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The Effect of SMS Reminders on Health Screening Uptake: A Randomized Experiment in Indonesia

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Abstract

As cardiovascular diseases (CVD) become the leading cause of death in low- and middle-income countries (LMICs), this raises new challenges for health systems. Regular screening is a key measure against CVD risk factors, but the uptake of such services remains low despite free provision. We conducted a randomized controlled trial in Indonesia to assess whether personalized and targeted text messages increase the usage of public screening services for diabetes and hypertension in the at-risk population. Our intervention increased screening uptake by 6.6 percentage points. Among those who received and read the messages, the effect size was 17 percentage points. We show that text messages can be effective in a context of a relatively new disease burden in LMICs, where population responses may still be shaped by low salience and missing screening routines.

Keywords: Health, Noncommunicable Diseases, Information, Health Systems, Screening Uptake, mHealth, text message reminder.

JEL codes: C93; D83; I12; I15; I18; O15

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1 Introduction

Promoting the adoption of preventive health behavior is a vital, yet continuously challenging task for health systems. This holds particularly true for cardiovascular diseases (CVD) in low- and middle-income countries (LMICs), where these health conditions are quickly rising to the leading causes of death. CVD can be effectively avoided though a special type of preventive health behavior: By participating in regular screenings, major CVD risks such as diabetes and hypertension can be prevented or managed through early detection. Diabetes and hypertension screening is possible at very low costs, and behavioral changes can be sufficient to control these conditions at very early stages. Yet, such screenings are underutilized in many LMICs (Geldsetzer et al., 2019; Manne-Goehler et al., 2019), even in settings with a free and easily accessible screening infrastructure, such as Indonesia. Here, individuals can receive screening free of charge at the local primary health center (Puskesmas) and at monthly community health meetings in their village (Posbindu). Reasons for the low demand for this type of CVD prevention include low levels of comprehensive CVD knowledge and salience, low sense of urgency, and logistical concerns (Sofyan et al., 2023; Widyaningsih et al., 2022).

We conducted a randomized controlled trial to test whether a low-cost, light-touch text message intervention can increase the uptake of hypertension and diabetes screening in Indonesia. The treatment group received two sets of three text messages, each sent before one of the monthly village screening dates between January and March 2020. The messages called upon the recipients to attend screening at the specified time and place and gave short information on CVD risk and the benefit of screening. The intervention was targeted at individuals over the age of 40, who are at increased risk to develop diabetes or hypertension and should be screened once a year according to WHO PEN screening guidelines (WHO, 2010). We randomly sampled 2,006 participants from two districts in Aceh province in a two-stage stratified design. Baseline data was collected in November and December 2019 and endline data was collected approximately one month after the last screening date via telephone surveys as the COVID-19 outbreak did not allow for in-person interviews.

We find that the intervention increased the uptake of screening services by 6.6 percentage points from 33% to 40%. For respondents who received at least one full set of messages and could remember any message content, the effect size was 17 percentage points. We do not detect a treatment effect on knowledge, measured as indices on the information provided in the text messages as well as on broader disease knowledge. Respondents who remember receiving our messages mostly recall that the content was on the advice and logistics to get screened, and one quarter of those remembered the information on higher age being a risk factor. We suspect that the intervention made this information more salient and served as a reminder to get screened. We cannot detect any spillovers to other household members.

We contribute to the literature that seeks to increase the uptake of under-used preventive health actions. Previous studies showed that other preventive health behavior can be improved with information and reminder interventions delivered via text messages, for example in the context of immunization (Banerjee et al., 2021; Jacobson Vann et al., 2018), dengue prevention (Dammert et al., 2014), smoking cessation (Whittaker et al., 2016), sexually transmitted diseases (Taylor et al., 2019), or cervical cancer (Tin et al., 2023). Given the potential of text messages to deliver effective interventions at low cost and high scalability, applying these to CVD prevention – where large population shares need to take up infrequent, but regular screenings visits – appears particularly promising. However, as CVDs are rather new to the disease burden in LMICs, it is unclear whether text messages are sufficient to increase screening uptake: The need to be screened might be less salient to the population, there is no routine of regular screening, screening offers are fairly new and thus might be unknown, and social norms to get screened might not exist. Furthermore, the main target group for CVD screening are middle-aged and older adults, which may engage differently with phone-based interventions and healthcare than younger populations do. Other, non-text message interventions to increase diabetes and hypertension screening uptake in LMICs are also rare: no rigorous evaluations were identified in Southeast Asia in a recent review (Fritz & Fromell, 2022), and the only other study we are aware of uses more intensive treatments, namely in-person scripts and pharmacy vouchers in Armenia (de Walque et al., 2022; Gong et al., 2020).

In the following chapter, we summarize the current prevalence of and screening for diabetes and hypertension in Indonesia. Then, we describe the experiment in detail by deriving the hypotheses from previous evidence and our own pre-studies, presenting the intervention design, estimation strategy, data collection and outcome definitions. Finally, we display and discuss the results.

2 Context

Similar to other LMICs, the burden of CVD is rising in Indonesia. From 1990 to 2019, the share of CVDs in causes of death rose from 20% to 38% (IHME, 2023). In 2019, high blood pressure and blood glucose were the leading two risk factors for mortality (IHME, 2023). The most recent national health survey from the Ministry of Health revealed that diabetes prevalence has risen to 11% and hypertension to 34% (Riskesdas, 2018), both above the global average. To battle this trend, the national government has started implementing targeted prevention programs. In the last decade, nationwide programs were established to integrate a division responsible for CVD needs in every community health center (*Puskesmas*) (Mahendradhata et al., 2017).

One main effort is the village screening program *Posbindu (Pos binaan terpadu*), which was rolled-out in Indonesia since 2015 (Direktorat Pencegahan Dan Pengendalian PTM, 2019). Once per month, trained nurses from the local *Puskesmas* offer information as well as screening and monitoring services for CVD to the general population at a central place within each village. This basic service is free of charge for the user and financed through a combination of the *Puskesmas* and village budget. Blood pressure and blood glucose measurements are part of every *Posbindu* (KKRI, 2019). At the village level, community health workers (*kader*) are responsible for organizing and advertising the meetings. In addition to *Posbindu*, it is possible to get free screening at the district's *Puskesmas* at all times, and for a charge of approximately 50,000 IDR[1] at private practices. However, the national health survey shows that the general population has rarely used the CVD screening services so far (Riskesdas, 2018; Widyaningsih et al., 2022). About one third of people above 45 years report that they never had their blood pressure checked, and around 70% never had their blood sugar level checked (Riskesdas, 2018).

This pattern of high diabetes and hypertension prevalence and low screening uptake is also observed in our study region in Aceh province: the diabetes and hypertension prevalence is slightly above the national average, and reported screening rates were below the national average in 2018 (Riskesdas, 2018). Studies from Aceh (Sofyan et al., 2023; Widyaningsih et al., 2022) and an own focus group discussion with 12 *kaders* from our study area revealed that *Posbindu* tends to be visited by older women and those who were already diagnosed. The *kaders* perceive it as more difficult to motivate the general population to attend the meetings even though sufficient time and equipment would be available. In addition, the province has close to universal health insurance coverage for over a decade, which makes it a suitable setting to study the demand-side barriers to screening uptake.

3 Method

3.1 The Intervention

Our intervention is a repeated set of SMS text messages on the necessity and logistics of diabetes and hypertension screening. It was designed to address disease misperceptions as well as behavioral barriers to screening uptake. The intervention was piloted in mid-January 2020 (see appendix D) and fielded from late January until March 2020.

[1] 3.56 USD at an exchange rate of 14032.02 IDR/USD, this charge includes blood pressure, blood glucose and additionally cholesterol and uric acid measurement.

Targeted mechanisms

Since high prevalence of CVDs is a rather new phenomenon in LMICs, individuals might not yet be aware of the role of screening as preventive health behavior, or might not have internalized regular check-ups. Text messages on screening dates might tackle several of these barriers: They might convey new information, thus update beliefs, make the screening decision more salient to the individual, thus serving as a reminder, or inform about a screening date.

To find out which factors keep at-risk individuals from taking up screening in the Acehnese context, we conducted a qualitative and a quantitative pre-study[2] (see Table A 2 for the detailed study timeline). For the qualitative arm, twelve in-depth semi-structured interviews with individuals from the target population were conducted in November 2019. These findings were quantified and extended in the quantitative baseline data collection from late November until December 2019 (see chapter 3.3 for data collection details).

These pre-studies showed that the majority of our respondents were informed about the main characteristics of hypertension and diabetes, as well as the possibility to screen free of charge. There are some perceived non-monetary costs such as fear of diagnosis and the notion that preventive health programs are designed for the elderly or women, but no strong stigmatization. On the other hand, respondents are aware that early treatment initiation can help and that especially diabetes likely leads to high treatment costs. However, to most respondents it was not salient that their age implied a higher risk for both conditions, and most did not know that one could have them without feeling any symptoms. Studies from other parts of Indonesia confirm that even if individuals could identify risk factors, the own susceptibility was underestimated (Pujilestari et al., 2014), and even diagnosed respondents did not yet internalize that the need for screening does not depend on feeling ill (Rahmawati & Bajorek, 2018). Informing individuals about the need for screening independent of symptoms and their age-based risk might thus increase screening uptake.

Reminders and fixed dates might make the decision for screening more salient and induce planning (Milkman et al., 2013), or increase the perceived urgency of screening. Similarly, evidence from other LMICs suggests that present bias can be a substantial barrier to screening uptake, as individuals postpone the health investment infinitely (Kremer et al., 2019). Fixed dates can be efficient countermeasures as they signal that individuals cannot decide between now or later, but only between now or never (Kremer et al., 2019). Hence, individuals might not procrastinate the health investment any longer, but might be inclined to take up screening at the fixed date. While the screening date is a

[2] The detailed design and findings will be made available in a separate paper.

non-binding deadline, the mere notion that missing the date implies a waiting period of one month might be effective to reduce naïve procrastination (O'Donoghue & Rabin, 2015).

Previous studies showed that impatient individuals are less likely to seek screening (Picone et al., 2004), resulting in a higher risk of underdiagnoses (Kim & Radoias, 2016). Increasing the salience of the time dimension might reinforce this heterogeneity, while deadline setting might help especially impatient individuals to take up screening. Similarly, more risk-averse individuals invest more in preventive health in some cases (Tsaneva, 2013), but not in all (Goldzahl, 2017; Picone et al., 2004), depending on how uncertain the outcomes of screening and treatment are perceived (Selden, 1993). Thus, the information conveyed in text messages might impact screening demand differently for relatively more and relatively less risk-averse individuals.

Finally, text messages could impact individuals beyond the targeted respondents due to information sharing, social learning, or mere convenience when respondents are accompanied to the screening facility. Spillovers of health interventions are rarely examined (Dupas & Miguel, 2017), but are of interest when analyzing the overall impact of an intervention. In the case of text messages, this might be particularly relevant, as they can be shared easily.

Thus, to assess the effectiveness of the intervention, we test the following hypotheses:

H1: The intervention increases screening uptake of the message recipient.

H2: The intervention increases screening and disease knowledge.

H3: There is a heterogeneous treatment effect along risk and time preferences.

H4: The intervention increases screening uptake of other household members.

Content & Personalization

The messages' content included the village-level *Posbindu*[3] screening date and location as well as selected information about hypertension and diabetes. We opted to emphasize the benefits of early screening uptake, in order to positively frame the messages, rectify respondents' misconceptions, and confirm their correct beliefs. Furthermore, as very few respondents were aware of age being a significant risk factor for diabetes and hypertension, we included this information to increase relevance and urgency for the recipients. Also, we included a note that the community health worker (*kader*) or the community health center (*Puskesmas*, abbreviated to PKM) can be contacted for further information. This aimed at increasing the trustworthiness and legitimacy of the messages, while at the same time providing respondents with contacts should any questions arise. To maximize their

[3] 17 out of 146 villages did not have a *Posbindu* screening during our study period. In these cases, participants were invited to the *Posbindu* in a neighboring village as participation is not restricted to village residents.

potential impact (e.g. Head et al. (2013)), the messages were personalized by providing village-level information, addressing the age of the recipient, as well as including the recipient's name in the greeting.

Based on these considerations, we formulated the following messages (see Table A 1 in the appendix for the translation of each message):

Message 1: Greetings [Mr/Ms name], do you know that [diabetes|hypertension| does not always show symptoms but can be treated better if detected earlier. Check for FREE at POSBINDU [date].

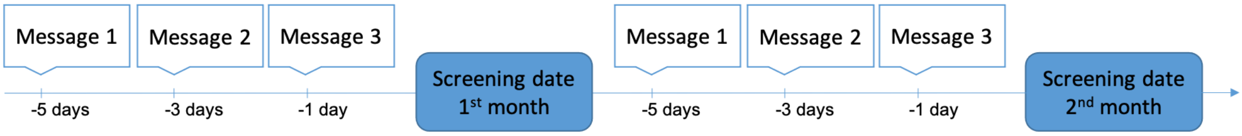
Message 2: Greetings [Mr/Ms name], do you know that people over 40 years old have a high risk of diabetes & hypertension? Ask kader / PKM & check for FREE at POSBINDU [date].

Message 3: Greetings [Mr/Ms name], remember to benefit from a FREE diabetes and hypertension CHECK in POSBINDU tomorrow morning at [place within the village]. Contact nearest kader or PKM.

Implementation

Each individual in the treatment group received six SMS messages to the telephone number that s/he chose to be his/her contact number at baseline. The respondent did not have to be the owner of the phone, but s/he needed to be accessible through the phone number. As depicted in Figure 1, three messages were sent before the first village screening date and three were sent before the second date one month later. In the first cycle, the first message addressed diabetes, while in the second cycle, it addressed hypertension. In both screening cycles, messages were sent five days, three days and one day before the screening date. For 12 respondents in the treatment group, the first screening date took place end of January 2020, whereas for everyone else in the treatment group it took place in February.[4] Most of the intervention period was not affected by the COVID-19 pandemic as *Posbindu* typically takes place in the beginning of a month and the second treatment cycle was therefore finished for most participants in early March. Puskesmas records show that at this time, Posbindu still took place regularly and attendance did not drop compared to the previous months.

Figure 1. Intervention timeline



[4] To not interfere with newly implemented recommendations of social distancing, SMS were no longer sent after March 24, 2020, such that 10 people did not receive the full second cycle of the text messages. In early March, case numbers were still very low in Indonesia (and none in Aceh) and there were no restrictions in place.

