COVID-19 Lockdown & Technology Engagement:
New Evidence from a Large Scale m-Health Intervention in India

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Content

Introduction

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- The ease of access to low-cost digital technology has made policy-makers push information dissemination by utilizing communication media at a mass scale
- Such intervention allows social planners to address information asymmetry arising from a digital divide between information-rich and information-poor people
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Information Dissemination

- A prominent example is of the Indian government introducing pre-recorded messages at the beginning of every phone call made by anyone within India after the COVID-19 pandemic
- Sadish et al. (2021) observed that till a quarter into the pandemic, misinformation was quite prevalent
- In particular, they show that pre-recorded messages leads to lesser engagement and less reduction in misinformation than direct phone calls
- While active phone calls can lead to more engagement, it has two problems for mass-scale intervention
  - It can be prohibitively expensive for implementation at a large scale
  - It is not well understood which factors affect such engagement

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Frictions in Technology Engagement

- Two mechanisms may drive the phenomenon of low engagement:
  - First, access to information itself might be low, for example, due to lack of resources to procure a communication device
  - Secondly, although people may have access to information, they may fail in utilizing the information due to frictions unobserved by the supplier of information
- A recent example is the failure of global uptake of contact tracing or vaccine registration apps (Ivers & Weitzner, 2020)
- What can be the disaggregate sources of these frictions for engaging with technology?

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Examining Technology Engagement

- We examine these questions using a unique database comprising 2 million call records of mobile-phone-based healthcare (m-Health hereafter) interventions on pregnant women in India
- Using difference-in-differences with time & user-level heterogeneity, we leverage the COVID-19 (first wave) driven lockdown in India as an exogenous shock
- Our starting point is the theoretical notion that technology engagement has an opportunity cost
- Lower opportunity cost of time due to lower wages as well as higher availability of time would positively affect technology engagement
- We hypothesize that technology engagement amongst the poor should be an outcome of three factors - the opportunity cost of time to engage, accessible channels of information, and availability of technology

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  - mHealth improving health worker's output - ThinkTB - Tyagi et al.(2020)
  - Text messages - Stop my smoking (SMS) - Ybarra et al.(2014)
  - m-Health effectiveness in developing countries - Betjeman et al.(2013), Ruton et al.(2018)
- Information Dissemination in Healthcare - Breza et al. (2021), Barili et al. (2021), Dupas,(2011), Rhee et al.(2005)
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Institutional Context - COVID-19 in India

- In India, the first case of COVID-19 was reported on 30th January 2020
- The total number of patients reached 107 by 15th March
- On March 22, the Government of India announced a strict lockdown
- The 68 days of four-phased-lockdown started from 24th March to 31st May 2020 to deal with COVID-19
- Except for essential facilities, most of India was closed during the 2020 lockdown
- The number of positive cases crossed 10.6 million in January 2021 and a devastating second wave followed the first wave

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Institutional Context - NGO ARMMAN

- ARMMAN, which stands for 'wish' in Hindi, is an acronym for Advancing Reduction in Mortality and Morbidity of Mothers, Children, And Neonates
- ARMMAN is an India-based non-profit organization that was set up with the purpose of improving the well-being of pregnant women, new mothers, infants, and children in their early years
- This study uses the database of mMitra, one of the first programs started by ARMMAN
- The program mMitra, which translates to a mobile friend, is a free mobile voice call service for enrolled women to receive critical healthcare information during their pregnancies

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Institutional Context - ARMMAN (Source:armman.org)

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- Majority of the women in mMitra belong to urban slums of Mumbai, Maharashtra
- There are two routes through which women can enroll in the mMitra program - Hospital vertical and Community vertical
- Once enrolled a women receives 141 individualized voice messages of 60-120 seconds
- The information transmitted in the calls is matched to the stage of women's pregnancy
- Calls are sent in the time slot and language chosen by the women
- A trained counselor can be informed about a delivery, abortion or change the phone number or time slot

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Research Proposition - I

- We measure technology engagement utilizing the call duration, i.e., the fraction of the total duration of the calls that the intended recipients listened to
- We hypothesize that due to time availability and lower opportunity cost due to the lockdown, women would spend more time listening to the calls containing pre-recorded messages on pregnancy-related information
- **Proposition 1**: Duration of calls heard by pregnant women increases during the COVID-19 induced lockdown
- Next, we study how heterogeneity in economic and demographic characteristics influence technology engagement behaviour

