Exploring the Mismatch Between Mobile Phone Adoption and Use Through Survey Data From Rural India and China

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***Abstract*—Persistent disciplinary and methodological divides between technology diffusion and adoption studies and the study of use and engagement with technology raise obstacles to understanding the development implications of mobile technology diffusion, for example in the area of healthcare access. As quantitative assessments in the area of health and technology almost exclusively rely on binary indicators of mobile phone adoption, it is not clear whether this is indeed a reasonable proxy that does not obscure the distributional implications of mobile phone use. This paper therefore compares patterns of mobile phone adoption and utilisation using original survey data from rural India and China. "Utilisation" here is assessed through a simple yet novel multidimensional index. The paper further assesses the role of these concepts as determinants of locally emerging forms of mobile-phone-aided healthcare-seeking behavior ("health action"). The investigation uses descriptive statistical analysis and multilevel logistic regression analysis, which provide evidence in support of the claims that (a) patterns of mobile phone diffusion and utilisation are related yet incongruent, that (b) mobile phones facilitate health action in both field sites to a notable extent, and that (c) the mobile phone utilisation index is a better predictor for phone-aided health action than mobile phone adoption. In light of the superiority of the utilisation index vis-à-vis binary measures of mobile phone adoption, other researchers can apply the survey instrument and technology utilisation concept developed in this paper to support the analysis of the social implications of technology diffusion.**

Keywords—mobile phones; technology adoption; technology use; rural India; rural China

I. INTRODUCTION

With estimated 7.1 billion mobile phone subscriptions in 2015, rapid global mobile phone diffusion has attracted broad interest in the development impacts of mobile technology in low- and middle-income countries [1]. The attention is particularly visible in the area of health, where nearly 1,100 mobile-phone-based (or "mHealth") projects are currently ongoing while the market for health-related smartphone applications is exploding [2, 3].

The research focus of the health-and-technology literature rests primarily on leveraging the now widely available technologies in order to improve health systems and health service delivery. For example, recent research by Tran, et al. [4] analyzed household phone ownership patterns in rural Bangladesh from 2008 to 2011 among a sample of more than 35,000 persons. Based on their analysis, the authors suggest that efforts to increase mobile phone ownership—ultimately aiming at full penetration among households—will help to "harness the full potential of connectivity using mobile phones as a platform" for interventions [4].

The broader field of "ICTD"—the study of information and communication technologies in development contexts—shares the motivation of seizing technological advancements for development processes [5, 6]. One-tenth of the publications in this domain actually focus on health, while two-thirds address the topics of "business" and "empowerment" [7]. However, this research still tends to focus on the enabling conditions and "readiness" of information technology, rather than its development impacts [8, 9]. And although the field of ICTD shares a fundamental interest in socioeconomic inequities in the form of "digital divides" [10], our current knowledge about the equity impacts of mobile phone diffusion on development outcomes is still rather limited [11-13].

Disciplinary and methodological divides appear to perpetuate some of the empirical gaps. An area where these divides become salient is the conceptualization and measurement of technology in development processes. For instance, whereas qualitative analyses of the social implications of technology in the fields of anthropology and sociology appreciate the conceptual richness and social embeddedness of mobile phone use [14-16], economists' quantitative assessments of mobile phone impacts tend to rely on narrow measures of "adoption" that focus on individual or household-level device ownership [17, 18]. Quantitative studies thus often reduce the qualitatively rich concepts of phone use to a binary measure of adoption that may or may not adequately reflect the diverse human engagement and interaction with technology.

Similar methodological divides surface in the health-and-technology literature. One the one hand, the few qualitative studies on mobile phone use and healthcare behavior exemplify the complex uses of mobile phones among healthcare-seeking

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individuals [14, 15, 19]. On the other hand, quantitative public health studies that go beyond a binary notion of mobile phone adoption are very scarce [20-23].

If we agree that mobile phone adoption and the actual utilization of the devices might follow divergent patterns, then the reliance on a binary indicator of personal or household adoption could mislead our understanding of the actual and potential development impact of technology and its distributional implications. This applies to healthcare as well as to other domains of ICTD.

This paper therefore calls for a more faithful assessment of the link between mobile phones and development processes. While prevailing narratives imply that the use of a technology follows directly from its adoption, it is by no means guaranteed that this is actually the case if adoption measures are based on ownership indicators. Likewise, not owning a technological object does not necessarily prevent individuals from using or benefitting from it (assuming it is beneficial). This problem is not new, but empirical analyses as well as scoping studies in the area of mHealth continue to rely on binary adoption metrics focused on technology ownership, and continue to make inferences for technology use and the potential impact of mHealth solutions on this basis.

This paper offers a method of capturing the utilisation of mobile phones instead of their mere adoption, using a simple aggregate index that combines the dimensions of technology access, functional breadth, and intensity of use. In order to test the suitability of this "utilisation index," the paper estimates a range of regression models linking mobile phone adoption as well as utilisation to the emergence of phone use in curative health action. Health action here is understood as a sequential process of remedying an illness through oneself or third parties including family members, doctors, and other actors [24]. The health action process begins with identifying an illness or a physical discomfort and potentially involves a wide range of sequential healthcare activities. Mobile phones may or may not be used at any point of those sequences in a variety of ways, for example by chatting with a relative, arranging a taxi, or calling a doctor for a home visit. This paper refers to healthcare sequences involving such health-related phone uses as "phone-aided health action." The field sites for the empirical study are poor, rural regions in India and China, chosen because of their particularly challenging healthcare environments while exhibiting comparable rates of mobile phone diffusion.

The analysis will demonstrate the suitability of the novel mobile phone utilisation index as a better predictor of phone-aided health action than conventional mobile phone adoption metrics. In addition, the phone utilisation index offers refined and discriminative analyses of digital inclusion and exclusion especially in contexts where mobile phones have diffused widely on the household and individual level.

The findings and the underlying methodology are of particular importance for analysts and solution developers in the area of mHealth and the broader field of mobile phones and development. On the one hand, an analytical and conceptual shift away from adoption towards utilisation can potentially help to understand patterns of inclusion and exclusion when considering mHealth interventions because some individuals remain systematically excluded even in high-diffusion settings. On the other hand, it is conceivable that, as phone-aided health action emerges locally along the lines of utilisation patterns, these local solutions enter into competition with mHealth and thus adversely influence service uptake. While this analysis takes place in the domain of health, the new utilisation index can help to explore whether similar conditions hold in other ICTD areas beyond healthcare, such as finance and education.

II. Objectives

This paper is intended to help bridge the disciplinary divide that creates a mismatch between the notions of technology diffusion and adoption on the one hand, and utilising and engaging with technology on the other. This mismatch raises obstacles to understanding the development implications of mobile technology diffusion, for example in the area of healthcare access. The research question thus addressed in this paper is, "Does a measure of mobile phone 'utilisation' offer superior analytical value compared to 'adoption' in the context of healthcare-related mobile phone use?"

Being part of a larger mixed-methods research project on the relationship between mobile phones and healthcare access in rural India and China, the paper applies a conceptual framework of technology use that was derived from preceding qualitative fieldwork and a review of the mobile technology literature (Fig. 1). Adoption-as-ownership in this framework is but one facet of a more encompassing notion of "utilising technology" that also incorporates the modalities of use in terms of functional breadth and intensity (which could be likened to "variety" and "amount" of use in Blank and Groselj [25]). In addition, "access to technology" has at least five sub-categories, namely exclusive personal ownership, shared ownership, access through borrowing, access through the market (or "renting"), and access through proxy users (who e.g. operate the phone for the owner). These categories can overlap for individual users. In addition, this conceptualization appreciates a broader range of indirect routes of access (which can have implications on the other dimensions of phone utilisation) in an attempt to produce a single though sub-divisible measure of mobile phone utilisation. Yet, in contrast to studies of "uses and gratifications" of technology, this conception does not account for different purposes such as social or economic uses [26-28]. The paper instead links general mobile phone utilisation patterns to a particular domain of human life, namely healthcare seeking.