The messages were sent out by the research team using the bulk SMS gateway provider *bulkgate*. We received delivery reports from the portal stating which messages failed to be delivered.

Treatment assignment was done in a random draw after baseline data collection in Stata 14 using the procedure proposed in DIME (2019). Half of the phone numbers were randomly allocated to the treatment group, which received the full intervention, while the control group received no intervention. Interviewers were fully blinded to treatment assignment, and could only infer treatment status from the answers the respondents gave at endline (in which the reception of messages was assessed after the screening behavior). Respondents were not aware of the existence of a control and treatment group throughout the study.

3.2 Estimation Strategy

We assess the impact of our intervention using intention-to-treat and local-average-treatment-effect estimates. Our regression specifications include the following outcome, treatment, and control variables, all of which were specified in the pre-analysis plan and implemented accordingly (Marcus et al., 2020).

Outcome Variables

Our primary outcome is screening uptake, which is measured in two ways. First, we use self-reported data at endline on whether respondents went to any diabetes or hypertension screening within the intervention period.[5] Secondly, we measure whether respondents went to at least one of the two *Posbindu* dates specified in our text message intervention.

Secondary outcomes are SMS-related knowledge, broader diabetes and hypertension knowledge, and household spillovers. SMS-related knowledge aims to capture the direct effect of the information that is transmitted in the messages, measured with seven questions (refer to appendix Table A 4 for the list of the questions). This results in a count index from 0 to 7, which increases by one for each correctly answered question that relates to the message content. We assess broader diabetes and hypertension knowledge to evaluate any knowledge impacts beyond the pure message content, for example through information obtained from the health staff during screening, or through information seeking. We measure broader diabetes and hypertension knowledge with ten questions derived from a model of the determinants of health seeking behavior (Becker, 1974; Janz & Becker, 1984) and aggregated into an index. The items enter the index in a coding such that can be influenced by information into a clear direction. An increase in the index therefore reflects both an increase in

[5] We further pre-specified the aim to measure screening uptake across all villages in the sample districts using *Posbindu* attendance rates from administrative data, but full access could not yet be granted.

knowledge and should, as the model hypothesizes, increase the propensity to take up screening services. We measure the individual dimensions using the survey items displayed in appendix Table A 5. For the main results, we use a count index that increases by one with each correctly answered knowledge question. To test the sensitivity of this result, we employ principal component analysis to reduce the dimensions to one variable, weighted by their explanatory power. This index gives a holistic picture of health knowledge with a focus on diabetes and hypertension.

We measure household spillovers through a binary variable indicating whether any other household members went for diabetes or hypertension screening within the intervention period.

Treatment Status

Treatment is defined in two ways. First, we categorize respondents into treatment and control group. Secondly, we define a "treatment exposure" variable, which indicates whether the respondent received all three messages in one month and can recall the content of at least one message. The former is measured using delivery reports from the bulk SMS provider. The latter is a self-reported measure collected at endline. It is based on listing at least one of the elements of our text messages when asked about the content of the CVD/ screening related message in an unaided recall question, if the respondent claims to have received such a message.

Variables for heterogeneous treatment effects

We measure risk and time preferences with one self-reported baseline survey question each, taken from and validated by the Global Preferences Survey (Falk et al., 2016, 2018). Patience is elicited by asking respondents to indicate how generally willing they are to give up something today in order to benefit from it in the future (on a scale from 0 to 10). Willingness-to-take risks is elicited by asking respondents to indicate on a scale from 0 to 10 how generally willing they are to take risks.

Control Variables

We measure age, sex, education, and phone ownership using self-reported survey questions. Furthermore, we construct a wealth index based on self-reported asset ownership using the standard DHS approach. All control variables were elicited at baseline.

Regression Specifications

We estimate treatment effects on primary and secondary outcomes in the following framework:

a) Intention-to-treat (ITT)

$$Y_i = \alpha + \beta Treat_i \; + \; \delta Control_i + \varepsilon_i \tag{1}$$

where *Y* is our outcome variable (screening uptake in the main specifications and household spillover effects, SMS-related knowledge, and broader hypertension and diabetes knowledge in secondary analyses), *Treat* is an indicator variable for treatment status, and *Control* denotes the variables age (continuous), sex (indicator for female), education (none as base category, indicators for primary, lower secondary, upper secondary, tertiary education), wealth (in quintiles, with lowest as base category), and phone ownership[6].

b) Local Average Treatment Effect (LATE)
Additionally, we estimate the local average treatment effect using an instrumental variable approach (Imbens & Angrist, 1994). Specifically, we use assigned treatment status to instrument the treatment exposure variable.

$$Exposed_i = \eta + \theta Treat_i \; + \pi \; Control_i + \upsilon_i \tag{2}$$

$$Y_i = \alpha + \beta \widehat{Exposed}_i \; + \delta \; Control_i + \varepsilon_i \tag{3}$$

We explore potential heterogeneities in treatment uptake along time and risk preferences using the following specification:

$$Y_i = \alpha + \beta Treat_i + \gamma Trait_i + \theta Trait_i * Treat_i + \delta \; Control_i \; + \varepsilon_i \tag{4}$$

Where $Trait$ is the respective continuous indicator of baseline risk or time preference.

Standard errors are clustered by phone number. For all main hypotheses, p-values are adjusted for multiple hypothesis testing following the Benjamini-and-Hochberg method (Benjamini & Hochberg, 1995).

3.3 Data and Sample Characteristics

<u>Sampling</u>

The baseline sample was drawn in a two-stage stratified random sampling procedure. First, we randomly drew 147 villages from a complete list of villages in the districts Aceh Besar and Banda Aceh. This draw was stratified by district to have an equal number of villages from the mostly rural Aceh Besar and the mostly urban provincial capital Banda Aceh (refer to appendix Figure A 1 for a map of the sampled villages). Within the villages, we selected households using a random walk following the procedure described in appendix B. Around half of the identified houses were found to

[6] Due to a technical problem, phone ownership was not elicited for 7 individuals. We created a separate indicator for missing phone ownership information to keep them in the estimation sample. Neither phone ownership nor the indicator are significantly different from zero in the regressions.

be occupied, out of which 85% agreed to undergo the short eligibility check. The eligibility criteria ensured that the respondent would be recommended to be screened on a yearly basis (being over the age of 40)[7], and is neither diagnosed with diabetes or hypertension nor adheres to the recommended screening schedules. Out of those who did the eligibility check, one third of households were eligible[8]. If several household members met the inclusion criteria, one was randomly chosen as respondent. This yielded a sample of 2,006 individuals[9]. The survey was introduced as a research study on the health of people over 40 in Aceh province, and respondents were asked to give a phone number through which they can be reached over the next months.

The endline survey was conducted from end of March until beginning of May 2020 and was shifted to phone interviews due to the outbreak of the COVID-19 pandemic (call pattern described in appendix Figure A 2). The analysis sample comprises 1,386 individuals, 704 of the control and 682 of the treatment group. This implies a re-contact rate of slightly more than 70%[10], which is high for a telephone survey, but lower than we expected from the planned in-person endline data collection. The endline sample is hence slightly smaller than was deemed necessary in the power calculation (see appendix B3).

Sample characteristics

We depict endline sample characteristics across treatment and control group in Table 1. The average age of the respondents is 50 years, slightly more than 60% of the sample population is female, and 73% have at least lower secondary education. Literacy in Bahasa Indonesia is over 90%. About two thirds of the respondents owned the phone that was used to contact them, the remainder were reachable through a phone owned by a family member or someone else. Compared to the same age group living in households with a mobile phone in the representative national socio-economic survey (SUSENAS 2017), our respondents are to a higher proportion female and slightly less educated, but generally similar across basic sociodemographic characteristics (see appendix Table A 7).

[7] We set the upper age limit of 70 to ensure that the respondent is able to complete the interview. Refer to appendix B for a detailed list and reasoning for each in- and exclusion criterion.

[8] Out of those ineligible, 36% did not have a member between the ages of 40 and 70, 28% had a member with a prior diabetes or hypertension diagnosis, 15% went for regular screening, in 8% of households eligible members were not at home and only 6% of households had to be excluded because they did not have any mobile phone (Table A 3).

[9] An additional 94 baseline respondents were excluded before randomization as they had not supplied us with a valid telephone number until the end of data collection. This also led to the drop-out of one village in the final sample.

[10] 1,412 respondents could be re-interviewed. Due to missing information on whether screening happened after the start of the intervention (the month of screening was not reported) for 23 respondents, and missing information on age, gender and wealth quintile for one respondent each, the final analyses sample consists of 1,386 respondents.

Table 1 Endline sample characteristics across treatment and control group

	Control group			Treatment group			
	Mean	Standard deviation	N	Mean	Standard deviation	N	p-value
Age	50.26	8.22	704	49.52	7.85	682	0.088
Female	0.64	0.48	704	0.61	0.49	682	0.285
Highest level of schooling							0.850
None	0.04	0.19	704	0.03	0.18	682	
Primary	0.23	0.42	704	0.24	0.42	682	
Junior Secondary	0.23	0.42	704	0.21	0.41	682	
Senior Secondary	0.35	0.48	704	0.36	0.48	682	
Tertiary	0.15	0.36	704	0.17	0.37	682	
Literacy	0.91	0.29	568	0.93	0.26	555	0.160
Wealth quintile							0.389
1	0.22	0.41	704	0.19	0.39	682	
2	0.19	0.39	704	0.18	0.38	682	
3	0.19	0.39	704	0.22	0.41	682	
4	0.20	0.40	704	0.19	0.39	682	
5	0.20	0.40	704	0.22	0.42	682	
Own phone	0.64	0.48	700	0.68	0.47	679	0.101
Joint F-test							0.270

Means, standard deviation and number of observations of main respondent characteristics by treatment group; p-values based on t-tests of difference in mean between treatment and control group, except in the case of the categorical variables education, wealth quintile, and the total, where we used F- tests on joint significance of the different levels respectively variables.

Balance and attrition

Treatment and control group were balanced across all key variables of interest at baseline, except for phone ownership, which was slightly higher in the treatment group (see appendix Table A 6). At endline, respondent age is slightly lower in the treatment group and the share of phone owners remains slightly higher. As displayed in appendix Table A 8 to Table A 10, there was no differential attrition between treatment and control group. There are no statistical differences in the demographics between the individuals of the treatment and control group lost to follow-up, except for a lower baseline disease knowledge in the treatment group at 10% significance. However, independent of treatment status, respondents who were lost to follow-up seem to be to a higher proportion female, less educated and knowledgeable about CVDs, less wealthy, and to a lesser proportion phone owners. These differences likely occur due to the need to shift the administration of the survey to the phone: Additional analyses reveal that phone ownership is more likely across younger, male, and better educated individuals from households in the highest wealth quintile. If controlling for all base characteristics simultaneously, having no educational degree and not being the phone owner are the only significant correlates of attrition (appendix Table A 11).

Treatment exposure

Within the treatment group, around 28% of respondents are classified as exposed to treatment, meaning that they received at least one full cycle of intervention messages and are able to recall at least one element of the message content. Technical issues regarding the delivery do not seem to pose a major barrier: According to the delivery reports, at least one full cycle of intervention messages was delivered in 97% of cases before one of the Posbindu dates. For 84% of our sample, we have also self-reported measures of exposure[11] (Figure A 5): Out of those who received at least one full cycle of messages, 30% could correctly recall at least one item of the message content, indicating that the messages were not only delivered, but also received, read, and understood. At the same time, there were very few information spillovers to the control group or any other exposure to similar information, as less than 5% of the control group report to have received any information on screening or Posbindu. We assess the exposure to the intervention more closely in appendix section G and show that groups who are more likely to be telephone owners (younger, male, and more educated) are more likely to recall the reception of the messages and their content.

4 Results

4.1 Screening uptake

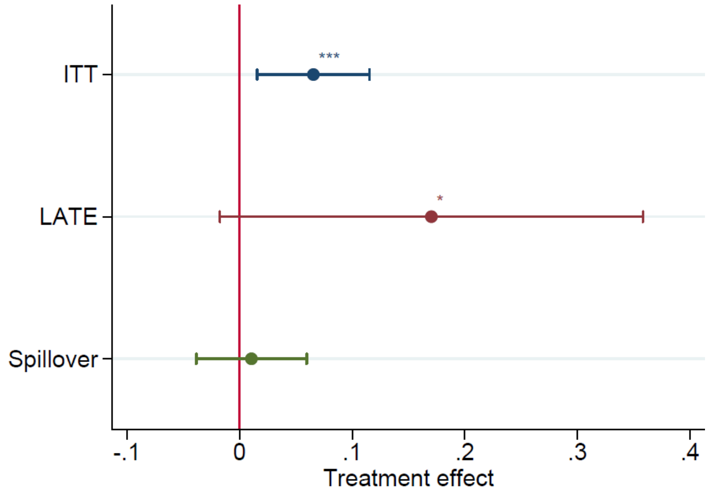
We find that our intervention had a positive effect on screening uptake of the message recipient (Figure 2). In the intention-to-treat analysis, treatment increased screening uptake from 33% in the control to 40% in the treatment group. This is an increase by around 6.6 percentage points (p.p.) or 20% at a statistical significance level of less than 1%. This effect is robust in all pre-specified model specifications (Table A 12), adjustments for multiple hypothesis testing (Table A 13) or alternative estimation strategies (Table A 15). When we instrument treatment exposure by treatment status in the LATE analysis, the treatment effect is more than twice as high (17 p.p.), albeit with a lower precision of the estimate than for the ITT due to the reduction in the sample size and hence a loss in statistical power. There is no significant different effect by phone ownership (Table A 20).

The effect on screening uptake of the message recipient did not lead to within-household spillover effects. We do not find evidence for other household members taking up screening more often, neither in the aggregate as displayed in Figure 2, nor when restricting the sample to household members in the same age group as our respondents (between the age of 40 and 70) (Table A 21). Receiving the

[11] As the questions about message content were asked only in the very end of the interview, the estimation sample for the LATE excludes 204 respondents who terminated the interview before this question. Respondents in this subsample are to a higher proportion male, to a lesser proportion phone owner, but otherwise similar.

messages through another household member's phone or a family phone could have increased other household member's attention to the messages, but even if accounting for phone ownership, we do not find evidence for substantial spillover effects (Table A 21).

