Enhancing SHPI impact via mobile phone-based awareness campaign in Mardan

- Trial Protocol -

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1. Introduction

Relevance. On the path towards Universal Health Coverage (UHC), many governments of low- and middle-income countries (LMICs) have implemented state-funded health insurance programs to reduce the financial barriers and are now increasingly expanding those to cover outpatient services (Das & Do, 2023; Reich et al., 2016). However, low insurance uptake rates often constrain the effectiveness of public and private health insurance schemes (Adebayo et al., 2015; James & Acharya, 2022). Insufficient awareness of potential scheme beneficiaries is among the sources of information frictions that could hinder program utilization.

SHP – I. During the last decade, Pakistan has been implementing social health protection programs in several provinces to improve healthcare access for the poor. In Khyber Pakhtunkhwa (KP) province, the Social Health Protection Initiative (SHPI) program began in 2015 (Phase I), gradually expanding the coverage of inpatient care from the poorest 21% households in four pilot districts to the entire population of the province by 2021. However, until recently, outpatient care (OPC) was not covered by SHPI, despite representing the most frequent health need. It remains a major financial burden for the poor, who paid for OPC services entirely out-of-pocket – a cost amounting to 73% of total out-of-pocket health expenditures (Pakistan Bureau of Statistics, 2023; Shaukat et al., 2024).

OPC scheme. Phase II of SHPI, co-financed by the German Development Bank (KfW), incorporates OPC into the social health protection package. The pilot OPC scheme is targeted at the poorest population in district Mardan using a poverty score which was assigned to households based on a proxy means test (PMT) initially for the national Benazir Income Support Program (BISP), with an eligibility cutoff of 26. After registering with an empaneled healthcare provider, core family members of eligible households are entitled to free OPC services up to certain limits. Service provision started in January 2026 in 51, predominantly public, healthcare facilities in Mardan. The results of the pilot will inform potential scale-up to other districts in KP.

Barriers. Existing evidence from Phase I evaluations and related studies in Pakistan highlighted persistent underutilization of the insurance benefits, even among those officially enrolled, often attributed to a lack of awareness (Helmsmüller & Stepanikova, 2023). These findings align with evidence from other LMICs that beneficiaries often remain unclear about which services are covered or how to navigate administrative steps, leading to suboptimal usage of health services (Banerjee et al., 2021; Panda et al., 2016; Thornton et al., 2010).

Evidence SMS nudges general. Mobile phone-based messaging has emerged as a promising low-cost tool to help change health behavior at scale. SMS (short message service) interventions have been used for reminders (e.g. vaccination, medication adherence), health education, and promoting service uptake. Evidence on past SMS interventions show its potential to improve health behavior and (to a lesser degree) health knowledge, though effect sizes vary and success depends on message design and context. Previous meta-studies found that text message interventions have a significant overall effect on health promotion and behavior change outcomes (Armanasco et al., 2017; Head et al., 2013).

Contribution. Despite a proven track record of mobile phone-based information interventions in targeting health behavior, in the specific context of health insurance uptake in LMICs, studies have found mixed, and often limited, effects of such information interventions. A randomized experiment in Burkina Faso found no effect of an information-intensive intervention involving phone calls on enrolment in a micro health insurance scheme (Bocoum et al., 2019). Similarly, an SMS intervention component in a more complex intervention design did not significantly affect social health protection scheme uptake in the Philippines, while subsidies and enrollment assistance were found to be more effective in increasing uptake (Capuno et al., 2016). This evidence highlights that information might not be sufficient to increase enrollment, but in previous studies financial barriers were also prevalent. In contrast, we study awareness barriers in a setting where the insurance is provided completely free of cost, hence shedding light on the importance of information relative to other non-financial barriers.

2. Intervention

2.1 Target group

Sampling. The study population is a subset of a larger random sample of 1,900 households from 38 villages in 16 union councils in District Mardan that participated in a baseline household CAPI survey conducted between January and February 2025. From this baseline sample, 539 households had a PMT score below the eligibility threshold for outpatient coverage based on the PMT information available to the research team at the time of sampling. A further 32 households were included as a result of a manual eligibility check conducted via the official portal of the SHPI program. After excluding one household without a valid mobile phone number, the final sample available for the intervention thus comprises 570 households.

