



The Social Implications of Technology Diffusion: Uncovering the Unintended Consequences of People's Health-Related Mobile Phone Use in Rural India and China

MARCO J. HAENSSGEN^{a,b} and PROOCHISTA ARIANA^{a,*}

^a *University of Oxford, UK*

^b *Green Templeton College, Oxford, UK*

Summary. — After three decades of mobile phone diffusion, thousands of mobile-phone-based health projects worldwide (“mHealth”), and hundreds of thousands of smartphone health applications, fundamental questions about the effect of phone diffusion on people's healthcare behavior continue to remain unanswered. This study investigated whether, in the absence of specific mHealth interventions, people make different healthcare decisions if they use mobile phones during an illness. Following mainstream narratives, we hypothesized that phone use during an illness (a) increases and (b) accelerates healthcare access.

Our study was based on original survey data from 800 respondents in rural Rajasthan (India) and Gansu (China), sampled from the general adult population in 2014 in a three-stage stratified cluster random sampling design. We analyzed single- and multi-level logistic, Poisson, and negative binomial regression models with cluster-robust standard errors. Contrary to other research at the intersection of mobile phones and healthcare, we captured actual health-related mobile phone use during people's illnesses irrespective of whether they own a phone.

Our analysis produced the first quantitative micro-evidence that patients' personal mobile phone use is correlated with their healthcare decisions. Despite a positive association between phone use and healthcare access, health-related phone use was also linked to delayed access to public doctors and nurses. We considered theoretical explanations for the observed patterns by augmenting transaction cost and information deficit arguments with the prevailing health system configuration and with notions of heuristic decision-making during the healthcare-seeking process.

Our study was a first step toward understanding the implications of mobile technology diffusion on health behavior in low- and middle-income countries in the absence of specific mHealth interventions. Future research will have to explore the causal relationships underlying these statistical associations. Such a link could potentially mean that development interventions aimed at improving access to healthcare continue to require conventional solutions to sustain healthcare equity.

© 2017 The Authors. Published by Elsevier Ltd. This is an open access article under the CC BY license (<http://creativecommons.org/licenses/by/4.0/>).

Key words — social implications of technology diffusion, mobile phones, healthcare access, India, China, mHealth

1. INTRODUCTION

The world has undergone a rapid mobile connectivity transition during the past decade: Up to 630 million new subscriptions per year were added in low- and middle-income countries (LMICs; 40% of this growth was occurred in India and China), and these countries now account for three in four mobile phone subscriptions worldwide (ITU, 2015a, 2015b). As mobile technology diffuses, hopes arise that previously stubborn development challenges can be overcome with their help (Duncombe, 2012: p. 2; Díaz Andrade & Urquhart, 2012: p. 289; Flor, 2015; Heeks, 2014: p. 2; Unwin, 2009: p. 1).

Public health actors have responded to this trend with 1,123 ongoing and planned “mHealth” projects worldwide (according to the mobile industry organization Groupe Speciale Mobile Association as of January 5, 2016; GSMA, 2016). mHealth interventions use mobile phones to improve health systems and health service delivery. LMICs dominate the mHealth landscape, representing eight of the top-ten countries by project count (GSMA, 2016, 2015). In addition to such specific interventions, Apple's *iTunes* smartphone application (“app”) store alone contains 101,672 health-related apps across the categories “Health & Fitness” and “Medical” (our count as of January 5, 2016), and the global health app market is expected to soar from a volume of \$2.4 billion in 2013 to \$26 billion by 2017 (Apple Inc., 2016;

research2guidance, 2014: p. 7). For comparison, the worldwide program expenditures of the Bill and Melinda Gates Foundation in 2014 amounted to \$4.8 billion (Bill & Melinda Gates Foundation, 2015: p. 14).

The excitement, enthusiasm, and activity surrounding mHealth reflect common narratives that mobile technology offers near-limitless public health “potential” and “tremendous opportunities” that should not go unharnessed (Agarwal & Labrique, 2014: p. 230; Philbrick, 2012: p. 6; Qiang, Yamamichi, Hausman, Miller, & Altman, 2012: p. 15; Rodin, 2010: p. 6; WHO, 2011: p. 1). Moreover, the emphasis on LMICs follows aspirations to deliver health services and information more efficiently, effectively, and equita-

* We thank Felix Reed-Tsochas, Xiaolan Fu, and Gari Clifford for helpful discussions in relation to research design and implementation. We further received excellent research assistance from IIHMR in Rajasthan, especially SD Gupta, Nutan Jain, Arindam Das, Jagjeet Prasad Singh, Vidya Bhushan Tripathi, and Matadin Sharma; and from Liu Xingrong and the School of Public Health at Lanzhou University, Li Jian, and Wang Wei in Gansu. We also acknowledge the competent work of our field investigators Manesh Kumar, Anil Kumar, Rupesh Sharma, Gaurav Singh, Avanes Kumar, and Shiv Shankar Sharma in Rajasthan and Xue Baobao, Li Yanan, Xie Surong, Gu Xiaoling, Liang Yanzhe, Hu Qi, Sun Yifan, and Niu Ben in Gansu. Final revision accepted: January 7, 2017.

bly—especially for otherwise disadvantaged groups (Anglada-Martinez *et al.*, 2015: p. 28; Kwan, Michael, & Kaonga, 2013: p. 27; van Heerden, Tomlinson, & Swartz, 2012: p. 394).

Despite the enthusiasm, fundamental questions about the healthcare implications of mobile phone use have remained unanswered. Based on our knowledge of the social implications of technology diffusion in high-, middle-, and low-income contexts (e.g. technological change influencing social roles and relationships), we should expect mobile phone diffusion to affect health and healthcare because it also influences other dimensions of development like political participation or economic activity. Yet the research on the healthcare consequences of mobile phone use among patients (which is the focus of this paper) remains surprisingly limited. A better understanding of positive as well as negative consequences of mobile phone use on people's health-seeking behavior is therefore important for the branch of mHealth that delivers interventions through this platform to patients.

As part of the broader study of the social implications of technology diffusion, this paper investigated the effect of mobile phones on people's healthcare-seeking behavior in two rural low- and middle-income contexts. We focused specifically on the health-related use of mobile phones regardless of whether somebody actually owns a phone (thus including uses by a third party for the patient) and on contexts where mHealth interventions are yet underdeveloped (as this would confound specific health interventions with more general processes of technological change). The overarching research question for this paper therefore was, "In the absence of specific mHealth interventions, do people make different healthcare decisions if they use a mobile phone during an illness?" To answer this question, we tested two hypotheses on the implications of phone-aided healthcare-seeking behavior, using novel survey data from rural Rajasthan (India) and rural Gansu (China):

H1. Compared to illness episodes that do not involve a mobile phone, phone-aided healthcare-seeking increases access to healthcare.

H2. Compared to illness episodes that do not involve a mobile phone, phone-aided healthcare-seeking leads to faster access to care.

Our analysis produced the first quantitative micro-evidence that patients' mobile phone use is correlated with decisions in their healthcare-seeking process. An implication of our study is that future patient-focused mHealth projects potentially compete with people's existing (non-mHealth) mobile-phone-based solutions, and mHealth interventions may have to combat adverse behaviors created by the mobile phone platform itself.

2. RELATED LITERATURE AND HYPOTHESES

This paper speaks to the technology diffusion literature, in particular to the social implications of technological change. Previous social sciences research has revealed that technology diffusion affects societal behavior and economic practices, on the basis of which we could expect mobile phones to have similar implications. While such research has been carried out with a focus on economic activity, political participation, and social interaction, the impact of phone diffusion on

healthcare as an important dimension of human development has been neglected. In response to this gap, we carried out the first quantitative study to explore the influence of mobile phone use on people's healthcare-seeking behavior in the absence of a specific intervention. Drawing on conventional transaction cost and information deficit arguments, we hypothesized that mobile phone diffusion increases and accelerates healthcare access.

(a) *The social implications of technology and mobile phone diffusion*

Our study started from the assumption that mobile phone use has health-specific implications that relate to the broader body of literature on the social implications of technology diffusion. According to this literature, a technological innovation evolves and interacts with society during the process of its diffusion (Brown, 1981: p. 174; Ling, 2012: pp. 4–50; Pedersen & Bunkenborg, 2012: p. 565). This process can lead to emerging and unexpected uses of the technology (as exemplified by Bijker (1995: p. 270), Cresswell (2002: pp. 182–185) and von Hippel (2010: pp. 414–415)), but it is also widely understood to have social, economic, and political implications.

Development-related outcomes often ensue where technical change interacts with social change, but there is no guarantee that technological change processes are advantageous from a development perspective (Murdock, Hartmann, & Gray, 1994: p. 148; Pfaffenberger, 1992: pp. 511–512). Anthropological, sociological, and economic studies have provided some first insights that the diffusion of mobile phones as information and communication technologies (ICTs) interacts with social change (for a selection of recent reviews, see e.g. Aker & Blumenstock, 2015; Aker & Mbiti, 2010; Duncombe, 2011; Jensen, 2010; Martin, 2014; May & Diga, 2015; Nakasone, Torero, & Minten, 2014; Porter, 2012; Walsham, 2010). Research in this area considers especially the economic consequences of mobile phone diffusion and LMIC-focused studies typically investigate the impacts on poverty levels of the general population and the market activities of farmers and entrepreneurs (Aker & Mbiti, 2010: pp. 213–214; Jensen, 2007: p. 896). Less research attention—mostly from high-income contexts—has been devoted to changes in social interactions and relationships emanating from phone diffusion (Miritello *et al.*, 2013; Roberts & Dunbar, 2011; Saramäki *et al.*, 2014). In addition, despite the rapid growth of phone-based interventions (e.g. information services) under the heading of "information and communication technologies for development" or "ICT4D" (Duncombe, 2012: p. 2; Díaz Andrade & Urquhart, 2012: p. 289; Flor, 2015; Heeks, 2014: p. 2; Unwin, 2009: p. 1), we do not yet understand sufficiently the behavior of mobile phones as platforms for mobile-phone-based development initiatives like mHealth (Aker & Mbiti, 2010: pp. 225–227).

Despite the limited evidence on the social implications of mobile phone diffusion, the growing body of anthropological, sociological, and economic research should lead us to expect that mobile phone diffusion entails social change. The domain of health—arguably an important dimension of development—is probably no exception.

(b) *Mobile phones in healthcare*

Research interest at the intersection of mobile technologies and healthcare in high-, middle-, and low-income countries has grown rapidly over the last decade. With at least 60 systematic reviews and reviews of reviews, the vast majority of

this literature focuses on the design and experimental evaluation of phone-based health interventions, or mHealth, and their enabling conditions. Many low-cost mHealth technologies are being developed against the backdrop of LMICs' healthcare challenges (Beratarrechea *et al.*, 2014: p. 79; Clifford, Blaya, Hall-Clifford, & Fraser, 2008: p. 5). For example, LMIC country health systems are routinely described to suffer from inadequate health service provision, insufficient health financing, low demand for formal healthcare, and problematic population health behaviors including unhealthy levels of alcohol and tobacco consumption (Das, Hammer, & Leonard, 2008: p. 102; Dow, Gertler, Schoeni, Strauss, & Thomas, 1997: pp. 19–22; Dupas, 2011: pp. 426–429; Kremer & Glennerster, 2011: pp. 273–276; WHO, 2013b: pp. 39, 144–153). mHealth is a response to the persistent healthcare challenges and inequities, covering a broad spectrum of services that involve end users as well as providers of healthcare services (Free *et al.*, 2013: p. 2). Patient-centered solutions include for example remote disease management, public health information provision, or diagnosis services (for a selection of recent reviews focusing on patient end-users and with reference to LMICs, see e.g. Al Dahdah, Desgrées Du Lou, & Méadel, 2015; Beratarrechea *et al.*, 2014; Bloomfield *et al.*, 2014; Cole-Lewis, 2013; Hall, Cole-Lewis, & Bernhardt, 2015; Hall, Fottrell, Wilkinson, & Byass, 2014; Mbuagbaw *et al.*, 2015; Noordam, Kuepper, Stekelenburg, & Milen, 2011; Steinhubl, Muse, & Topol, 2015; Tamrat & Kachnowski, 2012).¹

Surprisingly little research at the interface of health and mobile technology concerns the healthcare-seeking behavior implications of people's general mobile phone use (outside of specific phone-based interventions). Qualitative studies have documented locally emerging health-related uses of mobile phones before the term mHealth became popular (Burrell, 2010; Horst & Miller, 2006; Michael, 2008). Commonly described activities are, for example, calling family members to talk about illnesses and accessing health information via mobile broadband, both of which could affect people's healthcare-seeking behaviors (Doron, 2012; Fernández-Ardèvol, 2013; Muessig *et al.*, 2015; Oreglia, 2013; Tenhunen, 2008). Recent quantitative studies have confirmed that these activities emerge on a larger scale, and typically draw the conclusion that such emerging phone-aided behaviors create a favorable environment for further mHealth solutions while improving people's health behavior and healthcare access (Hampshire *et al.*, 2015; Khatun *et al.*, 2014; Labrique *et al.*, 2012).

Although people have been shown to incorporate mobile technology into their health-related behaviors even without specific health interventions, we do not know much about the healthcare implications of these emergent behaviors. A better understanding of emerging health-related phone use and its consequences is important because it relates to health as a dimension of human development, and because it may affect the way mHealth is viewed. If the healthcare effects of phones were positive, some mHealth interventions could be considered redundant because the phone itself would fulfill the purpose of mHealth already. If mobile phones were overwhelmingly detrimental to healthcare, questions could arise whether it is sensible to propose mobile-phone-based interventions to improve healthcare and equalize access.

(c) Research hypotheses

Given the widespread research on the social implications of mobile phones, the dearth of evidence on their healthcare

implications in low- and middle-income countries is rather puzzling. In the absence of this empirical evidence, the existing theoretical arguments on the effect on mobile phones on health behavior are limited to transaction cost and information deficit models.

In the area of patient health, transaction costs refer to the direct and indirect costs incurred in accessing and utilizing health products, services, or information. Information deficit arguments pertain to the perceived lack of information and knowledge among the target groups that mobile phones as ICTs could ameliorate. Both arguments are closely related. For example, Micevska (2005: p. 58) argues in terms of information deficits and states that “the costs of [health] information acquisition will fall and individual health will presumably improve [through mobile technologies]” when compared to alternative means such as postal networks or face-to-face interaction. In a similar vein, Dammert, Galdo, and Galdo (2014: p. 158) focus on transaction costs and claim that “mobile phone service[s] could facilitate the diffusion of knowledge and best practices, reduce transaction costs, and improve the delivery of public services.” Despite their limitations, we will use the transaction cost and information deficit arguments as a basis to formulate our hypotheses, given their widespread implicit use in the area of mobile phone and mHealth research (Higgs *et al.*, 2014: p. 184).

