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You've got a friend in me: How social networks and mobile phones facilitate healthcare access among marginalised groups in rural Thailand and Lao PDR

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ABSTRACT

The seeming "ubiquity" of mobile phones has spawned a wave of interventions that use mobiles as platforms for health service delivery (mHealth). Operating in more than 100 countries, mHealth interventions commonly aspire to make healthcare more inclusive and efficient. Yet, mobile phone diffusion also stimulates locally emerging forms of health-related phone use that could create new digital inequalities among marginalised groups or compete with mHealth and other technology-based development interventions.

We aim to inform this subject by asking, "*How do mobile phone use and social support networks influence rural treatment-seeking behaviours among marginalised groups?*" We hypothesise that (1) resource constraints drive marginalised groups towards informal healthcare access, and that (2) mobile phone use and social support networks facilitate access to formal healthcare with a bias towards private doctors. Analysing representative survey data from 2141 Thai and Lao villagers with descriptive statistics and multi-level regression models, we demonstrate that: (a) health-related phone use is concentrated among less marginalised groups, while social support networks are distributed more equitably; (b) marginalised villagers are more likely to utilise informal healthcare providers; and (c) mobile phones and social support networks are linked to increased yet delayed formal healthcare access that is directed towards public healthcare.

We conclude that mobile phone diffusion has a mildly positive association with rural healthcare access, operating in a similar fashion but without (yet) appearing to crowd out social support. However encouraging, this is problematic news for mHealth and technology-based development interventions. The potential behavioural consequences of "informal mHealth" reinforce the notion that mobile phones are a non-neutral platform for mHealth and development interventions. The long-term implications require more research, but the literature suggests that increasing phone-aided healthcare facilitation could undermine local social support networks and leave already marginalised rural dwellers in yet more precarious circumstances.

1. Introduction

> "*We must make sure that innovation and technology helps to reduce the inequities in our world, instead of becoming another reason people are left behind* [sic]." – Dr Tedros Adhanom Ghebreyesus, Director-General, World Health Organization (WHO, 2019b:v)

In light of common claims about the "ubiquity" of mobile phones around the globe and especially in low- and middle-income countries (LMICs), mobile phones and smartphone apps have received extensive attention as tools to revolutionise healthcare and contribute to the achievement of universal healthcare coverage. Notions like the "tremendous impact on emerging markets" (Manjunath, Revathi, & Dixit, 2011:4) and the "potential to transform the face of health service delivery across the globe" (WHO, 2011:1) by means of "harnessing this technology for improving the health of populations" (Krishna, Boren, & Balas, 2009:239) have shaped narratives and practice for nearly a decade. In line with the technological enthusiasm, the WHO (2016) report

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that 109 countries in 2016 operated at least one government-sanctioned phone-based health service delivery and surveillance programme (also referred to as mHealth; typically emergency hotlines and call centres).

The narratives are now gradually moving away from hyper-optimistic claims about the potential of mobile technology. Recently published guidelines by the WHO state for example that health interventions based on digital technology like mobile phones "should not exclude or jeopardize the provision of quality non-digital services in places where there is no access to the digital technologies or they are not acceptable or affordable for target communities" (WHO, 2019b:xi). Similarly, in the context of access to healthcare and education in LMICs, the Pathways for Prosperity Commission on Technology and Inclusive Development (2019:37) notes that, "If the same social norms that prohibit girls from walking longer distances to attend secondary school also limit their access to mobile technology (which could offer an alternative education medium), inequalities will not merely remain but may even be exacerbated." Also the often-cited problem of rapid and uncoordinated mHealth pilot studies ("pilotitis") especially in LMICs appears to be waning as programmes mature and countries integrate them better into their national health policies and digital strategies (Labrique, Vasudevan, Chang, & Mehl, 2013; WHO, 2016).

Despite the growing nuance in the rhetoric and practice on mHealth, and notwithstanding the growing evidence base (Labrique et al., 2013), a major problem in understanding the role of mHealth remains: We know worryingly little about the role of *mobile phones themselves* as platforms for health service delivery in LMICs. Existing mHealth evaluations focus on impacts brought about by adding a service onto the mobile platform, assuming implicitly that the platform is neutral or otherwise beneficial. However, emerging yet nascent social research on the role of health-related mobile phone use suggests that a large spectrum of "informal mHealth" emerges indigenously with the diffusion of mobile technology (Hampshire et al., 2015). mHealth research does not normally investigate how external intervention would fit into (or duplicate, or disrupt) this fluid landscape of people's healthcare solutions, nor what consequences emerging phone-aided health behaviours entail. Some of the informal mHealth uses could indeed be inequitable (e.g. over-utilising scarce healthcare resources that are then unavailable to digitally excluded groups) or outright harmful (e.g. consuming misleading health information), in which case formal mHealth interventions could reproduce existing inequalities, create new forms of exclusion, or just undo harms created by informal health-related uses of the mobile phone.

Our research responds to this knowledge gap and asks, "*How do mobile phone use and social support networks influence rural treatment-seeking behaviours among marginalised groups?*" In the spirit of the opening quote, we frame our analysis within the concept of marginalisation to explore whether mobile phone diffusion broadens or narrows opportunities among disadvantaged groups. In addition, to expand our understanding of landscapes of solutions with which newly diffused mobile phones may interact, we also examine the relative importance of social support networks in people's healthcare choices.

The presence of "support networks" in this study is defined as instances where personal relationships were involved in providing advice or help during an illness; health-related mobile phone use is defined as any phone use (by the patient or somebody acting on their behalf) in relation to their illness; and treatment-seeking behaviour is represented by the step-wise process that patients undergo during an illness episode, with particular focus on different types of healthcare access and the duration until various healthcare providers are being accessed. An illness episode in our study is a self-reported incidence of any acute illness or accident-related injury in the past two months. We conceptualise marginalisation as multiple dimensions of disadvantage that situate people at economic, social, and spatial margins of society.

Through an analysis of rural contexts in northern Thailand (Chiang Rai province) and southern Lao PDR (Salavan province), we demonstrate that marginalisation was associated with lower rates of private and higher rates of informal healthcare access, especially in the more resource-constrained context of rural Salavan. Although mobile phones were distributed less equitably than health-related social support, both mobile phones and social support were linked to disproportionate uptake of public healthcare among marginalised groups. While we detected an association between these facilitators and the delay until patients accessed public and private healthcare providers, more marginalised groups in Salavan also experienced comparatively faster access to public providers in the presence of health-related mobile phone use.

Our research is the first to quantitatively demonstrate the micro-level relationship between informal health-related mobile phone and social support within episodes of acute illness and injury, and it expands the empirical understanding of the treatment-seeking consequences of mobile phone use from previous research in India and China to Thailand and Lao PDR. Contrary to mainstream positions in mHealth research, our work demonstrates that health behaviours respond to situations of marginalisation, and that mobile phones in this context become part of a localised set of healthcare solutions in which they appear to fulfil similar functions as social support networks. On the one hand, this suggests that any new phone-based intervention may inadvertently interact and interfere with local solutions to solving healthcare access challenges, which emphasises the need for people-centric analyses of existing health behaviour prior to any mHealth intervention. On the other hand, the relative privilege and the potential unintended consequences (e.g. delayed access to care) associated with health-related mobile phone use underline the importance of interrogating the equity impact of ungoverned socio-technological change and of technical (health-related) interventions among marginalised groups in low- and middle-income countries.

2. Background

2.1. Poverty and marginalisation

While historically the income-centric definition of poverty had been pervasive (evident e.g. in the "bottom of the pyramid" approach to poverty alleviation, Peredo, Montgomery, & McLean, 2018), the contemporary consensus in development research and practice is that poverty is a multidimensional concept (Alkire & Foster, 2011; Rahnema, 2010; World Bank, 2018a). Marginalisation is closely related to multidimensional poverty, sometimes used as explanatory framework and sometimes as synonym for multidimensional poverty.[1] In this paper, our conceptualisation of marginalisation comprises multiple dimensions of disadvantage that situate people at economic, social, and spatial margins of society, with a particular emphasis on structural (i.e. non-individual) forms

[1] Similarly, close links and overlaps exist between marginalisation and the concepts of deprivation, vulnerability, and sustainable livelihoods. The main difference between marginality and marginalisation is that, if marginality is regarded as "the position of people on the edges, preventing their access to resources and opportunities, freedom of choices, and the development of personal capabilities;" then marginalisation can be considered to be the process in which people are pushed towards these "social, political, economic, ecological, and biophysical" edges of society (Sahli, 1981; von Braun & Gatzweiler, 2014:3). For the purposes of this paper, however, we treat marginalisation and marginality synonymously as a state of affairs (unless otherwise indicated as a process).

of exclusion, like discrimination or remoteness of location (von Braun & Gatzweiler, 2014).

The operationalisation and measurement of multidimensional poverty and its structural determinants vary considerably – both in terms of indicators and the levels on which they apply (Abebaw & Admassie, 2014; Ahmed, Hill, & Naeem, 2014; Alkire & Foster, 2011; Azeem, Mugera, & Schilizzi, 2018; Berman & Phillips, 2000; Kumar, 2014; Pattanaik & Xu, 2018; Steinert, Cluver, Melendez-Torres, & Vollmer, 2018; Sumner & Mallett, 2013). Among recent contributions to this field are for example Samuel, Alkire, Zavaleta, Mills, and Hammock (2018), who discuss the role of social isolation as an often-neglected facet of multidimensional poverty, exemplifying their arguments with cases of South Africa and Mozambique. Another example is Graw and Husmann (2014). Speaking to measurement on different levels, the authors assess marginalisation through indicators on the national level through per-capita income and political stability, and on the sub-national level through the prevalence of stunting and the travel time to the nearest city. Espinoza-Delgado and Klasen (2018) further argue that multidimensional poverty analyses typically focus on the household as unit of analysis, while assessments of intra-household inequality and gender-sensitive research require individual-level analysis. Moreover, Datzberger (2018) provides an example of how the various dimensions of marginalisation interact in the context of Uganda, where structural factors spanning social, economic, and political dimensions (e.g. social aspirations, labour market conditions, corruption) prevented poor people from benefitting from educational reforms (similar to the notion of fractal poverty traps; Barrett & Swallow, 2006).

Our study operationalised marginalisation through five indicators along three dimensions (see Section 3): social marginalisation (education and belonging to a minority group in a village), economic marginalisation (household assets), and spatial marginalisation (remoteness and travel time to nearest town). We considered healthcare access as outcome variable and health-related mobile phone use and social support as determinants of primary interest. We were conscious of the fact that marginalisation dimensions should ideally be grounded in the local context (Rahnema, 2010), and that they extend potentially much further than the three dimensions that we focussed on here – in principle, factors like healthcare access, use of technology, and access to social support networks could reasonably fall under the definition of marginalisation as well (Abebaw & Admassie, 2014; Samuel et al., 2018; van Dijk, 2005; von Braun & Gatzweiler, 2014). We therefore review the interrelationship of these factors in the following section.

2.2. Healthcare access and its links to marginalisation, social support networks, and technology

Access to healthcare considers the actual or potential utilisation of available services as part of a spectrum that variously includes healthcare needs and demand, treatment-seeking processes, access to and utilisation of healthcare (incl. barriers to access), and the ensuing health outcomes and other socio-economic consequences (Andersen, 1995; Bigdeli et al., 2012; Chuma, Okungu, & Molyneux, 2010; Gulliford et al., 2002; Levesque, Harris, & Russell, 2013). Empirical research in public health and medical anthropology has established a long list of factors influencing healthcare access, including, for example, the nature, severity, and stage of a patient's illness and their socio-economic background and health beliefs; trust in and perceptions of health provider quality; or societal perceptions of the health condition (Beals, 1976; Kroeger, 1983; Nyamongo, 2002; Shaikh, Haran, & Hatcher, 2008; Ward, Mertens, & Thomas, 1997). Marginalisation and multidimensional poverty have become a theme in healthcare access research as well (Barbosa & Cookson, 2019; Dupas, 2011; Obrist et al., 2007; Ribera & Hausmann-Muela, 2011).