Consent. All contacted households have previously participated in at least one survey interview conducted by the research team. During this baseline survey, respondents were asked whether they consented to being re-contacted and whether they agreed to receive information related to health or the SHPI via their mobile phones. Only households that provided such consent are included in the intervention.

Eligibility. The social health insurance program operates on a dynamic registry, so that households' current eligibility status may differ from the PMT score information we currently have available. The intervention messages therefore inform households about the outpatient scheme and their potential eligibility, and encourage them to verify their status through official program channels.

2.2 Intervention design and delivery

Overview. The intervention consists of three rounds of communication, implemented between February and March 2026, see Table 1. There is a single treatment arm and all treated households receive the same intervention and are exposed to all planned communication rounds. Households assigned to the control group do not receive any SMS or voice calls as part of the study, but, just as the treatment group, are exposed to the program's general communication and visibility campaign, which might include additional SMS.

Table 1: Intervention rounds

Rounds	**Primary outcomes targeted**	**Delivery channels**	**Message content**	**Timeline**
		SMS	Introduction, (Annex: SMS #1)	04.02.2026
1	Awareness of Eligibility and registration	SMS + Voicecall	Eligibility check instruction, services covered, registration verification (Annex: Voicecall #1, SMS #2 and #3)	05.02.2026
2	General utilization	SMS + Voicecall	Reminder on services and household member covered, empaneled health facilities (Annex: Voicecall #1 repeated; SMS to be drafted[1])	February 2026
3	Specific barriers in utilization	SMS + Voicecall	Specific barriers identified during the first two months, grievance mechanism (To be drafted[1])	March 2026

[1] Exact content will be specified when program implementation progresses and bottlenecks are identified.

Best practice design. The literature on effective messaging outlines several key best practices for information interventions. These include the use of personalized messages (Armanasco et al., 2017; Thakkar et al., 2016; Wald et al., 2015), repeated, spaced messaging (Fjeldsoe et al., 2009; Head et al., 2013), adjusting the frequency and timing of messages to avoid fatigue (Abroms et al., 2014), and sending reminders close to the desired action point (Marcus et al., 2024; Ødegård et al., 2022). Furthermore, effectiveness is enhanced by cultural tailoring and localized language use (Staton et al., 2024), designing barrier-specific interventions (Glanz & Bishop, 2010; Milkman et al., 2021), and employing behavioral nudges and strategic framing (Patel et al., 2023). These established best practices apply well to our case and policy environment, which features an early stage of scheme introduction, strong operational ties to implementing partners, and an eligibility database that allows for a targeted campaign, adjusting content to address concrete informational barriers, and personalization at scale.

Justification 2 channels. Limited literacy of rural populations may be a barrier to efficiency of SMS awareness campaigns, therefore, combined complex strategies have been increasingly implemented in LMICs (Crawford et al., 2014; Demsash et al., 2022). In Pakistan, previous studies have shown a preference for automated voice calls (“robocalls”) over text messages (Kazi et al., 2021). Consequently, households assigned to the treatment group receive a series of informational messages delivered via two channels: (1) Short Message Service (SMS) sent in Urdu (both Urdu script and Roman script, the latter being often easier to read on simpler phones), and (2) robocalls in Pashto. The robocalls serve the dual purpose of reinforcing information for those who cannot read Urdu and to allow for more detailed informational and motivational content.

Content, personalization. Crucially, content relevance and clarity determine whether mobile phone-based messages can change behavior. In designing message content, we drew on findings from our pre-studies in Mardan (phone surveys including qualitative and quantitative questions) and previous research about local misconceptions. Our messages explicitly address identified knowledge gaps by explaining eligibility and coverage. SMS messages include the first name of the intended recipient for personalization. Where applicable, messages also reference the nearest empaneled outpatient facility based on information from our baseline survey and list of empaneled facilities provided by the program. Robocalls do not include any personalized information. The exact wording of the introductory message (Round 1) is provided in the annex to this protocol. The wording of subsequent utilization and reminder messages will follow the same informational structure and tone. We have discussed and obtained approval for our Round 1 message from the SHPI program directly and will seek to obtain the same for subsequent rounds.