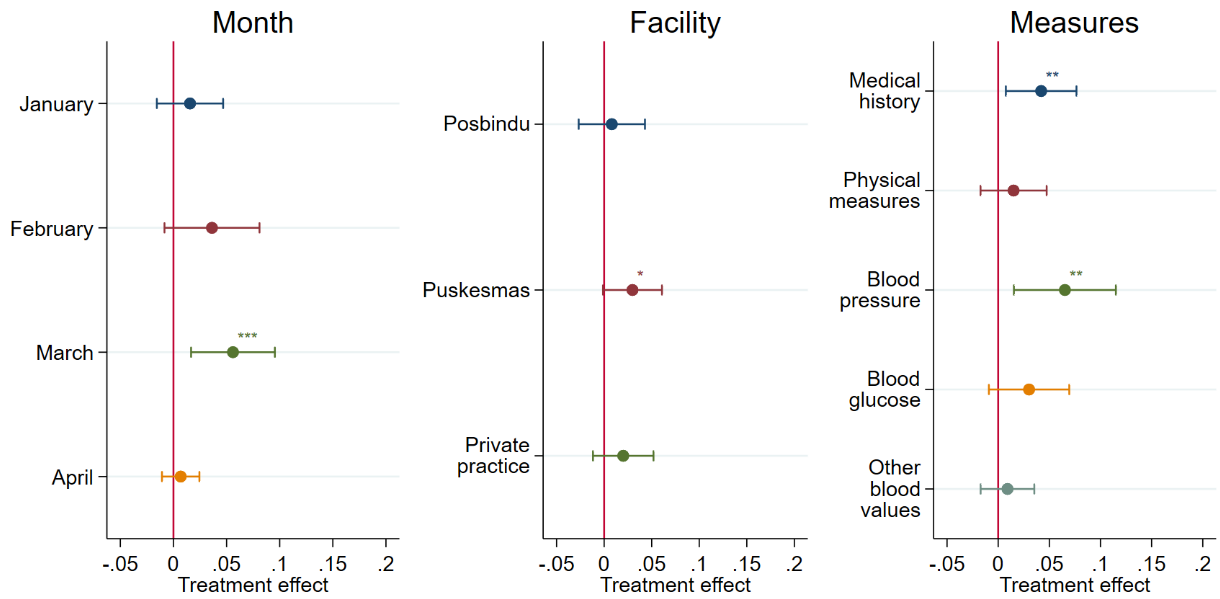
Figure 2 Treatment effect on screening uptake of the message recipient and household members.



*Point estimates of the treatment coefficient from equation 1 (ITT), the instrumented treatment coefficient from equation 3 (LATE) for the message recipient and other household members (ITT); outcome definition: at least one screening visit reported during the intervention period; controlling for age, gender, wealth and phone ownership; see Table A 12 for tabular display with and without covariates; displayed with 95% confidence intervals; * p < 0.1, ** p < 0.05, *** p < 0.01*

We further examine the timing and location of screening as well as the checks conducted during screening (Figure 3). The treatment is positively correlated with screening uptake in all post-treatment months, but only statistically significantly different from zero and comparable to the size of the aggregate treatment effect in March. As the text messages included references to both the *Puskesmas* and specific Posbindu meetings, we also disaggregate our analysis by screening provider and find a significant treatment effect only for the *Puskesmas screening locality.* Finally, respondents from the treatment group are significantly more likely to have had a blood pressure reading and checks of the medical history in the past months. Blood glucose testing, physical measurements, and other blood checks are also positively correlated with treatment, but not statistically significantly different from zero (Table A 24). As blood pressure readings were conducted during nearly all facility visits, irrespective of the facility type (Figure A 3), the impact on blood pressure readings closely mirrors the overall treatment effect.

Figure 3 Treatment effect on message recipient screening uptake by month and facility

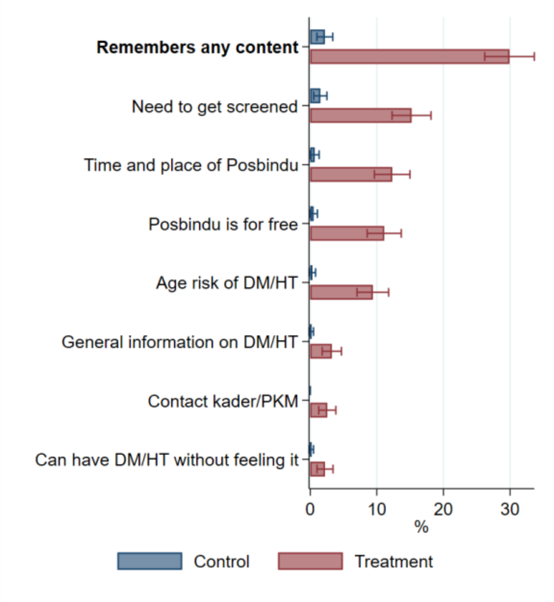


*Point estimates of treatment coefficient from equation 1 with different binary screening uptake indicators as outcomes (coded as 1 if the individual indicated to have gone to screening in the respective month/ facility and 0 otherwise); controlling for age, gender, wealth and phone ownership; see Table A 22 and Table A 23 for tabular display; displayed with 95% confidence intervals; * p < 0.1, ** p < 0.05, *** p < 0.01.*

4.2 Information and knowledge

To study the effects on information and knowledge, we first describe the information that respondents recall from the messages they received. Figure 4 shows that 30% of the treatment group can correctly recall at least one content element. The principal directive that the respondent should be tested for diabetes and hypertension is recalled most frequently (15%). This is followed by logistical components, as 12% and 11% of the treatment group remember that the messages contained information on when and where *Posbindu* takes place as well as that it offers free CVD check-ups. The disease-related information that is remembered most is that higher age also means a higher risk for diabetes or hypertension (9%). At the same time, only 2% recall the information that hypertension and diabetes can be asymptomatic.

Figure 4 Message components that are listed in an unaided recall question



Percent of treatment / control group that recalls the respective message component. Refer to section 3.1 for the description of all message components. DM=diabetes, HT=hypertension, PKM=Puskesmas. We asked for any information on health screening or Posbindu received in the past months. Note that this question was not answered by 204 respondents who ended the interview before reaching this question, see footnote 11.

Even though a substantial share of treated respondents remembers at least one element of the message content, we do not detect an increase in knowledge among the treated on any pre-defined knowledge indicator, as shown in Table 2. We can neither detect a treatment effect for the specific knowledge items mentioned in the text messages, nor for general diabetes and hypertension knowledge. These patterns hold when defining the indices via PCA rather than as a count index (Table A 16), and for each element of the respective index (Table A 17, Table A 18, Table A 19).

Table 2 Treatment effect on knowledge outcomes

	(1) SMS knowledge	(2) SMS knowledge	(3) General disease knowledge	(4) General disease knowledge
Treated	-0.0009	-0.0029	-0.0365	-0.0570
	(0.0609)	(0.0610)	(0.0616)	(0.0597)
Covariates	No	Yes	No	Yes
Observations	1088	1088	1042	1042

ITT estimates on SMS-related and general disease knowledge indices following equation 1. Both indices are standardized to a sample mean of 0 and a standard deviation of 1. Covariates are age, gender, wealth and phone ownership. Standard errors clustered at the phone-number level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.3 Heterogeneous treatment effects

We cannot detect any heterogeneous effects across time and risk preferences (Table 3). In most cases, the standard errors are also too large to retain the original treatment effect. One reason for not detecting any heterogeneous treatment effects might be that these self-reported measures are not strongly correlated with the screening decision in the intervention period. At baseline, we observed a significant correlation between patience and hypertension screening within the last year, but no correlation for willingness to take risk. Another reason might be that the endline sample is too small to detect any heterogeneity.

Table 3 Analysis of Heterogeneous Effects

	(1) Screened	(2) Screened	(3) Screened	(4) Screened
Treated	0.055	0.082	0.090	0.118**
	(0.051)	(0.051)	(0.057)	(0.057)
Willingness to take risk	0.001	0.007		
	(0.007)	(0.007)		
Treated x Willingness to take risk	0.001	-0.004		
	(0.010)	(0.010)		
Patience			0.005	0.008
			(0.006)	(0.006)
Treated x Patience			-0.006	-0.009
			(0.009)	(0.009)
Covariates	No	Yes	No	Yes
Obs.	1386	1386	1386	1386
Control group mean	0.3310	0.3310	0.3310	0.3310

*Results of regressing the binary screening indicator (=1 if at least one screening visit reported during the intervention period) on the binary treatment indicator, the respective time or risk preference as well as their interaction following equation 4; controlling for message recipient age, gender, wealth, and phone ownership; Standard errors clustered at the phone number in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01*

4.4 Discussion of mechanisms

Next, we discuss which mechanisms may have contributed to the effectiveness of the intervention. First, our text message included several points of information aimed at lowering knowledge barriers to screening uptake. However, we do not find strong evidence for this channel. We see that important disease misconceptions around the disease progression of hypertension and diabetes persist in our study population (Figure A 4). As detailed above, we further find that only a minority of respondents are able to recall disease-related information provided in the text messages and no significant treatment effect on knowledge measures (see section 4.2). Yet, the intervention might have been effective at increasing the salience for those who were already aware of it but did not yet act on it. We show that participants can recall mostly SMS content that they were already aware of and that called them to action. This is in line with other studies that showed SMS don't always increase knowledge, but can still work as a reminder or nudge despite not clearly transmitting new information (e.g.

Banerjee et al., 2020; Bettinger et al., 2021), and supported by the existence of a strong demand for reminders in medical adherence due to memory costs (Barron et al., 2022).

Moreover, our intervention allows us to gain insights on the facility choice individuals take. Further analyses indicate that framing, path dependency, and operating hours might have contributed to the take-up of screening at the primary health care facility: First, nearly all individuals (93%) who knew *Posbindu* saw it as a service for the elderly, potentially because a similar health service targeted at the population aged 65 and older exists. Thus, many respondents might perceive themselves as too young to use the service; a notion which is supported by the correlation of higher age with using Posbindu at endline and was also found in qualitative studies on Posbindu use in the area (Sofyan et al., 2023; Widyaningsih et al., 2022). This stresses the importance of carefully considering targeting and thereby framing effects in the design of community-based screening programs. Second, we observe that individuals in the treatment group were more likely to visit the same facility at which their last blood pressure or blood glucose check took place at baseline (Table A 25). This indicates that the respondents are used to going to a specific health facility, and thus might repeat this behavior as a response to our intervention, as it is the most salient or familiar option to them – a well-described heuristic when deciding between multiple options (DellaVigna, 2009; Shah & Ludwig, 2016). Alternative explanations might be that the previously visited facility is the facility which is the easiest to access, or with the highest trust or perceived comfort. Third, access might also play a role in the choice of the primary health care post over Posbindu. While Posbindu is typically the closest option, it is also the least flexible as it takes place only once a month. For respondents who did not go for screening, logistical considerations played a minor role overall, but among logistical reasons, time was the most pressing concern. This is in line with other studies from this context and in other LMICs that stress the importance of access times and durations of CVD screenings that are compatible with work and other responsibilities (Karunaratna et al., 2022; Sofyan et al., 2023; Widyaningsih et al., 2022).

Finally, as our intervention aimed at increasing preventive health behavior, treatment spillovers within social networks could constitute beneficial by-products. However, our analyses show that no significant spillovers onto other household members, overall and of the same age cohort, occurred. One potential implication of these findings may be that the intervention's key features of being light-touch and personalized may have come with a trade-off of few spillovers beyond the main respondent. Our findings contribute to sparse literature on spillover effects of messages aimed at increasing preventive health behavior. If examined, there are rarely detectable spillover effects, for example no spillovers to neighbors in a more intensive messaging campaign on dengue prevention in Peru (Dammert et al., 2014). On the other hand, Banerjee et al. (2020) detected substantial community spillovers in the setting of higher message saturation in the community and arguably high salience during the COVID-19 health emergency. In a high-income setting, Bouckaert et al. (2020) find intra-household spillovers according to the target population: Personal invitations for flu shots had positive effects on spouses and negative effects on children, such that the overall targeting of flu shots was improved.

4.5 Cost estimation

To improve the comparability of our text message reminders with other demand-enhancing interventions, we estimate the costs of our intervention per targeted person and per additionally screened person (Table 4). In the first column, we consider costs directly related to the intervention, i.e., costs of sending out the text messages and of inquiring the village-specific Posbindu details, assuming that any implementer would be able to target recipients using a register, such as a health insurance database. We base this estimate on the complete treatment group, rather than only the endline sample for a conservative estimate that assumes no treatment effect on the individuals lost to follow-up. In the second column, we additionally provide estimates on the screening costs occurring to the health system in the form of medical staff and material. We assume that a person presenting at a facility would take up 15 minutes of time with a medical practitioner, and price this using wage data from the National Statistical Office (Badan Pusat Statistik, 2021). In addition, we calculate the costs for blood glucose tests with a point-of-care machine, assuming that 47% of the individuals accessing the service are screened for diabetes (as observed in our sample). As every health worker has an own blood pressure monitor, no additional costs are borne for a blood pressure reading. For the scale-up, we assume that Posbindu dates can be transmitted directly to the implementer at a fix cost, such that these costs are not included in the scale-up calculation. On this basis, we estimate that a scale-up would cost IDR 5,277 or USD 0.38 per targeted person, and IDR 129,293 or USD 9.21 per additionally screened person.