In light of the literature's heavy reliance on phone-based interventions, our research is interested in the role of the mobile phone in influencing healthcare behavior in the *absence* of any such interventions. In order to explore the relationship between mobile phone use and healthcare-seeking behavior in a non-intervention setting, our two research hypotheses will cover the utilization of and delays to healthcare as important outcome indicators of healthcare seeking:

H1. Compared to illness episodes that do not involve a mobile phone, phone-aided healthcare seeking increases access to healthcare.

H2. Compared to illness episodes that do not involve a mobile phone, phone-aided healthcare seeking leads to faster access to care.

Development studies research is ultimately interested in the health and well-being of disadvantaged populations. Access is evidently only one among many determinants of health (Wagstaff, 2002). By focusing on the narrow concept of healthcare access, we have taken a small yet necessary first step toward a better understanding of the relationship between mobile phone diffusion and population health behavior. Our research therefore did not consider whether health-related mobile phone use is linked to the utilization of better quality providers, or whether phone use leads to better clinical outcomes for patients. This should be subject of future studies building on the basis of our research.

3. MATERIALS AND METHODS

(a) Field sites and data

We explored our hypotheses quantitatively, using original survey data from rural Rajasthan (India) and rural Gansu (China). The analysis was based on a survey sample of 800 adults, involving 400 60-min face-to-face interviews each in

field site (note that by “field sites” we mean the rural areas of the selected districts with Rajasthan and Gansu). We chose Rajasthan and Gansu because, by the time of survey design, they had exhibited rapid mobile phone diffusion (both states with 74 mobile subscriptions per 100 persons, Table 1) despite being among the poorest states in their respective countries. In addition, both states maintained only basic mHealth services in the shape of hotlines and text-message information services and continue to face challenges in delivering healthcare to their large yet dispersed rural populations (Planning Commission, 2011: p. 149; WHO, 2012; Whyte, 2010: pp. 14, 20; Yip *et al.*, 2012: p. 839). Such conditions resonate with mainstream narratives that call for mHealth interventions and therefore make rural Rajasthan and Gansu suitable for a study of health-related mobile phone use in the absence of (or prior to) widespread mHealth deployment. Table 1 summarizes basic socioeconomic statistics of the field sites at the time of survey design.

Following qualitative research in the field sites in 2013 (not reported here), survey data was collected from August to October 2014, using a three-stage stratified random sampling approach (see Table 2 for an overview; the survey implementation is described in more detail in Haenssger, 2015c). Our survey sampled adult respondents randomly from the general rural population of Rajasthan and Gansu, irrespective of whether they own a mobile phone or whether they had a recent illness. Sample weights were calculated using district-level census data in both sites (All descriptive statistics in sub-Section 4(a) are population weighted in order to provide a better representation of rural population patterns in Rajasthan and Gansu. Statistical analyses in the subsequent Sections 4(b) and 4(c) are unweighted but include sampling weights as a robustness check).² Our data set included information on self-reported mild and severe acute illness episodes in the year preceding the survey. An important feature of these episodes was that we recorded up to seven distinct steps in the healthcare-seeking process (i.e. the illness episode). Each step contained information about the type, duration, and location of the healthcare activity (e.g. self-care at home, treatment from private doctor); and any kinds of health-related mobile phone use that occurred during that particular activity. We also elicited the self-described symptoms for the illness episode, and each illness episode was completed with its symptoms having disappeared (as described in the next section, we refrain from judgements as to whether this was actually due to the treatment that the patients received). Illness episodes in this paper typically lasted less than two weeks but could extend to several months. In each country, the questionnaires were translated independently by two translators, and were tested and piloted extensively.

(b) Analysis

We have established elsewhere that personal mobile phone ownership is only a weak proxy of actual health-related mobile phone use (Haenssger, 2015a). Our analysis therefore examined people's actual health-related mobile phone use during an illness. We focused specifically on healthcare decisions rather than on clinical outcomes (which would require complementary facility assessments, and which introduce yet more complexity into the relationship between technology diffusion and health). We analyzed single- and multi-level regression models, given that the unit of analysis was the illness episode as nested within individuals and villages (Rabe-Hesketh & Skrondal, 2012a: pp. 875–876, 886; Rabe-Hesketh & Skrondal, 2012b: pp. 1–5). While multilevel models are preferable in theory given the nested nature of the data, they might not be more efficient in practice if observations within a cluster are not closely correlated. We used X^2 variance component tests to decide between single- and multi-level model specifications (whose results pointed in the same general direction), the test being specified as $\text{Prob.} > 1/4 * X^2(0) + 1/2 * X^2(1) + 1/4 * X^2(2)$ (Rabe-Hesketh & Skrondal, 2012a, 2012b). On the basis of this test, this paper reports single-level models for healthcare access (H1) and delays to access (discrete steps) (H2); and multi-level models for delays to access (elapsed days) (H2). In order to account for potential village-level clustering in single-level models, we estimated bootstrap standard errors with village-level clustering and carried out robustness checks with analyses sensitive to the complex survey design. All reported models in this paper were statistically significant at the 1% level, which is why we refrained from reporting *p*-values for model tests in the results. We explain our models below.

For Hypothesis 1, we analyzed people's likelihood of accessing specific types of healthcare providers, including public, private, informal, and no healthcare providers at all (considering the latter as a potentially problematic group that might be “excluded” from healthcare). Based on our fieldwork experiences in Rajasthan and Gansu, we distinguished these types of providers because they may respond differently to mobile phone use (e.g. public doctors in community hospitals might be bound to their post, while local private doctors could carry out home visits more easily), and patients may utilize different providers for different conditions (e.g. visiting a faith healer in Rajasthan because of a paralyzed limb while going to a hospital because of an accident). The main independent variable of interest was whether there was any health-related mobile phone use during the illness episode. We considered personal mobile phone use by the patient and phone use through other persons on behalf of the patient. Because of the binary “yes/

Table 1. Comparison of field site indicators (state level)

	Population (million)	Mobile subscriptions/100 Pop.	Life expectancy at birth (years)	Literacy rate 15+	Hospital beds/1,000 Pop.	Doctors/1,000 Pop.	Per capita GDP (USD)
Rajasthan	68.6 (2011)	0.74 (2012)	65.2 (2010)	67% (2011)	0.5 (2011)	0.1 (2011)	\$885 (2011)
India	1,247.4 (2011)	0.70 (2012)	66.5 (2010)	69% (2011)	0.7 (2011)	0.7 (2011)	\$1,461 (2011)
Gansu	25.6 (2011)	0.74 (2013)	75.7 (2010)	90% (2011)	3.3 (2011)	0.8 (2012)	\$3,130 (2011)
China	1,344.1 (2011)	0.89 (2013)	75.1 (2010)	95% (2010)	3.8 (2011)	1.9 (2012)	\$5,634 (2011)

Sources: Compiled from China Marketing Research (2014), Datanet India (2014), Government of India (2011: pp. 1, 34), IMF (2013), ISI Emerging Markets (2012), ISI Emerging Markets (2013), ITU (2015b), NBS (2011), NBS (2013), WHO (2013a), WHO and Ministry of Health P.R. China (2013:31), World Bank (2015).

Notes. Data on state/province level. Data year in parentheses. Country-level data year was matched to state-level data year as closely as possible to permit direct comparison.

Table 2. *Survey design overview*

	Rajasthan	Gansu
Sampling	3-Stage stratified cluster sampling 1. Random village selection, proportional to population size, stratified by distance to sub-district headquarter 2. Random household selection based on household listing 3. Random household member selection based on age-order tables	3-Stage stratified cluster sampling 1. Random village selection, stratified by distance to nearest township 2. Random household selection based on complete village mapping 3. Random household member selection based on age-order tables
Geographical scope	Districts of Rajsamand and Udaipur Sub-districts: 1. Rajsamand (Rajsamand) 2. Bhim (Rajsamand) 3. Girwa (Udaipur) 4. Jhadol (Udaipur) 5. Kherwara (Udaipur) 6. Kotra (Udaipur) 7. Mavli (Udaipur) 8. Salumber (Udaipur)	Districts of Baiyin, Dingxi, Lanzhou Sub-districts: 1. Baiyin (Baiyin) 2. Huining (Baiyin) 3. Lintao (Dingxi) 4. Tongwei (Dingxi) 5. Zhangxian (Dingxi) 6. Gaolan (Lanzhou) 7. Qilihe (Lanzhou) 8. Yuzhong (Lanzhou)
Sample size	400 rural dwellers in 16 villages	400 rural dwellers in 16 villages ^a

^aGansu data based on 398 observations. Two questionnaires were invalid and were dropped from the sample.

no” nature of the healthcare access variable, we estimated our models through logistic regression analysis (Greene, 2008: pp. 400–401, 770). We chose separate logistic regression models rather than one multinomial model because (a) of simplicity of presentation, (b) patients do not necessarily choose one healthcare option versus another but often combine different providers during one illness episode, and because (c) of the computational requirements of estimating three-level multinomial logistic regression models. The basic single-level logistic regression model with a matrix of covariates \mathbf{x}_i (see end of this section for the specification of the covariates), and a vector of parameters β takes the form

$$\text{logit}[P(y = 1|x_i)] = \beta\mathbf{x}_i, \quad (1)$$

where the probability of success $P(y = 1)$ is the natural log of the odds of achieving a positive result, conditional on \mathbf{x}_i (Hilbe, 2009: pp. 23–24). In a three-level random intercept logistic regression model framework, one 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):

$$\text{logit}[P(y = 1|x_{ijk}, \zeta_{jk}^{(2)}, \zeta_k^{(3)})] = (\zeta_{jk}^{(2)} + \zeta_k^{(3)}) + \beta\mathbf{x}_{ijk} \quad (2)$$

In our model, $\zeta_{jk}^{(2)}$ was the level-2 random intercept for individuals, and $\zeta_k^{(3)}$ was the level-3 random intercept for villages (Rabe-Hesketh & Skrondal, 2012a: 876).

For Hypothesis 2, we assessed the “speed” with which people accessed healthcare providers, using two measures: the number of “steps” of discrete healthcare activities until a health provider was first accessed, and the time in days that had elapsed until that point (note that this approach is different from assessing the total length of the healthcare-seeking process, which would pose severe endogeneity problems; see Section 5(a) for further discussion). We matched mobile phone use so that we only included those health-related uses that took place before or while the patient received healthcare, disregarding whatever occurred after the provider in question was accessed (e.g. if we are interested in access to a central hospital, we would consider phone calls with private doctors if they occurred beforehand, but not if they took place after the hospital access). Because the distribution of the count data was non-normal and the time data were additionally over-dispersed, we used Poisson regression analysis for the step

data and negative binomial regression models for the time data (Wooldridge, 2010: p. 736). (However, because multilevel Poisson models did not converge, robustness checks in a multilevel framework relied on ordinary least squares estimations as reported in the [Supplementary data](#)).

The Poisson model with a matrix of covariates \mathbf{x}_i , and a vector of parameters β takes the form

$$P(y_i|x_i) = (e^{-\mu_i} \mu_i^{y_i}) / (y_i!), \quad (3)$$

where $P(y_i|x_i)$ is the conditional expectation of the event y_i , $y_i!$ is y_i factorial, and $\ln(\mu_i) = \beta\mathbf{x}_i$ is the natural log of the mean (Cameron & Trivedi, 1998: p. 61; Rabe-Hesketh & Skrondal, 2012a: 376). In this model, y_i conditional on the covariates has a Poisson distribution with mean μ_i (Berk & MacDonald, 2008: p. 277; Rabe-Hesketh & Skrondal, 2012a: 376). In a three-level framework, this model would be expressed as

$$P(y_{ijk}|x_{ijk}, \zeta_{jk}^{(2)}, \zeta_k^{(3)}) = (e^{-\mu_{ijk}} \mu_{ijk}^{y_{ijk}}) / (y_{ijk}!), \quad (4)$$

with $\ln(\mu_{ijk}) = (\zeta_{jk}^{(2)} + \zeta_k^{(3)}) + \beta\mathbf{x}_{ijk}$ being the natural log of the mean.

The single-level negative binomial model is expressed as

$$P(y_i|x_i, \alpha) = ([\Gamma(y_i + \alpha^{-1})] / [\Gamma(y_i + 1)\Gamma(\alpha^{-1})]) \times [\alpha^{-1} / (\alpha^{-1} + \mu_i)]^{\alpha^{-1}} [\mu_i / (\alpha^{-1} + \mu_i)]^{y_i}, \quad (5)$$

where $\Gamma(\cdot)$ is the gamma function, α is the dispersion parameter, and $\ln(\mu_i) = \beta\mathbf{x}_i$ (Cameron & Trivedi, 1998: pp. 63, 71, 374–375). In the case of time data, the multi-level negative multinomial model exhibited a better goodness-of-fit than the single-level model. The three-level negative binomial model takes the form

$$P(y_{ijk}|x_{ijk}, \alpha, \zeta_{jk}^{(2)}, \zeta_k^{(3)}) = ([\Gamma(y_{ijk} + \alpha^{-1})] / [\Gamma(y_{ijk} + 1)\Gamma(\alpha^{-1})]) \times [\alpha^{-1} / (\alpha^{-1} + \mu_{ijk})]^{\alpha^{-1}} [\mu_{ijk} / (\alpha^{-1} + \mu_{ijk})]^{y_{ijk}}, \quad (6)$$

with $\ln(\mu_{ijk}) = (\zeta_{jk}^{(2)} + \zeta_k^{(3)}) + \beta\mathbf{x}_{ijk}$ for the two-level random intercept specification, where the random intercept terms $\zeta_{jk}^{(2)}$ and $\zeta_k^{(3)}$ are gamma distributed (Rabe-Hesketh & Skrondal, 2012a: 708–711; StataCorp, 2013a:125–127, 184).