One of the growing topics in healthcare access research is the role of social networks (Chuang & Schechter, 2015; Ellis, Vassilev, Kennedy, Moore, & Rogers, 2019; Perkins, Subramanian, & Christakis, 2015). For example, Herberholz and Phuntsho (2018) analyse survey data from Bhutan and document that rural healthcare choices are affected by social capital. Similar to the study by Pescosolido, Wright, Alegría, and Vera (1998) on mental health and social networks in Puerto Rico, the authors find that rural Bhutanese dwellers with extensive social networks have lower utilisation of higher-tier formal healthcare providers. However – like most research in this area (Pitkin Derose & Varda, 2009) – associations between social capital and treatment-seeking behaviour are only indirect (i.e. no direct measure of social network utilisation during an illness) and the direction of the documented impacts is mixed. The nature of social network influences among marginalised groups in LMICs requires therefore further research.

Another field of growing interest is the role of information and communication technology (ICT) in healthcare access in LMICs. We focus here on mobile phones as a type of ICT that is diffusing rapidly around the globe (teledensity now exceeds 100 mobile subscriptions per 100 people in both developed and developing countries according to ITU, 2019b), and which has experienced the fastest growth within ICT and development (ICTD) research (Gomez, Baron, & Fiore-Silfvast, 2012). Medical research contributions to this field have expanded rapidly into the terrain of how best to utilise phones as platforms for health service delivery and for promoting healthy behaviour especially among marginalised populations (Aranda-Jan, Mohutsiwa-Dibe, & Loukanova, 2014; Free et al., 2013a, 2013b; Lee et al., 2016; Mbuagbaw et al., 2015; van Heerden, Tomlinson, & Swartz, 2012). This large body of literature comprises more than 100 systematic reviews and reviews of reviews, but its instrumental perspective obscures the potential of mobile phones to act as non-neutral platforms for health interventions, and the phone's possible role in aggravating or mitigating inequalities among marginalised target populations in low- and middle-income countries.

While a similar emphasis on the instrumental use of ICT for development exists in social science research (Aker & Mbiti, 2010; Unwin, 2009b), social science research also considers the broader development implications of technology diffusion (Donner, 2009; Gagliardone, 2015; Jensen, 2007), and it is becoming increasingly theorised and critical as it interrogates persistent inequalities and the social role of mobile phones in general as well as in healthcare in particular (Dé, Pal, Sethi, Reddy, & Chitre, 2018; Gomez et al., 2012; Heeks & Wall, 2018; Jeffrey & Doron, 2013; Kleine, 2013; Lupton, 2014; Sein, Thapa, Hatakka, & Sæbø, 2019). While this body of work has the ability to challenge mainstream positions in medical mHealth research, the empirical evidence of the direct relationship between mobile technology and behaviours in low- and middle-income contexts remains circumstantial. For the purposes of this paper, two important gaps relating to the social consequences of technology diffusion are therefore worth discussing further.

The first gap is the relationship between social networks and the spread of mobile phones.[2] A small but growing number of studies indicate that the increasing use of mobile phones changes social network structures away from local friendship connections towards geographically dispersed kinship networks (Garretson, Fan, Mbatia, Miller, & Shrum, 2018; Horst & Miller, 2006; Miritello et al., 2013;

[2] We focus here primarily on the impact of mobile technology diffusion on social networks. For arguments regarding the role of the social context in shaping mobile phone diffusion, see e.g. Hahn and Kibora (2008); for arguments in the context of specific ICTD interventions, see e.g. Renken and Heeks (2018).

Palackal et al., 2011; Saramäki et al., 2014). Evidence on this point is provided by Riley (2018), who demonstrates how mobile money services in Tanzania facilitate the transfer of remittances during crises and help rural households to cushion the impact of rainfall shocks – but without spill-overs to other households in the same community. The study argues that the financial facilitation enabled by the mobile phone service could strengthen household-centric family networks at the expense of community-level support networks (Riley, 2018). More generally, the yet sparse research in this area suggests that mobile phone diffusion could affect social support networks in subtle ways by increasing the attention on one's closest contacts (Ling, 2008), which could create new divisions and inequalities among the rural poor. Whether and how mobile phone use intersects with the potential role of social support networks in treatment-seeking processes is therefore one of the focal areas of our study.

The second gap is the impact of mobile phone diffusion on healthcare access outside of specific health interventions. A nascent body of literature addresses the local emergence of phone-aided healthcare access and its consequences on behaviour, equity, and health outcomes. One of the first large-scale assessments of emerging mobile phone use is Khatun et al. (2014), who report that 1.9% of 2581 surveyed patients in Bangladesh contacted a health provider through a phone. A larger extent of health-related mobile phone use is observed by Hampshire et al. (2015), who surveyed 4626 youths aged 8–25 years across Ghana, Malawi, and South Africa, finding that around one-third of their respondents used a mobile phone for their own or someone else's illness in the 12-month period before their survey. These phones were used, among others, to contact family members for help or to find information online. However, like most studies in this area, the authors do not provide evidence on the treatment-seeking consequences of this emerging mobile phone use, for example patterns or timelines of healthcare access between people who use phones and people who do not.[3]

Our own research in this area has involved systematic assessments of the healthcare consequences of informal health-related mobile phone use in rural India and rural China. In Haenssgen and Ariana (2017), we analyse cross-sectional survey data from 800 villagers across both countries, detect a wide range of informal mobile phone use among 20% of the field site population in China and 7.5% in India, and find that these uses are linked to increased healthcare utilisation but also more delays to care – especially among more privileged segments of the rural population. Haenssgen (2018) expands this work with panel data from rural India, finding evidence consistent with the claim that the rural health system adapted to rapid mobile phone diffusion between 2005 and 2012 and increasingly excluded poor households without mobile phones from accessing care. However, and to the best of our knowledge, these are so far the only two low- and middle-income contexts in which detailed quantitative studies have tested the link between health-related mobile phone use and treatment-seeking behaviour. The present study therefore also aims to broaden our empirical knowledge towards other low- and middle-income contexts in Asia.

In short, our study contributes to the understanding of the healthcare consequences of socio-technological change in LMICs and their importance for technology-based health interventions. We will develop and explain the research hypotheses that guided our analysis in the following sub-section.

[3] A follow-up publication documents the informal health-related use of mobile phones among community health workers, suggesting that this bridged healthcare access gaps but could also put the health workers at a disadvantage, e.g. financially (Hampshire et al., 2017).

2.3. Hypotheses

What would we expect to happen in rural contexts where mobile phones are becoming increasingly prevalent? Firstly, not everyone in rural areas of LMICs is poor and marginalised. More privileged groups have a broader array of solutions (e.g. vehicles, money, social and professional networks) that facilitate their access to healthcare. Marginalised groups lack this diversity of means, which impedes their utilisation especially of formal (public and private) healthcare providers. We therefore hypothesise in the first instance that,

H1. Marginalised groups have fewer means to access formal treatment, driving them towards increased informal healthcare access.
H1a) Marginalisation links positively to informal healthcare access and negatively to formal healthcare access.
H1b) Marginalised groups experience longer delays to formal healthcare access.

Secondly, health-related mobile phone use can help individuals to overcome healthcare access constraints, opening a broader set of treatment options and sources of information – provided they are not among the most extremely marginalised groups. We argue that a similar effect arises from local social support networks, which, however, are distributed more equitably and provide facilitation for a larger group of marginalised people. In addition, our previous research and the literature lead us to hypothesise that the conspicuous performance of private healthcare providers and the signal of quality associated with user fees could drive health behaviours towards private rather than public health services (Dupas, 2011; Leventhal, Weinman, Leventhal, & Phillips, 2008):

H2. Social support and phone use help marginalised groups overcome constraints in accessing formal healthcare, but facilitation is directed towards private providers.
H2a) Facilitators like social support and phone use entail more and faster access to formal healthcare providers.
H2b) Private healthcare access increases disproportionately when marginalised groups involve social support and mobile phones.
H2c) Social support and phone use are less influential among non-marginalised groups.

Whether these hypotheses hold is to some extent subject to the local context of LMICs, considering the variability of health system, social, economic, and political structures and their relationship to local manifestations of marginalisation and health behaviour. We will accommodate the role of contextual variation through the comparative analysis of two sites with a comparable public health services structure but contrasting economic and infrastructural settings and different degrees of fragmentation and inclusion in their pluralistic health systems (we will also relate our findings to earlier research from rural India and rural China in the Discussion). We describe the methodology to test these hypotheses in the following section.

3. Material and methods

3.1. Research design and data collection

This paper arose from a broader social research project in the field of antimicrobial resistance (Haenssgen et al., 2018, research data available on UK Data Service via https://dx.doi.org/10.5255/UKDA-SN-853658), for which we selected Southeast Asia as a high-risk region (Ashley et al., 2014; Chereau, Opatowski, Tourdjman, & Vong, 2017). We chose the cases of Chiang Rai in Thailand and Salavan in Lao PDR because of their ethnic diversity (more than ten ethnic groups each), varied geographies (plateaus and mountainous areas), and both sites were among the poorest provinces in their respective countries (Coulombe, Epprecht, Pimhidzai, & Sisoulath, 2016; Office, 2016). In addition, both sites also had extensive yet porous borders with neighbouring countries, which often involved cross-border medical treatment especially from Lao PDR to Thailand (Apidechkul, Laingoen, & Suwannaporn, 2016; Bochaton, 2015; High, 2009; Sakboon, 2007). At the same time, Thailand as a middle-income country had a larger economy, more formalised healthcare provision, and better health outcomes than Lao PDR as a low-income country (World Bank, 2018b) – which provided opportunities for comparative analysis. We focused specifically on rural settings, where formal and informal health systems experienced greater infrastructural, human resource, financial, and regulatory constraints, and where economic, social, and spatial marginalisation were more widespread. Among the rural population, we considered specifically adults (aged 18 years and above). The total rural adult population in Chiang Rai was 522,000; the rural adult population in Salavan was 190,000 (Lao Statistics Bureau, 2015, 2016; National Statistical Office, 2012).

We collected cross-sectional survey data between November 2017 and May 2018 in a three-stage stratified cluster random survey design.[4] Stage 1 comprised the random selection of six primary sampling units (PSUs) in five purposively sampled districts in each site (see map in Fig. 1). The 30 selected PSUs per site corresponded to 69 administrative villages in Chiang Rai and 65 in Salavan. In Stage 2, we enumerated all residential dwellings in each PSU using satellite maps provided by *Google Maps* and *Bing Maps* (Haenssgen, 2015; Google Inc., 2017; Microsoft Corporation, 2017). From the approximately 30,000 enumerated structures, we selected 5% but at least 30 houses per PSU in an interval sample to ensure spatial representativeness in each PSU (with random starting points). In Stage 3, all household members in the selected dwellings were enumerated in the field, and one adult respondent was selected randomly for every five eligible household members.[5] The randomisation was implemented through tablets running the survey software *SurveyCTO* (Dobility Inc, 2017). The ensuing sample included 1158 villagers in Chiang Rai and 983 in Salavan. Treatment-seeking behaviour was recorded if a respondent or a child under their supervision experienced an acute illness or accident-related injury in the two months prior to the survey. We recorded 608 such illness episodes in Chiang Rai and 356 in Salavan.