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Research Proposition - II

- First, we hypothesize that the women who do not own phones would engage relatively more post the lockdown than the women who are phone owners
- Second, women enrolled via community channel would presumably face pecuniary, time-availability, or informational constraints that prevent them from going to the hospitals to acquire information
- Finally, We hypothesize that relatively richer households would be more likely to access technology
- **Proposition 2**: Technology engagement during the COVID-19 induced lockdown would be relatively higher for women who are non-owners, for women accessing information via community workers, and for women who belong to the high-income group

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Data

- By 2020, ARMMAN, with its mMitra program that started in 2013, had reached 2.29 million women
- Given the precise context and the knowledge of the users (the women), our focal technology (mobile phones), and the information supplier (ARMMAN), we keep track of the exact timing of information dissemination
- Our baseline sample comprises demographic and calls details of 116,449 women registered (identity anonymized) in the last six months of 2018 (Control Group)
- 135,696 women registered in the last six months of 2019 (Treatment Group)

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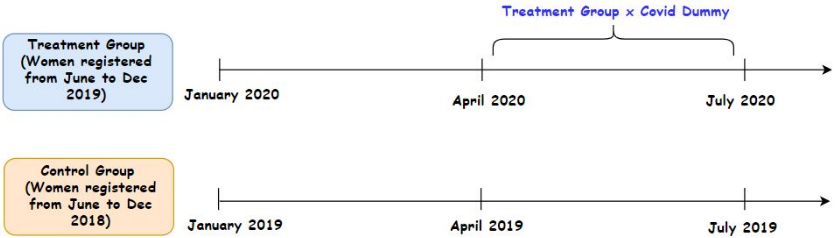
Data - Timeline



Data - Variable Description

Dependent Variables	Definition and Construction
Call Duration Percentage	If the call is picked up, this variable is calculated as (Call Duration/Call Length) * 100
Call Duration Range	Call duration percentage is divided into three zones - Red (Below 33%), Amber (33% to 66%), Green (Above 66%)
Independent Variables	**Definition and Construction**
Covid Dummy	Coded as 1 if the date of the call is April onwards, 0 otherwise
Treatment Group	Women belong to treatment group if she is called between January 2020 to July 2020 and the variable is coded as 1, it is 0 if she is called between January 2019 to July 2019
Husband Phone Owner	Coded as 1 if ownership of the registered mobile phone is with Husband, 0 if registered women herself is the phone owner
Enrolled via Community	Coded as 1 if a woman is enrolled in the program via community channel, 0 if registered via a visit to a hospital
Lower Income	Coded as 1 if the income of woman lies in the bottom half of the sample and 0 otherwise

Data - Summary Statistics

January 2020 to March 2020	N	Mean	S. Dev.	Min.	Max.
Call Duration (%)	4,02,809	45.46	33.686	0	100
Green	4,02,809	0.358	0.479	0	1
Amber	4,02,809	0.224	0.417	0	1
Red	4,02,809	0.416	0.493	0	1
Husband Phone Owner	3,54,512	0.255	0.436	0	1
Enrolled via Community	3,54,512	0.64	0.479	0	1
Low Income	3,54,512	0.536	0.498	0	1
April 2020 to July 2020	**N**	**Mean**	**S. Dev.**	**Min.**	**Max.**
Call Duration (%)	4,54,448	43.69	33.966	0	100
Green	4,54,448	0.332	0.476	0	1
Amber	4,54,448	0.228	0.419	0	1
Red	4,54,448	0.439	0.496	0	1
Husband Phone Owner	4,10,415	0.255	0.436	0	1
Enrolled via Community	4,10,415	0.63	0.482	0	1
Low Income	4,10,415	0.536	0.498	0	1

Data - Summary Statistics

January 19 to March 19	N	Mean	S. Dev.	Min.	Max.
Call Duration (%)	3,96,560	47.08	34.408	0	100
Green	3,96,560	0.388	0.487	0	1
Amber	3,96,560	0.213	0.409	0	1
Red	3,96,560	0.397	0.489	0	1
April 19 to July 19	**N**	**Mean**	**S. Dev.**	**Min.**	**Max.**
Call Duration (%)	6,46,344	44.01	33.100	0	100
Green	6,46,344	0.332	0.471	0	1
Amber	6,46,344	0.244	0.429	0	1
Red	6,46,344	0.423	0.494	0	1