Do no harm. The sender name displayed in SMS messages is “Khyber Medical University”. All messages explicitly state that the outpatient scheme is implemented by the Government of Khyber Pakhtunkhwa. All messages are purely informational in nature and have been approved by the program. They do not include persuasive language, incentives, or behavioral nudges beyond the provision of factual information, which is also publicly available through other channels. The intervention does not include an opt-out mechanism or a dedicated helpline. Messages do not require any response from recipients. Although studies indicate that interactive messaging (two-way communication) can build greater trust and engagement (Fjeldsoe et al., 2009; Ødegård et al., 2022; Wald et al., 2015), technical constraints prevent us from implementing a fully interactive messaging system. Instead, recipients of SMS messages and robocalls will be reminded of the channels that are available for the public to seek information about the scheme and their own eligibility / registration: the program helpline number and empaneled health facilities.

3. Hypotheses

Table 2: Hypotheses and key outcome variables

H1	**Awareness of the program and its design**
a	Treated households report a significantly higher level of awareness of the program than the control group.
	Variable: awareness_Jwandun *Definition:* Dummy variable = 1 if respondent knows the program by name ("Jwandun card") or is aware of services ("extension to outpatient services"). *Data sources:* Midline (phone), Endline (in-person) – survey respondent-level
b	Treated households achieve higher scores on a "knowledge index" combining individual measures of knowledge (e.g. covered services, covered household members, closest empaneled healthcare facilities) than the control group
	Variable: knowledge_Jwandun *Definition:* PCA-based composite of a set of questions about program design features. These questions will be drafted after the second and third intervention round is designed to ensure alignment with information provided. *Data sources:* Midline (phone, reduced version only due to timing before SMS rounds 2 and 3), Endline (in-person) – survey respondent-level
H2	**Awareness of eligibility**
a	Treated households are more likely to report that they have checked their eligibility or have verified their registration at a health facility.
	Variable: elig_reg_check *Definition:* Dummy variable = 1 if respondent reports that at least one household member has checked their eligibility via SMS, helpline or online portal, or has verified registration at a health facility. *Data sources:* Midline (phone), Endline (in-person) – household-level
H3	**Awareness of registration**
a	Treated households are more likely to report that they registered at a health facility.
	Variable: registered_any *Definition:* Dummy variable = 1 if respondent reports that at least one household member has registered for Jwandun Card at a health facility. *Data sources:* Midline (phone), Endline (in-person) – household-level, (Triangulation with program registration data possible if such data is accessible to us.)
b	Among treated households, a larger fraction of eligible (core) household members are reported to be registered.
	Variable: registered_hh_mem *Definition:* Ratio $\in [0,1]$, Fraction of core household members reported as registered over total number of core household members. *Data sources:* Midline (phone), Endline (in-person) – aggregate on household-level from member-level dataset
H4	**Utilization**
a	Treated households report more OPC visits than control households.
	Variable: opd_visits_nr *Definition:* Top-coded sum over OPC visits within last 4 weeks reported for each core household member individually, ≥ 0. *Dataset:* Endline (in-person) – aggregate on household-level from member-level dataset

b	Treated households are more likely to use empaneled facilities than control households.
	Variable: opd_empaneled *Definition:* Ratio $\in [0,1]$, Fraction of visits to an empaneled facility over all reported OPC visits in last 4 weeks amongst core household members *Dataset:* Endline (in-person) – aggregate on household-level from member-level dataset
c	Treated households are more likely to use the insurance to pay for outpatient care.
	Variable: opd_Jwandun *Definition:* Dummy variable = 1 if any household member reportedly used the insurance card to pay for outpatient care in the last four weeks. *Dataset:* Endline (in-person) – aggregate on household-level from member-level dataset; (Triangulation with program utilization data possible if such data is accessible to us.)