Table 4. Cost estimates

	Intervention costs	**Total costs**	**Scale-up (per Person)**
SMS	4,651,101	4,651,101	4,500
Request for Posbindu dates	1,000,000	1,000,000	
Medical staff		640,313	638
Blood glucose test		140,121	140
Per targeted person	5,629	6,406	5,277
Per additionally screened person	137,899	156,943	129,293
Per targeted person (USD)	0.40	0.46	0.38
Per additionally screened person (USD)	9.83	11.18	9.21

All prices denoted in IDR, unless noted differently. Costs are calculated based on the targeted 1,004 respondents of the treatment group after the baseline. SMS costs were EUR 300 and are converted with an exchange rate of 15503.67 IDR/EUR. Costs for medical staff were taken from the National Statistical Office (BPS) as monthly net wages for employees in the health sector with university degree and doubled to receive an upper bound of gross wages to the health system (Badan Pusat Statistik, 2021). It was assumed that medical staff would spend about 15 minutes on each examination. It was assumed that point-of-care machines were used for the blood glucose check, as they are used at the Posbindu, such that *one test would cost IDR 7,275, including lancet, stick, gloves, and disinfect. Costs for medical staff were calculated for the share of respondents who went to a screening facility due to the intervention (6%) times the share of treatment group respondents who were reached for the endline interview and for whom screening data was non-missing (68%). Costs for blood glucose tests were calculated for the share of respondents who went to a facility due to the intervention (6%) and conducted a blood glucose check (47% of the visitors) times the share of treatment group respondents who were reached for the endline interview and for whom screening data was non-missing (68%). USD were calculated using an exchange rate of 14032.02 IDR/USD. All costs were assessed between November 2019 and February 2020. If the targeted respondents who were not reached for the endline interview or for whom screening data is missing had the same treatment effect as the observed respondents, costs would reduce to USD 6.69 for the intervention costs, USD 8.04 for the total costs, and USD 6.70 for the scale-up costs per additionally screened person.*

5 Conclusion

Using an RCT in Indonesia, we find that personalized text messages can successfully increase diabetes and hypertension screening uptake among the population at risk. Sending two sets of three text messages before two village-based screening meetings increased screening rates by approximately 6.6 percentage points from 33% to 40%. For participants who received at least one full cycle of messages and remembered any message content, the effect size was 17 percentage points. The intervention specifically increased screening uptake at the community health center (Puskesmas) and for blood pressure. We cannot detect any spillover effects within households, treatment effects on knowledge indicators, or heterogeneous effects along levels of patience or willingness-to-take-risks.

Given that CVDs rapidly became the leading cause of death in Indonesia, and middle-income countries more generally, our study provides timely evidence that a light-touch SMS intervention can be an important component of CVD prevention strategies. The size of our treatment effect is comparable to other text message interventions on more salient preventive behavior in LMICs: With a risk ratio of 1.17, our findings lie between the results from the systematic reviews on immunization rates by Mekkonen et al. (2019) (RR: 1.11) and Jacobson Vann et al. (2018) (RR: 1.29). With an odds ratio of 1.28, the effect size is slightly lower than the average effect size of studies on STD detection as reported by Taylor et al. (2019) (OR: 1.73) or the effect size of a reminder text message after an invitation letter for screening in the United Kingdom by Sallis et al. (2019) (OR:1.40).

Our study adds to this literature in several ways: Our intervention took place in a setting where awareness of the nature of CVDs is still limited, and the proposed health behavior might not be salient in the everyday life of the targeted population. Also, routines of care seeking behavior had less time to develop in comparison to other diseases. This is also reflected in the scarcity of studies on interventions to increase CVD screening in low- and middle-income countries: In the context of South-East Asia, for example, there has been no previous study of CVD screening interventions, according to a recent systematic literature review (Fritz & Fromell, 2022). We show that text messages are effective in the absence of a high salience or established routine, and that also in this context, few, spot-on reminders are sufficient to nudge preventive health behavior. Also, we see that individuals tend to attend the same facilities they used before, underlying the importance of a pre-existing, accessible health care infrastructure.

Furthermore, our study shows that text message interventions can effectively work in middle age and older adults. While having a different mobile usage than younger age cohorts and still relying on indirect mobile access through phones of close contacts in large proportions, text message interventions targeting the elderly can have similar effect sizes compared to a general population.

An advantage of text message interventions is their comparatively low cost. We estimate that our intervention costs USD 11.18 per additionally screened person, incorporating the costs of the screening service. A scale-up might decrease these costs even further, especially if screening dates can be centrally collected. For people at higher risk due to preconditions, more intensive interventions might be a good addition to push screening rates even more, albeit at higher costs: Using personally delivered invitation letters and pharmacy voucher, de Walque et al. (2022) measure an increase in screening rates by even 15 to 30 percentage points at a cost of about 60 USD per screened person.

This study comes with some limitations regarding the recruitment of participants and the telephonic endline data collection. We cannot rule out that our in-person baseline survey already worked as a reminder to take up screening 2-3 months prior to the intervention. Both treatment and control group saw higher propensities to be screened from January onwards, so that the high control group uptake might in part be driven by our baseline visit. However, we can still detect a systematic difference between treatment and control group, especially as time to the baseline interview increased. Secondly, measuring the main outcome as self-report is subject to the concern of misreporting and social desirability bias. To minimize this concern, we added detailed follow-up questions on what happened at the screening visit and the consistency of the answers gives us confidence in the main result. Switching the endline data collection to the telephone was the only possibility after the outbreak of the COVID-19 pandemic, but poses additional limitations. First, we could only re-interview 70% of the sample, with significant attrition across several socioeconomic characteristics. To the extent that phone ownership is correlated with both, a higher rate of recall receiving the message and a lower probability to be lost to follow-up, it is likely that our treatment effect would be slightly smaller in this case. Secondly, respondents may be less trusting over a telephone call in comparison to face to face interviews conducted in the privacy of their own home. As our study team visited the respondents during baseline, we think this problem might be less severe compared to phone surveys when the call is the first point of contact. To minimize this concern further, we assigned the enumerator who visited the respondent at baseline whenever possible and re-introduced our team and the survey in the beginning of the interview.

With the expansion of mobile phone coverage around the globe, policy makers gain access to a new toolbox of low-cost and light-touch interventions at scale. We show that text messages can induce preventive health behavior and reduce the screening gap for fairly new, yet severe contributors to the health burden of middle-income countries. As universal health coverage expands and is digitalized, such text messages can become cost-effective and easily customizable measures to remind a target population of preventive health behavior and stimulate new health care habits.

6 List of References

Badan Pusat Statistik. (2021, November 8). *Average of Net Income per Month of Casual Worker by Province and Main Industry*. https://www.bps.go.id/subject/19/upah-buruh.html#subjekViewTab3

Banerjee, A., Alsan, M., Breza, E., Chandrasekhar, A. G., Chowdhury, A., Duflo, E., Goldsmith-Pinkham, P., & Olken, B. A. (2020). *Messages on COVID-19 Prevention in India Increased Symptoms Reporting and Adherence to Preventive Behaviors Among 25 Million Recipients with Similar Effects on Non-recipient Members of Their Communities* (Working Paper Nr. 27496). National Bureau of Economic Research. https://doi.org/10.3386/w27496

Banerjee, A., Chandrasekhar, A. G., Dalpath, S., Duflo, E., Floretta, J., Jackson, M. O., Kannan, H., Loza, F. N., Sankar, A., Schrimpf, A., & Shrestha, M. (2021). *Selecting the Most Effective Nudge: Evidence from a Large-Scale Experiment on Immunization* (Working Paper Nr. 28726). National Bureau of Economic Research. https://doi.org/10.3386/w28726

Barron, K., Damgaard, M. T., & Gravert, C. (2022). *When do reminders work? Memory constraints and medical adherence*. 66.

Becker, M. H. (1974). The Health Belief Model and Sick Role Behavior. *Health Education Monographs*, *2*(4), 409–419. https://doi.org/10.1177/109019817400200407

Benjamini, Y., & Hochberg, Y. (1995). Controlling the False Discovery Rate: A Practical and Powerful Approach to Multiple Testing. *Journal of the Royal Statistical Society. Series B (Methodological)*, *57*(1), 289–300.

Bettinger, E., Cunha, N., Lichand, G., & Madeira, R. (2021). *Are the Effects of Informational Interventions Driven by Salience?* (Nr. 350; Working Paper). University of Zurich, Department of Economics.

Bouckaert, N., Gielen, A. C., & Van Ourti, T. (2020). It runs in the family – Influenza vaccination and spillover effects. *Journal of Health Economics*, *74*, 102386. https://doi.org/10.1016/j.jhealeco.2020.102386

Chavarría, E., Diba, F., Marcus, M. E., Marthoenis, Reuter, A., Rogge, L., & Vollmer, S. (2021). Knowing Versus Doing: Protective Health Behaviour Against COVID-19 in Aceh, Indonesia. *The Journal of Development Studies*, *57*(8), 1245–1266. https://doi.org/10.1080/00220388.2021.1898594

Dammert, A. C., Galdo, J. C., & Galdo, V. (2014). Preventing dengue through mobile phones: Evidence from a field experiment in Peru. *Journal of Health Economics*, *35*, 147–161. https://doi.org/10.1016/j.jhealeco.2014.02.002

de Walque, D., Chukwuma, A., Ayivi-Guedehoussou, N., & Koshkakaryan, M. (2022). Invitations, incentives, and conditions: A randomized evaluation of demand-side interventions for health screenings. *Social Science & Medicine*, *296*, 114763. https://doi.org/10.1016/j.socscimed.2022.114763

DellaVigna, S. (2009). Psychology and Economics: Evidence from the Field. *Journal of Economic Literature*, *47*(2), 315–372. https://doi.org/10.1257/jel.47.2.315

DIME. (2019). *Randomization in Stata—DIME Wiki*. https://dimewiki.worldbank.org/index.php?title=Randomization_in_Stata&oldid=5389

Direktorat Pencegahan Dan Pengendalian PTM. (2019). *Laporan Kinerja 2018 (Performance Report 2018)* (S. 54). Kementerian Kesehatan Republik Indonesia. http://p2ptm.kemkes.go.id/uploads/VHcrbkVobjRzUDN3UCs4eUJ0dVBndz09/2019/07/Laporan_Kinerja_2018.pdf

Djimeu, E. W., & Houndolo, D.-G. (2016). *Power calculation for causal inference in social science: Sample size and minimum detectable effect determination*. International Initiative for Impact Evaluation (3ie).

Dupas, P., & Miguel, E. (2017). Chapter 1—Impacts and Determinants of Health Levels in Low-Income Countries. In A. V. Banerjee & E. Duflo (Hrsg.), *Handbook of Economic Field Experiments* (Bd. 2, S. 3–93). North-Holland. https://doi.org/10.1016/bs.hefe.2016.09.003

Falk, A., Becker, A., Dohmen, T., Enke, B., Huffman, D., & Sunde, U. (2018). Global Evidence on Economic Preferences. *The Quarterly Journal of Economics*, *133*(4), 1645–1692. https://doi.org/10.1093/qje/qjy013

Falk, A., Becker, A., Dohmen, T. J., Huffman, D., & Sunde, U. (2016). The Preference Survey Module: A Validated Instrument for Measuring Risk, Time, and Social Preferences. *IZA Discussion Papers*, *9674*, 66. https://doi.org/10.2139/ssrn.2725874

Fritz, M., & Fromell, H. (2022). How to dampen the surge of non-communicable diseases in Southeast Asia: Insights from a systematic review and meta-analysis. *Health Policy and Planning*, *37*(1), 152–167. https://doi.org/10.1093/heapol/czab138

Geldsetzer, P., Manne-Goehler, J., Marcus, M.-E., Ebert, C., Zhumadilov, Z., Wesseh, C. S., Tsabedze, L., Supiyev, A., Sturua, L., Bahendeka, S. K., Sibai, A. M., Quesnel-Crooks, S., Norov, B., Mwangi, K. J., Mwalim, O., Wong-McClure, R., Mayige, M. T., Martins, J. S., Lunet, N., … Jaacks, L. M. (2019). The state of hypertension care in 44 low-income and middle-income countries: A cross-sectional study of nationally representative individual-level data from 1·1 million adults. *The Lancet*. https://doi.org/10.1016/S0140-6736(19)30955-9

Goldzahl, L. (2017). Contributions of risk preference, time orientation and perceptions to breast cancer screening regularity. *Social Science & Medicine*, *185*, 147–157. https://doi.org/10.1016/j.socscimed.2017.04.037

Gong, E., Chukwuma, A., Ghazaryan, E., & de Walque, D. (2020). Invitations and incentives: A qualitative study of behavioral nudges for primary care screenings in Armenia. *BMC Health Services Research*, *20*(1), 1110. https://doi.org/10.1186/s12913-020-05967-z

Head, K. J., Noar, S. M., Iannarino, N. T., & Grant Harrington, N. (2013). Efficacy of text messaging-based interventions for health promotion: A meta-analysis. *Social Science & Medicine*, *97*, 41–48. https://doi.org/10.1016/j.socscimed.2013.08.003

IHME. (2023). *GBD Compare Data Visualization*. IHME, University of Washington. https://www.healthdata.org/indonesia

Imbens, G. W., & Angrist, J. D. (1994). Identification and Estimation of Local Average Treatment Effects. *Econometrica*, *62*(2), 467–475. https://doi.org/10.2307/2951620

Jacobson Vann, J. C., Jacobson, R. M., Coyne-Beasley, T., Asafu-Adjei, J. K., & Szilagyi, P. G. (2018). Patient reminder and recall interventions to improve immunization rates. *Cochrane Database of Systematic Reviews*. https://doi.org/10.1002/14651858.CD003941.pub3

Janz, N. K., & Becker, M. H. (1984). The Health Belief Model: A Decade Later. *Health Education Quarterly*, *11*(1), 1–47. https://doi.org/10.1177/109019818401100101

Karunaratna, S., Weerasinghe, M. C., Ranasinghe, T., Jayasuriya, R., Chandraratne, N., Herath, H., & Quaife, M. (2022). Improving uptake of non-communicable disease screening in Sri Lanka: Eliciting people's preferences using a discrete choice experiment. *Health Policy and Planning*, *37*(2), 218–231. https://doi.org/10.1093/heapol/czab141

Kim, Y., & Radoias, V. (2016). Education, individual time preferences, and asymptomatic disease detection. *Social Science & Medicine*, *150*, 15–22. https://doi.org/10.1016/j.socscimed.2015.11.051

KKRI. (2019). *Petunjuk Teknis Pos Pembinaan Terpadu (Posbindu) Bagi Kader*. Direktorat Pencegahan Dan Pengendalian Penyakit Tidak Menular. http://p2ptm.kemkes.go.id/uploads/VHcrbkVobjRzUDN3UCs4eUJ0dVBndz09/2019/03/Petunjuk_Teknis_POSBINDU_Bagi_Kader.pdf

Kremer, M., Rao, G., & Schilbach, F. (2019). Chapter 5—Behavioral development economics. In B. D. Bernheim, S. DellaVigna, & D. Laibson (Hrsg.), *Handbook of Behavioral Economics: Applications and Foundations 1* (Bd. 2, S. 345–458). North-Holland. https://doi.org/10.1016/bs.hesbe.2018.12.002

Mahendradhata, Y., Trisnantoro, L., Listyadewi, S., Soewondo, P., Marthias, T., Harimurti, P., & Prawira, J. (2017). *The Republic of Indonesia Health System Review* (Bd. 7). WHO.