The survey instrument was a 45-minute health behaviour questionnaire administered face-to-face in the local languages (Thai and Lao). The questionnaire was developed locally based on earlier qualitative research on health behaviour in Southeast Asia, supported by field testing and cognitive interviewing (cognitive interviews not reported here; Willis, 2015). Language difficulties arose due to the ethnic diversity in the field in 228 instances, which were resolved by recruiting local translators within the villages.

The surveys were implemented by locally recruited field teams that comprised six to eight field investigators plus two survey supervisors. The survey supervisors monitored the recruitment and data collection process, a project research officer conducted additional spot checks and provided ongoing refresher training for the survey team; and the principal investigator monitored the data collection process and data quality remotely via *SurveyCTO* monitoring tools. In less than 20 instances, incomplete or corrupted data required field investigators and survey supervisors to revisit a respondent.

3.2. Variables and data

The questionnaire covered demographic and socio-economic information, knowledge and attitudes about local healthcare providers and antibiotics, and treatment-seeking behaviour (see supplemental material). The main variables of interest in this study related to marginalisation, treatment-seeking behaviour, and its determinants (see Table 1 for summary statistics; variable descriptions are provided in Appendix Table A1).

Our operationalisation of marginalisation had three dimensions and five indicators. "Social marginalisation" was assessed through two indicators. The first indicator was education, where we defined a person to be marginalised if they had received no formal education at all (as opposed to at least one completed year of schooling). The second social marginalisation indicator was whether the ethnic group of the respondent represented less than 20% of the population in the village. The logic of this dimension was that an individual belonging to an ethnic minority group might have been more likely to face impediments in accessing healthcare if this group was also a minority in the same village. We defined the second dimension of "economic marginalisation" as individuals belonging to the bottom household wealth quintile in their respective site (i.e. Chiang Rai or Salavan). The third dimension was "spatial marginalisation," which we assessed with two indicators on the village level. The first indicator was whether the travel time to the nearest town exceeded more than 30 min by car. The second indicator was a semi-quantitative assessment of village remoteness by the survey team (peri-urban, rural, remote), whereby we defined "remote" villages as marginalised.[6]

The five indicators of marginalisation accounted for up to 41% of the sample in each site and they were weakly correlated with each other (see Appendix Table A2).[7] We aggregated these five indicators – comprising both absolute and relative forms of marginalisation on the individual, household, and village level – into an overall marginalisation index ranging from 0 [no indication of marginalisation] to 1 [all five indicators of marginalisation present]. We were conscious that these indicators were only proxies of a more complex and relational concept (which also has historical and political components), but they nonetheless enabled a first and consistent glimpse into the relationship between marginalisation and treatment-seeking behaviour.

Aside from marginalisation, we captured treatment-seeking processes for those respondents who indicated an illness or injury

[4] The research was reviewed and approved by [anonymised for blind peer review], the Mae Fah Luang University Research Ethics Committee on Human Research in Thailand (Ref. REH 60099), and the National Ethics Committee for Health Research in Lao PDR (Ref. NEHCR 074). We received permission to access the study villages from local security authorities and villages leaders, obtained informed verbal consent from all study participants, and compensated the survey respondents with small financial token of appreciation equivalent to GBP 1.00.

[5] A household was defined as a residential unit that shares a kitchen; eligible members were those who had typically resided in this household for at least six months prior to the survey and who were available for an interview.

[6] An alternative analysis could consider the role of different degrees of advantage rather than foregrounding conditions of marginalisation, in which case for instance continuous variables underlying the marginalisation indicators can be analysed as control variables (i.e. completed years of education instead of indicating villagers who are deprived of any formal education). Preliminary insights from such an analysis (see Supplemental Material) suggest for instance that the representation of the village ethnicity appears to be positively associated with informal healthcare access, particularly noticeably in Chiang Rai. Further research can explore such broader determinants of healthcare access, as has been helpfully suggested by an anonymous reviewer.

[7] The strongest correlations existed between the two spatial indicators with a correlation coefficient of 0.59 (significantly different from zero at $p < 0.01$), between wealth and education (0.35, $p < 0.01$), and wealth and remoteness (0.19, $p < 0.01$). Hypothesis test using Šidák adjustment, taking into account the number of hypothesis tests performed in pairwise comparison.

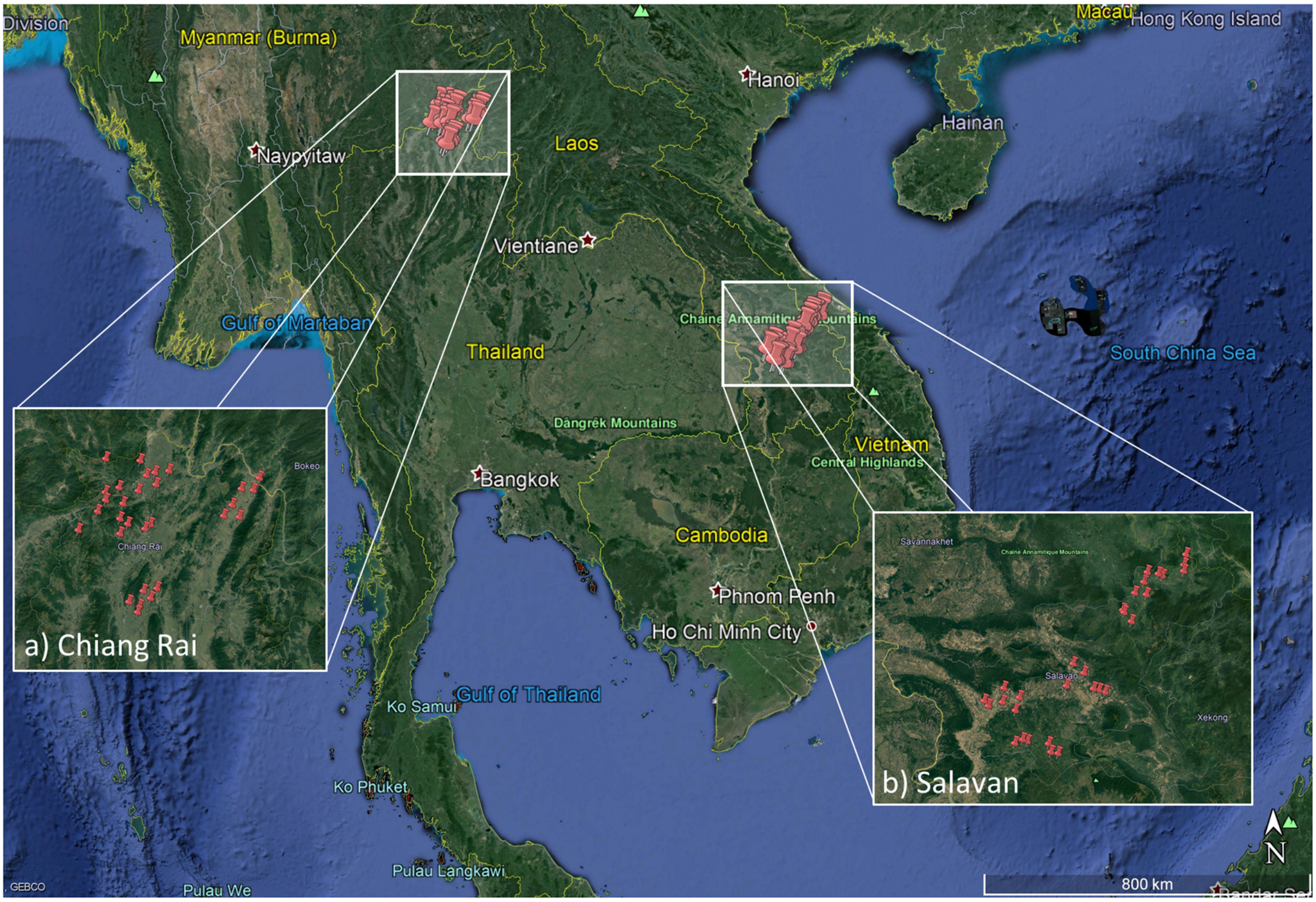

Fig 1. Field Sites and Sampled Villages in Thailand and Lao PDR. Source: Haenssgen et al. (2018).

in the past two months (and only those who had recovered again by the time of the survey). Each illness episode was captured as a sequence of "steps" from the moment when a discomfort or injury was detected. We recorded treatment decisions and duration of each of these steps, from which we could calculate the total illness duration as well as the various healthcare providers that the respondents accessed during the illness episode.

The principal influences on treatment-seeking behaviour of interest were the involvement of support networks and mobile phones use during an illness. Illness-related mobile phone use was assessed at every step of the treatment-seeking process (helping to gauge which practices took place before and after different types of healthcare access). The corresponding question in the survey questionnaire (see supplemental material, Question 15.5 k and following) was "Did you or anybody else use a mobile phone during this stage in connection with your condition?" together with the specific purpose/s and utilised mobile phone function/s. Based on previous health-related mobile phone research, the range of captured uses did not only pertain to calls to healthcare providers but also included non-call forms of use such as reminders and non-medical interactions such as summoning a taxi. Illness-related social support involved any person who provided any kind of help face-to-face and covered the complete illness episode to reduce cognitive demands on the respondent. The corresponding question in the survey questionnaire (Question 15.7 and following) was "Was anybody of your personal relationships involved in providing advice or help during the illness?" together with their relationship status as well as the various forms of support provided by each person. As Appendix Table A3 shows, these indicators overlapped partially. Fig. 4 in Section 5.2 illustrates the varied forms of health-related phone use and social support that were captured in the survey.

3.3. Analysis

We followed the empirical strategy of (Haenssgen & Ariana, 2017) and (Haenssgen & Ariana, 2017). We first contextualised the research using macro-level secondary data and literature. We then analysed the survey data descriptively to document living conditions, patterns of marginalisation, treatment-seeking behaviour, and the various ways in which people use mobile phones and activate their social support networks during an illness. All descriptive statistics were weighted using census data to be representative for the rural populations of Chiang Rai and Salavan (Heeringa, West, & Berglund, 2010). As part of the descriptive statistical analysis, we examined whether people with health-related mobile phones use and social support were less marginalised than people who did not experience such support, testing for statistical differences with Pearson X^2 tests for binary indicators of marginalisation and two-sided t-tests for the total marginalisation index.

To test our research hypotheses, we estimated healthcare access models for formal (public and private) and informal healthcare. Because this analysis took place on the illness level, only a subset of the total sample was included, namely those respondents who reported an acute illness or accident-related injury experienced by themselves or a child under their supervision in the two months prior to the survey (964 illness episodes among 2141 respondents). Owing to the different health systems in the field sites, we stratified the analysis along the sub-samples of Chiang Rai (n = 608) and Salavan (n = 356) before analysing the pooled

Table 1
Sample Description.

