (Y2.2)	other (Y2.3)	
A. Impact of *access* on the use of hospitals				
Effect				
Control group mean				
SE				
CI	[,]	[,]	[,]	[,]
Relative effect (%)				
Relative CI (%)	[,]	[,]	[,]	[,]
Sharpened q-values				
B. Impact of *using* digital clinic (D.1) on the use of hospitals				
Effect				
SE				
CI	[,]	[,]	[,]	[,]
Sharpened q-values				
N				

Notes: The table contains results on the utilization of specialized health care at hospitals: intention-to-treat (ITT) results for the impact of access to the digital clinic and average causal response (ACR) results for the impact of the use of the digital clinic, using a 9-month follow-up. The analysis sample is restricted to those aged 0–70. Estimators: OLS with Model 1 in Panel A (reduced-form), and 2SLS with Model 2 in Panel B (ACR). Covariates: fixed effects as listed in Section 6. Standard errors are clustered at the permanent address level (the level of randomization). Relative effects are calculated by dividing effect estimates by control group means and multiplying by 100. Sharpened q-values are reported to account for multiple hypothesis testing (Benjamini & Yekutieli, 2001). Outcome D.1 (the total utilization of the digital clinic in PPC) is used as the take-up outcome in the 2SLS estimation.

Table 5: Effects of Access and Utilization of Public Digital Clinic on the Utilization of Other Healthcare Sectors.

	Occupational HC		Private HC	
	in-person (Y3.1)	other (Y3.2)	in-person (Y3.3)	other (Y3.4)
A. Impact of *access* on the use of other healthcare sectors				
Effect				
Control group mean				
SE				
CI	[,]	[,]	[,]	[,]
Relative effect (%)				
Relative CI (%)	[,]	[,]	[,]	[,]
Sharpened q-values				
B. Impact of *using* digital clinic (D.1) on the use of other healthcare sectors				
Effect				
SE				
CI	[,]	[,]	[,]	[,]
Sharpened q-values				
N				

Notes: The table contains results on the utilization of other sectors of health care, occupational and private: intention-to-treat (ITT) results for the impact of access to the digital clinic and average causal response (ACR) results for the impact of the use of the digital clinic, using a 9-month follow-up. The analysis sample is restricted to those aged 0–70. Estimators: OLS with Model 1 in Panel A (reduced-form), and 2SLS with Model 2 in Panel B (ACR). Covariates: fixed effects as listed in Section 6. Standard errors are clustered at the permanent address level (the level of randomization). Relative effects are calculated by dividing effect estimates by control group means and multiplying by 100. Sharpened q-values are reported to account for multiple hypothesis testing (Benjamini & Yekutieli, 2001). Outcome D.1 (the total utilization of the digital clinic in PPC) is used as the take-up outcome in the 2SLS estimation.

7 Complementary analyses and next steps

For the final research paper or a set of papers, we may add more analyses compared to the SAP and PAP. Adding these analyses does not change our key research questions as stated in Section 1. We will label any post-blind analyses explicitly in the final research paper(s). We will also explicitly state that the results of the post-blind analyses are in nature more hypothesis-generating and hypothesis-confirming relative to the main pre-registered analyses. For example, we are considering extending the analyses with the aim of answering some of the following questions:

- Does the utilization of the public digital clinic increase the number of prescription initiations of certain drugs or referrals to medical examinations (a potential benefit/cost of improved access)?
- Does the utilization of the public digital clinic affect continuity of care?

Precision of the estimates: Based on the simulations documented earlier in the PAP, we anticipate that incorporating pre-exposure data with fixed effects estimates will effectively reduce variance in our estimations. However, we also may assess the robustness of our estimation strategy by exploring machine learning-based tools for flexible covariate adjustment in experimental data (see, *e.g.*, List et al., 2024).

Appendix A: Are there spillovers to traditional PPC?

There may be both a direct and an indirect impact of the experiment on access to traditional PPC. The direct effect is negative and caused by moving labor to the digital clinic (nurses and physicians, mostly nurses) from traditional PPC. The positive indirect effect potentially exists because digital clinic contacts (at least partially) substitute for traditional PPC. We expect that the spillover on access is largest for the care needs assessment telephone service and smaller for physician contacts due to institutional factors (gatekeeping by nurses at both digital clinics and traditional PPC).[15] The telephone service for the care needs assessment is centralized in Ostrobothnia (as the digital clinic will be) while other services in traditional PPC, such as in-person visits, are not as they are produced by traditional PPC clinics. The fact that the care needs assessment telephone service is centralized creates challenges for potential random saturation designs.

Consider the potential bias from spillovers via the following back-of-the-envelope model. Before the trial, the utilization of traditional PPC is the same (Y_0) for the treated and the control group due to the randomized treatment assignment. During the trial, suppose that the equilibrium is reached in three steps. In the first step, access to traditional PPC is reduced because some labor is transferred to the digital clinic. This reduces the use of traditional PPC by X units in both the treatment and control groups, with utilization being $Y_0 - X$ in both groups. In the second step, the treatment group has D digital clinic contacts (the control group 0). The substitution rate is α so that the utilization of traditional PPC is $Y_0 - X$ for the controls and becomes $Y_0 - X - \alpha D$ for the treated. In the third step, αD contacts to traditional PPC that became available because the treatment group did not consume them due to digital clinic contacts are allocated between the treatment and the control groups, increasing the use of traditional PPC. Ultimately, the utilization of traditional PPC is $Y_0 - X + \beta \alpha D$ for the controls and $Y_0 - X - \alpha D + (1-\beta)\alpha D$ for the treated.