Manne-Goehler, J., Geldsetzer, P., Agoudavi, K., Andall-Brereton, G., Aryal, K. K., Bicaba, B. W., Bovet, P., Brian, G., Dorobantu, M., Gathecha, G., Singh Gurung, M., Guwatudde, D., Msaidie, M., Houehanou, C., Houinato, D., Jorgensen, J. M. A., Kagaruki, G. B., Karki, K. B., Labadarios, D., … Jaacks, L. M. (2019). Health system performance for people with diabetes in 28 low- and middle-income countries: A cross-sectional study of nationally representative surveys. *PLOS Medicine*, *16*(3), e1002751. https://doi.org/10.1371/journal.pmed.1002751

Marcus, M. E., Reuter, A., Rogge, L., & Vollmer, S. (2020). *A Mobile Phone-based Intervention to Improve Health Screening Uptake: A Randomized Experiment in Indonesia*. AEA RCT Registry. https://doi.org/10.1257/rct.5047-2.0

Mekonnen, Z. A., Gelaye, K. A., Were, M. C., Gashu, K. D., & Tilahun, B. C. (2019). Effect of mobile text message reminders on routine childhood vaccination: A systematic review and meta-analysis. *Systematic Reviews*, *8*(1), 154. https://doi.org/10.1186/s13643-019-1054-0

Milkman, K. L., Beshears, J., Choi, J. J., Laibson, D., & Madrian, B. C. (2013). Planning prompts as a means of increasing preventive screening rates. *Preventive Medicine*, *56*(1), 92–93. https://doi.org/10.1016/j.ypmed.2012.10.021

O'Donoghue, T., & Rabin, M. (2015). Present Bias: Lessons Learned and To Be Learned. *American Economic Review*, *105*(5), 273–279. https://doi.org/10.1257/aer.p20151085

Osei, E., & Mashamba-Thompson, T. P. (2021). Mobile health applications for disease screening and treatment support in low-and middle-income countries: A narrative review. *Heliyon*, *7*(3), e06639. https://doi.org/10.1016/j.heliyon.2021.e06639

Picone, G., Sloan, F., & Taylor, Jr., D. (2004). Effects of Risk and Time Preference and Expected Longevity on Demand for Medical Tests. *Journal of Risk and Uncertainty*, *28*(1), 39–53. https://doi.org/10.1023/B:RISK.0000009435.11390.23

Pujilestari, C. U., Ng, N., Hakimi, M., & Eriksson, M. (2014). "It is not possible for me to have diabetes"–Community Perceptions on Diabetes and Its Risk Factors in Rural Purworejo District, Central Java, Indonesia. *Global Journal of Health Science*, *6*(5), p204. https://doi.org/10.5539/gjhs.v6n5p204

Rahmawati, R., & Bajorek, B. (2018). Understanding untreated hypertension from patients' point of view: A qualitative study in rural Yogyakarta province, Indonesia. *Chronic Illness*, *14*(3), 228–240. https://doi.org/10.1177/1742395317718034

Riskesdas. (2018). *Laboran Nasional Riskesdas 2018*. Badan Penelitian dan Pengembangan Kesehatan; Ministry of Health.

Sallis, A., Sherlock, J., Bonus, A., Saei, A., Gold, N., Vlaev, I., & Chadborn, T. (2019). Pre-notification and reminder SMS text messages with behaviourally informed invitation letters to improve uptake of NHS Health Checks: A factorial randomised controlled trial. *BMC Public Health*, *19*(1), 1162. https://doi.org/10.1186/s12889-019-7476-8

Selden, T. M. (1993). Uncertainty and health care spending by the poor: The health capital model revisited. *Journal of Health Economics*, *12*(1), 109–115. https://doi.org/10.1016/0167-6296(93)90043-E

Shah, A. K., & Ludwig, J. (2016). Option Awareness: The Psychology of What We Consider. *American Economic Review*, *106*(5), 425–429. https://doi.org/10.1257/aer.p20161098

Sofyan, H., Diba, F., Susanti, S. S., Marthoenis, M., Ichsan, I., Sasmita, N. R., Seuring, T., & Vollmer, S. (2023). The state of diabetes care and obstacles to better care in Aceh, Indonesia: A mixed-methods study. *BMC Health Services Research*, *23*(1), 271. https://doi.org/10.1186/s12913-023-09288-9

Taylor, D., Lunny, C., Lolić, P., Warje, O., Geldman, J., Wong, T., Gilbert, M., Lester, R., & Ogilvie, G. (2019). Effectiveness of text messaging interventions on prevention, detection, treatment, and knowledge outcomes for sexually transmitted infections (STIs)/HIV: A systematic review and meta-analysis. *Systematic Reviews*, *8*(1), 12. https://doi.org/10.1186/s13643-018-0921-4

Tin, K. N., Ngamjarus, C., Rattanakanokchai, S., Sothornwit, J., Aue-aungkul, A., Paing, A. K., Pattanittum, P., Jampathong, N., & Lumbiganon, P. (2023). Interventions to increase the uptake of cervical cancer screening in low- and middle-income countries: A systematic review and meta-analysis. *BMC Women's Health*, *23*(1), 120. https://doi.org/10.1186/s12905-023-02265-8

Tsaneva, M. (2013). The Effect of Risk Preferences on Household Use of Water Treatment. *Journal of Development Studies*, *49*(10), 1427–1435. https://doi.org/10.1080/00220388.2013.790960

Whittaker, R., McRobbie, H., Bullen, C., Rodgers, A., & Gu, Y. (2016). Mobile phone-based interventions for smoking cessation. *Cochrane Database of Systematic Reviews*. https://doi.org/10.1002/14651858.CD006611.pub4

WHO. (2010). *WHO PEN Protocol 1—Package of essential noncommunicable disease interventions for primary health care in low-resource settings*. https://www.who.int/ncds/management/Protocol1_HeartAttack_strokes_kidneyDisease.pdf?ua=1

Widyaningsih, V., Febrinasari, R. P., Pamungkasari, E. P., Mashuri, Y. A., Sumardiyono, S., Balgis, B., Koot, J., Landsman-Dijkstra, J., & Probandari, A. (2022). Missed opportunities in hypertension risk factors screening in Indonesia: A mixed-methods evaluation of integrated health post (POSBINDU) implementation. *BMJ Open*, *12*(2), e051315. https://doi.org/10.1136/bmjopen-2021-051315

7 Appendices

A. Wording of messages

Table A 1 Wording of messages

Message (English)	Message (Indonesian)	Sending date
Greetings [Mr/Ms] [name], do you know that diabetes does not always show symptoms but can be treated better if detected earlier. Check for FREE at POSBINDU [date]	Salam [Pak/Ibu] [name], tahukah Anda diabetes tdk selalu menunjukan gejala namun dapat diobati lbh baik jika diketahui lbh awal. Periksa GRATIS di POSBINDU [date]	5 days before the first village screening date
Greetings [Mr/Ms] [name], do you know that people over 40 years old have a high risk of diabetes & hypertension? Ask kader / PKM & check for FREE at POSBINDU [date]	Salam [Pak/Ibu] [name], tahukah Anda umur diatas 40 tahun memiliki risiko tinggi diabetes & darah tinggi? Tanyakan Kader/PKM & Periksa GRATIS di POSBINDU tgl [date]	3 days before the first village screening date
Greetings [Mr / Mrs] [name], remember to benefit from a FREE diabetes and hypertension CHECK in POSBINDU tomorrow morning at [place within the village]. Contact nearest kader or PKM.	Salam [Pak/Ibu] [name], Jangan Lupa untuk PERIKSA Darah Tinggi dan Diabetes GRATIS di POSBINDU Besok pagi di [place within village]. Hubungi Kader dan PKM terdekat	1 day before the first village screening date
Greetings [Mr/Ms] [name], remember that hypertension does not always show symptoms but can be treated if detected earlier. Check for FREE at POSBINDU [date]	Salam [Pak/Ibu] [name], ingatlah darah tinggi tdk selalu menunjukan gejala namun dapat diobati lbh baik jika diketahui lbh awal. Periksa GRATIS di POSBINDU [date]	5 days before the second village screening date
Greetings [Mr/Ms] [name], remember that people over 40 years old have a high risk of diabetes & hypertension. Ask Cadre / PKM & check for FREE at POSBINDU date [date]	Salam [Pak/Ibu] [name], ingatlah umur diatas 40 tahun memiliki risiko tinggi diabetes & darah tinggi. Tanyakan Kader/PKM & Periksa GRATIS di POSBINDU tgl [date]	3 days before the second village screening date
Greetings [Mr / Mrs] [name], remember to benefit from a FREE diabetes and hypertension CHECK in POSBINDU morning at [place within the village]. Contact nearest kader or PKM.	Salam [Pak/Ibu] [name], Jangan Lupa untuk PERIKSA Darah Tinggi dan Diabetes GRATIS di POSBINDU Besok pagi di [place within village]. Hubungi Kader dan PKM terdekat	1 day before the second village screening date

B. Data collection details

Table A 2 Data collection timeline

	2019			2020			
Month	**October**	**November**	**December**	**January**	**February**	**March**	**April**
Qualitative pre-studies							
Baseline data collection (enrolment)							
Treatment allocation				X			
Pilot Intervention				X			
Intervention							
Endline data collection							

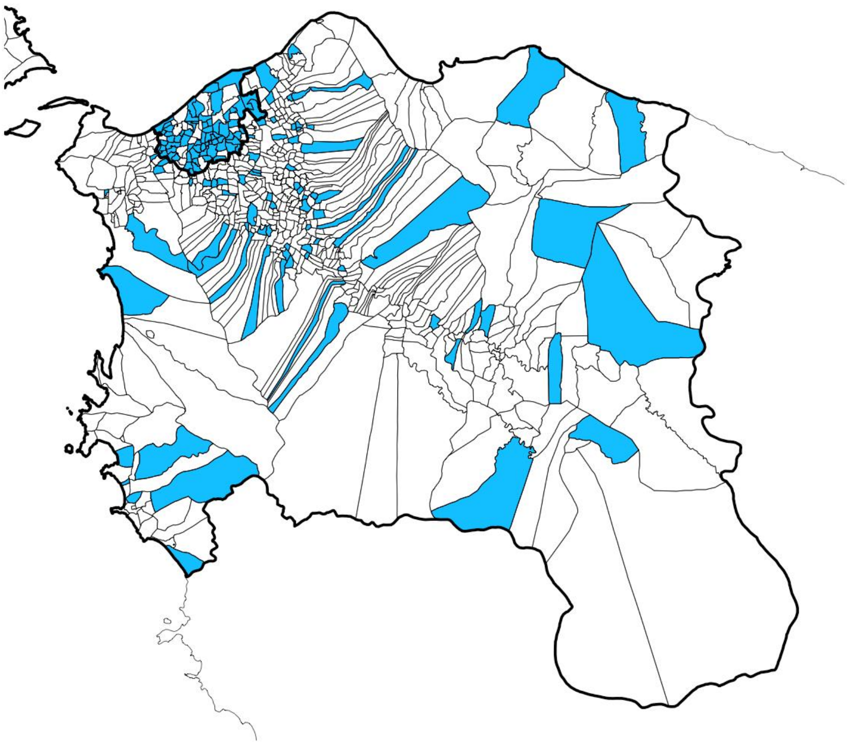


Figure A 1 Sample villages. Boundaries of the city Banda Aceh and the district Aceh Besar are in bold. Taken from the supplementary material in Chavarría et al. (2021).

B1 *Inclusion Criteria*

We targeted the population at high risk for CVDs, who do not yet adhere to the recommended screening schedule. Based on this, we formulated six inclusion and exclusion criteria:

1. The respondent must be between 40 and 70 years old. The WHO PEN Protocol for essential NCD interventions for primary health care in low-resource settings specifies that individuals over 40 years old should undergo routine screening for hypertension and diabetes (WHO, 2010).
2. The respondent cannot already be diagnosed with diabetes or hypertension, as this would render screening unnecessary.
3. The respondent did not undergo diabetes screening within the last year. Individuals that have done so seem to be adhering to recommended screening schedules, and would therefore not fall within our target population. Hypertension screening is not included in this restriction, as blood pressure checks are usually carried out whenever individuals visit a community health center and are hence much more common in this context.
4. The respondent must not be in regular care for another disease. If they are in regular contact with health system services, a lack of CVD screening may not stem from a lack of demand but rather from further downstream health system failures, which we do not aim to address in our intervention.
5. The respondent must be reachable via phone and text messages on either their own or another household member’s phone.
6. The respondent must be at home at the time of the interview. Logistically, it was not feasible to re-visit households. Furthermore, seeking out respondents outside of their home would have violated the comparability of interview conditions across our sample. For instance, respondents might feel most comfortable answering sensitive questions regarding their health in their own home. This criterion might bear the risk to exclude the working population, which we sought to reduce by extending the enumeration time to the evening and the weekends. Overall, this might not be as severe in our age group as in younger age groups, as some are retired already or work from home.

B2 *Random walk scheme*

Taken from the supplementary material in Chavarría et al. (2021).

The enumerators conducted the random walk according to the following instructions to ensure that the walk yields a representative sample of the target population:

1. Get permission and number of village subdivisions from the village head.
2. Ask for a description of the village boundaries, including remote houses.
3. Get the total number of houses in the village and divide this number by 100. This number indicates the skip-pattern of houses. It takes into account the aim of having around 20 respondents per village that should be evenly distributed throughout the village, how many interviews one enumerator can do in one day, and the likelihood of finding a household member that meets the inclusion criteria.
4. Then, randomly select which village subdivision to visit first and at which house (a random number between 1 and the skip number) to begin with. The count begins from the point of entry to the respective subdivision.
5. If a person is at home, check and record the eligibility and conduct the interview if the criteria are fulfilled and the respondent is willing to.
6. After each contact, continue with the next house according to the skip pattern.
7. In case of an empty house, contact the direct neighbor until an occupied house was found and record the number of empty houses.
8. When walking, turn left on every turn and only count houses to your left. Whenever you reach the end of the village subdivision or the road, turn around and continue.
9. One village was considered finished if 20 interviews were conducted or all houses that should be contacted according to the skip pattern were contacted.