Variable (Unit)		Total			Chiang Rai			Salavan		
		n	Mean	Std. Dev.	n	Mean	Std. Dev.	n	Mean	Std. Dev.
Controls	Female (0/1)	2141	0.55	(0.50)	1158	0.57	(0.50)	983	0.53	(0.50)
	Age (years)	2141	46.08	(16.40)	1158	51.99	(15.05)	983	39.12	(15.16)
	Household size (no. of members)	2141	4.81	(3.13)	1158	3.46	(1.84)	983	6.39	(3.58)
	Employment status: unemployed (0/1)	2140	0.15	(0.36)	1157	0.22	(0.42)	983	0.06	(0.24)
Marginalisation	Education (0/1)	2141	0.30	(0.46)	1158	0.27	(0.44)	983	0.33	(0.47)
	Ethnic Minority (0/1)	2141	0.09	(0.29)	1158	0.08	(0.27)	983	0.11	(0.31)
	Wealth (0/1)	2141	0.30	(0.46)	1158	0.22	(0.42)	983	0.38	(0.49)
	Travel time (0/1)	2139	0.32	(0.47)	1158	0.25	(0.43)	981	0.41	(0.49)
	Remoteness (0/1)	2139	0.20	(0.40)	1158	0.11	(0.31)	981	0.32	(0.47)
	Marginalisation index (0–1)	2139	0.24	(0.24)	1158	0.19	(0.24)	981	0.31	(0.24)
Healthcare preferences	Shops selling medicine (0/1)	2141	0.46	(0.50)	1158	0.69	(0.46)	983	0.19	(0.39)
	Traditional healers (0/1)	2141	0.48	(0.50)	1158	0.34	(0.47)	983	0.65	(0.48)
	Pharmacies (0/1)	2141	0.55	(0.50)	1158	0.53	(0.50)	983	0.57	(0.50)
	Private clinics/hospitals (0/1)	2141	0.64	(0.48)	1158	0.83	(0.37)	983	0.42	(0.49)
	Public primary care (0/1)	2141	0.83	(0.37)	1158	0.88	(0.32)	983	0.78	(0.42)
	Public hospitals (0/1)	2141	0.94	(0.23)	1158	0.95	(0.22)	983	0.94	(0.24)
Characteristics of illness episodes	Illness episode of child (0/1)	964	0.23	(0.42)	608	0.18	(0.39)	356	0.31	(0.46)
	Self-rated severity (1,2,3)	964	1.72	(0.74)	608	1.64	(0.76)	356	1.85	(0.67)
	Duration (days)	964	7.53	(10.52)	608	7.64	(11.92)	356	7.35	(7.59)
	Process steps (number)	964	2.27	(1.11)	608	2.13	(1.10)	356	2.51	(1.09)
	Public healthcare (0/1)	964	0.41	(0.49)	608	0.32	(0.47)	356	0.58	(0.49)
	Private healthcare (0/1)	964	0.22	(0.42)	608	0.26	(0.44)	356	0.16	(0.37)
	Informal healthcare (0/1)	964	0.09	(0.29)	608	0.11	(0.31)	356	0.06	(0.25)
	Health-related phone use (0/1)	964	0.20	(0.40)	608	0.24	(0.43)	356	0.12	(0.33)
	Health-related social support (0/1)	964	0.71	(0.45)	608	0.70	(0.46)	356	0.74	(0.44)
Public access	Duration until access (days)	398	2.21	(9.52)	192	2.96	(13.54)	206	1.51	(1.94)
	Steps until access (number)	398	1.69	(0.67)	192	1.67	(0.75)	206	1.71	(0.58)
	Phone use before/during access (0/1)	398	0.19	(0.39)	192	0.26	(0.44)	206	0.13	(0.34)
Private access	Duration until access (days)	216	1.72	(0.78)	159	1.74	(0.73)	57	1.67	(0.89)
	Steps until access (number)	216	2.26	(6.80)	159	2.51	(7.77)	57	1.58	(2.58)
	Phone use before/during access (0/1)	216	0.21	(0.41)	159	0.25	(0.44)	57	0.09	(0.29)
Informal access	Duration until access (days)	88	1.25	(2.28)	65	1.08	(2.16)	23	1.74	(2.56)
	Steps until access (number)	88	1.57	(0.72)	65	1.49	(0.69)	23	1.78	(0.80)
	Phone use before/during access (0/1)	88	0.13	(0.33)	65	0.14	(0.35)	23	0.09	(0.29)

Notes. Unweighted statistics.

sample (n = 964). Models that estimated the probability of healthcare access drew on the sample of all respondents, whereas models estimating the delay to access used the sub-sample of responses that accessed the respective type of care (e.g. the delay to public healthcare cannot be estimated for respondents who did not access any public provider, as indicated in the rows "public access," "private access," and "informal access" and their respective sample sizes in Table 1).

We estimated multi-level regression models of healthcare access because of the hierarchical structure of our data (i.e. illness episodes nested in individuals, nested in villages, nested in districts, nested in sites). Owing to the nature of the dependent variables, we estimated multi-level logistic regression models for the probability of accessing healthcare, and multi-level negative binomial models for the duration until healthcare access.[8] We estimated 3-level models for the respective site samples (individual, village, and district level), and 4-level models for the pooled sample (as before, plus site level). The multi-level specification thereby enabled us to correct the mean estimates of individual determinants of healthcare access through village-, district-, and site-level random effects (Rabe-Hesketh & Skrondal, 2012). The three-level specifications for the (1) logistic and (2) negative binomial random intercept regression models were:

$$\text{logit}\left[P\left(y=1|x_{ijk},\zeta_{jk}^{(2)},\zeta_{k}^{(3)}\right)\right]=\left(\zeta_{jk}^{(2)}+\zeta_{k}^{(3)}\right)+\beta x_{ijk} \quad (1)$$

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

In both models, subscripts i, j, and k denote individuals, villages, and districts; random intercept terms are denoted by $\zeta_{jk}{}^{(2)}$ and $\zeta_k{}^{(3)}$; and the matrix of covariates is denoted by $\boldsymbol{x}_{ijk}$. We also estimated all these models in single-level specifications (standard errors calculated with bootstrap estimation using 5000 replications, adjusted for clustering at village level). For consistency and comparability, we reported multi-level models wherever possible, even if variance component tests indicated that the multi-level specification did not add value over single-level models.

The covariates included control variables for gender, age, household size (based on household roster information), employment status (employed/unemployed, based on manually coded occupations including "Unemployed," "Retired," or "Student"), whether the illness was experienced by the respondent or a child under their supervision, and the self-rated severity of the episode (Leventhal et al., 2008). For Hypothesis 1, the main independent variables of interest were the individual marginalisation indicators and the aggregate marginalisation index. According to Hypotheses 1a and 1b, we expected positive associations between marginalisation and the probability of accessing informal healthcare (and/or

[8] We also estimated multi-level Poisson regression models for the number of steps until a healthcare provider was reached. However, these models were statistically insignificant and were omitted from reporting.

negative associations with public and private healthcare), and, conversely, negative associations between marginalisation and the delay until informal healthcare providers were reached (and/or positive associations with public and private healthcare).

For Hypothesis 2, we limited the analysis of marginalisation to the aggregate index to reduce complexity and considered health-related mobile phone use and social support as main variables of interest. Positive associations between these variables and public/private healthcare access (and negative associations for access delays) would be consistent with Hypothesis 2a irrespective of the degree of marginalisation of the patient. However, Hypotheses 2b and 2c required us to gauge the role of mobile phones and social support in relation to marginalisation. We were therefore especially interested in the interactions between marginalisation on the one hand, and health-related mobile phone use (PHONxMARG) and social support (SUPPxMARG) on the other hand. Positive interaction terms would then indicate that a combined effect of being marginalised and using phones for health-related issues is associated with a higher probability of access or a longer access delay.

4. Case context

This section introduces the development and health system context of Thailand and Lao PDR, and the relative position of Chiang Rai and Salavan therein. An overview of main indicators is presented in Table 2 together with reference values for LMICs. Latest available data from the World Bank showed relatively higher socio-economic indicators in Thailand. Extreme poverty at USD 1.90/day (in purchasing power parity) in Thailand had been near zero for more than a decade and 8% of the population lived below USD 5.50/day (i.e. the standard poverty line in upper-middle-income countries), while Lao PDR reported 23% and 85%, respectively. These differences were also reflected in other indicators, as Lao PDR exhibited relatively lower rates of literacy, access to basic sanitation, and mobile subscription teledensity. Within the two countries, Chiang Rai and Salavan were comparatively poor provinces. Salavan's poverty headcount ratio in 2015 was estimated at 48%, making it the poorest province in Lao PDR (Coulombe et al., 2016). Chiang Rai was situated in Thailand's poorest region, whose average monthly household income was 30% below the national average of THB 26,915 (approx. GBP 650) (Office, 2016). Both sites had a majority rural population – 89% of 397,000 inhabitants in Salavan and 61% out of 1.2 million in Chiang Rai (Lao Statistics Bureau, 2015; National Statistical Office, 2012).

The structure of the public health service delivery in Thailand and Lao PDR is comparable on paper, but the differences in practice are considerable. Both systems had a hospital at the provincial level to oversee health services (in our case, Chiang Rai Prachanukroh Hospital and Salavan Provincial Hospital). Service delivery on the district level was coordinated by the District Health Office (covering 50,000 people on average in Thailand and 30,000–70,000 people in Lao PDR), on the sub-district level by primary care units (covering on average 5000 people in Thailand and 7000 people in Lao PDR), and on the village level through village health volunteers (Akkhavong et al., 2014; Jongudomsuk et al., 2015). However, the macro data presented in Table 2 indicated more extensive funding and more favourable health outcomes in Thailand compared to Lao PDR. Thai per-capita health expenditure was more than four times higher than Lao PDR's, the latter of which comprised 46% out-of-pocket expenditure from households and 17% external expenditure (Thailand: 12% and 0%, respectively). These figures reflected on health outcomes (together with the aforementioned differences in poverty and infrastructural development): Thai life expectancy at birth was eight years higher and the under-five mortality rate was 53 deaths per 1000 live births lower than in Lao PDR.

Table 2
Development and Health Indicators.

	Thailand	Lao PDR	LMIC average
Gross domestic product per capita (US$ in purchasing power parity)	$17,910 (2017)	$7038 (2017)	$11,013 (2017)
Poverty rate (US$1.90/day, in purchasing power parity)	0% (2017)	23% (2012)	12% (2015)
Poverty rate (US$5.50/day, in purchasing power parity)	8% (2017)	85% (2012)	55% (2015)
Literacy rate (% of adult population)	93% (2015)	85% (2015)	84% (2016)
Mobile phone subscriptions (per 100 people)	176 (2017)	54 (2017)	99 (2017)
Access to at least basic sanitation (% of population)	95% (2015)	73% (2015)	62% (2015)
Total health expenditure (US$ per capita in purchasing power parity)	$635 (2016)	$155 (2016)	$534 (2016)
Out-of-pocket health expenditure (US$ per capita in purchasing power parity)	$77 (2016)	$72 (2016)	$219 (2016)
External health expenditure (US$ per capita in purchasing power parity)	$1 (2016)	$28 (2016)	$7 (2016)
Births attended by skilled healthcare staff (% of all registered births)	99% (2016)	64% (2017)	79% (2016)
Life expectancy at birth (years)	75 (2017)	67 (2017)	71 (2017)
Under-5 mortality rate (per 1000 live births)	10 (2017)	63 (2017)	43 (2017)

Source: ITU (2019a); World Bank (2018b).
Notes. Values in parentheses are year of latest available data.

Thailand has been able to achieve progress with ambitious universal healthcare policies especially from 2002 onwards, which involved the establishment of public primary care units in every sub-district (staffed with nurses) and a reduction of patients' co-payments to a maximum of THB 30 (GBP 0.75) per public healthcare visit (Jongudomsuk et al., 2015; Rieger, Wagner, & Bedi, 2017). Whereas indicators such as skilled birth attendance (Table 2) suggest that access to formal healthcare services was high, and although nominally every Thai citizen (and their children) with a national ID card was entitled to the low-cost and comprehensive primary and ambulatory care services, effective coverage of the universal healthcare policies had remained patchy (Neelsen, Limwattananon, O'Donnell, & van Doorslaer, 2019; Sumriddetchkajorn et al., 2019): Neelsen et al. (2019), Apidechkul et al. (2016), and Sakboon (2007) documented that especially informal workers and undocumented ethnic groups were discriminated and remain excluded from the public healthcare system (requiring continued out-of-pocket expenses to utilise public healthcare services), and analyses of health shocks have shown that people have continued to depend at least partially on social support to cover healthcare expenditure (Neelsen et al., 2019).