Methodology - Proposition 1 - Increase in Tech. Engagement

$$\mathrm{y_{i,t}} = \beta_0 + \beta_1 \mathrm{TreatedGroup_i} + \beta_2 CovidDummy_t + \\ \beta_3 TreatedGroup_i x CovidDummy_t + \theta_i + \delta_t + \epsilon_{i,t}$$

- where y_{it} is measured at the women-month level
- y_{it} is used as call duration percentage and call duration range in two separate estimates
- $TreatedGroup_i$ corresponds to whether women were registered in 2019 (1 for our treatment group) or registered in 2018 (0 for our control group)
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Methodology - Proposition 2 - Factors influencing Tech. Engagement

$$y_{i,t} = \beta_0 + \beta_1 \mathrm{Group_i} + \beta_2 CovidDummy_t + \beta_3 Group_i x CovidDummy_t + \theta_i + \delta_t + \epsilon_{i,t}$$

- where Group varies as
  - Husband being the phone-owner (equals to 1 as opposed to 0 representing the woman being the phone-owner)
  - Enrolled via Community Channel (equals to 1 as opposed to 0 representing direct enrolment via hospitals)
  - Lower-income Group (equals to 1 as opposed to 0 representing Higher-income group) for three different models
- All other variables have similar connotation and significance
- Our coefficient of interest is β_3

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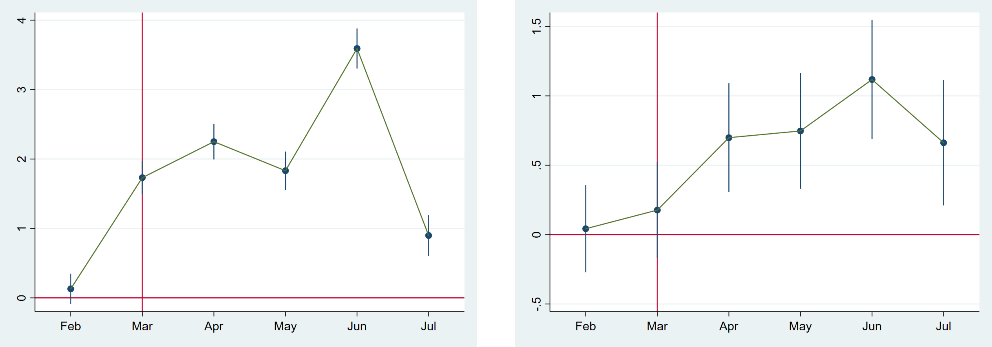
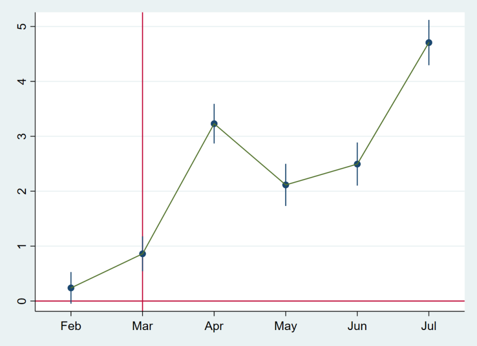
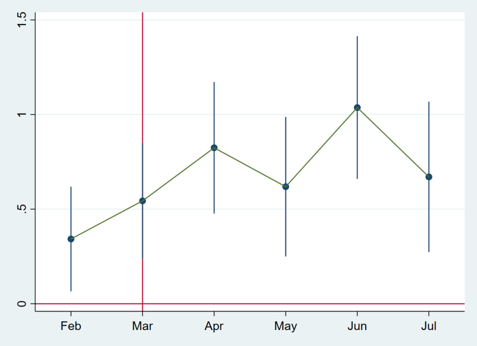
Pre-Trends - Duration Per.- Full Sample (Left) & Duration Per.- Ownership (Right)

$$\text{CallDurationPer.}_{i,t} = \beta_0 + \beta_1 \text{TreatedGroup}_i + \beta_2 Month_t + \sum \beta_t (TreatedGroup_i x Month_t) + \theta_i + \delta_t + \epsilon_{i,t}$$



Pre-Trends - Duration Per. - Enrollment Channel (Left) & Duration Per. - Income(Right)