Table A 3 Overview of baseline contacts

<table>
<tr><th></th><th>Total</th><th colspan="3">Of all contacts</th><th colspan="2">Of all consenting</th><th colspan="3">Of all eligible</th></tr>
<tr><td></td><td>Contacts</td><td>Empty houses</td><td>Refusal/ busy/ other</td><td>Consent</td><td>Eligible</td><td>Ineligible</td><td>Refusal</td><td>Incomplete</td><td>Complete</td></tr>
<tr><td>N</td><td>15,128</td><td>7,682</td><td>946</td><td>6,500</td><td>2,115</td><td>4,385</td><td>11</td><td>98</td><td>2,006</td></tr>
<tr><td></td><th colspan="9">Of all ineligible</th></tr>
<tr><td></td><td colspan="2">No member 40-70</td><td colspan="2">No member 40-70 present</td><td colspan="2">No phone access</td><td colspan="3">No member without diagnosis/ screening/care</td></tr>
<tr><td>N</td><td colspan="2">1,589</td><td colspan="2">414</td><td colspan="2">270</td><td colspan="3">2,112</td></tr>
</table>

Disaggregation of the number of contacts and respondents at baseline. Contacts refer to all dwelling units drawn by the random walk within the villages. Empty houses are dwellings where no one was present at the first contact, including dwellings which might not be inhabited. Refusal/busy/other denotes to reasons for non-participation stated at the first contact. Consent signifies that at least one household member agreed to respond to the screening questions to assess eligibility. Eligible refers to all contacts where at least one eligible member was present. Ineligible are all contacts where no member was eligible or no eligible member was present. Refusal denotes those (eligible) contacts for which no eligible member was willing to participate in the study. Incomplete denotes the interviews which were missing information on the telephone number. Complete refers to all conducted interviews with information on the telephone number. The columns 'no member 40-70' till 'no phone access' refer to the household eligibility criteria, the last column to the individual-level criteria (if multiple members were eligible, one was randomly selected). Among individuals, ineligibility could occur due to previous hypertension or diabetes diagnosis (59.36%), being in continued care (8.42%), being tested for diabetes in the last year (31.98%), or not answering one of the eligibility questions (0.24%). Taken from the supplementary material in Chavarría et al. (2021).

B3 *Power Calculations*

The following procedure of power calculation was set in the pre-analysis plan and under the assumption of an in-person endline data collection, which we had to deviate from due to the start of the COVID-19 pandemic.

The sample size was determined based on sufficient statistical power to determine a meaningful change in the primary outcome, screening uptake. Prior to baseline data collection, we could approximate the base levels of diabetes and hypertension separately from the most recent round of the Indonesian health survey Riskesdas (Riskesdas, 2018). This data supplies self-reported figures on whether the individual respondent attends screening regularly, irregularly or never, where regularly is defined as according to the doctor's advice for patients and once a year for the non-diagnosed. As our outcome is measured during approximately two months, the most appropriate base value is the *regular* category. The national average of the age group between 45 and 74 years is 5.2% for diabetes and 16.7% for hypertension screening[12]. As there are no previous studies on the effect of text message reminders on diabetes and hypertension screening, the minimum detectable effect size was approximated from studies that measure the effect of text message reminders on the initial take-up of other health services. A review on vaccination uptake found an average effect size of 4.5 percentage points (Jacobson Vann et al., 2018). With a power of 80% and 5% significance, a sample size of 1,800 individuals would be required to detect such an effect for both diabetes and hypertension screening. We would be able to detect a 4.4 percentage point increase for blood pressure measurement and a 2.6 percentage point increase in blood glucose measurement.[13] This implies that we would be able to detect a significant effect on any screening if at least 24 more respondents of the treatment group attend diabetes screening during the intervention period compared to the control group at the same time. With this sample size, we will also be likely to detect a small change in the secondary knowledge outcomes. For the SMS knowledge, the mean points of the treatment group need to be 0.1 points higher than for the control group, which means that on average every tenth respondent needs to know one item more. For the broader health knowledge index, we will be able to detect a 0.56 point difference, which means that on average about every other individual in the treatment group needs to know at least one item more than the control group. As these changes are smaller than a meaningful effect that we would expect to be a channel for the primary outcome, we expect to be able to detect every meaningful effect of the intervention on health knowledge.

We account for potential sample reductions by over-sampling by about 15%. The main reason for a high over-sampling rate is that we rely on functioning phone numbers for the intervention. The over-sampling also accounts for respondents that need to be excluded from the treatment group because the messages could not be delivered to their mobile phone. One reason might be that the respondent changed his/her telephone number, which is common in this context. We tried to avoid this by asking for a contact number that is likely to be active until April 2020, and by planning a short duration between baseline interview and intervention. Another reason might be a typo when entering the phone number. Non-compliance might be a problem if the respondent does not own a mobile phone and the stated contact person does not transfer the message. We minimize this by specifically asking for a contact person from whom a message can be received and by including the name of the recipient in

[12] From our baseline data, we know that slightly more individuals (23%) had a blood pressure check during the previous year. This would increase the minimal detectable effect size by 0.5 percentage points.

[13] We used the 3ie Sample size and minimum detectable effect calculator as described in Djimeu and Houndolo (2016). For screening uptake, we used the formula for binary outcomes and for the knowledge index the formula for continuous outcomes.

each message. Finally, we expect attrition at endline as it is likely that some respondents either cannot be found or are unavailable or unwilling to participate in a second interview. However, we expect overall attrition to be low: at baseline, each respondent has agreed to a second interview, we have taken detailed information on the place of residence (name, address, and geolocation), and we can contact him/her through the mobile phone number.

B4 *Calling procedure at endline*

Taken from the supplementary material in Chavarría et al. (2021).

The telephone interviews were scheduled according to the call pattern that is displayed below. Initially, each respondent received five calls, which were staggered with time delays of one hour to three days any at varying times of the day. After the second unanswered call, a standardized text message was sent announcing another call on the following day. Whenever feasible, the same enumerator who had visited the respondent during the baseline survey was deployed to call them during the phone interview, in order to maximize the response rate as well as the respondents' trust towards the enumerator. In the end of the data collection period, each number that was not answered during five calls received one additional call from another interviewer (with a different telephone number).

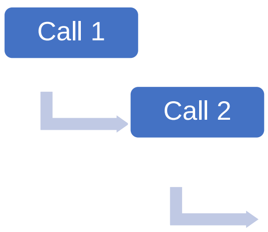


Figure A 2 Call Pattern at endline

C. Variable definitions

Table A 4 Composition SMS knowledge index

Question	***Coding***
"One can feel whether one experiences diabetes/ hypertension "	0 if (strongly) agree, 1 if (strongly) disagree
"It makes a difference to start diabetes/ hypertension treatment early"	0 if (strongly) disagree, 1 if (strongly) agree
Which risk factors of diabetes/ hypertension do you know?	1 if mentioned age, 0 otherwise
Have you ever heard of *Posbindu*?	0 if no, 1 if yes

Note: Each question with diabetes / hypertension is included for both diseases separately. "Don't know" coded as 0.

Table A 5 Composition knowledge index

Question	***Coding***
"Which risk factors of diabetes / hypertension do you know?"	1 count for each correctly identified factor
Do you know someone with diabetes/ hypertension?	Binary variable for the answers: Family member, friend, neighbour, other, none.
Which complications of disease diabetes/ hypertension do you know?	1 count for each correctly identified factor
"Who do you think should be screened?"	0 if "everyone who feels sick", 1 if "everyone" or "people at risk"
Which ways of controlling diabetes/ hypertension do you know?	1 count for each correctly identified factor
"It makes a difference to start treatment early"	0 if (strongly) disagree, 1 if (strongly) agree
"There is nothing one can do to prevent diabetes/ hypertension, it is destiny."	0 if (strongly) agree, 1 if (strongly) disagree
"One can feel whether you experience diabetes/ hypertension "	0 if (strongly) agree, 1 if (strongly) disagree
"Checking your level regularly helps to detect diabetes/ hypertension early"	0 if (strongly) disagree, 1 if (strongly) agree
"Diabetes/ hypertension is treatable"	0 if (strongly) disagree, 1 if (strongly) agree

Note: Each question with diabetes / hypertension is included for both diseases separately. "Don't know" coded as 0.

D. Intervention piloting

We piloted the messages in January 2020 to find out whether the contents were understandable, deemed trustworthy, and to assess whether the time of sending (morning/evening) and order of information (age as risk factor/having it without feeling it) mattered. However, the messages were not sent according to the time schedule of the intervention, i.e., not 5, 3 and 1 day before a *Posbindu* date. The messages 1 and 2 were sent to the respondents on two consecutive days, and respondents were interviewed via phone a few days after. In 10 out of 14 cases, the phone was answered on the designated survey day (no second contact attempts on another day were made). The messages were received in 9 out of 10 cases, although in two cases they were received by the children of the main respondent and were not yet transferred to him/her. In both cases, the *Posbindu* dates were a few weeks ahead, so the children might not have felt the urgency to deliver the message directly. We assumed that this would be different when the dates are close by.

Qualitative semi-structured interviews were conducted with the remaining eight respondents. All respondents confirmed that they trusted the message. Reasons stated were the connection to the interview conducted two months before, the mentioning of a public program (*Posbindu*) and the *kaders*, the mentioning of the respondent's name, and confirmation of the content by the *kader*. Most respondents remembered that the messages were reminding them to go to *Posbindu*, and some specifically mentioned the *Posbindu* date. Three respondents could recall that the messages contained information regarding diseases, and two additional respondents recalled information regarding risk factors. The respondents liked in particular that the messages served as reminders, and two respondents explicitly stated that they liked how the messages were written. Time of message sending and order of the messages did not appear to make a difference in how the messages were perceived.

While experimenter demand biases are always a concern in these types of interviews, we believe them to be minimal here. First of all, respondents may feel less inclined to cater to experimenter demand during phone interviews, as they are less personal than in-home visits. This was confirmed by our enumerators, who qualitatively assessed that respondents were likely to report their true opinions. Second of all, respondents always gave specific reasons and arguments for their opinions, making them more credible.

E. Sample characteristics and attrition

Table A 6 Baseline balance across treatment and control group

	Control group			Treatment group			
	Mean	Standard deviation	N	Mean	Standard deviation	N	p-value
Age	50.35	8.25	1,002	49.91	8.08	1,003	0.221
Female	0.64	0.48	1,001	0.64	0.48	1,003	0.936
Highest level of schooling							0.876
None	0.05	0.22	49	0.05	0.22	49	
Primary	0.25	0.43	253	0.24	0.42	236	
Junior Secondary	0.21	0.41	215	0.22	0.41	219	
Senior Secondary	0.35	0.48	346	0.35	0.48	348	
Tertiary	0.14	0.35	139	0.15	0.36	152	
Wealth quintile							0.611
1	0.22	0.42	225	0.21	0.41	213	
2	0.20	0.40	203	0.18	0.39	182	
3	0.19	0.39	192	0.20	0.40	200	
4	0.19	0.39	188	0.20	0.40	198	
5	0.19	0.39	193	0.21	0.41	211	
Own phone	0.58	0.49	995	0.62	0.49	1,000	0.044
Posbindu in own village	0.90	0.30	1,002	0.90	0.30	1,004	0.666
Ever had blood pressure or blood glucose checked	0.58	0.49	999	0.59	0.49	1,002	0.610
Disease knowledge index	18.30	5.53	925	17.97	5.42	936	0.190
Patience	5.73	2.83	1,002	5.70	2.86	1,004	0.823
Willingness to take risks	4.57	2.66	1,002	4.45	2.62	1,004	0.298
Joint F-test				0.868			

Means, standard deviation and number of observations of main respondent characteristics by treatment group; p-values based on t-tests of difference in mean between treatment and control group, except in the case of education and wealth quintile, where we used Pearson chi-squared tests due to the categorical nature of the variables.

Table A 7 Comparison of sample characteristics to SUSENAS

	SUSENAS Banda Aceh, Aceh Besar	Baseline	Endline
Age	50.5935	50.1203	49.9404
	(0.3088)	(0.1826)	(0.2306)
Above 50	0.4878	0.4656	0.4592
	(0.0207)	(0.0111)	(0.0142)
Female	0.5239	0.6379***	0.6224**
	(0.0207)	(0.0107)	(0.0161)
Education			
- Up to primary	0.2424	0.2926**	0.2720***
	(0.0188)	(0.0100)	(0.0162)
- Lower secondary	0.2347	0.2164	0.2188
	(0.0179)	(0.0092)	(0.0120)
- Upper secondary and above	0.5229	0.4910	0.5092**
	(0.0207)	(0.0109)	(0.0194)
Wealth above median		0.4923	0.5082**
		(0.0112)	(0.0201)
Banda Aceh	0.4074	0.4372	0.4511*
	(0.0182)	(0.0061)	(0.0220)
N	863	2,006	1,412

*SUSENAS samples are obtained from SUSENAS 2017 and restricted to respondents aged 40 – 70 with a mobile phone in the household. Standard errors accounting for survey design (sampling weights in SUSENAS, district stratification in both samples, PSU when comparing base- and endline sample) below mean; stars indicate significant difference from mean listed in previous column based on adjusted Wald test, * 0.1 ** 0.05 *** 0.01. Columns on SUSENAS and Baseline as in (Chavarría et al., 2021).*

Attrition

We test for differential attrition using three approaches. First, we test whether attrition differs across treatment and control group:

$$Attrit_i = \alpha + \beta T_i + \omega_i \qquad \text{(A1)}$$

Second, we analyze attrition based on the set of baseline characteristics used for testing balance across treatment and control group – namely age, sex, education, wealth quintile, knowledge index, time preferences, risk preferences, phone ownership and *Posbindu* in own village:

$$y_i = \alpha + \beta Attrit_i + \omega_i \qquad \text{(A2)}$$

Third, we examine whether these baseline characteristics of attrited treated individuals are significantly different from the attrited control individuals, restricting the sample to attriting respondents only:

$$(y_i | Attrit = 1) = \alpha + \beta T_i + \omega_i \qquad \text{(A3)}$$

Table A 8 Attrition I: between treatment and control group

	(1) Attrition
Treated	0.0273
	(0.0206)
Observations	2006

Regression of a binary attrition indicator (not re-interviewed at endline) on a binary treatment indicator (equation A1).
Standard errors clustered at the phone-number level in parentheses. * *p < 0.1,* ** *p < 0.05,* *** *p < 0.01.*