The modernisation and pharmaceuticalisation trends in the Thai health system have also gradually (though yet incompletely) shifted healthcare provision from traditional healing to public healthcare, complemented by an extensive private healthcare sector that contributed to persistent out-of-pocket expenditure in Thailand (still USD 77 per capita as shown in Table 2) and that accounted for an estimated 14% of formal outpatient visits (Bennett & Tangcharoensathien, 1994; Chuengsatiansup, Sringernyuang, & Paonil, 2000; Jongudomsuk et al., 2015; Neelsen et al., 2019; Tangcharoensathien, Patcharanarumol, Kulthanmanusorn, Saengruang, & Kosiyaporn, 2019). In Chiang Rai, private healthcare was provided by large private hospitals and registered private clinics operated by trained doctors, but also through unregistered clinics with doctors and nurses operating informally within their local communities, and through pharmacies with various degrees of compliance to government registration requirements – all of which tended to be available primarily in urban areas and larger villages. Nevertheless, informal healthcare still remained accessible and relatively more affordable especially in remote rural areas, including faith healers and traditional herbalists (providing treatment for free or for a small fee/donation) as well as grocery stores selling over-the-counter and at times (illegally) prescription pharmaceuticals (Haenssgen et al., 2018).

Despite growing formalisation, inclusion, and decentralisation, the Lao health system has remained chronically under-funded and under-staffed (Akkhavong et al., 2014; Ministry of Health, 2013; Qian et al., 2016).[9] Market-based since 1995, the financing model of the Lao healthcare system has fuelled out-of-pocket expenditure, while social protection schemes to improve inclusion and service coverage have made only slow progress (Akkhavong et al., 2014). For example, within southern Lao PDR, costs for outpatient consultation at public healthcare facilities had been capped to LAK 5000–20,000 depending on the type of primary, secondary, or tertiary care (GBP 0.50–2.00, as in Thailand upon production of national ID), but these co-payment ceilings did not cover medicines, which accounted for as much as 60% of out-of-pocket health expenditure (Akkhavong et al., 2014; WHO, 2019a). The Lao government has only in 2019 expanded this scheme to limit co-payments for medical treatment into a National Health Insurance, with priority groups like pregnant women being fully exempt from co-payments (WHO, 2019a). During our survey period, a financing and service gap had therefore remained, which was partly covered (or, some might argue, perpetuated) through external support like clinics run by non-governmental organisations, but also by the common model of public healthcare workers operating private clinics after or during their official working hours (Akkhavong et al., 2014).

Continuing gaps in formal healthcare provision have also provided space for traditional medicine. For instance, Sydara et al. (2005) found that 77% of their survey respondents in Champasak (Salavan's neighbouring province) used traditional medicine either in isolation or in combination with modern medicines. Contrary to Chiang Rai, Lao National Health Accounts indicated that traditional healers contributed for a substantial share of out-of-pocket expenditures, with cash and in-kind payments being equivalent to 77% of out-of-pocket payments for pharmaceuticals (Akkhavong et al., 2014). However, as in Chiang Rai, the role of traditional healers appeared to be declining – a recent study by Mayxay et al. (2013) documented that only 1.4% of patients with respiratory infections across rural and urban Lao PDR consulted a traditional healer in the first instance (esp. in situations where no other healthcare provider was available). Informal healthcare in Lao PDR also involved to a greater extent illegally operating and variously qualified doctors (e.g. ex-military doctors) and itinerant vendors who sell medicines procured from urban areas in villages (Akkhavong et al., 2014; Mayxay et al., 2013). Furthermore, where healthcare delivery gaps persisted in rural border areas, another avenue that was less pronounced in Chiang Rai is cross-border treatment seeking. However, the required costs and social relationships made cross-border treatment a less tangible option for the most marginalised among the rural population (Bochaton, 2015).

In short, despite their comparable public health services structure, Chiang Rai and Salavan had contrasting economic and infrastructural contexts and also exhibited different degrees of fragmentation and inclusion in their pluralistic health systems. These differences were partly reflected in the better health outcomes of Thailand, but marginalised groups in both Chiang Rai and Salavan remained prone to exclusion from formal healthcare services. At the same time, fine-grained and dependable data about healthcare utilisation on the community level are not typically available, especially with respect to the wide diversity of private and informal healthcare providers. Our survey data in the following section therefore also provided localised information about healthcare preferences and access patterns specifically in rural Chiang Rai and Salavan.

5. Descriptive statistical analysis: healthcare, marginalisation, and treatment-seeking behaviour

5.1. Living conditions and patterns of marginalisation

The village characteristics within the study sites are summarised in Table 3, including census data from 2010 (Chiang Rai) and 2015 (Salavan) for reference. An average village in the Chiang Rai sample had an estimated population of 582 inhabitants, whereas Salavan villages were relatively smaller with 453 inhabitants. The Chiang Rai villages also tended to have smaller households, a higher share of female dwellers, and a lower share of people in working age compared to Salavan. Mobile phones were owned by most households in the study sites: the survey data indicated a household ownership rate of 97% per village in rural Chiang Rai and 75% per village in Salavan.

The most common dimension of marginalisation in Chiang Rai was education with 25% of the rural population, whereas 44% of the rural Salavan population was spatially marginalised (travel time to nearest city). The average degree of marginalisation in the survey villages is depicted in Fig. 2. The Chiang Rai sample of 69 administrative villages had comparatively low rates of marginalisation, with 48% of villages having an average marginalisation index of less than 0.1 and 88% less than 0.5. In Salavan, only 20% of 65 villages had an average marginalisation of less than 0.1 and 78% less than 0.5. While the average marginalisation was higher in Salavan, it was also less polarised: the three worst-performing villages in Salavan had an average index of 0.71; compared to 0.78 in the Chiang Rai sample.

These patterns were similar on the individual level. The average marginalisation index in Chiang Rai was with 0.18 significantly lower than the average index of 0.28 in Salavan ($p < 0.01$), and the share of respondents with zero marginalisation in Chiang Rai was with 54% nearly twice as large as the share of 29% in Salavan. Yet, 6% of the Chiang Rai sample had an index score of 0.8 or 1.0, compared to 5% in Salavan, indicating that multidimensional marginalisation existed in both sites.

These patterns suggested that, if marginalisation in rural Chiang Rai was present, it was more likely to be multidimensional. In rural Salavan, marginalisation was more common but also more evenly distributed across the population.

5.2. Navigating healthcare landscapes

Both field sites had a wide range of formal and informal healthcare providers. Among people who experienced a recent illness or accident (45% of the total sample), the preferred healthcare providers in both sites were public hospitals and primary care units (96% and 91% in Chiang Rai, 94% and 74% in Salavan; light-blue bars in Fig. 3).[10] However, people's preferences bore only remote resemblance to actual healthcare choices during acute illnesses and injuries (dark-blue bars in Fig. 3). The largest share of healthcare

[9] These general problems were yet more accentuated in Salavan, which exhibited for instance one of the lowest healthcare worker density in Lao PDR (Sa-angchai et al., 2016).

[10] We collected this information for every participant in the survey. The expressed preferences on the individual level (as opposed to the sub-sample of people who had a recent illness) were not substantially different; they had the same rank order and differed by between zero and six percentage points.

Table 3
Characteristics of Survey Villages Compared to Provincial Average.

	Survey data		Census data	
	Chiang Rai	Salavan	Chiang Rai (in 2010)	Salavan (in 2015)
Village size	582[a]	453[a]	594[b]	369[b]
Household size	3.5	5.7	3.0	5.9
Female population share	51.4%	46.2%	50.0%	50.1%
Dependency ratio[c]	0.5	0.9	0.4	0.6[d]
Households owning mobile phones	96.7%[e]	75.4%[e]	86.4%	81.6%

Source: Primary survey data, National Statistical Office (2012), Lao Statistics Bureau (2016).
Notes. For each site, survey results represented simple average of administrative villages (69 in Chiang Rai, 65 in Salavan), wherein individual population-weighted statistics were aggregated on the village level.
a. Estimated based on enumerated household members and residential structures in each village, adjusted by share of incorrectly identified housing structures.
b. For comparability, village numbers based on data from National Geospatial-Intelligence Agency (2017).
c. Non-working-age population divided by working-age population (15–64 years).
d. Lao PDR national average for rural areas.
e. Average of village-level mobile phone diffusion. On the household level, the diffusion of mobile phones was 96.3% in Chiang Rai and 80.7% in Salavan.

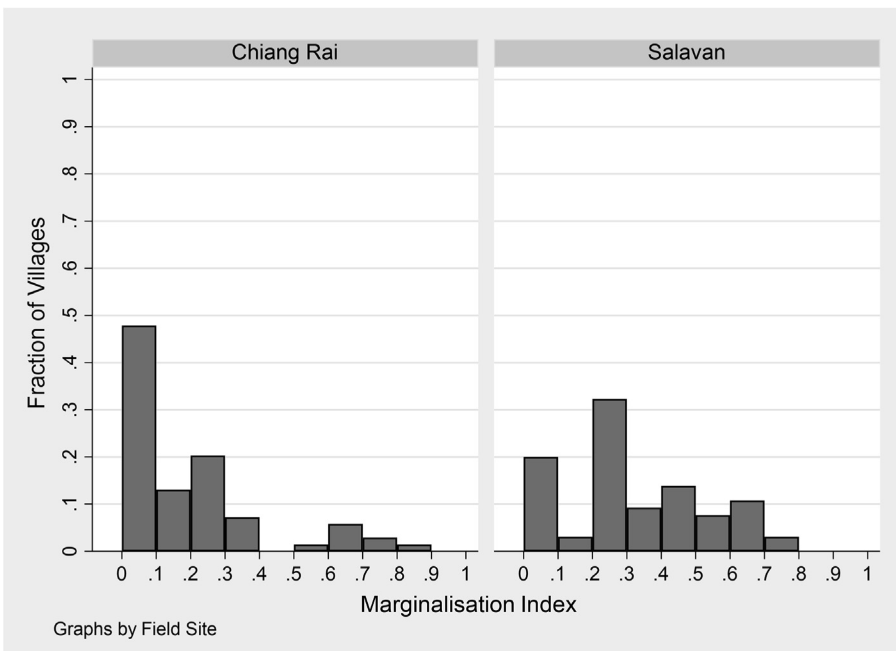

Fig. 2. Village-Level Marginalisation by Field Site. *Notes.* Sub-PSU level (i.e. administrative villages). Chiang Rai: n = 69; Salavan: n = 65. Individual population-weighted statistics were aggregated on the village level. Marginalisation defined as multiple dimensions of disadvantage that situate people at economic, social, and spatial margins of society. Approximated through aggregate index comprising binary indicators of education (zero years), ethnic minority (<20% of village ethnicity), wealth (bottom quintile of household wealth), travel time (>30 min to nearest town), and village remoteness.

utilisation in Chiang Rai involved private clinics (23% of illness episodes), followed by public primary care units (18%) and public hospitals (15%). In Salavan, 40% of the illness episodes involved a public primary care unit, 20% involved a public hospital, and 10% a pharmacy.[11] Patients thus navigated pluralistic healthcare systems in both sites.