Table 3. *Model specifications for hypotheses 1 and 2*

	Variables for Respective Hypotheses		Description
	H1	H2	
Dependent variables	Healthcare access		Separate binary variables; [1] if access to public/private/informal/no care Days elapsed until public/private/informal/any care Number of distinct activities until public/private/informal/any care
Independent variables of Interest	Any health-related phone use		[1] if any health-related phone by patient or third party (see Figure 3 for types), irrespective of phone ownership [1] if any health-related phone by patient or third party prior or during access to respective healthcare provider (see Figure 3 for types), irrespective of phone ownership
		Health-related phone use before/during access	Interaction: health-related phone use X country dummy (reported in Supplementary data)
Other control variables	SITE-PHONE interaction		
	Country dummy		[1] if Gansu, to account for site-fixed effects
	Self-reported severity of illness		[1] if illness is reported as “severe;” “mild” otherwise
	Sex		[1] if female, as observed by investigator
	Literacy		[1] if able to read mother tongue
	Education		Highest completed grade
	Age group		[1] 18–24, [2] 25–34, [3] 35–44, [4] 45–59, [5] 60+
	Household size		Number of members, having shared kitchen and residence for more than six months
	Sex of household head		[1] if female, as reported by respondent
	Education of household head		Highest completed grade
	Household mobility		[1] if parent/spouse/sibling/child lives outside village
	Self-rated health status		[1] “very good,” [2] “good,” [3] “moderate,” [4] “bad,” [5] “very bad”
	Activities of daily living		Average score of seven activities, each: [1] “no difficulty / no assistance,” [2] “mild diff. / no assist.,” [3] “moderate diff. / a bit of assist.,” [4] “severe diff. / a lot of assist.,” [5] “extreme diff. / cannot do”
	Knowledge about emergency hotline		[1] if partial or full knowledge of local ambulance hotline
	Knowledge about public health hotline		[1] if partial or full knowledge of local public health hotline
	Perceived ambulance response time		Controlling for remoteness and ambulance response; [1] “<10 min,” [2] “10–29 min,” [3] “30–59 min,” [4] “60–119 min,” [5] “>2 h,” [6] “would not come”
	Wealth quintile		5 quintiles, separately for each country based on principal component analysis of 19 household assets / amenities
	Patient considers various options for treatment (health provider preferences)		Separate binary variables of health provider preferences; [1] if patient considers for treatment: village clinics / health centers / community hospitals / private doctors / pharmacies / shops selling medicine / traditional healers / alternative medicine / web resources / other sources
	Distance to nearest healthcare provider		[1] “<10 min,” [2] “10–29 min,” [3] “30–59 min,” [4] “60–119 min,” [5] “>2 h”
	Household owns ICT assets		[1] if household owns radio/TV/PC/phone
	Household owns any kind of vehicle		[1] if household owns bike/motorcycle/tractor/car

Table 3 below specifies and explains the dependent variables, independent variables of interest, and other control variables in βx in the regression models (Table 4 summarizes the data). For all models, we controlled for 28 other potentially confounding variables including, among others, country-fixed effects, self-reported severity of the illness, socioeconomic characteristics of the patient (sex, age, wealth, etc.), health provider preferences, and the distance to the nearest formal health provider. Detailed results are reported in the Supplementary material together with robustness checks. Our robustness checks included single- and multi-level model fitting (single-level with bootstrap standard errors, based on 5,000 iterations and village-level resampling clusters), multicollinearity checks, estimation with sample weights, nested models, different func-

tional forms (ordinary least squares and probit regression for logistic regression models, and ordinary least squares for the Poisson and negative binomial regression models), dropping illnesses that lasted more than twelve months, dropping the least reliable survey responses as assessed by the field investigators in the post-interview part of the survey questionnaire (11 responses were rated with “low” trustworthiness), and estimating results for self-reported “mild” illnesses only. In addition, although all models in this paper are presented without interaction term for Rajasthan and Gansu (owing to better model efficiency and for consistent presentation throughout the paper), the Supplementary data includes interacted models for all robustness checks. The analysis was carried out using Stata 13 (StataCorp, 2013b).

Table 4. Sample data summary (unweighted)

	Total			Rajasthan			Gansu		
	<i>n</i>	Mean	SD	<i>n</i>	Mean	SD	<i>n</i>	Mean	SD
Accessed public provider (1 = yes)	669	0.57	(0.50)	313	0.55	(0.50)	356	0.58	(0.49)
Steps until public healthcare access	380	1.93	(0.76)	173	2.36	(0.74)	207	1.57	(0.56)
Days until public healthcare access	380	8.21	(26.90)	173	11.86	(30.05)	207	5.16	(23.59)
Accessed private provider (1 = yes)	669	0.39	(0.49)	313	0.69	(0.46)	356	0.14	(0.35)
Steps until private healthcare access	264	2.30	(0.79)	215	2.45	(0.76)	49	1.65	(0.56)
Days until private healthcare access	264	11.20	(33.70)	215	13.38	(37.01)	49	1.65	(2.24)
Accessed informal provider / family (1 = yes)	669	0.12	(0.33)	313	0.11	(0.31)	356	0.13	(0.34)
Steps until informal / family access	81	2.05	(0.91)	33	2.67	(0.92)	48	1.63	(0.61)
Days until informal / family access	81	23.10	(71.32)	33	43.79	(103.92)	48	8.88	(28.25)
Accessed no health provider at all (1 = no access)	669	0.12	(0.32)	313	0.03	(0.18)	356	0.19	(0.39)
Steps until any healthcare access	592	1.82	(0.55)	303	2.09	(0.44)	289	1.55	(0.51)
Days until any healthcare access	592	5.03	(15.81)	303	5.75	(10.57)	289	4.28	(19.86)
Any health-related phone use during illness (1 = yes)	669	0.12	(0.33)	313	0.06	(0.23)	356	0.18	(0.39)
Site dummy (1 = Gansu)	669	0.53	(0.50)	313	0.00	(0.00)	356	1.00	(0.00)
Self-rated severity (0 = "mild," 1 = "severe")	669	0.09	(0.28)	313	0.03	(0.18)	356	0.13	(0.34)
Sex (1 = Female)	669	0.58	(0.49)	313	0.55	(0.50)	356	0.61	(0.49)
Literacy (1 = can read)	669	0.46	(0.50)	313	0.38	(0.49)	356	0.54	(0.50)
Highest completed grade	669	3.59	(4.25)	313	3.04	(4.30)	356	4.06	(4.16)
Age group ^a	669	3.58	(1.29)	313	3.16	(1.31)	356	3.95	(1.16)
Household size	669	4.19	(2.20)	313	5.28	(2.23)	356	3.24	(1.67)
Sex of household head (1 = female)	669	0.09	(0.29)	313	0.06	(0.24)	356	0.11	(0.32)
Highest grade of household head	669	4.32	(4.02)	313	3.25	(4.11)	356	5.26	(3.69)
Any family member living outside of village (1 = yes)	669	0.55	(0.50)	313	0.14	(0.35)	356	0.91	(0.29)
Self-rated health status ^b	669	2.32	(1.12)	313	1.88	(0.85)	356	2.71	(1.18)
Activities of daily living score ^c	669	1.31	(0.55)	313	1.22	(0.48)	356	1.40	(0.59)
Knowledge of ambulance (1 = partial/full)	669	0.52	(0.50)	313	0.55	(0.50)	356	0.50	(0.50)
Knowledge of health hotline (1 = partial/full)	669	0.05	(0.2)	313	0.11	(0.31)	356	0.01	(0.09)
Perceived ambulance response time ^d	669	4.51	(1.72)	313	4.18	(1.78)	356	4.80	(1.62)
Wealth quintile (per country)	669	2.71	(1.37)	313	2.80	(1.39)	356	2.64	(1.35)
Considers local clinic for treatment (1 = yes)	669	0.64	(0.48)	313	0.69	(0.46)	356	0.60	(0.49)
Considers health centers for treatment (1 = yes)	669	0.40	(0.49)	313	0.27	(0.44)	356	0.51	(0.50)
Considers larger hospitals for treatment (1 = yes)	669	0.76	(0.43)	313	0.77	(0.42)	356	0.74	(0.44)
Considers private doctors for treatment (1 = yes)	669	0.63	(0.48)	313	0.89	(0.32)	356	0.40	(0.49)
Considers pharmacies for treatment (1 = yes)	669	0.19	(0.39)	313	0.01	(0.11)	356	0.35	(0.48)
Considers shops selling drugs for treatment (1 = yes)	669	0.16	(0.37)	313	0.06	(0.24)	356	0.25	(0.43)
Considers traditional healers for treatment (1 = yes)	669	0.19	(0.39)	313	0.40	(0.49)	356	0.00	(0.05)
Considers alternative medicine for treatment (1 = yes)	669	0.01	(0.08)	313	0.01	(0.10)	356	0.00	(0.05)
Considers web resources for treatment (1 = yes)	669	0.01	(0.12)	313	0.00	(0.00)	356	0.03	(0.17)
Considers other sources for treatment (1 = yes)	669	0.03	(0.17)	313	0.05	(0.23)	356	0.01	(0.09)
Distance to nearest healthcare provider ^e	669	1.87	(0.87)	313	1.87	(0.73)	356	1.87	(0.97)
Household owns ICT assets (1 = yes)	669	0.63	(0.48)	313	0.22	(0.42)	356	0.99	(0.09)
Household owns any kind of vehicle (1 = yes)	669	0.61	(0.49)	313	0.39	(0.49)	356	0.81	(0.39)

Note. SD is standard deviation.

^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 Average score of seven activities, each: 1 = "no difficulty/no assistance," 2 = "mild diff./no assist.," 3 = "moderate diff./a bit of assist.," 4 = "severe diff./a lot of assist.," 5 = "extreme diff./cannot do".

^d 1 = "<10 min.," 2 = "10–29 min.," 3 = "30–59 min.," 4 = "60–119 min.," 5 = ">2 h.," 6 = "would not come."

^e 1 = "<10 min.," 2 = "10–29 min.," 3 = "30–59 min.," 4 = "60–119 min.," 5 = ">2 h."

(c) *Ethics*

The research was approved by the Oxford Department of International Development's Departmental Research Ethics Committee in accordance with the procedures laid down by the University of Oxford for ethical approval of all research involving human participants (CUREC1A/ODID C1A 14-031). Local ethics approval was obtained from the Gansu Province Department of Statistics (2014/8), and the internal ethics commission of the Indian Institute of Health Management Research, Jaipur.

4. RESULTS

(a) *Descriptive statistics*

Although both field sites were relatively poor within their countries, had similar degrees of mobile phone penetration when the survey was designed, and faced comparable health-care challenges, the household survey data highlighted differences on the micro level in terms of age structure of the population, education, class composition, and physical household wealth (See Table 4 for the sample description and Table 5 for illness- and phone-related descriptive statistics. All descriptive statistics in this sub-section were population weighted in order to provide a better representation of rural population patterns in Rajasthan and Gansu. Statistical analyses presented in the subsequent sections were unweighted but included sampling weights as a robustness check). For example, 56% of the field site population in Rajasthan used very basic phones and less than one-quarter owned or shared an Internet-enabled feature or smartphone. The pattern was inverted in Gansu, where 56% of the adults owned or shared

an Internet-enabled phone and only one-quarter used very basic mobile phones.

Overall, 76% of the sample in Rajasthan and 80% in Gansu reported a mild or severe illness in the past twelve months. The five most common conditions and symptom categories in each field site are presented in Figure 1, dominated by fevers, pain, and the common cold. On the population level, 20% of the adults in Gansu used mobile phones personally or by a third party during an illness; in rural Rajasthan, it was 7.5%. Health-related uses of the phone involved third parties in 40% of these cases (acting on behalf of the patient), and only 30% of the health-related phone uses in the illness episodes involved the direct interaction with healthcare providers (others involved e.g. calling a taxi to a hospital or conversing with peers). Most health-related phone use occurred early during an illness, as 83% of all phone use took place in the first two steps of the healthcare-seeking process.

As Figure 2 indicates, healthcare access varied with health-related mobile phone use. Healthcare access to private providers in Rajasthan and to public providers in Gansu was slightly higher among people who reported that they used a mobile phone for a health-related purpose during their illness. People with health-related mobile phone use were also less likely to report no healthcare access at all. In addition, patients accessing public doctors in Rajasthan were less likely to report health-related mobile phone use.

Among the phone-aided healthcare-seeking activities, the most common tasks in Rajasthan were exchanging advice, calling a medical practitioner for home treatment, and making appointments; in Gansu, they were home calls, conversations about illnesses, and reassuring peers during the course of an illness (Figure 3). Conventional voice calls were the dominant mode of communication (rather than text messaging or mobile data use), and none of the activities described in Figure 3 were

Table 5. *Descriptive illness- and phone-related survey statistics (population weighted)*

		Rajasthan (n = 400)		Gansu (n = 398)	
		Mean	Standard deviation	Mean	Standard deviation
Illness episodes	Any mild or severe illness: % reported	0.76	(0.03)	0.80	(0.03)
	Mild illness: % reported	0.74	(0.03)	0.75	(0.04)
	Mild illness: average No. of steps	2.52 (n = 303)	(0.82)	2.29 (n = 309)	(0.79)
	Mild illness: average duration	26.50 (n = 303)	(56.22)	9.68 (n = 309)	(34.05)
	Severe illness: % reported	0.03	(0.01)	0.13	(0.03)
	Severe illness: average No. of steps	2.40 (n = 10)	(1.28)	2.43 (n = 47)	(0.84)
	Severe illness: average duration	114.00 (n = 10)	(133.02)	97.94 (n = 47)	(102.48)
Phone access in last 12 months	% Own mobile phone	0.47	(0.03)	0.77	(0.03)
	% Shared mobile phone	0.93	(0.02)	0.28	(0.03)
	% Borrowed/rented mobile phone	0.08	(0.02)	0.02	(0.01)
	% Third-party access	0.88	(0.02)	0.27	(0.04)
	% No Phone access at all	0.04	(0.01)	0.13	(0.03)
Owned/shared phone type	% Basic mobile phone	0.56	(0.03)	0.29	(0.03)
	% Feature phone	0.20	(0.03)	0.16	(0.02)
	% Smartphone	0.03	(0.01)	0.39	(0.04)
	% Don't know (shared mobile phone)	0.18	(0.03)	0.00	(0.00)
Mobile phone usage	% Made call in last 12 months	0.94	(0.01)	0.81	(0.03)
	% Received call in last 12 months	0.93	(0.01)	0.76	(0.03)
	% Sent SMS in last 12 months	0.21	(0.03)	0.43	(0.03)
	% Received SMS in last 12 months	0.09	(0.02)	0.33	(0.03)
	% Used Mobile Data in last 12 months	0.03	(0.01)	0.32	(0.04)

Notes. Standard deviation in parentheses. Statistics are population weighted across the field site districts using census data. Proportion as share of total adult population in field site, except for durations and steps of illness episodes, which were sub-sets of patients reporting an illness with sample sizes as indicated in parentheses.