4. Experimental Design

4.1 Randomization

Overview. The evaluation is implemented as an individually randomized controlled trial at the household level. The study sample consists of 570 households identified as potentially eligible for the outpatient extension of the social health insurance scheme based on available proxy-means test (PMT) information. Households are randomly assigned to either a treatment group receiving the information intervention or a control group in equal proportions.

Stratification. Randomization is conducted using a stratified random assignment procedure to improve balance across two key pre-treatment characteristics that are expected to be correlated with awareness of the insurance scheme and health care utilization: 1. We stratify by *tehsil*, an administrative unit below the district-level, due to findings from previous research that the implementation of the inpatient scheme varied by region (Helmsmüller & Landmann, 2022). Two adjacent tehsils with small sample sizes form one group however. 2 We stratify by *poverty score* which defines eligibility. We have three clusters: One group for which we do not have information on poverty scores, one above and one below 23.11, the median poverty score in our sample. Table 3 displays the sample size per strata.

Table 3: Sample size per strata

Tehsil / Poverty score	**Katlang and Takht Bhai**	**Ghari Kapoora**	**Mardan**	**Rustam**	**Missing**	**Total**
Below 23.11	81	57	69	46	0	253
Above 23.11	81	44	62	66	0	253
Missing	14	15	25	4	6	64
Total	**176**	**116**	**156**	**116**	**6**	**570**

Within each stratum, households are randomly assigned to treatment or control status using a reproducible randomization procedure in Stata prior to the intervention.

4.2 Main model specification

ITT. The primary analysis compares outcomes between households assigned to the treatment group and households assigned to the control group, following an intention-to-treat (ITT) approach. All households are analyzed according to their original random assignment, regardless of whether messages are successfully delivered or read.

Main model. Treatment effects are estimated using regression models that relate post-intervention outcomes to treatment assignment with strata fixed effects. Given the randomized design, these estimates capture the causal effect of receiving the informational intervention.

$$Y_{\{i,\ s,\text{endline}\}} = \beta_0 + \beta_1 \times 1(Treatment)_i + \gamma_s + \epsilon_{i,s}$$

Randomization inference. Statistical inference is based on randomization inference, which directly reflects the known random assignment mechanism. This approach does not rely on large-sample distributional assumptions and is well suited to the study's sample size and stratified design. P-values and confidence intervals are constructed by comparing observed treatment effects to the distribution of effects generated under repeated re-randomization consistent with the original assignment procedure.

Heterogeneous Effects. We will check heterogeneous effects for our stratification variables (tehsils and poverty score group) by including the respective interaction term in the above regression specification.

Given the small sample size, we do not expect to find significant heterogeneous effects in most outcomes. For hypotheses for which we find overall significant effects, we will test heterogeneity by age, by gender, by education and by a wealth index we generated by PCA of asset-ownership variables, as exploratory analysis.

4.3 Power calculations

Power calculations. Given the directional nature of our primary hypotheses that the intervention will increase program awareness and registration, we report power based on one-sided tests ($\alpha = 0.05$). With a fixed sample of 570 observations and a balanced assignment, the study achieves a statistical power of 80% to detect a standardized ITT effect of 0.21 standard deviations. Based on a 50% delivery success rate, derived from participation in the previous phone survey, this corresponds to a LATE of 0.42 standard deviations. This implies that for the intervention to be detected as statistically significant, the impact on households that are actually reached by the intervention must be moderate to large. Given the ongoing awareness campaign conducted by the program and the actual launch of service delivery in January 2026, we expect a baseline awareness of 50%. With our sample size, we can therefore detect an increase in awareness of 10.3 percentage points.