Table A 9 Attrition II: endline sample compared to those lost to follow-up

	(1) Age	(2) Female	(3) Education	(4) Wealth quintile	(5) Baseline disease knowledge	(6) Willingness to take risks	(7) Patience	(8) Own phone	(9) Own Posbindu
Attrition	0.638	0.055**	-0.218***	-0.182**	-1.041***	-0.057	-0.111	-0.200***	0.008
	(0.406)	(0.023)	(0.056)	(0.071)	(0.284)	(0.129)	(0.138)	(0.024)	(0.015)
Observations	2005	2004	2006	2005	1861	2006	2006	1995	2006

Separate regressions of each characteristic on the binary attrition indicator (not re-interviewed at endline) (equation A2).
*Standard errors clustered at the phone-number level in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01.*

Table A 10 Attrition III: between treatment and control in those lost to follow-up

	(1) Age	(2) Female	(3) Education	(4) Wealth quintile	(5) Baseline disease knowledge	(6) Willingness to take risks	(7) Patience	(8) Own phone	(9) Own *Posbindu*
Treated	0.131	0.060	0.047	0.042	-0.849*	-0.236	-0.246	0.065	0.029
	(0.690)	(0.038)	(0.096)	(0.119)	(0.487)	(0.218)	(0.230)	(0.041)	(0.024)
Observations	594	593	594	594	532	594	594	590	594

Separate regressions of each characteristic on the binary treatment indicator in the sample that was not re-interviewed at endline (equation A3).
*Standard errors clustered at the phone-number level in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01.*

Table A 11. Role of phone ownership for attrition

	(1) Own phone	(2) Attrition
Age	-0.008***	-0.000
	(0.001)	(0.001)
Female	-0.113***	0.032
	(0.021)	(0.021)
Primary	0.088*	-0.142***
	(0.050)	(0.054)
Junior Secondary	0.156***	-0.155***
	(0.053)	(0.056)
Senior Secondary	0.360***	-0.120**
	(0.051)	(0.055)
Higher	0.517***	-0.145**
	(0.053)	(0.060)
Wealth quintile 2	0.011	0.001
	(0.033)	(0.033)
Wealth quintile 3	0.043	-0.048
	(0.033)	(0.031)
Wealth quintile 4	0.042	-0.012
	(0.033)	(0.033)
Wealth quintile 5	0.079**	-0.028
	(0.034)	(0.034)
Own phone		-0.161***
		(0.023)
Observations	1991	1991

*Regression of the binary phone ownership indicator (column 1) and the binary attrition indicator (column 2) on the respective characteristics in the whole intervention sample. Reference categories: No formal education, wealth quintile 1; Coefficient estimates for education in column (2) are statistically not distinguishable from each other. Standard errors in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01.*

F. Main tables and robustness checks

Table A 12 Treatment effects on screening uptake, with and without covariates

	(1) ITT	(2) ITT	(3) LATE	(4) LATE	(5) Any other member	(6) Any other member
Treated	0.0576**	0.0656***	0.142	0.170*	0.0152	0.0106
	(0.0257)	(0.0254)	(0.0959)	(0.0959)	(0.0250)	(0.0250)
Covariates	No	Yes	No	Yes	No	Yes
Observations	1386	1386	1175	1175	1070	1070
Control group mean	0.331	0.331	0.357	0.357	0.205	0.205

*Results of regressing the binary screening uptake indicator following equation 1 for the message recipient (columns 1 and 2) and any other household member (columns 5, 6) and the local average treatment effect following equation 3 (columns 3, 4); if covariates are included, they are message recipient age, gender, wealth and phone ownership; standard errors clustered at the phone-number level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.*

Table A 13. Adjustments for multiple hypothesis testing in main specification for primary and secondary outcomes.

	(1) Screening uptake (ITT)	(2) Screening uptake (LATE)	(3) Spillovers	(4) SMS Knowledge	(5) General Knowledge
Treated	0.066	0.170	0.011	-0.002	-0.336
	(0.010)***	(0.076)*	(0.672)	(0.962)	(0.340)
	[0.090]*	[0.227]	[0.808]	[0.962]	[0.510]
Covariates	Yes	Yes	Yes	Yes	Yes
Observations	1386	1175	1070	1088	1042

*Results of regressing the binary screening uptake indicator following equation 1 for the message recipient (col 1) and any other household member (col 3), the respective knowledge index (col 4, 5), and the local average treatment effect following equation 3 (col 2); controlling for message recipient age, gender, wealth, and phone ownership; unadjusted p-values in parentheses, adjusted q-values following the Benjamini-Hochberg method for the 9 main hypotheses in square brackets. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.*

Table A 14. Adjustments for multiple hypothesis testing in main specification of heterogeneity analysis.

	Screening uptake	
	Willingness to take risks	Patience
Treated	0.082	0.118
	(0.105)	(0.037)**
	[0.236]	[0.165]
Treated x Preference	-0.004	-0.009
	(0.719)	(0.301)
	[0.808]	[0.510]
Covariates	Yes	Yes
Observations	1,386	1,386

*Treatment coefficients from estimating equation 4 controlling for message recipient age, gender, wealth, and phone ownership; unadjusted p-values in parentheses, adjusted q-values following the Benjamini-Hochberg method for the 9 main hypotheses in square brackets. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$*

Table A 15. Binary outcomes with probit and logit specifications.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Screening uptake		Heterogeneity: Risk		Heterogeneity: Time		Spillover	
	Probit	Logit	Probit	Logit	Probit	Logit	Probit	Logit
Treated	0.182***	0.301***	0.229	0.375	0.332**	0.546**	0.033	0.063
	(0.070)	(0.116)	(0.141)	(0.231)	(0.158)	(0.260)	(0.088)	(0.153)
Preference			0.019	0.031	0.022	0.036		
			(0.019)	(0.032)	(0.018)	(0.029)		
Treated x Preference			-0.010	-0.016	-0.026	-0.043		
			(0.027)	(0.044)	(0.025)	(0.040)		
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1386	1386	1386	1386	1386	1386	1065	1065

*Results of regressing the binary screening uptake indicator following equation 1 for the message recipient (col 1, 2) and any other household member (col 7, 8), as well as heterogeneous treatment effects along a continuous risk and time preference scale following equation 4; controlling for message recipient age, gender, wealth and phone ownership; each model is separately estimated using probit and logit; standard errors clustered at the phone-number level in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01*

Table A 16. Knowledge outcomes measured through PCA

	SMS knowledge (PCA)	SMS knowledge (PCA)	Disease knowledge (PCA)	Disease knowledge (PCA)
Treated	0.0215	0.00198	-0.0328	-0.0551
	(0.0596)	(0.0581)	(0.0612)	(0.0594)
Covariates	No	Yes	No	Yes
Obs.	1088	1088	1042	1042
Control group mean	-0.00301	-0.00301	0.0215	0.0215

Regressions for an alternative definition of both knowledge indices via Principal Component Analysis; if covariates are included, they are message recipient age, gender, wealth, and phone ownership; standard errors clustered at the phone-number level in parentheses. * *p < 0.1,* ** *p < 0.05,* *** *p < 0.01.*

Table A 17 Treatment effect on each element of the SMS knowledge index

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Feel it		Early treatment		Age risk		Knows
	Hypertension	Diabetes	Hypertension	Diabetes	Hypertension	Diabetes	Posbindu
Treated	0.0051	-0.0133	0.0040	-0.0033	-0.0171	0.0178	0.0047
	(0.0089)	(0.0156)	(0.0109)	(0.0129)	(0.0173)	(0.0163)	(0.0171)
Covar.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	1088	1088	1088	1088	1088	1088	1088
C. mean	0.0185	0.0775	0.9613	0.9502	0.1015	0.0664	0.9151

Regressions of the components of the SMS knowledge index as defined in Table A 4 on the binary treatment indicator controlling for message recipient age, gender, wealth, and phone ownership; standard errors clustered at the phone-number level in parentheses. * *p < 0.1,* ** *p < 0.05,* *** *p < 0.01.*

Table A 18 Treatment effect on each element of the disease knowledge index (Hypertension)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
		Number of				Share with correct answer				
	Risk Factors	Complica tions	Control	Target group	Start early	Destiny	Feel it	Regular checks	Treat-able	Know someone
Treated	-0.0627	0.0311	-0.0959	-0.0044	0.0026	0.0010	0.0072	-0.0134	-0.0022	0.0014
	(0.0680)	(0.0439)	(0.0705)	(0.0306)	(0.0106)	(0.0283)	(0.0140)	(0.0101)	(0.0189)	(0.0251)
Covar.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	1042	1042	1042	1042	1042	1042	1042	1042	1042	1042
C. mean	2.1612	1.1478	2.1440	0.5566	0.9655	0.2917	0.9424	0.9789	0.8983	0.7908

Regressions of the components of the disease knowledge index as defined in Table A 5 on the binary treatment indicator controlling for message recipient age, gender, wealth, and phone ownership; the outcomes in columns 1-3 are the number of correct items and binary measures in columns 4-10; standard errors clustered at the phone-number level in parentheses. * *p < 0.1,* ** *p < 0.05,* *** *p < 0.01.*

Table A 19 Treatment effect on each element of the general knowledge index (Diabetes)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
		Number of				Share with correct answer				
	Risk Factors	Complica tions	Control	Target group	Start early	Destiny	Feel it	Regular checks	Treat–able	Know someone
Treated	-0.0623	-0.1026	-0.0722	0.0138	-0.0047	0.0072	0.0258	0.0061	0.0172	0.0321
	(0.0607)	(0.0706)	(0.0628)	(0.0307)	(0.0125)	(0.0278)	(0.0226)	(0.0105)	(0.0268)	(0.0297)
Covar.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	1042	1042	1042	1042	1042	1042	1042	1042	1042	1042
C. mean	1.8330	1.6046	1.7697	0.5182	0.9559	0.2726	0.8292	0.9655	0.7486	0.6180

Regressions of the components of the disease knowledge index as defined in Table A 5 on the binary treatment indicator controlling for message recipient age, gender, wealth, and phone ownership; the outcomes in columns 1-3 are the number of correct items and binary measures in columns 4-10; standard errors clustered at the phone-number level in parentheses. * *p < 0.1,* ** *p < 0.05,* *** *p < 0.01.*

Table A 20. Heterogeneity by phone ownership

	(1)	(2)
	Screened	Screened
Treated	0.0630**	0.0631**
	(0.0317)	(0.0313)
Other's phone	0.0317	-0.0170
	(0.0367)	(0.0379)
Treated x other's phone	-0.0273	-0.00620
	(0.0544)	(0.0537)
Covariates	No	Yes
Obs.	1379	1379
Mean	0.333	0.333

Results of regressing the binary screening uptake indicator following equation 1 for the message recipient, but including an interaction term of the treatment indicator with phone ownership (excluding individuals with missing observation on phone ownership); if covariates are included, they are message recipient age, gender, wealth and phone ownership; standard errors clustered at the phone-number level in parentheses. * *p < 0.1,* ** *p < 0.05,* *** *p < 0.01.*

Table A 21 Different versions of spillover analysis

	(1) Any member (main specification)	(2) Member 40-70	(3) Other phone owner
Treated	0.0106	0.0134	0.0166
	(0.0250)	(0.0308)	(0.0304)
Other's phone			0.0400
			(0.0392)
			-0.0180
Treated x other's phone			(0.0530)
			0.0399
Covariates	Yes	Yes	Yes
Obs.	1070	727	1065
Mean	0.205	0.212	0.206

Results of regressing the binary indicator of household member screening uptake (col 1), screening uptake among other household members aged 40-70 years (col 2) on the binary treatment indicator following equation 1, and the heterogeneous treatment effect of the binary phone ownership indicator, which takes value 1 if the intervention was either received on a family phone or the private phone of another household member, and zero if it belongs to the message recipient (those with missing information excluded); controlling for age, gender, wealth and phone ownership; standard errors clustered at the phone-number level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A 22 Treatment effect on screening uptake by month

	(1) January	(2) February	(3) March	(4) April
Treated	0.0156	0.0363	0.0560***	0.0068
	(0.0159)	(0.0228)	(0.0201)	(0.0090)
Covariates	Yes	Yes	Yes	Yes
Obs.	1386	1386	1386	1386
Control group mean	0.0895	0.2216	0.1435	0.0256

*Results of regressing different binary screening uptake indicators on the binary treatment indicator (equation 1), controlling for age, gender, wealth and phone ownership; the outcome indicator takes the value 1 only if the individual indicated to have gone to screening in the respective month and zero otherwise; standard errors clustered at the phone-number level in parentheses; * p < 0.1, ** p < 0.05, *** p < 0.01.*

Table A 23 Treatment effect on screening uptake by location

	(1) Went on correct date to Posbindu	(2) Posbindu	(3) Puskesmas	(4) Private doctor/midwife
Treated	0.0067	0.0081	0.0298*	0.0201
	(0.0177)	(0.0178)	(0.0158)	(0.0162)
Covariates	Yes	Yes	Yes	Yes
Obs.	1386	1386	1386	1386
Control group mean	0.1335	0.1335	0.0810	0.0895

*Results of regressing different binary screening uptake indicators on the binary treatment indicator (equation 1), controlling for age, gender, wealth and phone ownership; the outcome indicator takes the value 1 only if the individual indicated to have gone to screening in the respective facility and zero otherwise; the screening outcome in col 1 additionally conditions on the correct month; standard errors clustered at the phone-number level in parentheses; * p < 0.1, ** p < 0.05, *** p < 0.01.*

Table A 24 Treatment effect on disaggregated screening outcome: kind of check done

	(1) Medical history	(2) Physical measurement	(3) Blood pressure	(4) Blood glucose	(5) Other blood check
Treated	0.0420**	0.0151	0.0652**	0.0302	0.0091
	(0.0176)	(0.0165)	(0.0254)	(0.0200)	(0.0134)
Covariates	Yes	Yes	Yes	Yes	Yes
Obs.	1386	1386	1386	1386	1386
Mean	0.1023	0.1009	0.3295	0.1548	0.0639

*Results of regressing different binary screening indicators on the binary treatment indicator (equation 1), controlling for age, gender, wealth and phone ownership; the outcome indicator takes the value 1 only if the individual indicated that at the screening visit the respective check was conducted and zero if the respondent either did not go for screening or did not get the respective check done despite going for screening; standard errors clustered at the phone-number level in parentheses; * p < 0.1, ** p < 0.05, *** p < 0.01.*