III. Methodology

The analysis in this paper draws on primary survey data collected from 400 adults each in rural Rajasthan and rural Gansu from August to October 2014 (Table I; case description in Section IV). The survey followed a three-stage stratified random sampling approach. First, 16 villages in each field site were randomly selected in a spatially stratified manner. Within each village, 25 households were chosen through systematic random sampling. In each household, age-order tables helped to select one member randomly for the interview. Population estimates based on these data pertain to the districts of Rajsamand and Udaipur in Rajasthan and the districts of Baiyin, Dingxi, and Lanzhou in Gansu.

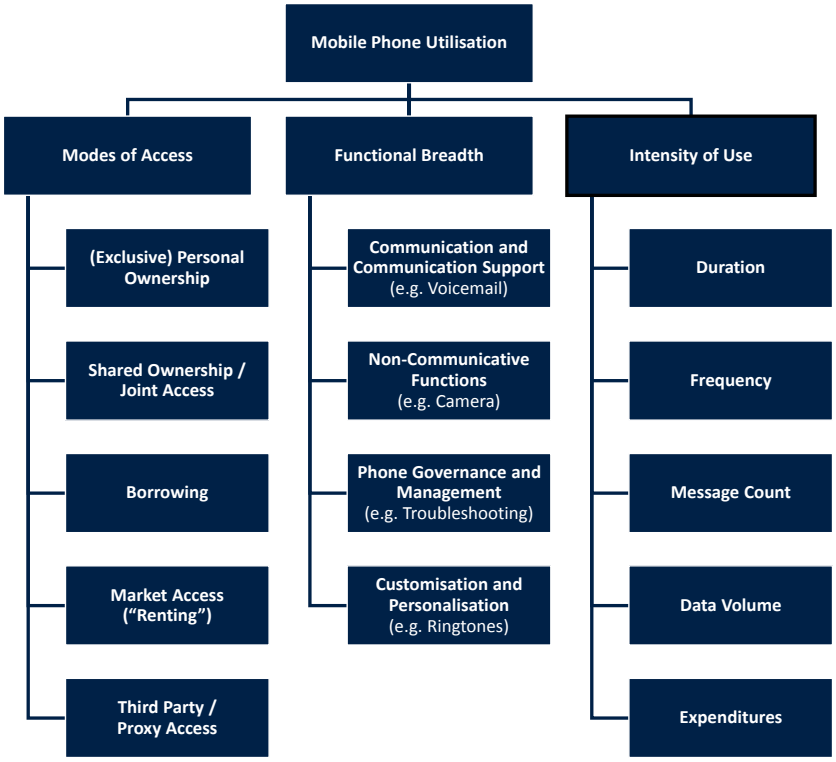

Fig. 1. Conceptual Components of Mobile Phone Utilisation

Sources: Own elaboration, derived from qualitative fieldwork and [15, 19, 29-35].

TABLE I. HOUSEHOLD SURVEY DATA USED IN THIS PAPER

	Rajasthan	Gansu
Sampling	**3-stage stratified cluster sampling** 1. Random village selection, proportional to population size and stratified by distance to sub-district headquarter 2. Systematic random household selection (manual household lists) 3. Random household member selection using age-order tables	**3-stage stratified cluster sampling** 1. Random village selection, stratified by distance to nearest township 2. Systematic random household selection (complete village maps) 3. Random household member selection using age-order tables
Geographical Scope	Districts of Rajsamand and Udaipur	Districts of Baiyin, Dingxi, and Lanzhou
Sample Size	400 rural dwellers in 16 villages	400 rural dwellers in 16 villages[a]

Source: Fieldwork data.
[a.] Gansu data based on 398 observations. Two questionnaires were invalid and have been dropped from the sample.

In order to assess "adoption," the survey captured the number of mobile phones owned by the respondent's household, transformed into a binary variable of either none or at least one mobile phone in the household. On the individual level, it captured whether the respondent owned a phone in the previous twelve months.

Only a small number of quantitative researchers have ventured beyond ownership-based technology adoption metrics [20, 25, 35-39]. In order to offer a methodological alternative, this study uses a novel, decomposable index of mobile phone utilisation. Constituent elements of this index are (i) the mode of phone access (i.e. personal/shared/borrowed/market/proxy access), (ii) the functional spectrum that the user exploits (i.e. ingoing/outgoing calls and text messaging, mobile data, tools), and (iii) the frequency with which these functions are used along each mode of access. The construction of the index is explained and illustrated in Appendix 1; Appendix 2 presents an excerpt of the survey questionnaire to capture two of the six dimensions included here.

The data set also captures individuals' disease episodes and the types of mobile phone use that arise therein. Based on people's self-described "severity" of an illness (mild, severe, chronic/long-term), up to three episodes per person were recorded. Each of these sequences of health action contain information on the patient's symptoms, the kind of health action at each stage and where the action took place (e.g. visit

to a private doctor 30 minutes from home), the duration of the stage, and whether a mobile phone was used. Phone use here captures all kinds of personal and proxy use that are directly related to the illness. This is not limited to advice calls and ambulance services, but can also include medicine orders, appointments, reassuring one's peers, talking about the illness as a conversation topic, amongst others.

This paper presents quantitative descriptive statistics from the survey to demonstrate the diversity of mobile phone utilisation among adopters and non-adopters. This procedure will examine how patterns of utilisatoin relate to mobile phone adoption, and whether we can observe the indigenous emergence of healthcare-related phone use among the general population in the field sites. As the survey data is collected in a multi-stage cluster random sampling design, all descriptive statistics are population-weighted using district-level census data from each field site.

The analysis further includes single- and multi-level logistics regression models in order to predict phone-aided health action. Logistics regression is necessary for this task because phone-aided health action in these models is a binary variable ("1" if a disease episode was phone aided, "0" otherwise). The analysis of the predictor variables takes place on the disease episode level rather than the individual because one person may report more than one disease episode. Disease episodes are nested within persons, and persons are nested within villages as primary sampling units. Multilevel logistic regression modeling is a useful approach to account for such a nested data structure [40, 41]. The current application considers three-level random-intercept logistic regression models. As the intercept terms can take different values for each individual and village, they help to account for unobserved heterogeneity across these groups when estimating the relationship between health action and phone use. The predictive power of the independent variables of interest (mobile phone use and adoption) is assessed through one-sided z-tests for hypothesis testing of the individual coefficients, and on Akaike and Bayesian information criteria for model goodness-of-fit comparison. Stata 13 was used to estimate the various logistic regression models [42].

IV. Case Description

Rajasthan and Gansu are the field sites on which this paper focuses. Comparable rates of mobile phone diffusion (subscription rates of 0.74 in both regions) and challenges in healthcare financing, health worker availability, the quality of available healthcare, and healthcare access difficulties due to mountainous terrain and remote settlements render these sites interesting for the analysis of mobile-phone-aided healthcare seeking [54-57]. At the same time, elementary phone-based health services exist in both places as they maintain medical ambulance hotlines through government-sanctioned phone numbers (108 in Rajasthan, 120 in Gansu), and medical advice hotlines are available via the phone numbers 12320 in Gansu and 104 in Rajasthan. Due to the relative paucity of landlines, these are *de facto* services for mobile phone users. Besides, mobile customers in both Gansu and Rajasthan can subscribe to chargeable ("value-added") services from mobile network operators in order to receive public health information as text messages on their phones. Table II compares socio-economic, teledensity, and healthcare indicators of Rajasthan and Gansu.