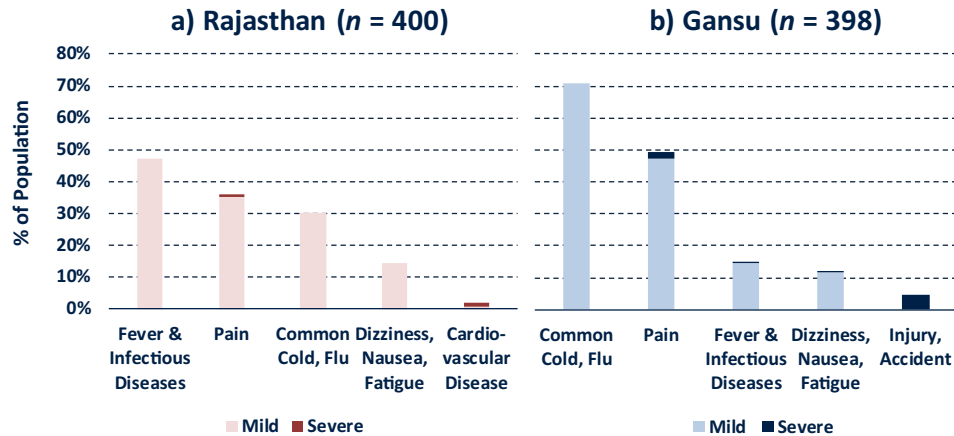


Figure 1. Top-5 self-described symptoms in field sites, by self-rated severity (population weighted). Notes. Underlying statistics were population weighted. Proportions as share of total adult population in field sites. Multiple answers per respondent possible.

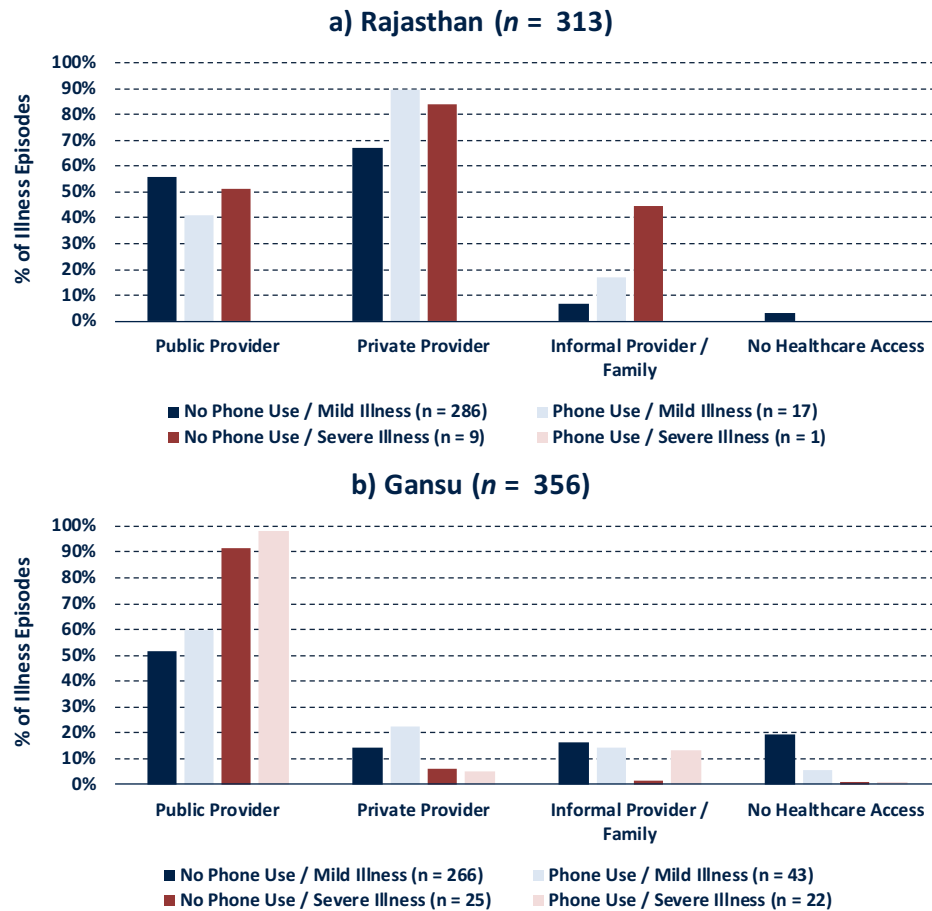


Figure 2. Healthcare utilization during illness across field sites, by self-rated severity and illness-related phone use (population weighted). Notes. Underlying statistics were population weighted. Proportions as share of all reported illness episodes in field sites. Multiple answers per episode possible. Respondents could report one self-described “mild” and one “severe” acute illness.

specific to more advanced phone functions like Internet use (e.g. home visits in Rajasthan were typically arranged by calling a private doctor). Every person who used a phone for a health-related purpose made at least one call (personally or via a third party). In Rajasthan, virtually no other mode was employed. Gansu respondents showed a slightly wider spectrum of modes, where 11% of the phone users also indi-

cated the use of mobile broadband and 3% used text messages. It is also noteworthy that the use of ambulance hotlines and other dedicated phone-based (mHealth) services was virtually non-existent: Only 3% of the population in each field site actually contacted ambulances, and no other mHealth service use was reported (e.g. public health information messaging, health advice hotlines, or treatment reminders).

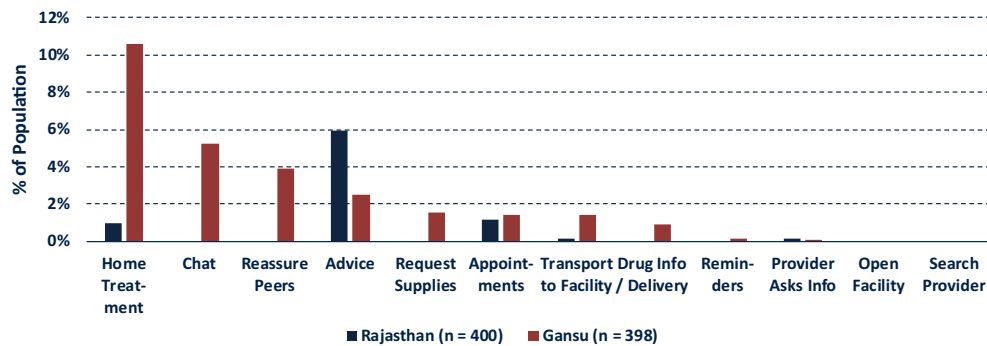


Figure 3. Purposes of health-related phone use during illness episodes across field sites (population weighted). Notes. Underlying statistics were population weighted. Proportions as share of total adult population in field sites. Multiple answers per respondent possible.

(b) Healthcare access

We explored our first hypothesis by regressing different types of healthcare access against health-related mobile phone use during any stage of the healthcare-seeking process. Although the access patterns for mobile phone users and non-users differ across the field sites (see Figure 2 in the previous section), interactions between mobile phone use and the country dummy tended to be statistically insignificant and were omitted from the reporting in this paper. However, the Supplementary material presents interaction models that indicate site-specific effects in some instances.

The main results of the regression analysis are shown in Table 6 (control variables are reported in detail in the Supplementary material). The reporting relies on single-level logistic regression results with bootstrap standard errors because multi-level models were in most cases inferior to single-level models (e.g. the individual-level intra-cluster correlation ranged from 0% to 16%). Controlling for health provider preferences and other drivers of healthcare access, a statistically significant positive link at the 5% level emerges between mobile phone use during an illness and access to private healthcare providers (Model 2). Model 2 indicates that the relationship between health-related phone use and private healthcare access is positive in Gansu and Rajasthan.

Logged coefficients in logistic regression models are difficult to interpret. We therefore make predictions at sample means (only varying country dummy and phone use) for models with a significant statistical relationship between phone use and healthcare access at least at the 10% level (i.e. access to private providers). The results of this exercise indicate that mobile phone users are 19.4 percentage points more likely to access

private healthcare in Rajasthan, and 12.3 percentage points more likely in Gansu. The predicted absolute and relative changes are shown in Table 7.

(c) Delays in healthcare seeking

In this section, we examine healthcare-seeking delays in terms of the steps and time elapsed until a provider was reached. We considered access to public, private, and informal and untrained providers (e.g. family, faith healers), and whether any formal or informal provider was involved during the illness episode. The main results of the analysis are shown in Table 8 containing the Poisson regression results for the step variables and Table 9 containing the negative binomial regression results for the delay variables (single-level models were more efficient for the Poisson regressions; multi-level models for the negative binomial regressions). It is worth noting that the sample sizes differ across the models because we can only compare the delays of phone users and non-users who actually accessed the respective providers (e.g. 380 illness

Table 7. Predicted relative and absolute change in healthcare access for phone-aided healthcare seeking (unweighted)

Access to private providers	
Rajasthan	+33.4% (+19.4 p.p.)
Gansu	+114.3% (+12.3 p.p.)

Notes. Absolute changes in percentage points in parentheses. Based on logistic regression Model 2 reported in Table 6. Unweighted predictions at constant sample means (only varying phone use and country dummy).

Table 6. Main results: effects of phone use on healthcare access (single-level logistic regression, unweighted)

(Model number)	Dependent variable			
	Access to public providers (1)	Access to private providers (2)	Access to informal providers, family, friends (3)	No access to any provider ^a (4)
Phone use	-0.10 (0.28)	0.91** (0.41)	0.12 (0.55)	-0.52 (1.29)
Site dummy (Gansu = 1)	-0.18 (0.35)	-2.44** (0.68)	-0.35 (0.99)	2.39 (3.13)
(28 control variables and constant term omitted from reporting)				
Number of observations (illness episodes)	669	669	669	669
Number of clusters (villages)	32	32	32	32

Notes. Coefficients reported. Bootstrap standard errors in parentheses. Analysis at illness episode level. Standard errors calculated with bootstrap estimation (5,000 replications) and adjusted for clustering at village level.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

^a Excludes family and friends.

Table 8. *Main results: association of phone use with steps to access (single-level poisson regression, unweighted)*

(Model number)	Dependent variable			
	Step # of public care (1)	Step # of private care (2)	Step # of informal care and family & friends (3)	Step # of any care (4)
Phone use	0.12* (0.06)	0.02 (0.07)	0.14 (0.24)	0.06 (0.04)
Site dummy (Gansu = 1)	-0.49*** (0.11)	-0.42*** (0.12)	-0.44 (0.43)	-0.27*** (0.06)
(28 control variables and constant term omitted from reporting)				
Number of observations (illness episodes)	380	264	81	592
Number of clusters (villages)	32	29	25	32

Notes. Coefficients reported. Bootstrap standard errors in parentheses. Analysis at illness episode level. Standard errors calculated with bootstrap estimation (5,000 replications) and adjusted for clustering at village level.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 9. *Main results: association of phone use with time to access (multi-level negative binomial regression, unweighted)*

(Model number)	Dependent variable			
	Delay until public care (1)	Delay until private care (2)	Delay until informal care and family & friends ^a (3)	Delay until any care (4)
Phone use	0.74*** (0.29)	0.53* (0.30)	0.50 (0.79)	0.35* (0.21)
Site dummy (Gansu = 1)	-2.29** (0.49)	-1.71** (0.49)	-4.77** (1.45)	-1.29** (0.37)
(28 control variables and constant term omitted from reporting)				
Number of level 1 observations (illness episodes)	380	264	81	592
Number of level 2 observations (individuals)	360	261	N/A ^a	565
Number of level 3 observations (villages)	32	29	25	32
Variance component test	<0.01	<0.01	1.00	<0.01

Notes. Coefficients reported. Standard errors in parentheses. Analysis at illness episode level.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

^aTwo-level model estimated because one illness episode per individual.

Table 10. *Predicted relative and absolute change in delays to healthcare access for phone-aided health action (unweighted)*

	Access to public providers		Access to private providers	Access to any healthcare provider ^b
	Process steps	Delays in days ^a	Delay in days ^a	Delay in days ^a
Rajasthan	+12.6% (+0.30 steps)	+110.5% (+8.32 days)	+69.4% (+3.16 days)	+41.7% (+1.50 days)
Gansu	+12.6% (+0.19 steps)	+110.5% (+0.85 days)	+69.4% (+0.57 days)	+41.7% (+0.41 days)

Notes. Absolute changes in parentheses. Based on regression Model 1 in Table 8 and Models 1, 2, and 4 in Table 9. Unweighted predictions at constant sample means (only varying phone use and country dummy).

^aConservative prediction, based on fixed part of multi-level model only.

^bExcludes family and friends.

episodes involve public doctors and nurses). Positive coefficients in these tables correspond to longer delays in terms of steps and days until healthcare access, or, in other words, less speedy healthcare-seeking processes.

The Poisson regression models yielded statistically significant positive results for the step at which patients accessed public healthcare providers (Table 8, Model 1). The negative binomial regression model indicated a statistically significant positive relationship between health-related phone use and public healthcare access at the 1% level (Table 9, Model 1) and with private providers and any kind of healthcare at the 10% level (Table 9, Models 2 and 4). The principal insight of these tables is that health-related mobile phone use is associated with delays to accessing healthcare in terms of discrete healthcare activities (public healthcare) and days elapsed since the onset of a discomfort (public, private, and overall access).

Contrary to expectations, none of the results indicate a link between health-related mobile phone use and *faster* healthcare access. (Site-specific effects reported in the [Supplementary material](#) indicate that access to informal healthcare in Rajasthan may be an exception.)

Table 10 contains the predicted absolute and relative changes in delays where people used mobile phones for an illness-related purpose (calculated for steps and days; absolute changes in parentheses). The table indicates more pronounced delays to public healthcare access where patients use mobile phones. For example, phone use in the healthcare-seeking process was associated with a 0.85-day additional delay in public healthcare access in Gansu and 8.32 days in Rajasthan, holding other variables constant at the sample means. The number of discrete activities carried out before accessing public doctors and nurses was 12.6% higher among phone users. Fur-

thermore, health-related mobile phone use was associated with a 69.4% longer delay to the first contact with private doctors, and overall access to formal or informal healthcare providers was 41.7% slower among mobile phone users.

5. DISCUSSION

This paper set out to test two hypotheses in order to examine whether mobile phone use leads people to make different healthcare decisions (compared to people who do not use a mobile phone for a health-related purpose during their illness). The hypotheses focused on two facets of healthcare utilization, suggesting that phone-aided healthcare seeking increases access to healthcare (H1) and leads to faster access to healthcare (H2). Our analysis of original cross-sectional survey data from rural Rajasthan and Gansu revealed significant statistical associations in support of H1 and opposed to H2. The causal direction underlying these associations could be explored in future studies using longitudinal experimental or quasi-experimental research designs. This section discusses the limitations of our cross-sectional study, the interpretation of our analysis in light of the research hypotheses, the theoretical explanation of the observed patterns within and beyond transaction cost arguments, and the policy implications if our interpretation of the results can be established more firmly in future research.