4.4 Threats to internal validity and alternative specification

Attrition and non-response. Based on experience from previous research on the same target group, we do not expect systematic attrition in the in-person endline survey, and item non-response is unlikely to pose a serious threat to internal validity. We therefore do not plan on using imputation techniques. Non-response rates in the midline phone survey are expected to be higher and may arise from changes in phone numbers, connectivity problems, or repeated unavailability of respondents. Since the phone survey will use the same caller identification (KMU) as the SMS and robocall intervention, non-response may be correlated with treatment status. We will therefore test for differential attrition between treatment and control groups by comparing response rates and baseline characteristics of respondents and non-respondents, and by estimating attrition regressions with treatment assignment as the main explanatory variable. In the presence of systematic attrition, we will assess the robustness of our estimates using Lee bounds (Lee, 2009).

Outliers. We expect some mis-reporting in the quantitative variables on health care utilization and expenditures. Variables in our baseline survey were cleaned by top-coding variables for utilization (inpatient, outpatient, neglected health care) at the 90th percentile. We used top coding for the recorded health care expenditures for the most recent visit (inpatient and outpatient respectively) at the 95% percentile.

Multiple hypothesis testing. We specify a total of eight main hypotheses. To account for multiple hypothesis testing, we will report results adjusted for multiple inference using a False Discovery Rate (FDR) approach. Specifically, we will compute sharpened q-values following Anderson (2008) applied to p-values obtained from the main randomization inference specification. Adjusted results will be reported alongside unadjusted estimates. We note that multiple testing adjustments reduce the probability of false positives at the cost of lower statistical power; therefore, where adjusted results are inconclusive, we will transparently report effect sizes and, where applicable, the contributions of individual components within indices.

LATE. As an exploratory analysis, we will estimate local average treatment effects using randomized assignment as an instrument for treatment receipt using two alternative definitions of treatment receipt. First, treatment receipt will be measured using delivery log data for the SMS and robocall campaign. For Hypotheses 1 and 2, treatment receipt is defined as successful delivery of Round 1 of the campaign. For Hypotheses 3 and 4, treatment receipt additionally requires successful delivery of Rounds 2 and 3, which contain information on registration and utilization. Because this technical definition of non-receipt is likely to be correlated with non-response in the phone survey, LATE estimates will primarily be based on outcomes measured in the in-person endline survey.

Second, we will construct an alternative, more restrictive compliance measure based on both successful technical delivery and self-reported receipt and consumption of the messages (reading SMS or listening to robocalls). We note that the implementing agency plans to conduct a separate SMS awareness campaign, which may limit respondents' ability to distinguish between campaigns and may introduce misclassification in self-reported receipt. Any LATE estimates based on self-reported measures will therefore be interpreted with caution.

Robustness checks. We will conduct a number of robustness checks which include the following:

- *Alternative regression models:*
    - Use logit/ probit specifications for outcomes measured in dummy variables
    - Include control variables: age, gender, household size, highest education level in household (above / below median), wealth index (PCA-based index on asset variables), self-reported health status at baseline (for individual-level outcomes), and baseline number of visits to inpatient care (past 12 months) and outpatient care (past 4 weeks)
- *Inference:*
    - Apply asymptotic inference instead of randomization inference by calculating p-values based on sampling distributions
    - Cluster standard errors at union council level (administrative unit below tehsil-level)
- *Alternative variables:*
    - Top-code the health care utilization variables at the 95th percentile (instead of the 90th percentile) and the health care expenditure variables at the 99th percentile (instead if the 95th percentile).

5. Data

5.1 Baseline data

Two surveys, variables. We have baseline data from an extensive in-person household survey conducted in January to February 2025 with all households and a shorter phone survey conducted in September 2025 where we reached 246 households from our sample. The in-person baseline collected detailed information on household demographics, socio-economic and health status, inpatient and outpatient health care utilization for each core household member separately, health expenditures, insurance awareness, and psychosocial indicators. The phone survey questions focused on healthcare utilization, health expenditures, knowledge about the OPC scheme rules, household eligibility, and registration status.

Administrative data. We furthermore have access to poverty scores for most households. Poverty scores are kept in a dynamic registry and we have access to data from spring 2024 for some households and from spring 2025 for other households.