TABLE II. Comparison of Field Site Indicators

	Rajasthan	Gansu
Population (million)	68.6 (2011)	25.6 (2011)
Mobile Subscriptions / 100 Pop.	0.74 (2012)	0.74 (2013)
Life Expectancy at Birth (years)	65.2 (2010)	75.7 (2010)
Literacy Rate 15+	67% (2011)	90% (2011)
Hospital Beds / 1,000 Pop.	0.5 (2011)	3.3 (2011)
Doctors / 1,000 Pop.	0.1 (2011)	0.8 (2012)
Per Capita GDP (USD)	$885 (2011)	$3,130 (2011)

Sources: Own elaboration, compiled from [43-53].

Both public health systems in rural Rajasthan and Gansu have a three-tier structure in which basic medical care from limitedly trained nurses and "village doctors" is available at the lowest community level. These providers would refer a patient to small hospitals at the town level, which are staffed with medically trained doctors (i.e. the first referral unit or the first contact point with a doctor). On the third level are county-level hospitals with specialist doctors and 30 beds or more. Aside from this public health service structure, Rajasthan displays a wide range of private providers with different degrees of medical training, in addition to traditional faith healers and alternative systems of medicine such as Ayurveda. In Gansu, private practitioners are less common and people have more widespread access to pharmacies and shops selling medicines.

V. Results

The main findings emerging from the presentation are that (a) configurations of mobile phone utilisation do not map closely onto phone diffusion patterns, (b) phones emerge in both sites as a common tool to aid health action, and (c) mobile phone utilisation is a better predictor than adoption for the emergence of phone-aided health action on the individual level.

A. *Patterns of Mobile Phone Adoption and Use*

Although Rajasthan and Gansu had comparable rates of teledensity when the survey was designed, the survey data reveal a notable degree of divergence of mobile phone utilisation as well as access across the two sites.

At the first glance, mobile phones have diffused widely in both sites, with 78 percent of Rajasthani households and 90 percent of the households in the Gansu site owning at least one mobile. Access patterns on the individual level—shown in Fig. 2—indicate that 47 percent of adults in Rajasthan and 78 percent in Gansu had owned a phone in the 12 months preceding the survey. The figure also indicates that shared ownership and third-party access to phones are more common in the Rajasthan site. As a result, we can observe the counterintuitive detail that a larger portion of individuals in Gansu does not have any regular access to a mobile phone, although a much larger share of the population owns one.

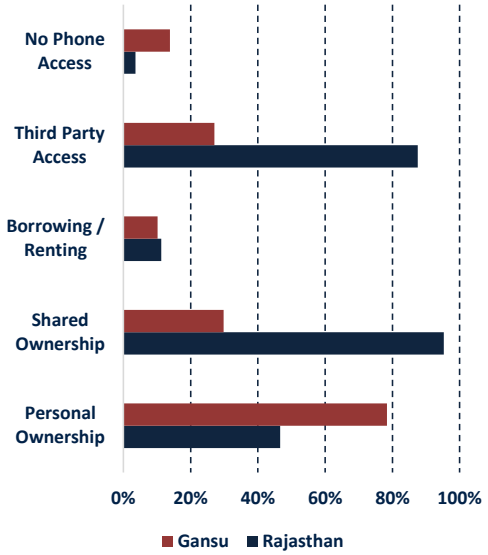

Fig. 2. Share of Field Site Populations That has Access to Mobile Phones

Source: Own illustration, derived from fieldwork data.
Notes. *N* = 798. Statistics based on monthly or more frequent access in last 12 months. Categories can overlap (except "no phone access"). Underlying statistics are population-weighted using census data. Proportion as share of total adult population in field site.

The data offer further insights into the patterns of mobile phone utilisation in both field sites. In Fig. 3 is displayed the distribution of the field site populations across different levels of mobile phone utilisation (in index intervals of 0.1). Fig. 4 summarizes the overall utilisation index and its sub-indices across Rajasthan and Gansu. These graphs show that, for example, only five percent of the rural population in the Indian field site fall into the lowest bracket of mobile phone utilisation scores, whereas this is the case for 20 percent in the Gansu site (Fig. 3). At the same time, the survey participants in Rajasthan have lower average utilisation that is concentrated in the lower two-fifths of the index scale. Gansu residents have a more homogeneous distribution of use: 24 percent in Gansu fall into the top-three brackets of phone utilisation, but only three percent in Rajasthan (Fig. 3). We can also observe that the utilisation of mobile phones through proxy users in Rajasthan is nearly as high as people's personal mobile phone use. In contrast, borrowers exhibit very low usage vis-à-vis owners and sharers. Despite wider access in Rajasthan, average mobile phone utilisation is therefore higher in Gansu (Fig. 4).

To examine the relationship between adoption and use patterns, Fig. 5 maps the share of various modes of phone access for each bracket of the utilisation index. We can observe that household mobile phone ownership (single solid lines) and personal ownership (single dashed lines) are positively correlated with the index. However, we can also see that, among the people in the lowest utilisation-bracket (below a score of 0.1), nearly 20 percent of the residents in the Gansu field sites own a phone, and 40 percent of the low-users' households have a mobile phone. Moreover, the graph shows the divergent sharing and proxy use patterns across the field sites. Shared ownership (single dotted lines) increases rapidly in the Indian site, reaching 100 percent at the second-lowest index bracket. In contrast, no index bracket in Gansu exhibits more than a 40 percent portion of shared access, and sharing tends to decline among higher index scores. Proxy access (double dotted lines) in each site follows similar patterns, though in Gansu we can observe that more than 60 percent of users in the second-highest index bracket report that a third party operates a phone for them. Borrowing patterns (double solid lines) fluctuate at low levels of up to 30 percent across the index spectrum in both field sites.

These patterns illustrate the incongruence between ownership and use. On average 88 percent of the individuals in Gansu in the index bracket 0.2-0.3 own a mobile phone and 98 percent of their households have a phone as well. Individuals in Rajasthan achieve the same score with an average of 23 percent personal and 76 percent household phone ownership. Perhaps more importantly, the index also helps to discriminate between users in situations where technology diffusion is very high; that is, where nearly everyone is expected to own a mobile phone. For instance, in Gansu, older persons living in atomistic households and having low technical literacy have more difficulty utilizing seemingly "diffused" technology. The comparatively frequent occurrence of very low mobile phone utilisation reflects these difficulties.

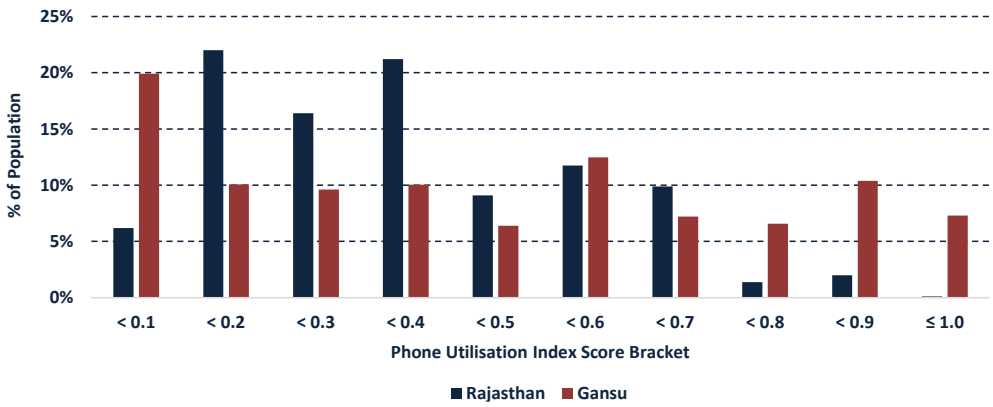

Fig. 3. Distribution of Phone Utilisation Index Across Total Population in Field Sites

Source: Own illustration, derived from fieldwork data.
Notes. *N* = 798. Underlying statistics are population-weighted using census data. Proportion as share of total adult population in field site. Total population including phone owners and non-owners.