Social support networks and mobile phones intersected treatment-seeking processes routinely. With 69% of all treatment-seeking processes in Chiang Rai and 70% Salavan, social support was common in both sites. Support networks involved especially household members and relatives (91% of social support cases in Chiang Rai, 97% in Salavan), while social contacts outside the extended family were only activated in 10% of all cases in both sites. The main reasons for support networks to be involved (left panel in Fig. 4) were the provision of healthcare or attending to the patient. Other common tasks were bringing food and supplies for the patients (esp. in Chiang Rai, e.g. if patients were hospitalised), helping with transport and household chores, or bringing medicine to the patient. One in four contacts in Chiang Rai and one in three in Salavan also specifically offered health-related advice. In the context of Salavan, where marginalisation was more widespread and health expenditure occurred more often out of pocket, social contacts also provided money relatively frequently (26% of all cases).

Health-related mobile phone use was less frequent than the involvement of social support, taking place in 26% of all illness episodes in Chiang Rai and in 15% in Salavan (or 34% and 28%, if general conversations about health were included in the indicator). The right panel in Fig. 4 shows the range of health-related purposes to which mobile phones were being put - by the patients themselves or somebody else on their behalf. The most common purposes included advice and diagnosis (e.g. by calling a family member or looking symptoms up on the Internet) and reassuring and updating family members about the progression of the illness.

[11] The disjunction between preferences and choices may be partly due to the exclusion of chronic conditions from the treatment-seeking patterns.

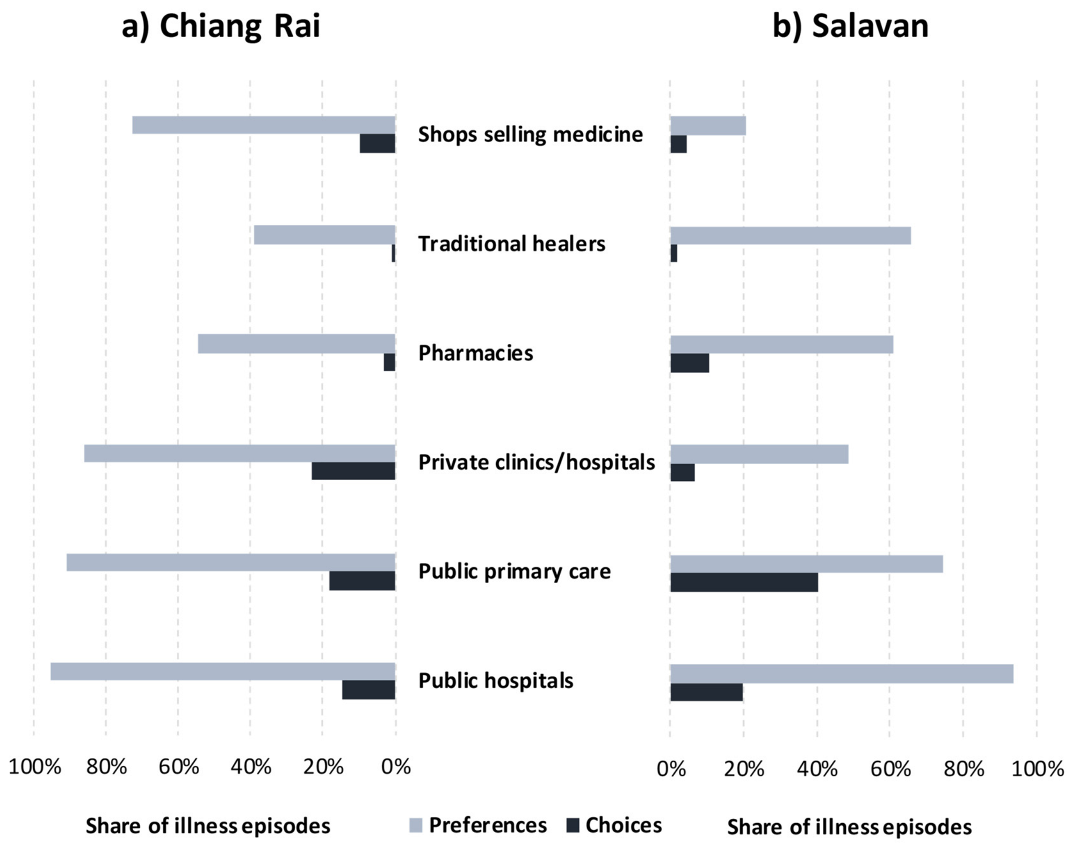

Fig. 3. Reported Healthcare Provider Preferences and Actual Healthcare Choices During Illness. *Notes.* Illness-episode level (healthcare preferences on individual level including people without illness episodes were not systematically different from illness-level response pattern). Multiple responses per instance possible. Population-weighted statistics, accounting for complex survey design. Chiang Rai: n = 608; Salavan: n = 356.

Phone calls were the main channel for communication and were used in more than 90% of all cases of health-related mobile phone use in both sites, followed by mobile data in 28% of cases in Chiang Rai and 12% in Salavan. Only a small minority of cases involved text messages or other functions like reminders. A further observation during our field research was that villagers in Salavan typically left their mobile phones at home when they left their house for agricultural work, thereby rendering it essentially akin to a fixed-line phone.

Although they appeared to fulfil slightly different purposes, the spectrum of uses to which social support and mobile phones were put suggested that they played a facilitating role in people's treatment-seeking processes. But were more privileged rural groups also more likely to experience facilitation from social support networks and through mobile phones? Fig. 5 examines if this was the case by plotting the differences in marginalisation between people who did and who did not report health-related mobile phone use and social support. Negative values (bars pointing to the right) indicate that beneficiaries of phones/support were less marginalised. The figure demonstrates in the bottom panel that the relatively small group of health-related phone users was systematically less marginalised than non-users; the difference of which was statistically significant across several indicators in Salavan. In contrast, people who activated health-related social support networks were not clearly more or less marginalised. These data suggest that mobile phones were more likely to be used among privileged groups, whereas social support had a more egalitarian character. However, less than 15% of all mobile phone uses did *not* involve additional face-to-face social support (or up to 4% of all illness episodes), which suggested that an inequitable distribution of mobile phones could only have a limited impact (see Appendix Table A3).[12] The next section examines in detail how social networks and mobile phones were linked to treatment-seeking patterns.

6. Regression analysis: determinants of healthcare access and delays

6.1. Marginalisation

We first considered the role of marginalisation and its individual dimensions as determinants of (1) healthcare access and of (2) the duration until healthcare providers were reached. In Table 4,

[12] This assumes that mobile phones and social support networks are substitutes rather than complementary in their possible role as facilitators. This assumption is consistent with the analysis in Section 6. Further exploratory analysis to assess the extent of such possible substitution included estimating the regression models in Section 6.2 separately by phone use and social support. The signs of the point estimates for social support and phone use were consistent in the majority of cases (all models except informal healthcare in Chiang Rai and Salavan). While the non-interacted coefficients for phone use and social support were independently statistically significant in the cases of public healthcare in Salavan and public/private healthcare access in the pooled sample, their interaction with marginalisation was only consistent and statistically significant for access to public healthcare in the pooled sample. However, interactions between phone use and social support (independent of marginalisation) were not statistically significant in all cases except private healthcare access in Salavan and public healthcare access in the pooled sample (at the ten percent level), and no three-way interaction between phone use, social support, and marginalisation was statistically significant. The evidence therefore points towards a mild degree of substitution. The main results of these regression models are included in the Supplemental Material.

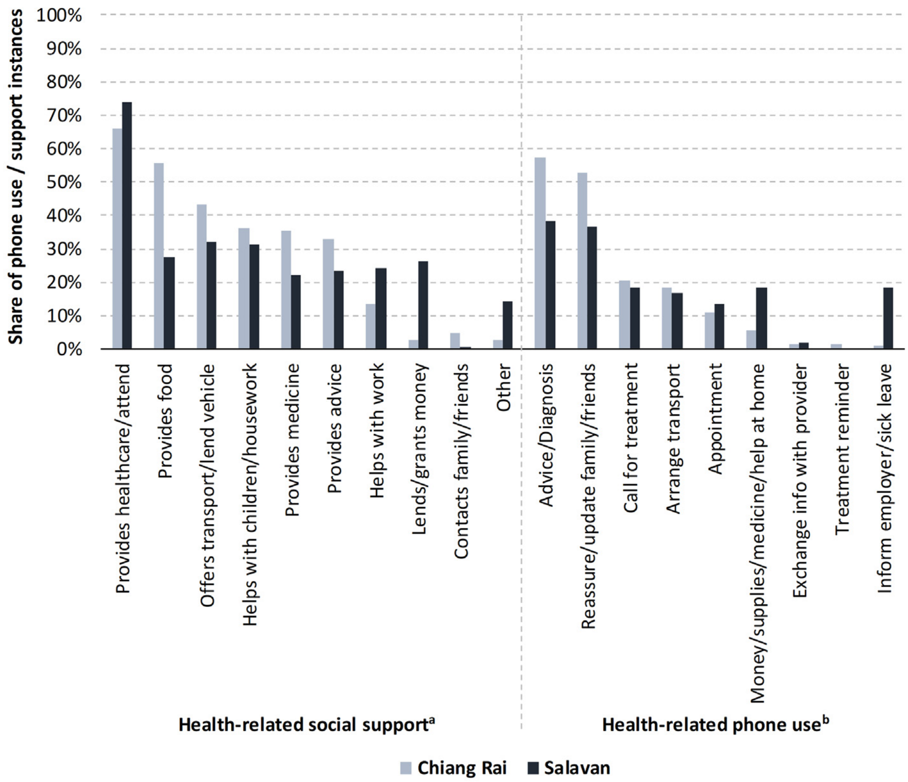

Fig. 4. Functions of Health-related Phone Use and Support Networks. *Notes.* Population-weighted statistics, accounting for complex survey design. Multiple responses per instance possible. [a]Illness-episode level, including only instances in which other people were involved during the illness. Chiang Rai: n = 426; Salavan: n = 262. [b]Illness-step level, including only instances in which health-related mobile phone use occurred (excluding non-health-related phone use and general conversations about health on the phone). Chiang Rai: n = 218; Salavan: n = 60.

we present the regression results for access to healthcare; in Table 5 for the duration until patients reached the various healthcare providers. For both tables, we present multi-level models, or single-level regression models in case the multi-level regressions did not converge (non-convergence arose due to homogeneity as well as small sample sizes in the case of healthcare duration).[13] Overall, we found that marginalisation was associated with healthcare access in Salavan and in the pooled sample, suggesting that more marginalised groups tended to access more informal and less private healthcare. However, we did not identify a systematic statistical relationship between marginalisation and public healthcare access or delays until access.

The regression results in Table 4 suggest no clear pattern for the individual dimensions of marginalisation, but the overall index was linked negatively to private and positively to informal healthcare access in the pooled sample and in the site-specific subsample for Salavan. For illustration, the pooled sample models would predict that a patient in Chiang Rai with three dimensions of marginalisation had a 14.6% probability of accessing private healthcare, compared to 18.1% for a patient with two dimensions of marginalisation. In Salavan, the same patients would have a 12.5% vs. 15.6% predicted probability of private healthcare access. In contrast, more marginalised patients were predicted to have higher informal healthcare access, for instance 13.2% vs. 10.5% in Chiang Rai and 12.4% vs. 9.7% in Salavan (comparing predictions with 3 vs. 2 dimensions of marginalisation). However, Table 5 indicates that marginalisation was not systematically associated with the time elapsed until patients accessed public, private, or informal healthcare providers – neither in its individual dimensions nor as overall index.[14]

6.2. Health-related phone use and social support

As the final step in our analysis, this section presents the regression models linking mobile phone use and social support to rural treatment-seeking behaviour. Following the structure of the preceding section, the main results are again presented in separate tables for access to healthcare (Table 6) and duration until patients reached the various healthcare providers (Table 7). To reduce complexity, we limited the presentation of the models to either the basic models with the marginalisation index, health-related phone use, and social support as independent variables, or the interaction models if the PHONxMARG and SUPPxMARG interaction terms were statistically significant at least at the 10-percent level (see Appendix Tables A4 and A5 for the complete set of models). We

[13] The significance of the associations described in this and the following section were only weakly sensitive to the multi- or single-level model specifications. The conclusions of this analysis do not vary substantively if either specification was chosen.