[15] For reference, the digital clinic of the Wellbeing Services County of Pirkanmaa produced 31,000 contacts during its first two months. During the first month, there were 80,900 calls to the care needs assessment telephone service, which was 8,300 fewer calls than in the previous month. Source: https://www.pirha.fi/w/digiklinikalle-rekisteroitynyt-jo-yli-45-000-kayttajaa-pirkanmaalla, accessed on July 24th 2024.

Thus, the difference is $-2\beta\alpha D \in [-2\alpha D, 0]$ for $\beta \in [0,1]$. From this expression, we can see that it is the coefficient β which can make the estimated effect differ from the true effect ($-\alpha D$).

The back-of-the-envelope model suggests that there are two cases in which the estimated effect is unbiased: either 1) the substitution rate is zero ($\alpha = 0$) or 2) the potential spillover affects the potential outcomes of the treatment and the control group similarly ($\beta = 0.5$). In other words, the αD contacts with traditional PPC that became available because the treatment group did not consume them due to digital clinic contacts should be allocated equally between the treatment and the control groups. If these contacts are disproportionately allocated to the control (treatment) group, we would overestimate (underestimate) the substitution rate.

We believe that $\beta > 0.5$ and that our empirical approach overestimates the substitution rate. The logic is as follows. Suppose that 1) all health shocks can be ordered based on their severity, 2) the gatekeeping system leads to a situation where only the most severe (but not all) health shocks lead to a PPC contact, and 3) the distribution of health shock severity is uniform (unrealistic but assumed for simplicity) and the same for the treated and controls (in other words, no health effects from access to the digital clinic). Then, the difference in PPC use (including both the traditional PPC and digital clinics) between the treated and the controls would be $(1-\alpha)D$ at the second step of the above-described back-of-the-envelope model, before the αD contacts with traditional PPC that became available because the treatment group did not consume them due to digital clinic contacts are reallocated. If $\alpha \in]0, 0.5]$, then $(1-\alpha)D \geq \alpha D$, implying that the control group has αD or more untreated health shocks that are more severe than all the untreated health shocks in the treatment group, leading to $\beta = 1$. If $\alpha = 1$, then the utilization of PPC is the same for the treated and the controls ($Y_0 - X$), implying that $\beta = 0.5$ because the distribution of the untreated health shocks is the same for the treated and the controls. Finally, if $\alpha \in]0.5, 1[$, then $(1-\alpha)D \in]0, 0.5D[$ while $\alpha D \in]0.5D, D[$, implying that the majority of the contacts with traditional PPC that became available because the treatment group did not consume them due to digital clinic contacts are reallocated to the control group, with $\beta \in]0.5, 1[$. In fact, $\beta = \frac{1}{2\alpha}$

decreases for $\alpha \in]0.5,1[$.[16] Under the assumptions listed above, the previous results suggest that for $\alpha \in]0,0.5]$ our estimator would overestimate the substitution rate by a factor of 2 while for $\alpha \in]0.5,1[$ we would always estimate a substitution rate of 1.

The main limitation of the proposed experiment and the related analyses is that they do not take into account the potential spillover effects of the experiment on access to traditional PPC. How serious is this limitation? The answer is ultimately subjective, but we are not overly worried about the potential spillovers. Importantly, it would be unrealistic to assume that the αD contacts with traditional PPC that were not consumed by the treatment group due to the digital clinic would all be reallocated to the treatment and the control group (traditional PPC is not that supply-constrained). A more realistic model would thus contain an additional parameter $\gamma \in (0,1)$ in the expressions for the utilization of traditional PPC, which would become $Y_0 - X + \beta\gamma\alpha D$ for the controls and $Y_0 - X - \alpha D + (1-\beta)\gamma\alpha D$ for the treated. Thus, the difference is $-2\beta\gamma\alpha D - (1-\gamma)\alpha D$ instead of the earlier $-2\beta\alpha D$. From these expressions, it can easily be verified using inequalities that the bias is smaller once $\gamma \in (0,1)$ is included in the model.

Second, it would be unrealistic to assume that the newly available traditional PPC contacts are allocated entirely based on health shock severity. In other words, it would be unrealistic to assume that the newly available traditional PPC contacts are allocated entirely to one of the two treatment groups ($\beta = 1$ or $\beta = 0$), limiting the size of the potential bias. For example, $\beta = \frac{2}{3}$ ($\beta = \frac{3}{5}$) [$\beta = \frac{4}{7}$] would lead us to overestimate the substitution rate only by a factor of 1.33 (1.2) [1.14].

One way to measure changes in access to traditional PPC is to track the mean and maximum response time of the call-back service for care needs assessment. The Wellbeing Services County of Ostrobothnia follows these indicators regularly, and they should be also followed regularly throughout the trial. However, a simple before-and-after analysis of response times can be highly sensitive to time effects. Alternatively, we could compare the evolution in the outcomes before and after the experiment between the control group in Ostrobothnia and

[16] $\beta = \frac{(1-\alpha)D + [\alpha D - (1-\alpha)D]/2}{\alpha D} = \frac{1}{2\alpha}$ for $\alpha \in]0.5,1[$

individuals residing in other wellbeing services counties in a difference-in-differences (DID) framework. However, we believe that the signal would be modest relative to noise in this analysis (lack of power).[17]

[17]This hypothesis is based on the findings of two earlier studies that examine the impacts of copayment changes on the utilization of traditional PPC in Finland, both based on a DID approach and having a much larger population in analysis than we would have for testing spillovers (Haaga et al., 2024a; Haaga et al., 2024b).

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