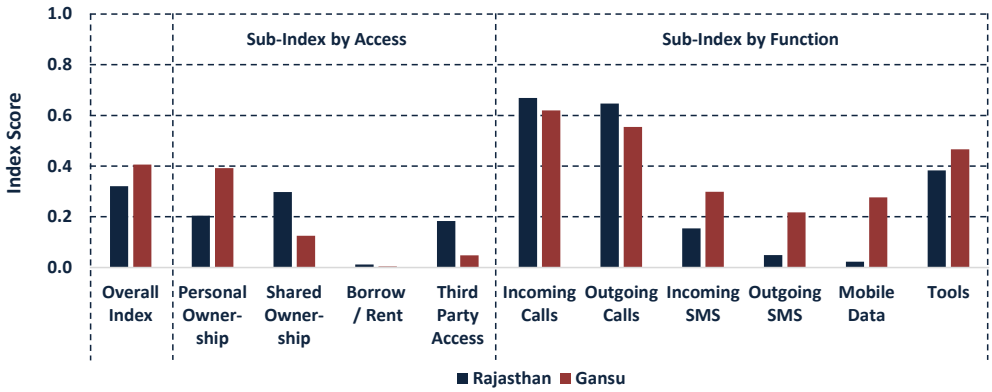

Fig. 4. Average Phone Utilisation Index and Sub-Index Scores Across Total Populations in Field Sites

Source: Own illustration, derived from fieldwork data.
Notes. *N* = 798. Underlying statistics are population-weighted using census data. Average scores based on total adult population. Total population including phone owners and non-owners.

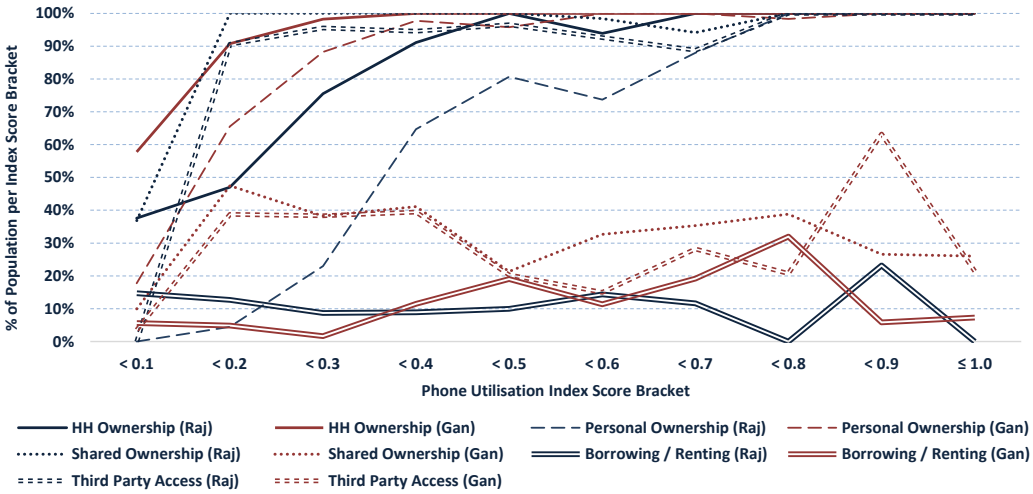

Fig. 5. Mobile Phone Access for Population in Each 0.1-Bracket of the Phone Utilisation Index

Source: Own illustration, derived from fieldwork data.
Notes. *N* = 798. Underlying statistics are population-weighted using census data. Proportion as share of total adult population per field site in respective index bracket. Total population including phone owners and non-owners. Categories can overlap. HH is household, Raj is Rajasthan, Gan is Gansu.

B. Emergence of Phone-Aided Health Action

This section demonstrates that mobile phones permeate health behaviors in rural Rajasthan and Gansu rather commonly. Fig. 6 shows the portion of the total population in each field site that reported healthcare-related uses of mobile phones, using four different criteria. The first indicator pertains to the health providers and solutions that the respondent would consider for treatment. Asked if any of these could be accessed with the help of mobile phones, 8 percent of the Rajasthan and 36 percent of the Gansu site population indicate that this would be possible (and would then go on specifying for which purposes). The second indicator asked whether the respondent has ever used a mobile phone for another person's health problem (providing a range of possible options), which was confirmed by 12 and 56 percent in Rajasthan and Gansu, respectively. Indicator three focuses on the illness episodes reported by the survey respondents, showing that one-fifth of the rural population in Gansu exhibit phone-aided health action; in rural Rajasthan, it is still 7.5 percent. Aggregating these three indicators into an "overall" measure, we can establish that one-fifth of the Rajasthan respondents report one form of phone-aided health action or another, and nearly two-thirds of the respondents in Gansu.

Whichever measure we apply, mobile phones emerge as a (perhaps surprisingly widespread) tool in the healthcare-seeking process in both field sites. Even according to the most conservative indicator—that is, mobile phone use in recent personal health action—at least one in thirteen adults in the Rajasthan site has had some experience with healthcare-related phone uses; and many more in Gansu. This demonstrates that mobile phones enter personal healthcare behaviors (rather than being a neutral platform for potential public service delivery). We have previously seen that groups of individuals appear to be excluded from phone utilisation despite widespread mobile diffusion. The present evidence in this section suggest that, where the target group uses phones, new interventions may have to compete with existing local solutions. Low uptake of a phone-based service may therefore be a result of redundancy as well as exclusion.

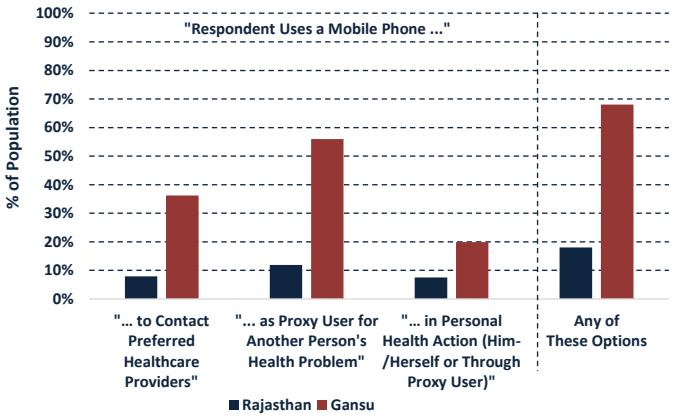

Fig. 6. Share of Total Field Site Populations Using Mobile Phones for Healthcare-Related Purposes

Source: Own illustration, derived from fieldwork data.
Notes. N = 798. Underlying statistics are population-weighted. Percentages as share of total adult population in field site. Total population including phone owners and non-owners. Categories can overlap.

C. Adoption vs. Use in Predicting Phone-Aided Health Action

What drives the emergence of these local mobile-phone-based solutions? A simple comparison of health seekers by phone ownership (Table III) suggests that one-third of those persons reporting phone-aided health action in Rajasthan and one-sixth in Gansu had not owned a mobile phone in the year preceding the survey. Likewise, personal phone ownership does not directly translate into health-related uses as five in six Rajasthani phone owners and three in four Gansu owners have not used a phone during their reported illnesses.