[14] Among the control variables, a perhaps surprising observation is that the severity of illnesses was not linked to shorter durations to healthcare access in any model, and it exhibited statistically significant positive associations with public and private healthcare access in Chiang Rai and all forms of healthcare access in the pooled sample A possible interpretation is that more severe cases involved bed-ridden patients treated at home and the prospect of more expensive treatment. Later analysis in the next section will also link mobile phone use systematically to delayed access, but note that the correlation between the severity and health-related mobile phone use was weak, with correlation coefficients of 0.17 in Chiang Rai and 0.07 in Salavan.

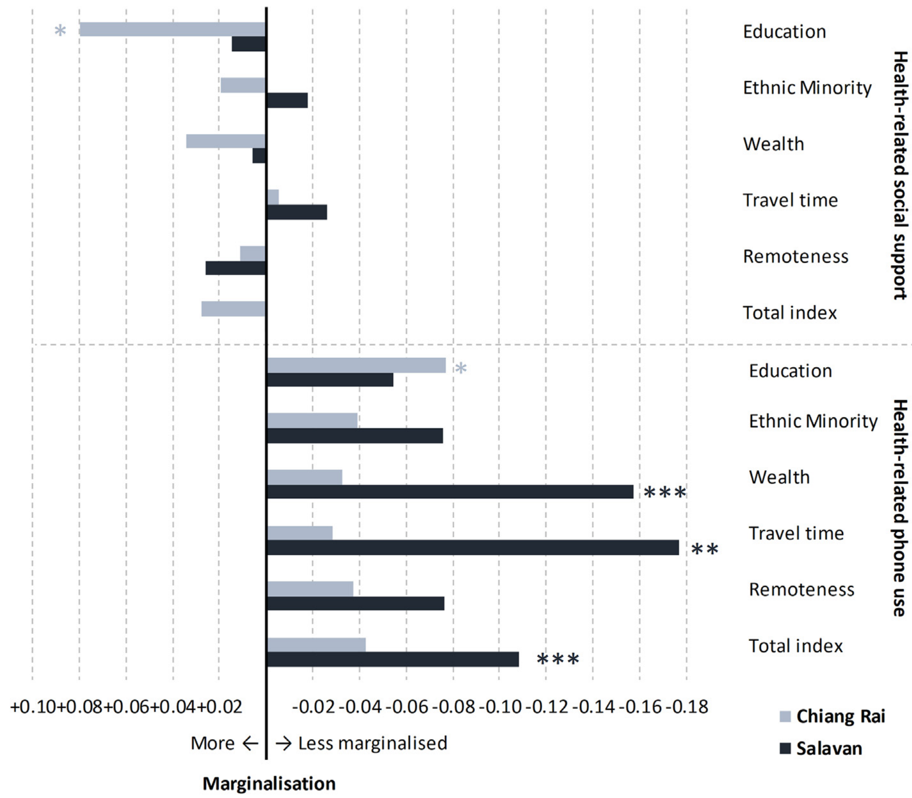

Fig. 5. Differences in Marginalisation Between (1) Patients Using Phones and (2) Patients With Health-Related Social Support Compared to People who (1) do not use Phones and (2) Involve Social Support Networks. *Notes.* Illness-episode level. Chiang Rai: n = 608; Salavan: n = 356. Hypothesis tests using Pearson X^2 tests for binary variables (i.e. individual dimensions of marginalisation) and two-sided t-tests for total marginalisation index. Population-weighted statistics, accounting for complex survey design. Marginalisation defined as multiple dimensions of disadvantage that situate people at economic, social, and spatial margins of society. Approximated through aggregate index comprising binary indicators of education (zero years), ethnic minority (<20% of village ethnicity), wealth (bottom quintile of household wealth), travel time (>30 min to nearest town), and village remoteness. $^*p$ < 0.1, $^{**}p$ < 0.05, $^{***}p$ < 0.01.

omitted from reporting the control variables and the constant term; the full specifications including coefficients for control variables are presented in the supplemental material.

Table 6 documents the main results of the multi-level regression models of access to healthcare. Overall, the results indicate that, with the inclusion of mobile phones and social support, the marginalisation index retained a statistically significant association (independently or as part of an interaction term) with public healthcare access in Chiang Rai, and with all forms of healthcare access in Salavan and the pooled sample. Furthermore, mobile phones or social support were significantly linked with public and private healthcare access in both individual samples and to all types of healthcare access in the pooled sample. To illustrate these relationships: the predicted rate of public healthcare access in rural Salavan remained virtually constant between 56% and 59% from zero to full marginalisation. In contrast, people experiencing health-related phone use had a predicted rate of 60% public healthcare access if they had a zero marginalisation index, 85% for one marginalisation dimension, 96% for two, and near-universal public healthcare access for people with three or more dimensions of marginalisation. Drawing on the pooled sample, Fig. 6 depicts the relationship between marginalisation and health-related phone use (Row a) and health-related social support (Row b) for public (Column 1), private (Column 2), and informal healthcare access (Column 3). Light-grey markers indicate health-related phone use (Row a) or social support (Row b). The predicted rates of healthcare access using the pooled sample suggested that mobile phone use and social support related to marginalisation in similar ways (with the exception of informal healthcare access, where access among marginalised phone users was predicted to be lower than among non-users).

In Table 7, we focus again on the duration until healthcare access. Although the previous section indicated no direct relationship between marginalisation and the duration until healthcare access, when health-related mobile phone use and social support were added to the models, especially phone use emerged as a statistically significant predictor. Independently of marginalisation, phone use was statistically significant and positive for public and private healthcare in Chiang Rai and in the pooled sample. The association indicated that people using mobile phones for health-related purposes also experienced longer delays until they accessed public and private care. However, the negative PHONxMARG interaction term for public healthcare access in Salavan indicated that faster healthcare access was present among phone users with a marginalisation index of 0.6 or above. Among non-marginalised groups, health-related mobile phone use was linked to longer durations. In contrast, social support was linked only to private and informal healthcare in the pooled sample – and in a similar direction as health-related mobile phone use. Considering the pooled sample, the results indicate that mobile phone use was associated with 1.5 days slower access to public healthcare and 3.2 days slower private healthcare access compared to illnesses where no mobile phones were used (model predictions). Social support in the pooled sample was associated with 1.2 additional days until private healthcare access.

Table 4
Access to Healthcare and Marginalisation: Regression Results.

	Chiang Rai						Salavan						Pooled Sample					
	Public care		Private care		Informal care		Public care		Private care		Informal care[b]		Public care		Private care		Informal care	
(Model Number)	(1)	(2)	(3)	(4)	(5)[a]	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
Marginalisation[c] Social (education)	−0.48*		0.19		−0.13		−0.08		−0.86		0.20		−0.24		−0.11		0.08	
	(0.29)		(0.29)		(0.35)		(0.36)		(0.61)		(0.62)		(0.23)		(0.25)		(0.31)	
Social (ethnic minority)	0.84**		−0.58		−1.26*		−0.20		−0.04		−0.09		0.54*		−0.41		−0.62	
	(0.36)		(0.41)		(0.72)		(0.46)		(0.56)		(0.86)		(0.28)		(0.33)		(0.51)	
Economic (wealth)	0.66**		−0.08		−0.19		−0.15		−0.77		0.69		0.38*		−0.32		−0.05	
	(0.28)		(0.28)		(0.38)		(0.41)		(0.61)		(0.68)		(0.23)		(0.25)		(0.31)	
Spatial (travel time)	−0.51		0.35		0.84***		0.61		−1.27**		3.33**		0.06		−0.52		1.35***	
	(0.39)		(0.44)		(0.26)		(0.52)		(0.51)		(1.41)		(0.36)		(0.33)		(0.37)	
Spatial (remoteness)	0.45		−1.45**		0.34		0.15		0.37		−0.41		0.24		−0.14		−0.20	
	(0.53)		(0.65)		(0.52)		(0.57)		(0.52)		(1.28)		(0.43)		(0.41)		(0.42)	
Marginalisation Index		0.67		−0.86		0.87		0.33		−2.71**		3.19**		0.77		−1.43***		1.44**
		(0.50)		(0.54)		(0.60)		(0.87)		(1.11)		(1.57)		(0.48)		(0.50)		(0.62)
Illness severity	1.02***	1.02***	0.98***	0.43***	0.43***	−0.04	−0.04	0.68***	0.68***	−0.21	−0.24	0.56	0.63	0.93***	0.92***	0.28**	0.29**	0.01
	(0.13)	(0.13)	(0.13)	(0.12)	(0.12)	(0.20)	(0.18)	(0.22)	(0.22)	(0.27)	(0.27)	(0.41)	(0.42)	(0.11)	(0.11)	(0.11)	(0.11)	(0.16)
Adult/child (1 = child)	0.96***	0.85***	0.86***	0.29	0.29	−1.27*	−1.24**	0.30	0.29	−0.05	−0.06	−0.01	−0.12	0.57***	0.57***	0.18	0.17	−0.63*
	(0.25)	(0.26)	(0.26)	(0.27)	(0.27)	(0.71)	(0.50)	(0.29)	(0.29)	(0.37)	(0.37)	(0.58)	(0.58)	(0.19)	(0.19)	(0.21)	(0.21)	(0.33)
Gender (1 = female)	0.25	0.28	0.22	0.17	0.20	0.30	0.29	0.39	0.33	−0.46	−0.51	0.70	0.53	0.27	0.22	−0.04	−0.02	0.39
	(0.21)	(0.21)	(0.21)	(0.21)	(0.21)	(0.28)	(0.28)	(0.30)	(0.29)	(0.36)	(0.35)	(0.64)	(0.63)	(0.17)	(0.17)	(0.18)	(0.18)	(0.25)
Age	0.01	0.01	0.00	0.01	0.01*	−0.00	−0.00	0.00	0.00	−0.01	−0.01	−0.01	−0.02	0.00	−0.00	0.01	0.01	0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Household size	0.01	0.10	0.09	−0.02	−0.02	0.03	0.02	0.08	0.08*	−0.12*	−0.12	−0.05	−0.03	0.11***	0.11***	−0.08*	−0.07*	−0.07
	(0.01)	(0.06)	(0.06)	(0.06)	(0.06)	(0.07)	(0.08)	(0.05)	(0.05)	(0.07)	(0.07)	(0.12)	(0.12)	(0.04)	(0.04)	(0.04)	(0.04)	(0.06)
Unemployed (1 = yes)	0.01	−0.20	−0.11	−0.32	−0.32	−0.93**	−1.02**	0.34	0.40	0.18	0.16	0.00	0.00	−0.06	−0.04	−0.10	−0.11	−1.09**
	(0.01)	(0.26)	(0.25)	(0.26)	(0.26)	(0.41)	(0.43)	(0.67)	(0.67)	(0.76)	(0.74)	(.)	(.)	(0.24)	(0.23)	(0.24)	(0.24)	(0.43)
Constant	−4.24***	−3.80***	−3.27***	−2.08***	−2.34***	−2.19***	−2.17***	−1.89**	−1.73**	0.05	0.08	−6.71***	−5.94***	−3.00***	−2.73***	−1.68***	−1.79***	−2.63***
	(0.63)	(0.60)	(0.54)	(0.59)	(0.54)	(0.71)	(0.73)	(0.88)	(0.82)	(1.03)	(1.05)	(2.07)	(1.85)	(0.54)	(0.51)	(0.54)	(0.52)	(0.69)
Pseudo R^2					0.07													
Variance Component Test	0.08	<0.01	0.06	0.03		0.07	<0.01	<0.01	0.02	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	0.47	0.04
Log likelihood	−322.4	−329.0	−333.6	−336.7	−192.8	−197.9	−198.8	−199.8	−130.6	−133.0	−65.3	−67.9	−534.7	−537.3	−481.8	−482.3	−273.1	−279.4
X^2	83.96	75.37	23.58	18.00	24.46	13.45	17.71	15.88	18.18	12.82	10.98	8.76	93.78	90.07	20.23	19.17	29.91	17.82
N_1 (Individuals)	608	608	608	608	608	608	356	356	356	356	339	339	964	964	964	964	964	964
N_2 (Villages)	30	30	30	30		30	30	30	30	30	30	30	60	60	60	60	60	60
N_3 (Districts)	5	5	5	5		5	5	5	5	5	5	5	10	10	10	10	10	10
N_4 (Sites)													2	2	2	2	2	2