(a) *Limitations*

It is worth pointing out some of the main limitations of this study, how we addressed them through our analysis, and what sources of bias remain. The aspects we focus on below include confounding effects and reverse causation, interview and recall biases, reporting and salience biases, and the external validity of the results.

Our study dealt with confounding effects and reverse causation in four ways: First, we controlled in our regression models for a broad range of factors such as household wealth and health provider preferences. Second, the impact of wealth as a confounder was further mitigated because the analysis did not focus solely on those people who own mobile phones, but it also included individuals who had a third party operate the phone on their behalf. Third, the extensive involvement of third parties made it also less probable (though not impossible) that other personal characteristics of patients confounded phone use. Fourth, only a minority of mobile communication patterns involved the direct correspondence between patient and healthcare provider, which reduced the risk of reverse causation as patients could also use phones to facilitate access to healthcare providers who would otherwise be unresponsive to direct interaction (e.g. by calling a taxi). While endogeneity issues cannot be ruled out conclusively in a cross-sectional study like ours, the findings suggested at least a significant association between phone use and health behavior that warrants further research.

Recall and social desirability biases are another common problem in research involving retrospective health questions (Ann & Cornelius, 2006; Coughlin, 1990). Consensus in epidemiological studies is that long recall periods can influence and bias reporting, for example along educational strata (Das, Hammer, & Sánchez-Paramo, 2012; Feikin *et al.*, 2010; Kroeger, 1983). The customary recall period in epidemiological and health research is between 14 and 30 days in low- and middle-income countries (Ahmed, Adams, Chowdhury, & Bhuiya, 2000; Asenso-Okyere & Dzator, 1997; Gotsadze,

Bennett, Ranson, & Gzirishvili, 2005). For the purposes of the present study, which sampled respondents from the general adult population, such short recall periods would have led to infeasibly small samples, and it would have been insensitive to the fact that illness episodes often extend beyond a fortnight and occasionally up to one year. At the same time, it is important to reiterate that ours was not an epidemiological study that aimed to ascertain the precise prevalence rate of a particular health condition, but a health behavior study that aimed to understand whether and how mobile phone use might influence the processes which patients undergo.

We therefore chose to include illness episodes that were remembered by the respondent and that ended within the last year in order to capture a wider range of healthcare behaviors. Our previous qualitative research eliciting patients' illness episodes in Rajasthan and Gansu (not reported here) showed that patients were comfortable recalling and describing those episodes in detail, including how mobile phones were being used (Haenssge, 2015b). In order to mitigate the risk of reporting and recall biases in our research, the use of mobile phones was elicited explicitly for each step in a particular illness episode in line with our qualitative data collection, and its specificities had to be justified subsequently (however, the finer grain of the questions relative to simple ownership questions may have inadvertently led to lower reported levels of phone use where respondents were unsure). For instance, if a phone was used, the respondent had to explain how it was used, who used it, for which purpose, and who was contacted (if applicable). The survey fieldworkers were trained in this procedure intensively over five days plus a one-day pilot study. We further excluded chronic, long-term, and recurrent illnesses from the group comparison to limit the recall period (considering that chronic disease management is often a target of mHealth programs (Free *et al.*, 2013), future research may investigate behaviors associated to chronic illness in particular).

All this does not rule out recall biases conclusively, and there remains a residual risk that socio-economic control variables are not fully able to capture potential biases in recall between poorer and more affluent as well as between more and less educated people. It is, however, unclear whether any recall bias would alter systematically the conclusions drawn from the analysis, given that neither respondent's education (measured by completed grades and literacy) nor their household wealth (as measured by a wealth index and wealth quintiles) were correlated with their reporting of a "mild" or "severe" illness (correlation coefficients in Rajasthan and China ranged from -0.098 to $+0.059$).

Lastly, the nature of the study does not permit the findings to be extrapolated to other contexts. It may very well be that our field sites are the only two examples where we can observe the patterns illustrated above. The interpretation of the results therefore has to pertain specifically to the field sites, rather than rural low- and middle-income contexts more generally. However, in the absence of other quantitative evidence, our findings can be understood as the first step and a methodological starting point toward a knowledge base on the relationship between mobile technology diffusion and healthcare behavior in LMICs in the absence of specific mHealth interventions.

(b) *Hypotheses*

In light of the cross-sectional study design, we cannot establish causal claims about the relationship between mobile phone use and healthcare behavior. The statistical findings

of our analysis nevertheless helped us to inform our two research hypotheses.

Hypothesis 1 stated that health-related mobile phone use increases access to healthcare providers. Our findings from rural Rajasthan and Gansu showed a positive association of such phone use with access to private healthcare providers. This association is largely consistent with H1: although we cannot conclusively state at this stage that mobile phone use increases access, the positive link to healthcare utilization suggests that this is indeed a possibility in rural Rajasthan and Gansu. (Robustness checks with interaction models reported in the [Supplementary material](#) indicate that site-specific patterns may be more complicated yet largely consistent with this conclusion.)

Hypothesis 2 stated that health-related mobile phone use leads to faster access to healthcare. In order to inform this hypothesis, we explored the association between health-related mobile phone use and the time and steps until the first healthcare provider is reached during an illness. Contrary to expectations, the regression results indicated that mobile phone use is associated with slower (or at least not accelerated) healthcare access. A possible interpretation of this pattern is that mobile phones simply enable the complex trajectories that health seekers desire, or that longer and more tedious processes lead people to resort to mobile phones, but the characteristics of our healthcare-seeking data (83% of all phone use taking place in the first two steps of an illness episode) suggest that this is improbable. In addition, should complicated and severe symptoms prompt individuals to use mobile phones, we would continue to expect that access to the first point of care is faster with a phone than without, which is not borne out by the data. We could consider marginal scenarios where individuals have “optimal” delays to public healthcare (e.g. because they called a friend who advised only to access a health center when the illness actually requires it), but we interpret the results in sum as opposed to Hypothesis 2.

(c) *Theoretical research directions beyond transaction costs and information deficits*

If the interpretation of our findings in light of the research hypotheses holds—and further experimental and quasi-experimental research is necessary to establish the causal link—then we would have to reconsider the appropriateness of transaction cost and information deficit arguments to explain that mobile phone diffusion affects people’s health behavior in rural India and China by (a) increasing but also (b) complicating access. We argue in this section that transaction costs and information deficits can help to explain such patterns if they are considered in connection with uncertainty in human decision-making and within the prevailing health systems configuration.

Arguments based on information deficits and transaction costs would suggest that mobile phones help patients to gather more information about healthcare providers and solutions, and to act on this information more efficiently because mobile communication is faster and cheaper than alternative means ([Aker & Blumenstock, 2015](#); [Aker & Mbiti, 2010](#); [Dammert et al., 2014](#)). An improvement in healthcare access would follow in terms of uptake and speed, provided that people have complete information about which course of action is effective and advisable given their symptoms and available healthcare resources, and provided that they make “perfectly rational” healthcare decisions based on this information (note that deviations from the theoretical construct of “rationality” should not necessarily be deemed “irrational” or “random” behav-

ior). Such a “rational” decision model could respect other factors including patient preferences and cultural norms ([Andersen, 1995](#): p. 6; [Dupas, 2011](#):431; [Luoto, Levine, & Albert, 2011](#): pp. 2–4; [Oster & Thornton, 2012](#): p. 1291; [Rhee et al., 2005](#): p. 8). Were we only to consider healthcare utilization as in Hypothesis 1, the positive association between health-related phone use and access to private doctors would be consistent with this argument, although it would suggest that people have preferences for private over public healthcare that cannot be satisfied sufficiently without mobile phones. However, the inconsistency between our findings and Hypothesis 2 suggests that this explanation may be incomplete.

Theories from the behavioral and information economics literature can help to reconcile the otherwise conflicting observations, and to consider possible implications of mobile phone diffusion on healthcare-seeking behavior more broadly. Behavioral economists have long argued that humans have difficulty assessing the health risks and costs of activities such as smoking ([Cawley & Ruhm, 2011](#): pp. 137–139). The same difficulty applies during illnesses because patients do not know with certainty whether a particular form of treatment from a particular provider is going to succeed ([Arrow, 1963](#): pp. 948–952; [Balsa, Seiler, McGuire, & Bloche, 2003](#): pp. 203–205; [Blomqvist, 1991](#): pp. 411–412; [Scott, 2000](#): p. 1178). Absence of dependable, affordable, and accessible diagnosis mechanisms (assuming such exist) aggravates the uncertainty because patients can often only venture an educated guess about the nature of their illness based on their own or their peers’ experiences. Treatment decisions resulting from such self-diagnosis can be unsatisfactory. This is illustrated by [Cohen, Dupas, and Schaner \(2012](#): p. 57): 68.5% of their Kenyan household sample reported that they had a case of malaria in the past month. The households often decided to purchase antimalarial medication at kiosks, but a diagnostic test showed that only one-third of adults using such medication actually had malaria ([Cohen et al., 2012](#): p. 9; [Dupas, 2011](#): p. 427).

Patients therefore experience uncertainty regarding both the nature of their illness and the efficacy of treatment choices. They also face numerous competing demands like earning an income or rearing children, which can make immediate access to healthcare difficult. For instance, a recent study on health system utilization in Western Kenya argued that “competing priorities in a poor community, such as gathering water and firewood, limit how much time people have for clinic visits” ([Bigogo et al., 2010](#): p. 971).

In light of uncertainty and constraint, it is possible that patients’ decision-making does not reflect the theoretical and simplifying notion of perfect rationality under full information, but rather heuristic “rules-of-thumb” in order to simplify the decision ([Tversky & Kahneman, 1974](#): p. 1124; one could extend the argument to third parties acting together with patients or on their behalf). Healthcare decisions based on simplifying rules about the effectiveness of treatment options may be influenced by user fees that signal quality; conspicuous practices and procedures that suggest expertise of the healthcare provider; or personal relationships with the provider that promise availability ([Leventhal, Weinman, Leventhal, & Phillips, 2008](#): pp. 487–489). In addition, a patient’s self-diagnosis may be shaped by his or her illness history, by common illnesses in the same community (e.g. malaria), or by the duration and intensity of the symptoms ([Leventhal et al., 2008](#): pp. 485–486; [Reynolds & McKee, 2011](#): p. 466).

We emphasize here heuristics and decision-making under constraint because we argue that mobile phones influence health behaviors through this channel. Which exact decision-

making rules govern the behavior of phone users is not known and requires more research (e.g. field experiments). We may nevertheless hypothesize that mobile phones lower the barriers for diagnosis and treatment with unforeseen results if the underlying healthcare decisions are based on necessarily simplifying rules about diagnosis and the effectiveness of treatment. If all else is equal, a healthcare-seeking process involving mobile phones may enable people to contact a provider easily where costs (or other barriers) would otherwise have been prohibitive, to explore seemingly more promising healthcare options in order to avoid a little-trusted local doctor, or to speak to a relative and receive their view about what should be done. However, if the facilitated behaviors are driven by heuristic rules-of-thumb rather than fully informed decisions about the present and future costs and benefits of all available treatment options, there is no guarantee that they automatically lead to desirable courses of action from a medical perspective. It is instead more probable that mobile phones facilitate a spectrum of behaviors that includes adverse and unexpected as well as effective health action. This can potentially lead to more rather than less complex healthcare itineraries, which is consistent with the patterns observed in our data and in contrast to our simplistic transaction-cost-based Hypothesis 2 that phone use necessarily leads to faster access to healthcare.

In addition, some providers may be more responsive to mobile phone interaction because of physical accessibility, job descriptions involving visits to local residents, personal relationships, or profit interests (Meachael, 2006: pp. 169–170). Phone-aided options may lower patients' thresholds for diagnosis and treatment for some providers but not others, biasing the ensuing behavior toward "responsive" actors. Clearly not all forms of phone use during an illness involve direct correspondence (in our study, it is 30% of health-related phone use), but the heterogeneous associations between mobile phone use and access to public and private healthcare access in our data lend support to this argument. The positive association between phone use and private healthcare access in Gansu and Rajasthan may therefore be explained by their higher responsiveness to patients' phone use.

It is too early for a theory of phone-aided health behavior and this section only discussed starting points for further empirical and theoretical work at the interface of mobile phone diffusion and health behavior. Yet, if we acknowledge that healthcare seeking resembles heuristic decision-making under constraint, we are able to reconcile our quantitative findings and theory. On the one hand, by reducing the barriers (or "transaction costs") for diagnosis and treatment, mobile phones invite increased utilization of the health system. However, this could also lead to inefficient over-utilization of scarce healthcare resources, and more access need not mean faster access if people delay healthcare decisions because of an increased sense of safety and security that is often reported to emanate from mobile phone usage (e.g. de Silva & Zainudeen, 2007: p. 11; Gagliardone, 2015: p. 10; Ling, 2012: pp. 115–118; Souter *et al.*, 2005: p. 79). On the other hand, phone-aided behavior is biased toward those providers who are more responsive to phone use. It is thus possible that the mobile phone diffusion process leads to improved behaviors where the health system is transparent, regulated effectively, and where well-qualified first-level providers are encouraged to engage with patients on the phone. However, it is questionable whether the somewhat obscure and fragmented healthcare landscapes of rural Rajasthan and Gansu meet these conditions.

(d) *Implications for digital development and mHealth*

Policy implications in the ICTD and mHealth literature commonly focus on how to exploit the positive potential of mobile phone diffusion (Andersson & Hatakka, 2013: p. 293; Dodson, Sterling, & Bennett, 2012; Heeks, 2014: p. 12; Khatun *et al.*, 2014: p. 9; Roztocki & Weistroffer, 2014: p. 351). Although multiple interpretations of our study results are possible,³ and although the causal direction of our findings will have to be established in future research, we focus our discussion on the potential negative implications of mobile phone diffusion in order to complement existing mHealth positions.

One possible interpretation of our cross-sectional findings is that mobile phone use during an illness increases access to healthcare. This can mean that phone users have an advantage over non-users in accessing healthcare, and this advantage might be rooted in pre-existing social, economic, and spatial divisions (as has been shown elsewhere, e.g. in Burrell, 2010; Wyche, Simiyu, & Othieno, 2016). However, increased access can also lead to inefficient health system over-utilization by phone users, which could crowd out more vulnerable groups. Additional complexity of phone-aided behaviors as suggested by delayed access to healthcare can come at a cost, too—not just in terms of direct and indirect health expenditure for the patient, but also delays that could make an emergency condition life threatening.⁴

What would have to be done if the interplay of ungoverned technology diffusion and health behavior adaptation does indeed yield such unintended side effects? It appears imprudent to restrict and regulate population access to mobile technology in such a scenario, but advocating for an mHealth intervention to boost more equitable access to healthcare may be equally insensitive if its own platform reinforces inefficient healthcare resource allocation.