TABLE III. PHONE OWNERSHIP IN PHONE-AIDED HEALTH ACTION

		Phone use in any health issue?			
		Rajasthan		Gansu	
		No	Yes	No	Yes
Respondent owns phone?	No	49.5 %	3.6 %	17.9 %	4.0 %
	Yes	41.0 %	5.9 %	58.4 %	19.8 %

Source: Own elaboration, derived from fieldwork data.
Notes. N = 683, excluding respondents who have not reported illness. Statistics are population-weighted using census data. Gansu values adding to 100.1% due to rounding errors.

Because there are non-owners who exhibit phone-aided health action, and because there are owners who choose not to use a mobile phone when seeking healthcare, the remainder of this section examines whether "mobile phone use" as measured by a utilisation index is indeed superior to the concept of mobile phone adoption as ownership. If the analysis reveals that mobile phone access and local forms of phone-aided health action are linked, then dedicated mobile health services may create redundancies for these individuals. In addition, should it surface that mobile phone utilisation is a better predictor than adoption, it could suggest that interventions aiming at phone owners may be misguided if they neglect people's actual engagement with the technology.

Eight models were estimated, each in a single- and a multi-level framework. The models are distinguished by their principal independent variable(s) of interest being:

1) the mobile phone utilisation index,
2) the index and household mobile phone ownership,
3) access sub-indices and household phone ownership,
4) function sub-indices and household phone ownership,
5) personal mobile phone ownership,
6) household mobile phone ownership,
7) personal and household mobile phone ownership, and
8) access through personal / shared / borrowed mobile phones and household phone ownership.

For the sake of brevity, the reporting is restricted to the main results of the multilevel random-intercept models. Single-level logistics regression estimates yielded the same conclusions (i.e., signs and significance levels are consistent). Detailed regression results are shown in Appendix 3.

The main results across Models 1 to 8 are shown in Table IV, omitting control variables and the constant term (a result is "significant" if its p-value is below 0.1). Whereas Models 1 to 4 based on the phone utilisation index are significant at the one-percent level, Models 6 to 8 are only significant at the five-percent level and Model 5 only at the ten-percent level (see "Model test" in Table IV). As the variance component tests in the last row indicate, the multilevel structure is appropriate for all specifications.

The results show that all models exhibit a significant positive relationship between health-related phone uses and people's access to and utilisation of mobile technology. This can be interpreted as evidence that mobile technology diffusion contributes to the emergence of innovative local solutions to healthcare-seeking problems (rather than e.g. one person or service provider facilitating all phone-aided health action).

A comparison of the different indicators and models yields further insights. Model fitness as indicated by the Akaike Information Criterion suggests that the models containing the mobile phone utilisation sub-indices have the largest explanatory power, followed by Models 2 and 1. Judging by the Bayesian Information Criterion, which penalizes model complexity to a greater extent, Models 1 and 2 are the best estimates. The model containing only mobile phone ownership (alongside other controls) emerges as the least suitable according to either information criterion.

As far as the individual variables are concerned, the mobile phone utilisation index is consistently more significant than personal or household-level mobile phone ownership. Personal mobile phone ownership is only significant at the five-percent level (Model 5) and becomes insignificant when combined with household mobile phone ownership (Model 7). Both personal and household mobile phone ownership are weaker predictors than the mobile phone use index.

In short, the analysis shows that personal phone ownership is a relatively weak and inefficient predictor for the emergence of phone-aided healthcare seeking when compared to the index of mobile phone utilisation. Although household ownership predicts the outcome better than personal ownership, neither (in connection as well as in isolation) is superior to the mobile phone utilisation index. In addition, the high prevalence of household phone ownership (78 percent in Rajasthan, 90

percent in Gansu) suggests that the *absence* of household phones explains the *non-emergence* of phone-aided health action, rather than *vice versa*. The binary adoption indicator would be unable to predict the limited emergence of phone-aided health action among the majority of household phone owners.

TABLE IV. MAIN RESULTS OF THREE-LEVEL RANDOM-INTERCEPT LOGISTIC REGRESSION MODELS

	Model No.							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Phone utilisation index (aggregate)	4.300***	3.920***						
Utilisation sub-index (owned)			1.659**					
Utilisation sub-index (shared)			0.740					
Utilisation sub-index (borrowed)			5.259					
Utilisation sub-index (3rd party)			5.769***					
Utilisation sub-index (incoming call)				1.026*				
Utilisation sub-index (outgoing call)				1.32**				
Utilisation sub-index (incoming SMS)				-0.159				
Utilisation sub-index (outgoing SMS				1.555***				
Utilisation sub-index (mobile data)				-0.065				
Utilisation sub-index (tools)				0.098				
Household owns phone		1.454**	1.515**	1.283**		2.020***	1.833***	1.632**
Respondent owns phone					0.712**		0.395	0.521
Shared phone								0.841***
Borrowed phone								1.079**
Model test	0.0012	0.0006	< 0.0001	< 0.0001	0.0520	0.0365	0.0364	0.0152
Akaike Information Criterion	654.136	649.243	645.479	646.279	684.471	676.686	677.431	665.808
Bayesian Information Criterion	836.117	836.013	846.616	856.994	866.452	858.666	864.201	862.155
Intra-class correlation: respondent level	0.23	0.23	0.25	0.20	0.21	0.22	0.21	0.14
Intra-class correlation: village level	0.28	0.24	0.25	0.20	0.43	0.41	0.39	0.27
Variance component test	< 0.0001	0.0001	0.0001	0.0004	< 0.0001	< 0.0001	< 0.0001	0.0041

Source: Own elaboration, derived from fieldwork data.
Notes. Coefficients reported. Control variables omitted (including household assets, health provider availability and preferences, gender, age, education, physical health status, awareness about and response time of health hotlines, household size, household head characteristics, family dispersion, remoteness of village, and severity of illness). Level 1: N_1 = 888 disease episodes. Level 2: N_2 = 681 respondents. Level 3: N_3 = 32 villages. Model test reporting Prob. > Wald X^2. Variance component test reporting Prob. > $\frac{1}{4}*X^2(0) + \frac{1}{2}*X^2(1) + \frac{1}{4}*X^2(2)$.
*p < 0.1, **p < 0.05, ***p < 0.01.

VI. CONCLUSION

This paper set out to investigate the relationship between mobile phone adoption and utilisation in the context of healthcare access in rural India and China. Evidence has lent support to the claims that patterns of mobile phone diffusion and utilisation are related yet incongruent, that mobile phones facilitate health action in both field sites to a notable extent, and that mobile phone utilisation is a better predictor for phone-aided health action than mobile phone adoption. The analysis was carried out in light of the persistent focus on technology adoption rather than its actual use in much of the diffusion literature. This distinction is non-trivial because people may remain excluded from a technology despite its apparent adoption.

It is important to stress the limitations of this study. The cross-sectional design makes it difficult to establish causal claims, even though there are compelling theoretical reasons to assume that causality runs from general-purpose phone utilisation towards phone-aided health action, rather than healthcare requirements fostering the diffusion and usage of technology. In addition, as the data was generated through retrospective face-to-face interviews, it is plausible that recall and social desirability biases influence the analysis. This is particularly possible with regard to the prevalence of phone-aided health behaviours illustrated in Section V.B. (e.g. the rather large share of reported proxy use for others). Although the sequential elicitation of illness episodes with specific information required for reported phone use was meant to mitigate this problem, it is impossible to rule out residual biases. Lastly, it is not sensible to extrapolate from the present study settings to other geographical regions. However, given that the findings were derived from two distinct locations with diverse sociocultural contexts, future research may explore whether the conclusions hold elsewhere.