Results - Call duration percentage increase during COVID-19 lockdown

	(1)	(2)	(3)
Treatment Group x Covid Dummy	1.732***	1.695***	1.530***
	[0.087]	[0.087]	[0.088]
Covid Dummy	-4.733***	-5.495***	-6.785***
	[0.065]	[0.085]	[0.089]
Treatment Group	-1.065***	-1.058***	
	[0.126]	[0.126]	
Individual Fixed Effects	No	No	Yes
Month Fixed Effects	No	Yes	Yes
Observations	1,391,647	1,391,647	1,391,647
Number of Women	252,145	252,145	252,145

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Results - Call duration percentage amongst different groups during COVID-19 lockdown

	(1) Ownership	(2) Enroll Channel	(3) Income
Husband Phone Owner x Covid Dummy	0.731***		
	[0.134]		
Enrolled via Community x Covid Dummy		2.756***	
		[0.123]	
Low Income x Covid Dummy			0.494***
			[0.118]
Covid Dummy	-5.755***	-7.306***	-5.833***
	[0.107]	[0.128]	[0.120]
Individual Fixed Effects	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes
Observations	764,927	764,927	764,927
Number of Women	135,696	135,696	135,696

Results - Change in Call Duration range during COVID-19 lockdown

	(1) Green	(2) Amber	(3) Red
Treatment Group x Covid Dummy	0.036***	-0.031***	-0.005***
	[0.001]	[0.001]	[0.001]
Covid Dummy	-0.103***	0.030***	0.073***
	[0.001]	[0.002]	[0.001]
Individual Fixed Effects	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes
Observations	1,391,647	1,391,647	1,391,647
Number of Women	252,145	252,145	252,145

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Results - Call Duration range for different groups during COVID-19 lockdown

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		Ownership			Enrolment Channel			Income	
	Green	Amber	Red	Green	Amber	Red	Green	Amber	Red
Husband Phone Owner x Covid Dummy	0.015***	-0.009***	-0.007***						
	[0.002]	[0.002]	[0.002]						
Enrolled via Community x Covid Dummy				0.045***	-0.015***	-0.030***			
				[0.002]	[0.002]	[0.002]			
Low Income x Covid Dummy							0.011***	-0.006***	-0.005**
							[0.002]	[0.002]	[0.002]
Private Hospital Choice x Covid Dummy									
Covid Dummy	-0.070***	-0.006***	0.076***	-0.094***	0.001	0.092***	-0.072***	-0.005**	0.076***
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
Individual Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	764,927	764,927	764,927	764,927	764,927	764,927	764,927	764,927	764,927
Number of Women	135,696	135,696	135,696	135,696	135,696	135,696	135,696	135,696	135,696

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Robustness - Coarsened Exact Matching

	(1) Full Sample	(2) Ownership	(3) Enroll Channel	(4) Income
Treatment Group x Covid Dummy	1.705***			
	[0.090]			
Husband Phone Owner x Covid Dummy		0.758***		
		[0.138]		
Enrolled via Community x Covid Dummy			2.851***	
			[0.125]	
Low Income x Covid Dummy				0.498***
				[0.123]
Covid Dummy	-6.976***	-5.941***	-7.442***	-5.939***
	[0.092]	[0.107]	[0.131]	[0.120]
Individual Fixed Effects	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes
Observations	1,391,680	764,585	764,845	764,768
Number of Women	252,150	135,633	135,678	135,668

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Conceptual Framework

We assume a generic representative woman with utility following constant elasticity of substitution (CES) utility function (Zabalza, 1983) along with budget constraint

$$\text{Max. } U(t,c) = (\alpha t^{\rho} + (1-\alpha) c^{\rho})^{1/\rho}$$
$$\text{Subjected to } P_c c + wt = w$$

- t represents technology engagement
- c represents all other consumption
- P_c is the price of all other consumption of the representative women
- w is her wage rate
- α and ρ are share and substitution parameters respectively

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Conceptual Framework

We maximize the utility subject to the budget constraint to obtain t* in equilibrium given by

$$t^* = [1 + {P_c}^{1-r} A^{-r} w^{r-1}]^{-1}$$

where r is elasticity of substitution given by $1/(1\text{-}\rho)$ and $A = \alpha/(1\text{-}\alpha)$.
Differentiating t* with respect to w we get

$$\frac{\partial t^*}{\partial w} = \frac{(-1)(r-1)P_c^{1-r}A^{-r}w^{r-2}}{[1+P_c^{1-r}A^{-r}w^{r-1}]^2}$$