On the demand side of health-related mobile phone use, some authors have advocated that users be educated about the (health-related) engagement with mobile technology, for example through primary and secondary school curricula (Bailin, Milanaik, & Adesman, 2014: p. 616; Buhi, Daley, Fuhrmann, & Smith, 2009: p. 110; Day, 2014: p. 187; Hampshire *et al.*, 2015: p. 98). Education about proper phone use could be a means to reduce adverse behaviors and the potential crowding out of non-users. However, such activities may also reproduce healthcare inequities between users and non-users of mobile phones, provided that the users now achieve more effective healthcare access while other, potentially more marginalized, groups remain excluded from some or all phone use. In order to promote equitable access to healthcare, it may be more effective to focus educational activities on health problems and health behavior more generally (rather than only phone-aided behaviors). Another problem is that such activities would not reach individuals outside of the education system, such as adults. Educational activities aiming to limit health system over-utilization could therefore target phone users when they interact with the health system, for example by doctors pointing out appropriate channels of communication to patients who call them.

Regulatory intervention on the healthcare supply side could be another way to rectify problems related to inefficient health system over-use. Where inequitable healthcare access is a concern, patients would require functioning and efficient routes to the health system that do not depend on mobile phone use, for instance through public transport or regular and dependable drop-in clinics at health centers (see e.g. Healy & McKee, 2004: pp. 352–353). Such supply-side responses to increasing

phone-aided health action are an issue yet to be resolved, but further health systems research in this area may gradually help to develop a knowledge base on effective policy responses.

Since the practice of mHealth interventions is likely to continue in the future, there are at least two further points that patient-centered mHealth developers, implementers, and health policy makers could take away from our study. On the one hand, considering the breadth of health-related phone uses that have emerged in our field sites in the absence of extensive mHealth intervention, user acceptance issues may arise if people's existing local solutions compete with a new intervention. Vassilev *et al.* (2015: p. 23) advise that telehealth initiatives be "integrated into everyday life and healthcare routines." Our research suggests that, beyond harmonization with everyday "routines," also people's existing conventional and phone-aided healthcare behaviors deserve attention. Common concerns about epidemiological priorities like cardiovascular diseases should not be neglected, but it may be worthwhile for designers and implementers of mHealth solutions to start with questions like, "How does my target group behave, which solutions do they already have available, and how can I guide and improve their behaviour?" Such a person-centered approach could avoid potentially redundant interventions that risk undermining user acceptance.

On the other hand, the sustainability of patient-centered mHealth solutions may be in doubt where the mobile phone platform undermines those outcomes that the mHealth intervention means to improve. For example, if mobile phones promote the inefficient use of scarce healthcare resources, we may ask whether a healthcare intervention ought to be mobile-phone-based, potentially creating a situation where the technological intervention would only undo the harm that the platform inflicts (e.g. in the case of mobile-phone supported referral; Mehl *et al.*, 2015: p. 255). However, given the research gap in this area, we need a broader knowledge base on how mobile phone use affects health action in order to identify instances where mHealth interventions are warranted and where not.

6. CONCLUSION

We set out to investigate whether, in the absence of targeted interventions, people make different healthcare decisions if they use mobile phones during an illness. To this end, we carried out an exploratory study using a novel, cross-sectional data set of healthcare behavior among the general adult population in rural Rajasthan (India) and Gansu (China)—irrespective of whether the respondent owned a phone.

To the best of our knowledge, this is the first study that identified a statistical association between mobile phone use and healthcare access behavior among the rural adult population in LMICs in the absence of a specific phone-based healthcare intervention. Our research findings indicated that mobile phone use in rural Rajasthan and Gansu is associated with higher access to healthcare, but also with more complex and time-consuming behaviors. A causal link underlying this relationship needs to be established in future studies, but our exploratory study and theoretical discussion suggested that such a relationship between phone diffusion and healthcare access might have mixed consequences for healthcare as an important facet of international development. For example, it could be regarded a positive outcome if the spread of mobile phones means that now digitally included groups are able to

better navigate fragmented healthcare systems and to coordinate transportation to previously inaccessible health providers. However, increased access for phone users (be they owners or not) may come at the expense of groups who are excluded systematically from digital diffusion processes because of pre-existing patterns of economic, social, or spatial marginalization. More access to healthcare encouraged by mobile phone use could also be detrimental for the patient if it means increased out-of-pocket expenditures for unnecessary treatment.

If the statistical associations detected in our study do indeed hint at a causal link between phone diffusion and population health behavior, then it would also have a bearing on the introduction of specific phone-based health interventions (mHealth) that are targeted at patients as end users. As we observed that people use mobile phones for health-related purposes even before mHealth is introduced, new interventions might inadvertently have to compete with people's existing phone-based healthcare solutions. This could manifest itself for example in the form of low "user acceptance," even if an mHealth solution is more desirable from a clinical perspective than prevailing healthcare-seeking practices. In addition, if future research links mobile phone use to problematic patterns of health behavior and healthcare access (e.g. delays in access, inefficient overuse of scarce resources), then we may have to reconsider whether a patient-centered healthcare intervention ought to be mobile-phone-based (e.g. mobile-phone supported referral; Mehl *et al.*, 2015: p. 255). In such a context, an mHealth intervention could potentially create a situation where the technological solution only undoes the harm that the mobile platform inflicts. Non-mHealth solutions for healthcare access and behavior change may be preferred in such circumstances.

At present, these causal claims are merely hypotheses that emerged from this study and that require future research. For example, research designs using natural experiments could explore whether mobile phone diffusion makes personal healthcare access more efficient and "appropriate" depending on people's symptoms, and whether it intensifies competition for scarce healthcare resources between users and non-users of mobile phones. Field experiments may help to understand whether and which heuristic decision-making routines underlie phone-aided health behavior. This paper offered theoretical starting points to formulate such hypotheses, and methodological ones to study the influence of phones on healthcare-seeking behavior in depth.

It is important to understand our conclusions in the context of exploratory research in two comparatively poor field sites where mobile phones have diffused fast and where healthcare access remains an issue. Cultural, social, technological, infrastructural, and health system differences are likely to influence the relationship between mobile phone diffusion and healthcare access in these and other contexts. At the same time, the two culturally and socio-economically distinct sites produced findings that reveal a consistent association between phone diffusion and healthcare access, thereby extending the recently emerging literature that has started to examine mobile phone use in the context of challenging healthcare access (Hampshire *et al.*, 2015; Khatun *et al.*, 2014; Tran *et al.*, 2015; Zurovac *et al.*, 2013). This makes rural Gansu and Rajasthan at least two noteworthy cases on a research agenda that calls for more social sciences research to build a comprehensive knowledge base on the healthcare implications of mobile phone diffusion around the globe. The tools and techniques suggested in our paper may help along the way.

NOTES

1. A substantial portion of the literature also investigates the direct health effects of mobile phone use, such as mobile phone radiation, exploding batteries, electrical shocks, distraction during the operation of road vehicles, or mobile phones as bacterial repositories (Ben *et al.*, 2009; Brady *et al.*, 2011; Jeffrey & Doron, 2013: pp. 212–213; Karabagli, Köse, & Çetin, 2006; Karger, 2005; Mechael, 2006: p. 144; Patrick, Griswold, Raab, & Intille, 2008: p. 178; Visvanathan, Gibb, & Brady, 2011; Wang *et al.*, 2012: p. 212; Wilson & Stimpson, 2010).
2. The surveys were intended to be representative on the district level, but a fundamental problem in face-to-face rural surveys is that the daytime population in the village is different from the registered population. We calculated sample weights using census data in both field sites to adjust the results of the descriptive statistical analysis to be representative on the district level (Heeringa, West, & Berglund, 2010: p. 38). The underlying census data stem from 2010 (Gansu) and 2011 (Rajasthan) (Government of India, 2011: p. 1; NBS, 2011). However, sample weights for the

descriptive statistical analysis do not entirely rule out that the underlying sample has atypical characteristics when compared to people who commute to work outside the village (Fowler, 2009: pp. 62–67).

3. More research is needed to establish which interpretation applies in which context and for which groups. For example, it is plausible that phone users think of a given illness as less severe if they are able to access advice that helps them understand its nature and find relief. In this particular case, mobile phone use would directly contribute to improved subjective well-being. We thank an anonymous reviewer for raising this point.

4. Additional qualitative and quantitative exploratory analyses [not reported here] pointed at interactions between disease severity and phone use, according to which phone users may be more likely to use health services for mild health conditions. Future research may investigate this link further.

REFERENCES

- Ann, L. A., & Cornelius, L. J. (2006). *Designing and conducting health surveys: A comprehensive guide* (3rd ed.) San Francisco, CA: Wiley.
- Agarwal, S., & Labrique, A. (2014). Newborn health on the line: The potential mhealth applications. *JAMA*, 312(3), 229–230. <http://dx.doi.org/10.1001/jama.2014.6371>.
- Ahmed, S. M., Adams, A. M., Chowdhury, M., & Bhuiya, A. (2000). Gender, socioeconomic development and health-seeking behaviour in Bangladesh. *Social Science & Medicine*, 51(3), 361–371. [http://dx.doi.org/10.1016/S0277-9536\(99\)00461-X](http://dx.doi.org/10.1016/S0277-9536(99)00461-X).
- Aker, J. C., & Blumenstock, J. E. (2015). The economic impacts of new technologies in Africa. In C. Monga, & J. Y. Lin (Eds.). *The Oxford handbook of Africa and economics: Policies and practices* (Vol. II, pp. 354–371).
- Aker, J. C., & Mbiti, I. M. (2010). Mobile phones and economic development in Africa. *The Journal of Economic Perspectives*, 24(3), 207–232. <http://dx.doi.org/10.2307/20799163>.
- Al Dahdah, M., Desgrées Du Lou, A., & Méadel, C. (2015). Mobile health and maternal care: A winning combination for healthcare in the developing world?. *Health Policy and Technology*, 4(3), 225–231. <http://dx.doi.org/10.1016/j.hlpt.2015.04.002>.
- Andersen, R. M. (1995). Revisiting the behavioral model and access to medical care: Does it matter?. *Journal of Health and Social Behavior*, 36(1), 1–10. <http://dx.doi.org/10.2307/2137284>.
- Andersson, A., & Hatakka, M. (2013). *What are we doing? Theories used in ICT4D research* Paper presented at the 12th international conference on social implications of computers in developing countries, 19–22 May, 2013, Ocho Rios, Jamaica.
- Anglada-Martinez, H., Riu-Viladoms, G., Martin-Conde, M., Rovira-Illamola, M., Sotoca-Momblona, J. M., & Codina-Jane, C. (2015). Does mHealth increase adherence to medication? Results of a systematic review. *International Journal of Clinical Practice*, 69(1), 9–32. <http://dx.doi.org/10.1111/ijcp.12582>.
- Apple Inc. (2016). iTunes preview: App store Retrieved 05 January 2015, from <https://itunes.apple.com/gb/genre/ios/id36?mt=8>.
- Arrow, K. J. (1963). Uncertainty and the welfare economics of medical care. *The American Economic Review*, 53(5), 941–973. <http://dx.doi.org/10.2307/1812044>.
- Asenso-Okyere, W. K., & Dzator, J. A. (1997). Household cost of seeking malaria care. A retrospective study of two districts in Ghana. *Social Science & Medicine*, 45(5), 659–667. [http://dx.doi.org/10.1016/S0277-9536\(96\)00383-8](http://dx.doi.org/10.1016/S0277-9536(96)00383-8).
- Bailin, A., Milanaik, R., & Adesman, A. (2014). Health implications of new age technologies for adolescents: A review of the research. *Current Opinion in Pediatrics*, 26(5), 605–619. <http://dx.doi.org/10.1097/MOP.0000000000000140>.
- Balsa, A. I., Seiler, N., McGuire, T. G., & Bloche, M. G. (2003). Clinical uncertainty and healthcare disparities. *American Journal of Law & Medicine*, 29(2&3), 203–219.
- Ben, D., Ma, B., Liu, L., Xia, Z., Zhang, W., & Liu, F. (2009). Unusual burns with combined injuries caused by mobile phone explosion: Watch out for the “mini-bomb”!. *Journal of Burn Care & Research*, 30(6). <http://dx.doi.org/10.1097/BCR.0b013e3181bf8c0>.
- Beratarrechea, A., Lee, A. G., Willner, J. M., Jahangir, E., Ciapponi, A., & Rubinstein, A. (2014). The impact of mobile health interventions on chronic disease outcomes in developing countries: A systematic review. *Telemedicine and e-Health*, 20(1), 75–82. <http://dx.doi.org/10.1089/tmj.2012.0328>.
- Berk, R., & MacDonald, J. M. (2008). Overdispersion and poisson regression. *Journal of Quantitative Criminology*, 24(3), 269–284. <http://dx.doi.org/10.1007/s10940-008-9048-4>.
- Bigogo, G., Audi, A., Aura, B., Aol, G., Breiman, R. F., & Feikin, D. R. (2010). Health-seeking patterns among participants of population-based morbidity surveillance in rural western Kenya: Implications for calculating disease rates. *International Journal of Infectious Diseases*, 14(11), e967–e973. <http://dx.doi.org/10.1016/j.ijid.2010.05.016>.
- Bijker, W. E. (1995). *Of bicycles, bakelites, and bulbs: Toward a theory of sociotechnical change*. Cambridge, MA: MIT Press.
- Bill & Melinda Gates Foundation (2015). *Consolidated financial statements*. Seattle, WA: BMGF.
- Blomqvist, Å. (1991). The doctor as double agent: Information asymmetry, health insurance, and medical care. *Journal of Health Economics*, 10(4), 411–432. [http://dx.doi.org/10.1016/0167-6296\(91\)90023-G](http://dx.doi.org/10.1016/0167-6296(91)90023-G).
- Bloomfield, G. S., Vedanthan, R., Vasudevan, L., Kithei, A., Were, M., & Velazquez, E. J. (2014). Mobile health for non-communicable diseases in Sub-Saharan Africa: A systematic review of the literature and strategic framework for research. *Global Health*, 10(49). <http://dx.doi.org/10.1186/1744-8603-10-49>.
- Brady, R. R., Hunt, A. C., Visvanathan, A., Rodrigues, M. A., Graham, C., Rae, C., ... Gibb, A. P. (2011). Mobile phone technology and hospitalized patients: A cross-sectional surveillance study of bacterial colonization, and patient opinions and behaviours. *Clinical Microbiology and Infection*, 17(6), 830–835. <http://dx.doi.org/10.1111/j.1469-0691.2011.03493.x>.
- Brown, L. A. (1981). *Innovation diffusion: A new perspective*. London: Methuen.
- Buhi, E. R., Daley, E. M., Fuhrmann, H. J., & Smith, S. A. (2009). An observational study of how young people search for online sexual health information. *Journal of American College Health*, 58(2), 101–111. <http://dx.doi.org/10.1080/07448480903221236>.
- Burrell, J. (2010). Evaluating shared access: Social equality and the circulation of mobile phones in rural Uganda. *Journal of Computer-Mediated Communication*, 15(2), 230–250. <http://dx.doi.org/10.1111/j.1083-6101.2010.01518.x>.
- Cameron, A. C., & Trivedi, P. K. (1998). *Regression analysis of count data*. Cambridge: Cambridge University Press.