It is therefore plausible conclude that a simple measure of mobile phone "utilisation" can offer superior analytical value compared to "adoption" in the context of healthcare-related mobile phone use. But the independent emergence of phone-aided health action in the field sites is noteworthy as well. Although each field site provides ambulance hotlines, public health hotlines, and network-operator-provided public health text messages, health related uses of mobile phones emerge locally among patients and in direct interaction with the health providers. Ambulances are among the very few instances where any such dedicated service use was actually reported by

the respondents. It is possible that the low uptake is a result of unreliable and ill-targeted services that do not address healthcare issues in remote rural areas. For example, one-quarter of the Rajasthani sample and only one-eighth in Gansu would indicate that ambulance services would arrive within half an hour in the village. At the same time, it is possible that government-sanctioned and commercial phone-based services compete with people's local phone-aided solutions: where people are accustomed to calling their local doctors directly for advice, a new public health hotline may have difficulty in convincing health seekers of superior service. Low uptake of a phone-based service may therefore not solely arise from digital exclusion, but also from inadvertent competition with local solutions as well as inadequate service delivery. Future research may explore whether patterns of service rejection overlap with locally emerging, utilisation-driven phone-aided health action.

The survey instrument developed for this research can aid assessments of the social implications of technology. The analytical value of the index results from its incorporation of personal and third party use across different types of technology access and usage modalities. Using relatively simple means to establish the index—based on a survey instrument requiring approximately 10-15 minutes of interview time and a basic scoring method—the measure outlined here can be incorporated into other studies, thereby helping to go beyond conventional measures of mobile phone adoption. Furthermore, the index can be amended for other applications. For example, where symbolic uses of mobile phones are deemed relevant for the analysis [e.g., 39], the frequency of mobile phone personalization might be captured as an additional functional dimension of use.

In conclusion, the evidence presented in this article suggests that a stronger focus on technology utilisation can better inform the analysis of socio-technological developments and their distributional implications. By offering a relatively simple method of capturing this concept on the micro level, this paper hopes to contribute to the methodological conversation in ICTD, and ultimately to a better understanding of the socio-economic equity implications of the activities of the Society on Social Implications of Technology.

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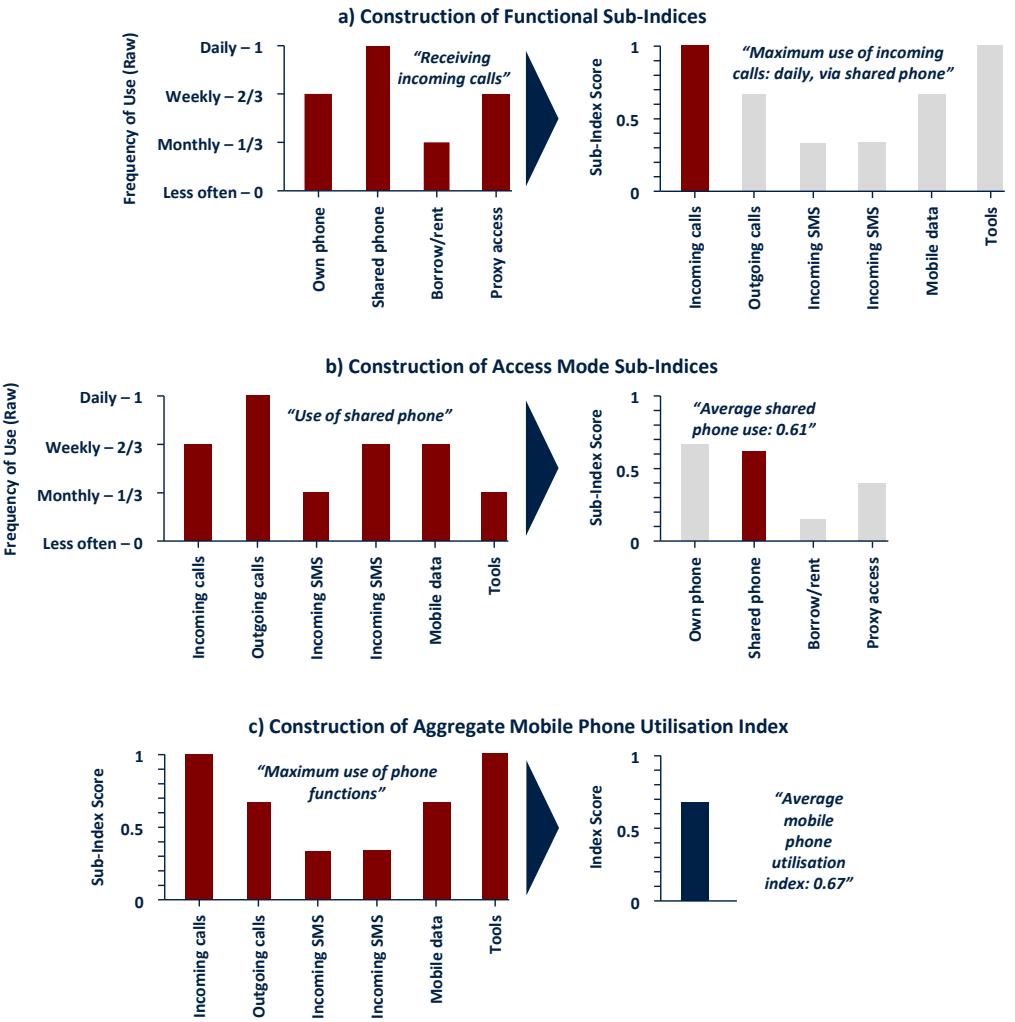
APPENDIX 1: SCHEMATIC ILLUSTRATION OF MOBILE PHONE UTILISATION INDEX CONSTRUCTION



Source: Own illustration.
Note. Illustration not based on actual data

The graphs in Appendix 1 illustrate how the phone utilisation index and its sub-indices are constructed. The raw data feeding into the index covers the frequency of using the main mobile phone functions in the twelve months preceding the survey. The raw frequency has four levels, ranging from "1 – daily or more often" to "0 – less often than monthly." This data was collected for different access modes, regardless whether or not the respondent owns the phone. In Panel (a), sub-indices by function are developed, based on the maximum use of a function across four routes of access. The functions considered here are incoming and outgoing calls and text messages as well as mobile internet and tool use (e.g. calendar, calculator). Panel (b) shows the sub-indices by access mode. For each channel, the average score across all six functions is calculated (these access sub-indices are only used for fine-grained analysis and do not feed into the aggregate index). Lastly, Panel (c) demonstrates the aggregation of the six functional sub-indices into one single index. The averaging procedure is similar to Panel (b), with the difference that each functional sub-index already contains the maximum use across the access routes. By integrating information on people's intensity of mobile phone use across functions and direct and indirect routes of access, the mobile phone utilization index goes beyond the conventional assessments of technology adoption.