Since P_c, A, β, r, w are all positive values, and the denominator being a squared term is always positive. Therefore, $\frac{\partial t^*}{\partial w} < 0$ if $r > 1$

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We maximize the utility subject to the budget constraint to obtain t* in equilibrium given by

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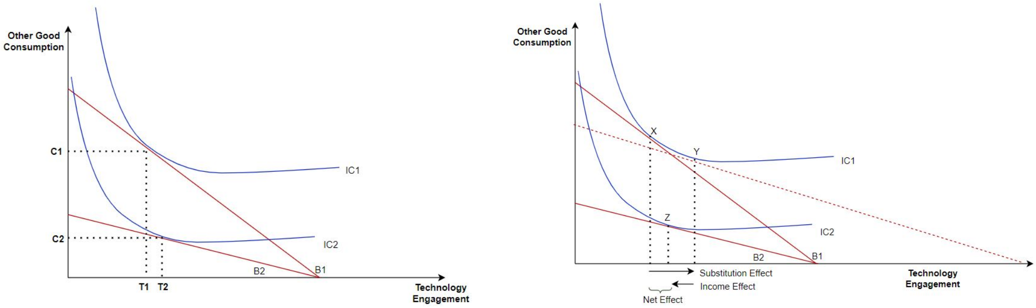
Conceptual Framework - Indifference Curves



Summary

- This paper caters to the gap in understanding how various factors of economic and non-economic nature influence the intensive margins of engagement
- We use difference-in-differences setup to establish that compared to the previous year there has been a sizeable increase in technology engagement of pregnant women during the COVID-19 lock downs
- Given the increase in technology engagement, we examine the factors influencing the choice of engage with technology
- We find that heterogeneity in ownership, enrolment channel, and monthly income, have significant effects on technology engagement
- We complement the above analysis with call duration ranges to characterize the switch of women from one range to another

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Policy Implications

- Our study contributes to the intersection of three different strands of the literature on technology engagement, m-Health, and the effects of economic and demographic factors influencing technology engagement behaviour
- Following the renewed impetus on technology in the world recovering from pandemic, we attend to calls for nuanced understanding of how digitization affects the information-rich/poor
- In contrast to many recent studies showing an adverse impact of the pandemic for women, our findings show that all is not lost
- There seems to be still some light at the end of a gender distorted global tunnel
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Limitations & Future Work

- We note that mMitra has a geographically concentrated base, with a majority of enrolments being from the urban slums of Mumbai, India
- This limits demographic variation in the data
- However, since the main mechanism is based on trade-offs in time, income, and channels in accessing information, we consider our results to be relatively robust towards other unobserved demographic characteristics
- Future works can explore the degree of persistence of this behavioural shift
- It would be interesting to examine in future if technology engagement of the nature we study translate into positive effects on health outcomes of individuals

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Thank You !!

Appendix - Institutional Context - ARMMAN

armman

ADVANCING REDUCTION IN MORTALITY AND MORBIDITY OF MOTHERS, CHILDREN AND NEONATES

mMitra

पंजीकरण फॉर्म

नाम : .... दिनांक: ....

फोन नंबर ☐☐☐☐☐☐☐☐☐☐ उम्र (आयु): .... साल

फोन कौन इस्तेमाल कर रहा है? खुद ☐ पति ☐ पारिवारिक फोन ☐ पडोसी ☐ अन्य ☐

अन्य फोन नंबर : ☐☐☐☐☐☐☐☐☐☐

अन्य फोन कौन इस्तेमाल कर रहा है? खुद ☐ पति ☐ पारिवारिक फोन ☐ पडोसी ☐ अन्य ☐

पूरा पता:– ....

शिक्षा: निरक्षर ☐ 1-5 ☐ 6-9 ☐ 10 पास ☐ 12 पास ☐ ग्रेज्युएट ☐ पोस्ट ग्रेज्युएट ☐

महीने की आमदनी : (5000 से कम) (5000-10000) (10001-15000) (15001-20000) (20001-25000) (25001-30000) (30000 से ज्यादा)

चुना हुआ समय : (8.30-10.30) (10.30-12.30) (12.30-3.30) (3.30-5.30) (5.30-7.30) (7.30-9.30)

मोबाईल संदेश सुनने के लिये चुनी हुई भाषा : हिंदी / मराठी

(प्रसूतिपूर्व जानकारी) **ANC data & Pregnancy history** (गर्भावस्था का इतिहास)

अंतिम माहवारी का दिन (LMP):- ..../......../........ , G........ P........ S........ L........ A........