- Cawley, J., & Ruhm, C. J. (2011). The economics of risky health behaviors. In M. V. Pauly, T. G. McGuire, & P. P. Barros (Eds.), *Handbook of health economics* (Vol. 2, pp. 95–199). Amsterdam: Elsevier.
- China Marketing Research (2014). China data online Retrieved November 19, 2014, from <http://chinadataonline.org>.
- Clifford, G. D., Blaya, J. A., Hall-Clifford, R., & Fraser, H. S. (2008). Medical information systems: A foundation for healthcare technologies in developing countries. *BioMedical Engineering Online*, 7, 18. <http://dx.doi.org/10.1186/1475-925X-7-18>.
- Cohen, J., Dupas, P., & Schaner, S. G. (2012). *Price subsidies, diagnostic tests, and targeting of malaria treatment: evidence from a randomized controlled trial National Bureau of economic research working paper series*.
- Cole-Lewis, H. (2013). mhealthy behavior studies: Lessons from a systematic review. In J. Donner, & P. Mechael (Eds.), *mHealth in practice: Mobile technology for health promotion in the developing world* (pp. 32–47). London: Bloomsbury Academic.
- Coughlin, S. S. (1990). Recall bias in epidemiologic studies. *Journal of Clinical Epidemiology*, 43(1), 87–91. [http://dx.doi.org/10.1016/0895-4356\(90\)90060-3](http://dx.doi.org/10.1016/0895-4356(90)90060-3).
- Cresswell, R. (2002). Of mills and waterwheels: The hidden parameters of technological choice. In P. Lemonnier (Ed.), *Technological choices: Transformation in material cultures since the neolithic* (pp. 181–213). London: Routledge.
- 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. <http://dx.doi.org/10.1016/j.jhealeco.2014.02.002>.
- Das, J., Hammer, J., & Leonard, K. (2008). The quality of medical advice in low-income countries. *The Journal of Economic Perspectives*, 22(2), 93–114. <http://dx.doi.org/10.2307/27648243>.
- Das, J., Hammer, J., & Sánchez-Paramo, C. (2012). The impact of recall periods on reported morbidity and health seeking behavior. *Journal of Development Economics*, 98(1), 76–88. <http://dx.doi.org/10.1016/j.jdeveco.2011.07.001>.
- Datanet India (2014). Indiastat Retrieved November 19, 2014, from www.indiastat.com.
- Day, A. (2014). Getting the ‘blues’: The existence, diffusion and influence of pornography on young peoples’ sexual health in Sierra Leone. *Culture, Health & Sexuality*, 16(2), 178–189. <http://dx.doi.org/10.1080/13691058.2013.855819>.
- de Silva, H., & Zainudeen, A. (2007). *Teleuse on a shoestring: poverty reduction through telecom access at the 'bottom of the pyramid'* Paper presented at the centre for poverty analysis annual symposium on poverty research in Sri Lanka, Colombo, December 6–7, 2007.
- Díaz Andrade, A., & Urquhart, C. (2012). Unveiling the modernity bias: A critical examination of the politics of ICT4D. *Information Technology for Development*, 18(4), 281–292. <http://dx.doi.org/10.1080/02681102.2011.643204>.
- Dodson, L. L., Sterling, S. R., & Bennett, J. K. (2012). Considering failure: Eight years of ITID research. *Information Technologies & International Development*, 9(2, ICTD2012 special issue), 19–34.
- Doron, A. (2012). Mobile persons: Cell phones, gender and the self in North India. *The Asia Pacific Journal of Anthropology*, 13(5), 414–433. <http://dx.doi.org/10.1080/14442213.2012.726253>.
- Dow, W., Gertler, P., Schoeni, R. F., Strauss, J., & Thomas, D. (1997). *Health care prices, health and labor outcomes: Experimental evidence RAND working paper series*. Santa Monica, CA: RAND.
- Duncombe, R. (2011). Researching impact of mobile phones for development: Concepts, methods and lessons for practice. *Information Technology for Development*, 17(4), 268–288. <http://dx.doi.org/10.1080/02681102.2011.561279>.
- Duncombe, R. (2012). *Understanding mobile phone impact on livelihoods in developing countries: A new research framework Manchester Centre for development informatics working paper*. Manchester: Centre for Development Informatics, Institute for Development Policy and Management.
- Dupas, P. (2011). Health behavior in developing countries. *Annual Review of Economics*, 3(1), 425–449. <http://dx.doi.org/10.1146/annurev-economics-111809-125029>.
- Feikin, D. R., Audi, A., Olack, B., Bigogo, G. M., Polyak, C., Burke, H., ... Breiman, R. F. (2010). Evaluation of the optimal recall period for disease symptoms in home-based morbidity surveillance in rural and urban Kenya. *International Journal of Epidemiology*. <http://dx.doi.org/10.1093/ije/dyp374>.
- Fernández-Ardévol, M. (2013). *Exploring the use of mobile communications in a retirement home in Toronto: Preliminary results IN3 working paper*. Barcelona: Internet Interdisciplinary Institute.
- Flor, A. (2015). Constructing theories of change for information society impact research. In A. Chib, J. May, & R. Barrantes (Eds.), *Impact of information society research in the global south* (pp. 45–62). Springer Singapore.
- Fowler, F. J. (2009). *Survey research methods* (4th ed.) Thousand Oaks, CA: Sage Publications.
- Free, C., Phillips, G., Galli, L., Watson, L., Felix, L., Edwards, P., ... Haines, A. (2013). The effectiveness of mobile-health technology-based health behaviour change or disease management interventions for health care consumers: A systematic review. *PLoS Medicine*, 10(1), e1001362. <http://dx.doi.org/10.1371/journal.pmed.1001362>.
- Gagliardone, I. (2015). ‘Can you hear me?’ Mobile-radio interactions and governance in Africa. *New Media & Society*, 1–16. <http://dx.doi.org/10.1177/1461444815581148>, [ahead of print].
- Gotsadze, G., Bennett, S., Ranson, K., & Gzirishvili, D. (2005). Health care-seeking behaviour and out-of-pocket payments in Tbilisi, Georgia. *Health Policy and Planning*, 20(4), 232–242. <http://dx.doi.org/10.1093/heapol/czi029>.
- Government of India (2011). *Census of India 2011: Rajasthan: Provisional population totals*. New Delhi: Office of the Registrar General & Census Commissioner.
- Greene, W. H. (2008). *Econometric analysis* (6th ed.) Upper Saddle River, N.J.: Pearson/Prentice Hall.
- GSMA (2015). GSMA mHealth tracker Retrieved May 19, 2015, from <http://www.gsma.com/mobilefordevelopment/programmes/mhealth/mhealth-deployment-tracker>.
- GSMA (2016). GSMA mHealth tracker Retrieved 25 March 2016, from <http://www.gsma.com/mobilefordevelopment/programmes/mhealth/mhealth-deployment-tracker>.
- Haenssger, M. J. (2015a). Exploring the mismatch between mobile phone adoption and use through survey data from rural India and China. In *Proceedings of the 2015 IEEE international symposium on technology and society (ISTAS)* (pp. 1–15). <http://dx.doi.org/10.1109/ISTAS.2015.7439402>.
- Haenssger, M.J. *Mobile phone diffusion and rural healthcare access in India and China*. (D.Phil. Thesis), 2015b, University of Oxford, Oxford. Retrieved from <http://ora.ox.ac.uk/objects/uuid:3f48fc8b-5414-4851-926b-07a57eed6cfe>.
- Haenssger, M. J. (2015c). Satellite-aided survey sampling and implementation in low- and middle-income contexts: A low-cost/low-tech alternative. *Emerging Themes in Epidemiology*, 12(20). <http://dx.doi.org/10.1186/s12982-015-0041-8>.
- Hall, A. K., Cole-Lewis, H., & Bernhardt, J. M. (2015). Mobile text messaging for health: A systematic review of reviews. *Annual Review of Public Health*, 36(1), 393–415. <http://dx.doi.org/10.1146/annurev-pub-health-031914-122855>.
- Hall, C. S., Fottrell, E., Wilkinson, S., & Byass, P. (2014). Assessing the impact of mHealth interventions in low- and middle-income countries – What has been shown to work?. *Global Health Action*, 7(25606). <http://dx.doi.org/10.3402/gha.v7.25606>.
- Hampshire, K., Porter, G., Owusu, S. A., Mariwah, S., Abane, A., Robson, E., ... Milner, J. (2015). Informal m-health: How are young people using mobile phones to bridge healthcare gaps in Sub-Saharan Africa?. *Social Science & Medicine*, 142, 90–99. <http://dx.doi.org/10.1016/j.socscimed.2015.07.033>.
- Healy, J., & McKee, M. (2004). Delivering health services in diverse societies. In J. Healy, & M. McKee (Eds.), *Accessing healthcare: Responding to diversity* (pp. 351–369). Oxford: Oxford University Press.
- Heeks, R. (2014). *ICT4D 2016: New priorities for ICT4D policy, practice and WSIS in a post-2015 world development informatics working paper series*. Manchester: Institute for Development Policy and Management.
- Heeringa, S., West, B. T., & Berglund, P. A. (2010). *Applied survey data analysis*. Boca Raton, FL: Chapman & Hall/CRC.
- Higgs, E. S., Goldberg, A. B., Labrique, A. B., Cook, S. H., Schmid, C., Cole, C. F., & Obregón, R. A. (2014). Understanding the role of mHealth and other media interventions for behavior change to enhance child survival and development in low- and middle-income countries: An evidence review. *Journal of Health Communication*, 19 (sup1), 164–189. <http://dx.doi.org/10.1080/10810730.2014.929763>.
- Hilbe, J. M. (2009). *Logistic regression models*. London: Chapman & Hall.