More formally, the calculations for the aggregate utilisation index $I^{(\text{aggregate})}$ and the sub-indices by function ($I_f^{(\text{function})}$) and access ($I_{mode}^{(\text{access})}$) can be expressed as

$$I^{(\text{aggregate})} = \Sigma_f^F [\max(x_{f,\,own}, x_{f,\,share}, x_{f,\,borr./rent}, x_{f,\,3rd})] \,/\, F, \quad (1)$$

$$I_f^{(\text{function})} = \max(x_{f,\,own}, x_{f,\,share}, x_{f,\,borr./rent}, x_{f,\,3rd}), \quad (2)$$

$$I_{mode}^{(\text{access})} = \Sigma_f^F (x_{f,\,mode}) \,/\, F, \quad (3)$$

where f contains the functions considered here, F is the total number of functional indicators (six in our case), *mode* is one of the four modes {*own*, *share*, *borr./rent*, *3rd*}, and $x_{f,\,own}$, $x_{f,\,share}$, $x_{f,\,borr./rent}$, and $x_{f,\,3rd}$ are intensities of use for function f across each of the four modes of access. x here can assume the values {0, 1/3, 2/3, 1} corresponding to the frequency of use being less than monthly, monthly, weekly, and daily or more often. The aggregate index $I^{(\text{aggregate})}$ is the average utilisation of the phone across all functions F. The use of each individual function f is calculated as the maximum use of the function along each mode of access (owning, sharing, borrowing/renting, third party use). The average is then calculated by summing each maximised functional use f and dividing the total by the number of functional dimensions F. The functional sub-index $I_f^{(\text{function})}$ for function f is simply the maximum intensity across the four access modes. The access mode sub-index $I_{mode}^{(\text{access})}$ is the sum intensity x across all functions j for a given mode, divided by the total number of functions F.

APPENDIX 2: EXTRACT FROM SURVEY INSTRUMENT ON MOBILE PHONE UTILISATION

16. Over the **last twelve months**, have you owned a mobile phone and/or shared a phone with anyone? [***if (a) and (b) are both "no", go to Question 17***]	a) Have you **owned** a phone in the last twelve months?	Yes ..... 1 No 2
	b) Whether or not you owned a phone, have you **shared** a phone with anyone in the last twelve months? (E.g. you may share a mobile phone with friends or with a family member. Sharing is different from borrowing, where you may have to ask for the permission to use another phone)	Yes ..... 1 ➔ [***go to Q 16.1***] No 2
16.12. If you know how to use the following functions, please tell me how often in the last twelve months **you typically used them for yourself and by yourself on the phone you owned or shared**. I will ask you later if you did any of these for other people or if you required help. Let me go through them one-by-one.	a) How often have you *received* calls on this phone (for yourself)? (typically in the last twelve months)	Daily or more often ..... 1 Weekly / a few times per week ..... 2 Monthly / a few times per month ..... 3 Less often or never ..... 4 Do not know this function 5
	b) How often have you *made* calls on this phone (for yourself)? (typically in the last twelve months)	Daily or more often ..... 1 Weekly / a few times per week ..... 2 Monthly / a few times per month ..... 3 Less often or never ..... 4 Do not know this function 5
16.13. Now please tell me how often in the last twelve months **you typically used these functions for someone else on the phone you owned or shared**. For example, this could be for your children, for your parents, for your neighbours, or anyone else.	a) How often have you *taken* calls on this phone for someone else? (typically in the last twelve months)	Daily or more often ..... 1 Weekly / a few times per week ..... 2 Monthly / a few times per month ..... 3 Less often or never ..... 4 Do not know this function 5
	b) How often have you *made* calls on this phone for someone else? (typically in the last twelve months)	Daily or more often ..... 1 Weekly / a few times per week ..... 2 Monthly / a few times per month ..... 3 Less often or never ..... 4 Do not know this function 5
16.14. And now I would like to know if **someone else** over the last twelve months **did these activities for you or helped you** doing some of these activities with the phone that you have owned or shared. This could be for example your children or your neighbours helping you to use the phone or to use it for you when you are busy.	a) How often has someone else *taken* calls on this phone for you? (typically in the last twelve months)	Daily or more often ..... 1 Weekly / a few times per week ..... 2 Monthly / a few times per month ..... 3 Less often or never ..... 4 Do not know this function 5
	b) How often has someone else *made* calls on this phone for you? (typically in the last twelve months)	Daily or more often ..... 1 Weekly / a few times per week ..... 2 Monthly / a few times per month ..... 3 Less often or never ..... 4 Do not know this function 5
17. Over the last twelve months, have you **borrowed** a mobile phone or **paid** someone for using a mobile phone? This could be a neighbour or a phone shop, for example. This does not include phones that you share with someone.		Yes .....1 No .....2 ➔ [***go to Q 17.6***]
17.4. If you know how to use the following functions, please tell me how often over the last twelve months **you typically used them for yourself and by yourself on the phone you borrowed or paid for**. I will ask you later if you did any of these activities for other people or if you required help.	a) How often have you borrowed a phone to *receive* calls (for yourself)? (typically in the last twelve months)	Daily or more often ..... 1 Weekly / a few times per week ..... 2 Monthly / a few times per month ..... 3 Less often or never ..... 4 Do not know this function 5
	b) How often have you borrowed a phone to *make* calls (for yourself)? (typically in the last twelve months)	Daily or more often ..... 1 Weekly / a few times per week ..... 2 Monthly / a few times per month ..... 3 Less often or never ..... 4 Do not know this function 5
17.5. I would now like you to tell me how often it happened in the last twelve months that **you borrowed a mobile phone and used it for someone else, other than the person you borrowed the phone from**. For example, this could be to make a call for a neighbour who does not have a phone, or to send a text message on behalf of your parents, or you had to borrow a phone because someone else had an accident.	a) How often have you borrowed a phone to *receive* calls for someone else? (typically in the last twelve months)	Daily or more often ..... 1 Weekly / a few times per week ..... 2 Monthly / a few times per month ..... 3 Less often or never ..... 4 Do not know this function 5
	b) How often have you borrowed a phone to *make* calls for someone else? (typically in the last twelve months)	Daily or more often ..... 1 Weekly / a few times per week ..... 2 Monthly / a few times per month ..... 3 Less often or never ..... 4 Do not know this function 5
17.6. Now I would like to ask you how often it happened in the last twelve months that **another person operated their phone for you or helped you to use it**. For example, you could not use their phone so they did it for you, or you asked to borrow the phone but the phone owner insisted that he or she dials the number, or helped you to do that.	a) How often has another phone owner *received* calls for you? (typically in the last twelve months) [***emphasise borrowing, not sharing***]	Daily or more often ..... 1 Weekly / a few times per week ..... 2 Monthly / a few times per month ..... 3 Less often or never ..... 4 Do not know this function 5
	b) How often has another phone owner *made* calls for you? (typically in the last twelve months)	Daily or more often ..... 1 Weekly / a few times per week ..... 2 Monthly / a few times per month ..... 3 Less often or never ..... 4 Do not know this function 5

Source: Survey Fieldwork.

Note. Extract only pertaining to incoming and outgoing calls. Other elicited functions include incoming and outgoing text messages, mobile data use, phone book, call register, alarm/calendar/calculator.

APPENDIX 3: STATISTICAL DISCUSSION AND DETAILED REGRESSION RESULTS

The basic logistic regression model with an intercept α, a matrix of covariates $\boldsymbol{x}$, and a vector of parameters $\boldsymbol{\beta}$ takes the form

$$\text{logit}[P(y = 1|\, \boldsymbol{x}_i)] = \alpha + \boldsymbol{\beta}\boldsymbol{x}_i, \qquad (4)$$

where the probability of success $P(y = 1)$ is the natural log of the odds of achieving a positive result conditional on $\boldsymbol{x}_i$ [59].