(**G-** कितने बार पेटसे है, **P-** कितने बार प्रसूति हुई, **S-** मृत बालक, **L-** जीवित बच्चे कितने है, **A-** गर्भपात–20 हप्ते पहले)

प्रसूति पंजीकृत है?: हाँ /नही

यदि हाँ, तो कहाँ : सरकारी अस्पताल/ निजी अस्पताल (प्राईवेट) पंजीकरण की तारीख :..........

पिछले गर्भावस्था के दौरान आई हुई समस्या : रक्तचाप / मधुमेह (Diabetes) / सिजेरीयन / थायरोईड / फायबर / प्राकृतिक गर्भपात / कद कम होना / समय से पहले प्रसूति / ॲनिमिया(खून की कमी) /अन्य..........

प्रसूति का नियोजन : सरकारी अस्पताल / निजी अस्पताल (प्राईवेट) /अन्य ....

(प्रसूति के बाद की जानकारी) **PNC data**

बच्चे की जन्मतिथि : ..../......../........ , (पूरे दिन की प्रसूति/ कम दिनों की प्रसूति)

प्रसूति कहॉ हुई ?: सरकारी अस्पताल / निजी अस्पताल (प्राईवेट) /घर /अन्य

प्रसूति का तरीका : प्राकृतिक (Normal) / सिजेरीयन

प्रसूति के बाद कोई दवाईयाँ ले रही है? यदि हां तो कौनसी ?:..........

सखी का नाम :

संस्था/अस्पताल का नाम :

प्रोजेक्ट अफसर का नाम :

Institutional Context - ARMMAN

ADVANCING REDUCTION IN MORTALITY AND MORBIDITY OF MOTHERS, CHILDREN AND NEONATES

<u>सहमती पत्र</u>

mमित्र नि:शुल्क मोबाईल संदेश सेवा प्राप्त करने के लिये सहमती पत्र

<u>mमित्र मोबाईल संदेश सेवा के बारे मे -</u>

mमित्र यह अरमान संस्थाव्दारा भारत के विभिन्न नागरी समुदायोमे दी जानेवाली नि:शुल्क मोबाईल संदेश सेवा हैं। इस सेवा मे महिलाओंको उनके गर्भावस्था से लेकर बच्चा होने तक और उसके बाद बच्चा एक साल का होने तक सेहत के बारे में किस तरह से खयाल रखना चाहिये इस के बारे मे जानकारी देते हैं। इस सेवा का मुख्य उद्देश भारत मे स्थित मातामृत्यू और बालमृत्यू का प्रमाण कम करना हैं। साथ ही में महिला एवंम बच्चों की सेहत को लेकर जनजागरण करना भी हैं।

यह नि:शुल्क मोबाईल संदेश महिलाए गर्भावस्था के दौरान हफ्ते में दो बार ; बच्चे के जन्म के बाद हफ्ते में हर रोज एक बार; दुसरे हफ्ते से बच्चा तीन महिने का होने तक हफ्ते में दो बार; और चोथे महिने से लेकर बच्चा एक साल का होने तक हफ्ते में एक बार इस तरह से सुनाए जाते हैं।

मैं ____________________________ क्षेत्रीय पर्यवेक्षक के हैसियत से नियुक्त हूँ। श्रीमती ________________________ इनको उन्हे समझ में आनेवाली भाषा के माध्यम से हमारा mमित्र प्रकल्प/कार्यक्रम समझा दिया हैं। उन्हे इस कार्यक्रम के उपयोगिता और फायदे के बारे में पूरी समझ दी गयी हैं। और खुद को इस कार्यक्रम के तहत पंजीकरण करने की उनकी इच्छा हैं। अंत: इसके लिये जरुरी जानकारी संस्था को देकर वह खुद की पूरी सहमती के साथ इस कार्यक्रम के लिये पंजीकरण करवा रही हैं।

क्षेत्रीय पर्यवेक्षक की स्वाक्षरी ________________

दिनांक:

मैं ____________________________ ऐसा लिख के देती हूँ की मुझे mमित्र नि:शुल्क मोबाईल संदेश सुविधा की पूरी जानकारी मिल गयी हैं और वह मेरे समझ में भी आ गयी हैं। संस्था के सदस्योने मुझे समझ में आनेवाली भाषा के माध्यम में यह कार्यक्रम की स्पष्टता दी हैं और इस नि:शुल्क मोबाईल संदेश सुविधा के लिये में खुद को पंजीकृत करना चाहती हूँ| इस संपूर्ण प्रक्रिया के लिये मेरी पूरी सहमती हैं। उपर निर्द्रशित किये हुए समय पत्रिका नुसार नि:शुल्क मोबाईल संदेश सुविधा के लिये मैं खुद को पंजीकृत करना चाहती हूँ | इस संपूर्ण प्रक्रिया के लिये मेरी पूरी सहमती हैं। उपर निर्द्रशित किये हुए समय पत्रिका नुसार नि:शुल्क प्राप्त करने के लिये मुझे कोई आपत्ती नही हैं। यह संदेश मुझे आप भेज सकते हैं।

लाभार्थी की स्वाक्षरी ________________

दिनांक:

UNIVERSITY OF SUSSEX

Literature Review - Technology engagement through m-Health

There are three components within this literature

- The first caters to how mobile technology has been useful to improve **health workers'** output
- ThinkTB - Tyagi et al., (2020), ImTecho - Modi et al. (2019), ICDS-CAS - Nimmagadda et al. (2019) , ReMiND - (Prinja et al., 2018)
- Second, m-Health literature also in the past focused on how **text messages** can help consumers change their health behaviors
- Project Masiluleke in South Africa (Canales, 2011), Text to Change in Uganda (Chib et al., 2012), Text2Teach in Philippines (Roble, 2018, p. 2), Stop my smoking (SMS) in USA (Ybarra et al., 2014) (Scott-Sheldon et al., 2016) (Carpenter Cook, 2008)

Literature Review - Technology engagement through m-Health

- Third strand is concerned about m-Health usage and **effectiveness in developing countries**
- Betjeman et al., (2013) believe that m-Health can improve and reduce costs, especially in rural areas
- Countering this perspective, Eckman et al., (2016) argue that most m-Health projects are generic and thus less beneficial for individual needs
- Ruton et al., (2018) suggest that m-Health should not be standalone but considered part of a more comprehensive intervention package
- Gleason (2015) suggests that security, cost, interoperability, scalability, and lack of local knowledge are barriers to the use and development of m-Health initiatives

Literature Review - Information Dissemination in Healthcare

- Cawley & Ruhm, (2011), studied how information dissemination impacts health behaviors resulting in favorable health outcomes
- Chatterjee et al., (2018) study the role of spatial peers in diffusion of information and show how it increases uptake of universal health insurance
- Other studies show that information provided through telemedicine centers increases access and uptake of health care programs (Mohanan et al. (2016); Delana et al., 2019)
- Madajewicz et al., (2007) show that informing households that their well water has arsenic increased the likelihood of them switching to a safer well
- Dupas, (2011a) finds that adolescent girls change their sexual behavior in response to information on the HIV

Literature Review - Information Dissemination in Healthcare

- Rhee et al., (2005) find that 49% of households that had received the educational component impregnated their bed nets to fight against malaria
- Still, the merits of more information in health care are complex (Phelps, 1992)
- The informational impact depends on the quality and time of information and to whom it is provided (Dupas, 2011b)

Our research differs from existing studies in two ways;

- First, mMitra is not a one-time intervention program
- Second, the impact of information dissemination gets studied in the presence of exogenous COVID-19 health shock with outcomes studied varying from call duration to call drop

Literature Review - Health shock & behavior

- Frank (2004) suggests that in matters related to health, consumers make choices in fear and urgency, trusting the expert
- Thus, health space can be a fertile ground for behavioral economics researchers
- There are existing studies on assessing the effect of health shocks on community mitigation efforts (Aburto et al., 2010), crisis management and self-protection (Bennett et al., 2015), natural adoption of protective health behavior (Agüero & Beleche, 2017), and immediate response under risk of death (Dupas, 2011b)
- Our study advances this literature given the grand challenge of maternal mortality in public health settings of developing economies like India, especially when they are hit by an external shock like a pandemic