- Horst, H. A., & Miller, D. (2006). *The cell phone: An anthropology of communication*. Oxford: Berg.
- IMF (2013). World economic outlook database April 2013 Retrieved June 22, 2013, from International Monetary Fund Web site: <http://www.imf.org/external/pubs/ft/weo/2013/01/weodata/index.aspx>.
- ISI Emerging Markets (2012). *ICT sector India*. New York, NY: ISI Emerging Markets.
- ISI Emerging Markets (2013). *ICT sector China*. New York, NY: ISI Emerging Markets.
- ITU (2015a). Key ICT indicators for developed and developing countries and the world (totals and penetration rates) Retrieved July 21, 2015, from International Telecommunication Union Web site: http://www.itu.int/en/ITU-D/Statistics/Documents/statistics/2015/ITU_Key_2005-2015 ICT_data.xls.
- ITU (2015b). Time series by country: Mobile-cellular subscriptions 2000-2013 Retrieved April 13, 2015, from International Telecommunication Union Web site: http://www.itu.int/en/ITU-D/Statistics/Documents/statistics/2014/Mobile_cellular_2000-2013.xls.
- Jeffrey, R., & Doron, A. (2013). *The great Indian phone book: How the cheap cell phone changes business, politics, and daily life*. London: Hurst.
- Jensen, R. (2007). The digital divide: Information (technology), market performance, and welfare in the South Indian fisheries sector. *Quarterly Journal of Economics*, 122(3), 879–924.
- Jensen, R. T. (2010). Information, efficiency, and welfare in agricultural markets. *Agricultural Economics*, 41, 203–216. <http://dx.doi.org/10.1111/j.1574-0862.2010.00501.x>.
- Karabagli, Y., Köse, A. A., & Çetin, C. (2006). Partial thickness burns caused by a spontaneously exploding mobile phone. *Burns*, 32(7), 922–924. <http://dx.doi.org/10.1016/j.burns.2006.03.009>.
- Karger, C. P. (2005). Mobile phones and health: A literature overview. *Zeitschrift für Medizinische Physik*, 15(2), 73–85. <http://dx.doi.org/10.1078/0939-3889-00248>.
- Khatun, F., Hanifi, S. M., Iqbal, M., Rasheed, S., Rahman, M. S., Ahmed, T., ... Bhuiya, A. (2014). Prospects of mHealth services in Bangladesh: Recent evidence from Chakaria. *PLoS One*, 9(11), e111413. <http://dx.doi.org/10.1371/journal.pone.0111413>.
- Kremer, M., & Glennerster, R. (2011). Improving health in developing countries: Evidence from randomized evaluations. In M. V. Pauly, T. G. McGuire, & P. P. Barros (Eds.), *Handbook of health economics* (Vol. 2, pp. 201–315). Amsterdam: Elsevier.
- Kroeger, A. (1983). Health interview surveys in developing countries: A review of the methods and results. *International Journal of Epidemiology*, 12(4), 465–481. <http://dx.doi.org/10.1093/ije/12.4.465>.
- Kwan, A., Mechael, P., & Kaonga, N. N. (2013). State of behavior change initiatives and how mobile phones are transforming it. In J. Donner, & P. Mechael (Eds.), *mHealth in practice: Mobile technology for health promotion in the developing world* (pp. 15–31). London: Bloomsbury Academic.
- Labrique, A. B., Sikder, S. S., Mehara, S., Wu, L., Huq, R., Ali, H., ... West, K. (2012). Mobile phone ownership and widespread mHealth use in 168,231 women of reproductive age in rural Bangladesh. *Journal of Mobile Technology in Medicine*, 1(4S), 26. <http://dx.doi.org/10.7309/jmtm.48>.
- Leventhal, H., Weinman, J., Leventhal, E. A., & Phillips, L. A. (2008). Health psychology: The search for pathways between behavior and health. *Annual Review of Psychology*, 59(1), 477–505. <http://dx.doi.org/10.1146/annurev.psych.59.103006.093643>.
- Ling, R. S. (2012). *Taken for grantedness: The embedding of mobile communication into society*. Cambridge, MA: MIT Press.
- Luoto, J., Levine, D., & Albert, J. (2011). *Information and persuasion: achieving safe water behaviors in Kenya working paper*. Santa Monica, CA: RAND Corporation.
- Martin, J. A. (2014). Mobile media and political participation: Defining and developing an emerging field. *Mobile Media & Communication*, 2(2), 173–195. <http://dx.doi.org/10.1177/2050157914520847>.
- May, J., & Diga, K. (2015). Progress towards resolving the measurement link between ICT and poverty reduction. In A. Chib, J. May, & R. Barrantes (Eds.), *Impact of information society research in the global south* (pp. 83–104). Springer Singapore.
- Mbuagbaw, L., Mursleen, S., Lytvy, L., Smieja, M., Dolovich, L., & Thabane, L. (2015). Mobile phone text messaging interventions for HIV and other chronic diseases: An overview of systematic reviews and framework for evidence transfer. *BMC Health Services Research*, 15(33). <http://dx.doi.org/10.1186/s12913-014-0654-6>.
- Mechael, P. (2006). *Exploring health-related uses of mobile phones: An Egyptian case study* [unpublished PhD thesis]. London: London School of Hygiene and Tropical Medicine.
- Mechael, P. (2008). Health services and mobiles: A case from Egypt. In J. E. Katz (Ed.), *Handbook of mobile communication studies* (pp. 91–103). Cambridge, MA: MIT Press.
- Mehl, G., Vasudevan, L., Gonsalves, L., Berg, M., Seimon, T., Temmerman, M., & Labrique, A. (2015). Harnessing mHealth in low-resource settings to overcome health system constraints and achieve universal access to healthcare. In L. A. Marsch, S. E. Lord, & J. Dallery (Eds.), *Behavioural healthcare and technology: Using science-based innovations to transform practice* (pp. 239–263). New York, NY: Oxford University Press.
- Micevska, M. (2005). Telecommunications, public health, and demand for health-related information and infrastructure. *Information Technologies and International Development*, 2(3), 57–72.
- Miritello, G., Moro, E., Lara, R., Martínez-López, R., Belchamber, J., Roberts, S. G. B., & Dunbar, R. I. M. (2013). Time as a limited resource: Communication strategy in mobile phone networks. *Social Networks*, 35(1), 89–95. <http://dx.doi.org/10.1016/j.socnet.2013.01.003>.
- Muessig, K. E., Bien, C. H., Wei, C., Lo, E. J., Yang, M., Tucker, J. D., ... Hightow-Weidman, L. B. (2015). A mixed-methods study on the acceptability of using eHealth for HIV prevention and sexual health care among men who have sex with men in China. *Journal of Medical Internet Research*, 17(4), e100. <http://dx.doi.org/10.2196/jmir.3370>.
- Murdock, G., Hartmann, P., & Gray, P. (1994). Contextualizing home computing: Resources and practices. In R. Silverstone, & E. Hirsch (Eds.), *Consuming technologies: Media and information in domestic spaces* (pp. 136–149). London: Routledge.
- Nakasone, E., Torero, M., & Minten, B. (2014). The power of information: The ICT revolution in agricultural development. *Annual Review of Resource Economics*, 6(1), 533–550. <http://dx.doi.org/10.1146/annurev-resource-100913-012714>.
- NBS (2011). 甘肃省2010年第六次全国人口普查主要数据公报 [Gansu Province in 2010 the sixth national census data bulletin] Retrieved June 15, 2013, from National Bureau of Statistics of China Web site: http://www.stats.gov.cn/was40/gjttj_detail.jsp?channelid=2912&record=30.
- NBS (2013). China statistical database Retrieved July 23, 2013, from National Bureau of Statistics of China Web site: <http://219.235.129.58/welcome.do>.
- Noordam, A. C., Kuepper, B. M., Stekelenburg, J., & Milen, A. (2011). Improvement of maternal health services through the use of mobile phones. *Tropical Medicine & International Health*, 16(5), 622–626. <http://dx.doi.org/10.1111/j.1365-3156.2011.02747.x>.
- Oreglia, E. (2013). When technology doesn't fit: information sharing practices among farmers in rural China. In *Proceedings of the sixth international conference on information and communication technologies and development: Full papers – Vol. 1* (pp. 165–176). Cape Town: Association for Computing Machinery.
- Oster, E., & Thornton, R. (2012). Determinants of technology adoption: Peer effects in menstrual cup take-up. *Journal of the European Economic Association*, 10(6), 1263–1293. <http://dx.doi.org/10.1111/j.1542-4774.2012.01090.x>.
- Patrick, K., Griswold, W. G., Raab, F., & Intille, S. S. (2008). Health and the mobile phone. *American Journal of Preventive Medicine*, 35(2), 177–181. <http://dx.doi.org/10.1016/j.amepre.2008.05.001>.
- Pedersen, M. A., & Bunkenborg, M. (2012). Roads that separate: Sino-mongolian relations in the inner Asian desert. *Mobilities*, 7(4), 555–569. <http://dx.doi.org/10.1080/17450101.2012.718938>.
- Pfaffenberger, B. (1992). Social anthropology of technology. *Annual Review of Anthropology*, 21, 491–516. <http://dx.doi.org/10.2307/2155997>.
- Philbrick, W. C. (2012). *Leveraging technologies for maternal, newborn & child development*. Washington, DC: mHealth Alliance.
- Planning Commission (2011). *Mid-term appraisal: Eleventh five year plan 2007–2012*. New Delhi: Government of India.
- Porter, G. (2012). Mobile phones, livelihoods and the poor in Sub-Saharan Africa: Review and prospect. *Geography Compass*, 6(5), 241–259. <http://dx.doi.org/10.1111/j.1749-8198.2012.00484.x>.
- Qiang, C. Z., Yamamichi, M., Hausman, V., Miller, R., & Altman, D. (2012). *Mobile applications for the health sector*. Washington, DC: World Bank.

- Rabe-Hesketh, S., & Skrondal, A. (2012a). *Multilevel and longitudinal modeling using Stata: Categorical responses, counts, and survival* (3rd ed. Vol. II). College Station, TX: Stata Press.
- Rabe-Hesketh, S., & Skrondal, A. (2012b). *Multilevel and longitudinal modeling using Stata: continuous responses* (3rd ed. Vol. I). College Station, TX: Stata Press.
- research2guidance (2014). *mHealth app developer economics 2014: The state of the art of mHealth app publishing*. Berlin: research2guidance.
- Reynolds, L., & McKee, M. (2011). Serve the people or close the sale? Profit-driven overuse of injections and infusions in China's market-based healthcare system. *The International Journal of Health Planning and Management*, 26(4), 449–470. <http://dx.doi.org/10.1002/hpm.1112>.
- Rhee, M., Sissoko, M., Perry, S., McFarland, W., Parsonnet, J., & Doumbo, O. (2005). Use of insecticide-treated nets (ITNs) following a malaria education intervention in Piron, Mali: A control trial with systematic allocation of households. *Malaria Journal*, 4, 35. <http://dx.doi.org/10.1186/1475-2875-4-35>.
- Roberts, S. G. B., & Dunbar, R. I. M. (2011). The costs of family and friends: An 18-month longitudinal study of relationship maintenance and decay. *Evolution and Human Behavior*, 32(3), 186–197. <http://dx.doi.org/10.1016/j.evolhumbehav.2010.08.005>.
- Rodin, J. (2010). *Keynote address* Paper presented at the mHealth Summit, Washington, DC, November 10, 2010.
- Roztocki, N., & Weistroffer, H. R. (2014). Information and communication technology in transition economies: An assessment of research trends. *Information Technology for Development*, 21(3), 330–364. <http://dx.doi.org/10.1080/02681102.2014.891498>.
- Saramäki, J., Leicht, E. A., López, E., Roberts, S. G. B., Reed-Tsochas, F., & Dunbar, R. I. M. (2014). Persistence of social signatures in human communication. *Proceedings of the National Academy of Sciences*, 111(3), 942–947. <http://dx.doi.org/10.1073/pnas.1308540110>.
- Scott, A. (2000). Economics of general practice. In J. C. Anthony, & P. N. Joseph (Eds.). *Handbook of health economics* (Vol. 1, Part B, pp. 1175–1200). Amsterdam: Elsevier.
- Souter, D., Scott, N., Garforth, C., Jain, R., Mascarenhas, O., & McKemey, K. (2005). *The economic impact of telecommunications on rural livelihoods and poverty reduction: A study of rural communities in India (Gujarat), Mozambique and Tanzania*. London: UK Department for International Development.
- StataCorp (2013a). *Stata multilevel mixed-effects reference manual: Release 13*. College Station, TX: Stata Corp LP.
- StataCorp (2013b). *Stata statistical software: Release 13*. College Station, TX: StataCorp LP.
- Steinhubl, S. R., Muse, E. D., & Topol, E. J. (2015). The emerging field of mobile health. *Science Translational Medicine*, 7(283). <http://dx.doi.org/10.1126/scitranslmed.aaa3487>.
- Tamrat, T., & Kachnowski, S. (2012). Special delivery: An analysis of mHealth in maternal and newborn health programs and their outcomes around the world. *Maternal and Child Health Journal*, 16(5), 1092–1101. <http://dx.doi.org/10.1007/s10995-011-0836-3>.
- Tenhunen, S. (2008). Mobile technology in the village: ICTs, culture, and social logistics in India. *Journal of the Royal Anthropological Institute*, 14(3), 515–534. <http://dx.doi.org/10.1111/j.1467-9655.2008.00515.x>.
- Tran, M. C., Labrique, A. B., Mehra, S., Ali, H., Shaikh, S., Mitra, M., ... West, K. Jr., (2015). Analyzing the mobile “digital divide”: Changing determinants of household phone ownership over time in rural Bangladesh. *JMIR mHealth uHealth*, 3(1), e24. <http://dx.doi.org/10.2196/mhealth.3663>.
- Tversky, A., & Kahneman, D. (1974). Judgment under uncertainty: Heuristics and biases. *Science*, 185(4157), 1124–1131.
- Unwin, T. (2009). Introduction. In T. Unwin (Ed.), *ICT4D: Information and communication technology for development* (pp. 1–6). Cambridge: Cambridge University Press.
- van Heerden, A., Tomlinson, M., & Swartz, L. (2012). Point of care in your pocket: A research agenda for the field of m-health. *Bulletin of the World Health Organization*, 90(5), 393–394.
- Vassilev, I., Rowsell, A., Pope, C., Kennedy, A., O’Cathain, A., Salisbury, C., & Rogers, A. (2015). Assessing the implementability of telehealth interventions for self-management support: A realist review. *Implementation Science*, 10(59).
- Visvanathan, A., Gibb, A. P., & Brady, R. R. (2011). Increasing clinical presence of mobile communication technology: Avoiding the pitfalls. *Telemedicine Journal and E-Health*, 17(8), 656–661. <http://dx.doi.org/10.1089/tmj.2011.0018>.
- von Hippel, E. (2010). Open user innovation. In H. H. Bronwyn, & R. Nathan (Eds.). *Handbook of the economics of innovation* (Vol. 1, pp. 411–427). Amsterdam: North-Holland.
- Wagstaff, A. (2002). Poverty and health sector inequalities. *Bulletin of the World Health Organization*, 80(2), 97–105.
- Walsham, G. (2010). ICTs for the broader development of India: an analysis of the literature. *Electronic Journal of Information Systems in Developing Countries*, 41(4), 1–20.
- Wang, Q., Ping, P., Zhao, X., Chu, G., Sun, J., & Chen, C. (2012). Thermal runaway caused fire and explosion of lithium ion battery. *Journal of Power Sources*, 208, 210–224. <http://dx.doi.org/10.1016/j.jpowsour.2012.02.038>.
- WHO (2011). *mHealth: New horizons for health through mobile technologies*. Geneva: World Health Organization.
- WHO (2012). Global health expenditure database: Table of key indicators, sources and methods by country and indicators [Data file] Retrieved from: http://apps.who.int/nha/database/StandardReport.aspx?ID=REP_WEB_MINI_TEMPLATE_WEB_VERSION.
- WHO (2013a). Global health observatory data repository Retrieved June 22, 2013, from World Health Organization Web site: <http://apps.who.int/gho/data/node.main>.
- WHO (2013b). *World health statistics 2013*. Geneva: World Health Organization.
- WHO, & Ministry of Health P.R. China (2013). *China-WHO country cooperation strategy 2013–2015: Bridging the past towards a new era of collaboration*. Geneva: World Health Organization.
- Whyte, M. K. (2010). The paradoxes of rural-urban inequality in contemporary China. In M. K. Whyte (Ed.), *One country, two societies: Rural-urban inequality in contemporary China* (pp. 1–25). Cambridge, MA: Harvard University Press.
- Wilson, F. A., & Stimpson, J. P. (2010). Trends in fatalities from distracted driving in the United States, 1999 to 2008. *American Journal of Public Health*, 100(11), 2213–2219. <http://dx.doi.org/10.2105/ajph.2009.187179>.
- Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data* (2nd ed.) Cambridge, MA: MIT Press.
- World Bank (2015). World databank: world development indicators Retrieved May 28, 2015, from <http://databank.worldbank.org/data/views/variableselection/selectvariables.aspx?source=world-development-indicators#>.
- Wyche, S., Simiyu, N., & Othieno, M. E. (2016). Mobile phones as amplifiers of social inequality among rural Kenyan women. *ACM Transaction Computer-Human Interaction*, 23(3). <http://dx.doi.org/10.1145/2911982>, Article 14.
- Yip, W. C.-M., Hsiao, W. C., Chen, W., Hu, S., Ma, J., & Maynard, A. (2012). Early appraisal of China’s huge and complex health-care reforms. *The Lancet*, 379(9818), 833–842. [http://dx.doi.org/10.1016/S0140-6736\(11\)61880-1](http://dx.doi.org/10.1016/S0140-6736(11)61880-1).
- Zurovac, D., Otieno, G., Kigen, S., Mbithi, A. M., Muturi, A., Snow, R. W., & Nyandigisi, A. (2013). Ownership and use of mobile phones among health workers, caregivers of sick children and adult patients in Kenya: Cross-sectional national survey. *Global Health*, 9(20). <http://dx.doi.org/10.1186/1744-8603-9-20>.

APPENDIX A. SUPPLEMENTARY DATA

Supplementary data associated with this article can be found, in the online version, at <http://dx.doi.org/10.1016/j.worlddev.2017.01.014>.