Baseline balance. In Annex 3, we provide the baseline balance table following the randomization inference methodology to determine statistical significance (Heß, 2017). The p-values were generated by permuting treatment assignment 1,000 times within the original strata as per our base model. This approach is justified as it is consistent with the stratified randomization design, ensuring that the p-values remain valid even in the presence of small or unbalanced strata, and providing the most rigorous evidence that the groups are balanced at the baseline. We additionally provide the balance table based on traditional asymptotic t-tests in Annex 3.

5.2 Follow-up data

We will conduct two rounds of data collection and additionally use administrative data if available:

- ***Midline survey.*** We plan to collect midline data via a short phone survey in mid-February 2026 (before Ramadan) after the first round of the information campaign to capture short-term effects. The questionnaire will be based on the baseline phone survey and will in particular gather data on our main variables specified in the hypotheses above.
- ***Endline survey.*** An in-person endline is scheduled for the months of April / May 2026 (after Ramadan). The survey will follow-up on midline data for the evaluation of this trial, but will also include the more extensive survey modules from the in-person baseline. The data will also be used for a rigorous evaluation of the OPC extension to SHPI under a separate research component.
- ***Administrative data.*** We have requested access to administrative data from the program on enrolment, claims and utilization records. If access is granted, KMU will link the data to our sample by matching on CNICs. The data can be used to triangulate self-reported outcomes.
- ***Trial implementation data.*** SMS and robocall delivery logs, including data on duration of the call, and a short phone survey will be used to verify receipt and recall of messages.

5.3 Adherence to ethical standards

Ethical clearance. All data collection protocols adhere to ethical standards: Ethical approval for the data collection protocol was obtained from the Friedrich-Alexander-University Erlangen-Nürnberg, Germany, and the Khyber Medical University, Pakistan, prior to our baseline survey, and can be shared upon request.

Informed consent. In particular, informed consent to obtain in the survey was obtained from all respondents prior to our baseline survey after a presentation of the survey objectives, and permission to contact the household again has been obtained in each survey round.

Personal identifiers. Confidentiality is rigorously maintained: Personal identifiers (CNICs, phone numbers, GPS data) is stored on Pakistani servers and not shared with the German research group. Only pseudonymized data reaches Germany and in Germany, the data will only be reported on aggregated level; this is explained to the participants beforehand.

Sensitive data. In the interview, we ask potentially sensitive questions about illness history and associated costs of individual household members, awareness of and experience with insurance, as well as physical and mental health and experiences with stress and discrimination. Each question allows for the possibility of non-response. Data collection is organized in a way that male interviewers interview men, female interviewers interview women, wherever this is desired by the respondent. The questionnaire is screened for culturally sensitive issues by the Pakistani team members.

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Annex 1 : Contents Round 1

SMS #1: Introduction

„Dear [name] [Sahib/Bibi]. This is the Khyber Medical University research team that visited you for a health survey earlier last year. There is an important update regarding the Sehat Sahulat Program in district Mardan. More details will be provided soon."

SMS #2

"Dear [name] [Sahib/Bibi]. The Government of Khyber Pakhtunkhwa has launched "Jwandun Card" to provide free OPD care for poor families in district Mardan when needed. It covers doctor consultation fees, treatment costs, laboratory tests, and medicines. To check your eligibility, text your CNIC number to 9930 or visit verify.slichealth.org. For more information, call 0800 89898."

SMS #3

"Dear [name] [Sahib/Bibi], if you are eligible for the Jwandun Card and have not registered yet, go to your nearest designated OPC facility to register.

[Name of the preferred facility if listed / name of the next empanelled facility for your village]"

Voicecall #1

"Salam [Hello]!

We are from Khyber Medical University. You participated in our health survey earlier last year, and we are following up with an important update.

The Government of Khyber Pakhtunkhwa, through its Sehat Card Program, has launched a new program called the Jwandun Card to provide free outpatient services to poorest families whenever they need medical care. The Jwandun Card covers doctor consultations, laboratory and diagnostic tests, treatment of diseases, vaccinations, medicines, child care, and other services at the designated facility with which one is registered, at no cost.