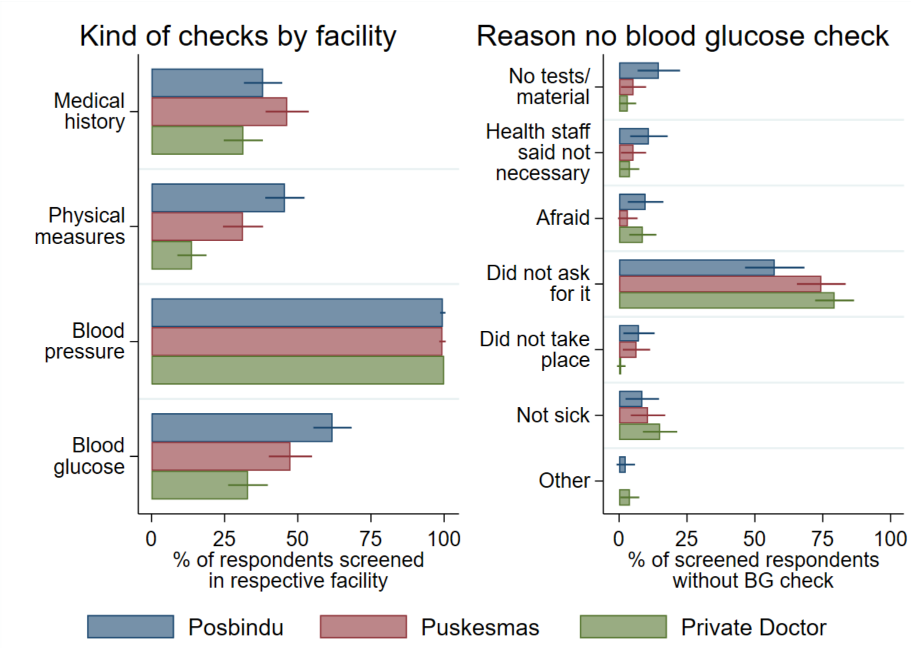
Table A 25 Treatment effect on persistence in facility choice

	(1)	(2)	(3)	(4)
	All respondents		Respondents screened at baseline	
	Visited same facility	Visited Posbindu, PKM or private doctor again	Visited same facility	Visited Posbindu, PKM or private doctor again
Treated	0.0388*	0.0332*	0.0623*	0.0519*
	(0.0161)	(0.0148)	(0.0259)	(0.0239)
Covariates	Yes	Yes	Yes	Yes
Obs.	1397	1397	835	835
Mean	0.0820	0.0693	0.137	0.116

*Results of regressing different binary screening uptake indicators on the binary treatment indicator (equation 1), controlling for age, gender, wealth and phone ownership; the outcome indicator takes the value 1 if the facility type at which the individual was screened at base- and endline are identical, and zero otherwise. Col. 1-2 include no screening both at base- and endline as "same facility". Standard errors clustered at the phone-number level in parentheses; * p < 0.1, ** p < 0.05, *** p < 0.01.*

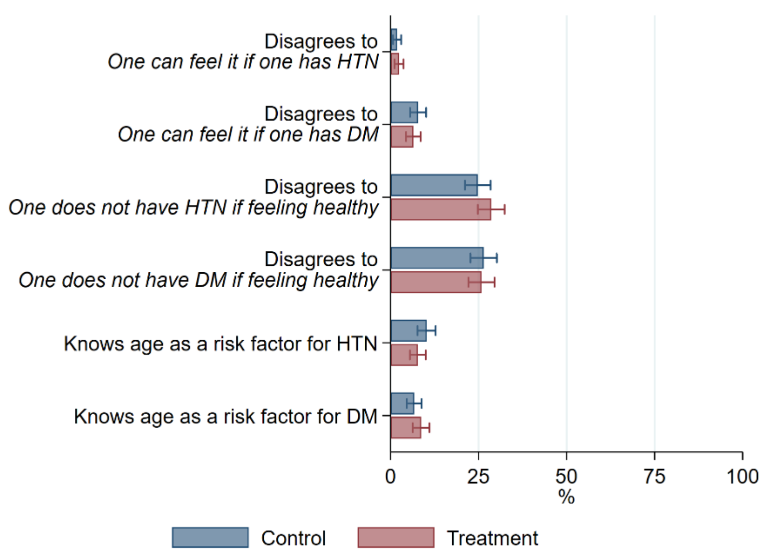
G. Additional figures

Figure A 3 Medical checks performed by facilities



Right: self-report of which practices were performed at the screening visit since baseline (if any); each component was read to the respondent and s/he answered "yes" or "no"; left: if the blood glucose check was replied with "no", respondents were asked for the reasons in an unaided recall questions, the answers were grouped as depicted.

Figure A 4 Remaining knowledge gaps



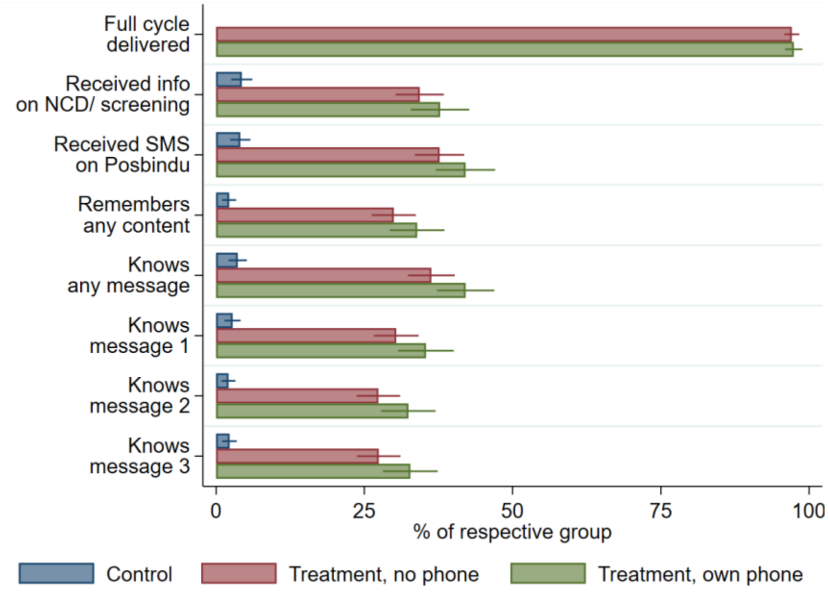
H. Details on treatment exposure

For an allocated message recipient to be fully exposed to the intended treatment, s/he needs to receive, become aware of, read, understand, and trust the messages. As stated above, message delivery by the provider appears not to pose a barrier. However, after delivery the information content appears to be lost in a large share of individuals, as less than half of treated respondents report to having received any NCD-related information (Figure A 5). Phone ownership appears to be one potential determining factor: While 41% of treated phone owners remember having received any information, this share drops to 26% in the treated individuals without a phone. This discrepancy appears to be partly explained by a lack of transferal of the message content from the designated phone owner to the respondent: 51% of the phone owners who were assigned by the respondents as contact person admitted they transmit messages only sometimes, rarely, or never (response rate: 55%). This suggests that as the share of phone owners is expected to increase over time, SMS intervention such as this one may have the potential to elicit greater exposure rates as well.

Moreover, while we do not find large shares of illiteracy in our sample, our messages might be ignored if there is already an overload of information via SMS. However, only 13% of respondents report they would like to generally receive fewer text message. At the same time, 59% would like to receive fewer text messages with advertisement. While in our sample, a majority classified the intervention text messages as official announcements rather than advertisement, this does suggest that associating text messages with official health services may be a key factor in mitigating information overload.

Taken together, population groups who are more likely to be telephone owners (younger, male and more educated) will be more likely to be exposed to the intervention. See Table A 26 for a detailed list of socio-demographic and other baseline characteristics by different exposure measures.

Figure A 5 Exposure to Treatment



"Full cycle delivered" is based on the provider delivery reports, the remaining indicators are based on the respondent's self-report at endline;"Knows any content" indicates whether the respondent could name any message content when asked in an open-ended question (compare Figure 4); "Knows any message" until "Knows message 3" is based on whether the respondent remembered the respective message when the enumerator read it out.

Table A 26 Characteristics of sub-groups of treatment group who remember receiving messages on CVDs and specific elements of these messages

	Total treatment	Received message	LATE definition	Remembers content on: Screening need	Posbindu logistics	Posbindu free	Age risk
Demographics							
Age	49.52	48.31***	48.45	47.64	48.36	48.42	49.60*
	(7.85)	(7.55)	(7.43)	(7.29)	(6.76)	(7.54)	(8.01)
Female	0.61	0.56*	0.56	0.54	0.60	0.55	0.56
	(0.49)	(0.50)	(0.50)	(0.50)	(0.49)	(0.50)	(0.50)
Education							
- None							
	0.03	0.02	0.02	0.01	0.00	0.00	0.02
- Primary	(0.18)	(0.12)	(0.13)	(0.11)	(0.00)	(0.00)	(0.13)
	0.24	0.18**	0.18	0.15	0.19	0.19	0.18
- Lower Secondary	(0.42)	(0.39)	(0.38)	(0.36)	(0.40)	(0.39)	(0.39)
	0.21	0.18	0.17	0.20	0.21	0.17	0.11
- Higher Secondary	(0.41)	(0.39)	(0.38)	(0.40)	(0.41)	(0.38)	(0.31)
	0.36	0.43***	0.43	0.42	0.42	0.45	0.38
- Tertiary	(0.48)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.49)
	0.17	0.20	0.21	0.22	0.18	0.19	0.31**
Banda Aceh	(0.37)	(0.40)	(0.41)	(0.42)	(0.39)	(0.39)	(0.47)
	0.52	0.50	0.50	0.51	0.44	0.31***	0.51
SMS-related characteristics							
Phone owner	0.68	0.80***	0.80	0.79	0.81	0.77	0.80
	(0.47)	(0.40)	(0.40)	(0.41)	(0.40)	(0.43)	(0.40)
Messages							
- daily	0.48	0.57***	0.58	0.66**	0.58	0.60	0.61
	(0.50)	(0.50)	(0.50)	(0.48)	(0.50)	(0.49)	(0.49)
- < daily	0.36	0.39	0.38	0.30**	0.36	0.38	0.39
	(0.48)	(0.49)	(0.49)	(0.46)	(0.48)	(0.49)	(0.49)
- never	0.16	0.04***	0.04	0.04	0.06	0.02	0.00*
	(0.37)	(0.19)	(0.20)	(0.19)	(0.24)	(0.13)	(0.00)
Messenger use	0.47	0.48	0.49	0.61***	0.55	0.56	0.52
	(0.50)	(0.50)	(0.50)	(0.49)	(0.50)	(0.50)	(0.51)
Prefers less SMS							
- in general	0.15	0.22***	0.23	0.23	0.29*	0.14**	0.24
	(0.36)	(0.42)	(0.42)	(0.42)	(0.46)	(0.35)	(0.43)
- advertisement	0.60	0.57	0.57	0.61	0.54	0.66*	0.53
	(0.49)	(0.50)	(0.50)	(0.49)	(0.50)	(0.48)	(0.50)
- no	0.25	0.21*	0.20	0.16	0.17	0.21	0.22
	(0.44)	(0.41)	(0.40)	(0.37)	(0.38)	(0.41)	(0.42)
Baseline characteristics							
Disease knowledge	18.42	19.58***	19.72	19.99	19.10	19.87	20.00
	(5.30)	(4.88)	(5.00)	(5.20)	(4.42)	(4.99)	(4.44)
H- feel it	0.12	0.10	0.11	0.10	0.07	0.06	0.09
	(0.33)	(0.30)	(0.31)	(0.30)	(0.26)	(0.24)	(0.29)
D- feel it	0.19	0.19	0.20	0.23	0.13	0.16	0.18
	(0.39)	(0.39)	(0.40)	(0.42)	(0.34)	(0.37)	(0.39)
H- start early	0.95	0.96	0.95	0.93*	1.00**	0.95	0.98
	(0.22)	(0.20)	(0.21)	(0.25)	(0.00)	(0.21)	(0.13)
D- start early	0.94	0.94	0.94	0.92	0.99**	0.94	0.96
	(0.24)	(0.23)	(0.24)	(0.27)	(0.12)	(0.25)	(0.19)
H- age risk	0.06	0.05	0.05	0.07	0.03	0.05	0.02
	(0.23)	(0.22)	(0.21)	(0.25)	(0.17)	(0.21)	(0.13)
D- age risk	0.04	0.05	0.06	0.09**	0.06	0.06	0.04
	(0.20)	(0.22)	(0.24)	(0.29)	(0.23)	(0.25)	(0.19)
Knows Posbindu	0.50	0.56*	0.56	0.53	0.53	0.63	0.64
	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.49)	(0.49)

Ever screened	0.59	0.61	0.57***	0.56	0.65	0.64	0.64
	(0.49)	(0.49)	(0.50)	(0.50)	(0.48)	(0.48)	(0.49)
Last year screened	0.29	0.28	0.25*	0.06***	0.15***	0.22	0.37
	(0.45)	(0.45)	(0.43)	(0.24)	(0.36)	(0.42)	(0.49)
N	682	199	172	89	72	65	55

*Simple means of the respective characteristic across groups: complete treatment group, individuals who stated to have received a message on Posbindu, those who received at least one full message cycle according to the delivery reports and remember any message content (LATE definition) and the four most commonly recalled content elements: the recommendation to take up screening, when and where Posbindu takes place, that Posbindu is free and higher age implies a higher CVD risk. Standard deviations in parentheses below mean; stars indicate the p-value of the two-sample t-test for difference of the respective group and characteristic compared to the rest of the treatment group; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.*

I. Administrative information

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Ethics

All necessary ethics approvals are in place.

Ethics approval and confirmation of adherence to European data protection laws issued by University of Göttingen's ethics commission

Ethics approval issued by the ethics board of the nursing faculty of Syiah Kuala University, Banda Aceh, Indonesia

Declaration of Interest

None.

Data availability

The data that support the findings of this study are available upon reasonable request in Göttingen Research Online at https://data.goettingen-research-online.de, DOI 10.25625/SE4IDP, and will be made publicly available after publication of this study. The questionnaires are publicly available in the repository.

Published Working Paper

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