The analysis of the predictor variables takes place on the disease episode level rather than the individual because one person may report more than one disease episode. Disease episodes are nested within persons, and persons are nested within villages as primary sampling units. Multilevel logistic regression modeling is a useful approach to account for such a nested data structure [40, 41]. For the current application, let us consider a three-level random-intercept logistic regression model, according to which a random intercept term each is assigned to the second and third level of the model (e.g. to individuals j and villages k in the current case):

$$\text{logit}[P(y = 1|\, \boldsymbol{x}_{ijk}, \zeta_{jk}^{(2)}, \zeta_k^{(3)})] = (\alpha + \zeta_{jk}^{(2)} + \zeta_k^{(3)}) + \boldsymbol{\beta}\boldsymbol{x}_{ijk} \qquad (5)$$

In this model, $\zeta_{jk}^{(2)}$ is the level-2 random intercept for individuals, and $\zeta_k^{(3)}$ is the level-3 random intercept for villages [41]. As the intercept terms can take different values for each individual and village, they help to account for unobserved heterogeneity across these groups when estimating the relationship between health action and phone use.

The multilevel random intercept models for the empirical analysis are specified as follows:

$$\text{logit}[P(y = 1|\, \boldsymbol{x}_{\text{Indep., } ijk}, \boldsymbol{x}_{\text{Controls, } ijk}, \zeta_{jk}^{(2)}, \zeta_k^{(3)})] = (\alpha + \zeta_{jk}^{(2)} + \zeta_k^{(3)}) + \boldsymbol{\beta}_{\text{Indep.}}\boldsymbol{x}_{\text{Indep., } ijk} + \boldsymbol{\beta}\boldsymbol{x}_{\text{Controls, } ijk} \qquad (6)$$

In this model, $\boldsymbol{x}_{\text{Indep., } ijk}$ denotes the vector or matrix of the independent variable(s) of interest according to Models 1 to 8 across disease episodes i, individuals j, and villages k, with $\boldsymbol{\beta}_{\text{Indep.}}$ being the corresponding set of parameters. The matrix $\boldsymbol{x}_{\text{Controls, } ijk}$ contains additional control variables to correct for other potential determinants of mobile-phone-aided health action. These controls include a country dummy, complementary and substituting household assets and an aggregate asset index, health provider preferences, distance to the nearest doctor, gender, age, education, physical health status, awareness about and response time of health hotlines, household size, household head characteristics, family dispersion, remoteness of the village, and the self-perceived severity of the reported illness episode. Full model results are shown illustratively for Models 2 and 7 in Table V below.

TABLE V. COMPLETE RESULTS OF THREE-LEVEL RANDOM-INTERCEPT LOGISTIC REGRESSION MODELS 2 AND 7

	Model No.							
	(2)				(7)			
	Coef.	Std. Err.	z	P > z	Coef.	Std. Err.	z	P > z
Illness episode is "chronic"	0.953	0.270	3.530	0.000	0.909	0.284	3.210	0.001
Illness episode is "severe"	1.964	0.435	4.520	0.000	2.104	0.474	4.440	0.000
Country dummy	0.012	0.818	0.010	0.989	0.238	0.902	0.260	0.792
Village is remote (dummy)	-0.557	0.468	-1.190	0.234	-0.478	0.507	-0.940	0.346
Gender (1 = female)	0.288	0.305	0.940	0.345	0.140	0.340	0.410	0.680
Literacy (1 = literate)	0.381	0.441	0.860	0.388	0.653	0.501	1.300	0.193
Highest completed grade	-0.106	0.059	-1.810	0.070	-0.051	0.064	-0.790	0.430
Age group[a]	0.159	0.143	1.120	0.264	-0.005	0.155	-0.030	0.975
Household size	-0.083	0.076	-1.090	0.276	-0.079	0.084	-0.940	0.349
Gender (household head) (1 = female)	1.094	0.400	2.730	0.006	1.223	0.467	2.620	0.009
Highest completed grade (household head)	0.031	0.040	0.780	0.437	0.039	0.045	0.870	0.382
Family members living outside village	0.139	0.379	0.370	0.714	0.117	0.424	0.280	0.782
Self-rated health[b]	0.269	0.139	1.930	0.053	0.204	0.156	1.310	0.190
Activities of daily living (score)[c]	-0.097	0.268	-0.360	0.718	-0.083	0.305	-0.270	0.785
Knows ambulance hotline (1 = is aware)	-0.021	0.291	-0.070	0.942	0.005	0.333	0.020	0.987
Knows public health hotline (1 = is aware)	0.176	0.707	0.250	0.803	0.163	0.776	0.210	0.834
Perceived ambulance response time[d]	0.074	0.085	0.880	0.380	0.062	0.095	0.660	0.512
Distance to closest health provider[e]	0.183	0.167	1.100	0.272	0.140	0.186	0.760	0.450
Resp. considers village clinic / nurse	0.356	0.319	1.110	0.265	0.362	0.361	1.000	0.316
Resp. considers small hospital	0.631	0.287	2.200	0.028	0.678	0.324	2.090	0.036
Resp. considers county hospital	0.433	0.311	1.390	0.164	0.558	0.357	1.560	0.118
Resp. considers private doctor	-0.439	0.286	-1.530	0.125	-0.388	0.324	-1.200	0.232
Resp. considers pharmacy	0.543	0.293	1.850	0.064	0.556	0.337	1.650	0.099
Resp. considers drug shop	0.377	0.305	1.230	0.217	0.270	0.352	0.770	0.443
Resp. considers traditional healer	0.197	0.527	0.370	0.709	0.280	0.570	0.490	0.624
Resp. considers alternative medicine	1.443	1.423	1.010	0.311	1.815	1.571	1.150	0.248
Resp. considers internet sources	0.026	0.823	0.030	0.975	0.829	0.955	0.870	0.386
Resp. considers other providers	0.421	0.723	0.580	0.561	0.465	0.811	0.570	0.567
Household asset index	0.327	0.144	2.280	0.023	0.417	0.165	2.530	0.011
Household owns radio	0.480	0.367	1.310	0.190	0.517	0.424	1.220	0.223
Household owns TV set	0.543	0.519	1.050	0.296	0.617	0.561	1.100	0.272
Household owns computer	-0.562	0.489	-1.150	0.250	-0.452	0.545	-0.830	0.407
Household owns vehicles	-0.747	0.329	-2.270	0.023	-0.888	0.379	-2.340	0.019
Household owns landline phone	-0.014	0.413	-0.040	0.972	-0.503	0.476	-1.060	0.290
Household owns mobile phone	1.454	0.616	2.360	0.018	1.833	0.682	2.690	0.007
Phone utilisation index	3.920	0.769	5.100	0.000				
Resp. owns phone					0.395	0.353	1.120	0.263
Constant	-8.731	2.069	-4.220	0.000	-8.268	2.211	-3.740	0.000
Variance parameter, village level	0.974	0.527			1.140			
Variance parameter, respondent level	0.039	0.598			0.969			
Log likelihood	-285.621				-299.715			

Source: Own elaboration, derived from fieldwork data.

Notes. Coefficients reported. Level 1: N_1 = 888 disease episodes. Level 2: N_2 = 681 respondents. Level 3: N_3 = 32 villages.

[a.] 1 = "18-24 years," 2 = "25-34 years," 3 = "35-44 years," 4 = "45-59 years," 5 = "60+ years."

[b.] 1 = "very good," 2 = "good," 3 = "moderate," 4 = "bad," 5 = "very bad."

[c.] Computed as average score of seven activities, each coded: 1 = "no difficulty / no assistance," 2 = "mild difficulty / no assistance," 3 = "moderate difficulty / a bit of assistance," 4 = "severe difficulty / a lot of assistance," 5 = "extreme difficulty / cannot do."

[d.] 1 = "< 10 min," 2 = "10-29 min," 3 = "30-59 min," 4 = "60-119 min," 5 = "> 2 hours," 6 = "would not come."

[e.] 1 = "< 10 min," 2 = "10-29 min," 3 = "30-59 min," 4 = "60-119 min," 5 = "> 2 hours."