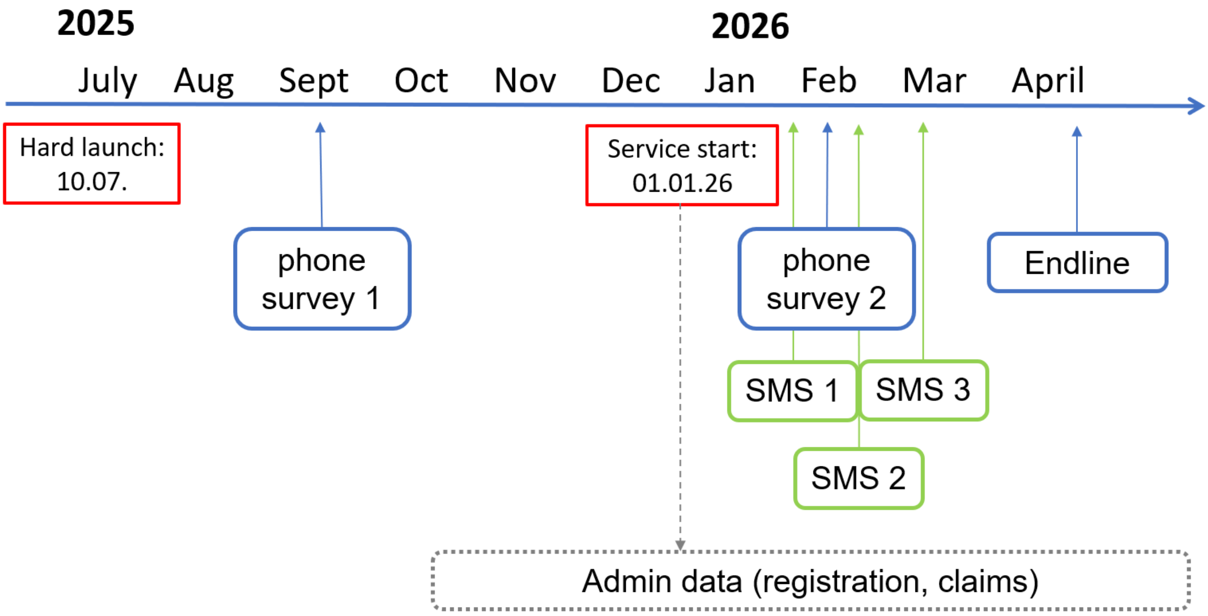
The Jwandun Card covers the husband, wife, their unmarried children, and their parents.

The Government of Khyber Pakhtunkhwa invites you to check your eligibility. This is easy. Text your CNIC number to 9930. Any member of your family can use this method to check their eligibility.

If you are eligible, you can register at the nearest designated health facility. If you are unsure about your registration status, you can confirm it at the designated health facility.

Once you are registered, you and your family can get medical care whenever you need it, without financial worry. Thank you."

Annex 2: Timeline



Annex 3: Balance table

Annex 3. Baseline balance

	(1) Treatment		(2) Control			(1)-(2) Difference
Variable	N	Mean	N	Mean	Total N	Diff (RI p-value)
Respondent's age	274	44.161 (0.787)	279	43.459 (0.750)	553	0.702 (0.512)
Respondent's gender	279	0.423 (0.030)	283	0.470 (0.030)	562	-0.047 (0.250)
Respondent's level of formal education	275	2.047 (0.113)	279	2.222 (0.127)	554	-0.175 (0.299)
Household size	280	8.343 (0.154)	284	8.588 (0.167)	564	-0.245 (0.265)
Number of children below the age of 6 in the HH	273	0.835 (0.065)	272	0.952 (0.076)	545	-0.117 (0.251)
BISP PMT score (2023)	252	22.562 (0.234)	254	22.864 (0.226)	506	-0.302 (0.187)
Asset index	280	0.071 (0.083)	284	-0.063 (0.083)	564	0.133 (0.258)
Respondent's health status (1-5)	275	2.793 (0.079)	279	2.663 (0.070)	554	0.130 (0.205)
Awareness of health cost reduction program	280	0.204 (0.024)	281	0.224 (0.025)	561	-0.021 (0.525)
Awareness of Sehat Card / SSP	230	0.778 (0.027)	224	0.808 (0.026)	454	-0.030 (0.416)
HH members ever used Sehat Card / SSP	120	0.542 (0.046)	122	0.549 (0.045)	242	-0.008 (0.923)
Number of IPD visits of HH (12 months)	273	0.381 (0.060)	272	0.316 (0.053)	545	0.065 (0.424)
Number of OPC visits of HH (1 month)	273	6.656 (0.380)	272	6.507 (0.385)	545	0.148 (0.760)
Number of neglected OPC cases of HH (1 month)	273	2.700 (0.267)	272	2.342 (0.253)	545	0.358 (0.306)
HH was sampled using the random walk procedure	273	0.425 (0.030)	272	0.452 (0.030)	545	-0.027 (0.534)
HH is eligible as of August 2025 (SMS check)	266	0.602 (0.030)	266	0.564 (0.030)	532	0.038 (0.388)
Presence of simple mobile phone in HH	273	0.791 (0.025)	272	0.809 (0.024)	545	-0.018 (0.618)
Presence of smartphone in HH	273	0.465 (0.030)	272	0.460 (0.030)	545	0.006 (0.913)

Note: Values in parentheses in columns (1) and (2) are standard errors. Values in parentheses in the last column (1)-(2) are p-values from randomization inference (RI). Significance: ***=.01, **=.05, *=.1.

Annex 3. Baseline balance

Variable	N	(1) Treatment Mean/(SE)	N	(2) Control Mean/(SE)	N	(1)-(2) Pairwise t-test Mean differences
Respondent's age	274	44.161 (0.787)	279	43.459 (0.750)	505	0.702
Respondent's gender	279	0.423 (0.030)	283	0.470 (0.030)	506	-0.047
Respondent's level of formal education	275	2.047 (0.113)	279	2.222 (0.127)	506	-0.175
Household size	280	8.343 (0.154)	284	8.588 (0.167)	506	-0.245
Number of children below the age of 6 in the HH	273	0.835 (0.065)	272	0.952 (0.076)	506	-0.117
BISP PMT score (2023)	252	22.562 (0.234)	254	22.864 (0.226)	506	-0.302
Asset index	280	0.071 (0.083)	284	-0.063 (0.083)	506	0.133
Respondent's health status (1-5)	275	2.793 (0.079)	279	2.663 (0.070)	506	0.130
Awareness of health cost reduction program	280	0.204 (0.024)	281	0.224 (0.025)	506	-0.021
Awareness of Sehat Card / SSP	230	0.778 (0.027)	224	0.808 (0.026)	416	-0.030
HH members ever used Sehat Card / SSP	120	0.542 (0.046)	122	0.549 (0.045)	228	-0.008
Number of IPD visits of HH (12 months)	273	0.381 (0.060)	272	0.316 (0.053)	506	0.065
Number of OPC visits of HH (1 month)	273	6.656 (0.380)	272	6.507 (0.385)	506	0.148
Number of neglected OPC cases of HH (1 month)	273	2.700 (0.267)	272	2.342 (0.253)	506	0.358
HH was sampled using the random walk procedure	273	0.425 (0.030)	272	0.452 (0.030)	506	-0.027
HH is eligible as of August 2025 (SMS check)	266	0.602 (0.030)	266	0.564 (0.030)	476	0.038
Presence of simple mobile phone in HH	273	0.791 (0.025)	272	0.809 (0.024)	506	-0.018
Presence of smartphone in HH	273	0.465 (0.030)	272	0.460 (0.030)	506	0.006

Covariate(s) used in pairwise regressions: [i.uc_group_t i.pmt_level]. Significance: ***=.01, **=.05, *=.1.