Notes. Coefficients reported. Standard errors in parentheses. Analysis at illness-episode level. N_1 – N_4 are sample sizes on the various levels, ranging from 356 to 964 on the lowest level of analysis.
*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.
[a.] Single-level models reported because multi-level models did not converge. Standard errors calculated with bootstrap estimation using 5000 replications and clustered at village level.
[b.] 17 observations dropped due to collinearity.
[c.] Marginalisation defined as multiple dimensions of disadvantage that situate people at economic, social, and spatial margins of society. Approximated through aggregate index comprising binary indicators of education (zero years), ethnic minority (<20% of village ethnicity), wealth (bottom quintile of household wealth), travel time (>30 min to nearest town), and village remoteness.

Table 5
Duration Until Healthcare Access and Marginalisation: Regression Results.

		Chiang Rai						Salavan						Pooled Sample					
		Public care		Private care		Informal care[a]		Public care		Private care		Informal care[a]		Public care		Private care		Informal care	
(Model Number)		(1	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
Marginalisation[b]	Social (education)	0.65		0.15		0.07		−0.07		−1.56		0.85		0.21		−0.05		0.16	
		(0.41)		(0.39)		(1.53)		(0.20)		(5.47)		(282.77)		(0.20)		(0.35)		(0.51)	
	Social (ethnic minority)	−0.20		−0.24		0.86		0.19		−0.74		−1.85		0.04		−0.32		−0.34	
		(0.42)		(0.53)		(12.21)		(0.27)		(13.59)		(560.65)		(0.25)		(0.45)		(0.95)	
	Economic (wealth)	−0.09		−0.09		1.72		0.04		0.13		−0.02		−0.08		0.11		0.79*	
		(0.35)		(0.40)		(1.99)		(0.24)		(3.38)		(950.51)		(0.19)		(0.32)		(0.48)	
	Spatial (travel time)	−0.54		−0.96**		−0.43		−0.20		0.89		−0.29		−0.23		−0.36		−0.48	
		(0.57)		(0.46)		(0.74)		(0.24)		(0.94)		(353.82)		(0.29)		(0.39)		(0.41)	
	Spatial (remoteness)	0.36		0.62		−1.44		−0.07		0.11		−0.35		0.05		0.38		−0.28	
		(0.75)		(0.73)		(9.87)		(0.26)		(1.16)		(645.68)		(0.33)		(0.47)		(0.59)	
	Marginalisation Index		0.25		−0.45		−0.12		−0.32		0.96		−0.17		−0.01		−0.02		0.24
			(0.63)		(0.67)		(1.34)		(0.46)		(1.09)		(19.46)		(0.39)		(0.60)		(0.73)
Illness severity		0.31*	0.28	0.33*	0.54***	0.50***	0.45	0.28	0.04	0.03	−0.18	−0.12	0.88	1.03	0.20*	0.21**	0.41***	0.41***	0.56**
		(0.18)	(0.18)	(0.18)	(0.16)	(0.16)	(0.32)	(0.43)	(0.12)	(0.12)	(0.47)	(0.33)	(36.02)	(8.66)	(0.11)	(0.11)	(0.15)	(0.15)	(0.24)
Adult/child (1 = child)		−0.93***	−0.79**	−0.75**	−0.77**	−0.78**	0.04	−0.25	−0.52***	−0.52***	−0.45	−0.56	0.52	0.21	−0.64***	−0.61***	−0.63**	−0.61**	0.34
		(0.34)	(0.35)	(0.34)	(0.36)	(0.35)	(3.22)	(2.91)	(0.18)	(0.18)	(0.43)	(0.47)	(517.31)	(12.38)	(0.18)	(0.18)	(0.28)	(0.28)	(0.56)
Gender (1 = female)		−0.29	−0.32	−0.20	0.06	0.21	0.25	0.34	0.08	0.09	0.77	0.51	−1.14	−0.46	−0.07	−0.02	0.28	0.27	0.12
		(0.29)	(0.30)	(0.29)	(0.31)	(0.28)	(0.57)	(0.46)	(0.18)	(0.17)	(0.48)	(0.46)	(286.54)	(23.85)	(0.17)	(0.16)	(0.25)	(0.23)	(0.40)
Age		−0.00	−0.01	0.00	−0.01	−0.01	0.06*	0.05**	−0.00	−0.00	0.01	0.01	0.01	0.01	0.00	0.01	−0.00	−0.00	0.04**
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)	(7.14)	(0.36)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Household size		−0.00	−0.13	−0.12	0.01	0.03	0.02	0.06	0.02	0.01	−0.15*	−0.12	0.02	−0.04	−0.03	−0.03	−0.04	−0.03	0.05
		(0.01)	(0.08)	(0.08)	(0.08)	(0.08)	(0.22)	(0.23)	(0.02)	(0.02)	(0.08)	(0.10)	(118.51)	(2.35)	(0.03)	(0.03)	(0.06)	(0.06)	(0.11)
Unemployed (1 = yes)		−0.00	0.01	−0.07	−0.18	−0.20	−0.77	0.18	−0.15	−0.15	−1.32	−1.11	0.00	0.00	−0.09	−0.13	−0.30	−0.30	−0.35
		(0.01)	(0.35)	(0.33)	(0.34)	(0.34)	(13.16)	(5.87)	(0.40)	(0.39)	(13.73)	(0.98)	(0.00)	(0.00)	(0.24)	(0.24)	(0.31)	(0.31)	(0.72)
Constant		1.67*	1.44	0.76	0.46	0.15	−4.01**	−3.22**	0.48	0.49	0.64	0.68	−1.19	−1.68	0.46	0.28	0.12	0.15	−2.80**
		(0.97)	(0.91)	(0.82)	(0.71)	(0.65)	(1.77)	(1.34)	(0.46)	(0.44)	(1.29)	(1.09)	(724.90)	(22.74)	(0.44)	(0.41)	(0.57)	(0.53)	(1.14)
Pseudo R^2						0.10	0.05			0.06		0.21	0.14						
Variance Component Test		0.06	0.00	0.19	0.05			0.08	0.07		0.36			0.00	0.00	0.02	0.04	0.37	0.44
Log likelihood		−364.5	−366.2	−302.8	−305.0	−80.4	−84.9	−337.7	−338.3	−90.3	−94.0	−32.5	−35.4	−724.6	−725.6	−401.6	−402.3	−123.2	−125.8
X^2		19.77	16.57	24.26	18.48	7.16	6.25	10.62	9.25	10.28	4.83	0.54	0.10	24.95	22.92	18.81	17.56	20.45	13.65
N_1 (Individuals)		192	192	159	159	65	65	206	206	57	57	23	23	398	398	216	216	88	88
N_2 (Villages)		30	30	30	30			29	29		16			59	59	46	46	34	34
N_3 (Districts)		5	5	5	5			5	5		5			10	10	10	10	9	9
N_4 (Sites)														2	2	2	2	2	2

Notes. Coefficients reported. Standard errors in parentheses. Analysis at illness-episode level. N_1 – N_4 are sample sizes on the various levels, ranging from 23 to 398 on the lowest level of analysis.
*p < 0.1, **p < 0.05, ***p < 0.01.
[a.] Single-level models reported because multi-level models did not converge. Standard errors calculated with bootstrap estimation using 5000 replications and clustered at village level.
[b.] Marginalisation defined as multiple dimensions of disadvantage that situate people at economic, social, and spatial margins of society. Approximated through aggregate index comprising binary indicators of education (zero years), ethnic minority (<20% of village ethnicity), wealth (bottom quintile of household wealth), travel time (>30 min to nearest town), and village remoteness.

Table 6
Access to Healthcare and Situational Facilitators: Main Regression Results.

	Dependent Variable										
	Chiang Rai				Salavan			Pooled Sample			
	Public care[a]		Private care	Informal care	Public care	Private care	Informal care[b]	Public care[a]		Private care	Informal care
(Model Number)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Marginalisation Index[c]	0.43	−1.25	−0.79	0.86	0.19	−2.10*	3.12*	0.50	−0.41	−1.35***	1.78***
	(0.56)	(1.00)	(0.55)	(0.60)	(0.95)	(1.17)	(1.60)	(0.52)	(0.79)	(0.50)	(0.65)
Health-related phone use	0.13	0.45*	0.45**	−0.25	0.14	1.36**	−0.27	0.19	0.67***	0.43**	0.32
	(0.30)	(0.24)	(0.22)	(0.33)	(0.62)	(0.64)	(0.91)	(0.27)	(0.21)	(0.20)	(0.41)
Health-related social support	0.42*	−0.05	0.38	0.10	0.66**	0.94**	−0.38	0.53***	0.15	0.55***	0.00
	(0.25)	(0.31)	(0.24)	(0.30)	(0.32)	(0.43)	(0.59)	(0.19)	(0.26)	(0.21)	(0.26)
PHONxMARG	1.86*				9.20***	−16.99**		2.81***			−3.28*
	(1.10)				(3.45)	(6.60)		(1.06)			(1.75)
SUPPxMARG		2.68**							1.74**		
		(1.06)							(0.80)		
(control variables [age, gender, household size, employment status, illness severity, adult/child illness], constant term, and multi-level variance parameters omitted)											
Variance Component Test	<0.01	<0.01	0.03	0.07	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	0.06
Log likelihood	−323.6	−321.4	−333.1	−197.6	−187.0	−124.6	−67.6	−523.1	−524.4	−475.7	−276.8
χ^2	79.98	81.51	24.28	14.05	30.46	22.11	9.05	105.34	105.24	31.82	22.46
N_1 (Individuals)	608	608	608	608	356	356	339	964	964	964	964
N_2 (Villages)	30	30	30	30	30	30	30	60	60	60	60
N_3 (Districts)	5	5	5	5	5	5	5	10	10	10	10
N_4 (Sites)								2	2	2	2

Notes. Coefficients reported. Standard errors in parentheses. Analysis at illness-episode level. N_1 – N_4 indicate sample sizes on the various levels, ranging from 356 to 964 on the lowest level of analysis.
*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.
a. Both PHONxMARG and SUPPxMARG models yielded statistically significant interaction terms.
b. 17 observations dropped due to collinearity.
c. Marginalisation defined as multiple dimensions of disadvantage that situate people at economic, social, and spatial margins of society. Approximated through aggregate index comprising binary indicators of education (zero years), ethnic minority (<20% of village ethnicity), wealth (bottom quintile of household wealth), travel time (>30 min to nearest town), and village remoteness.

Table 7
Duration Until Healthcare Access and Situational Facilitators: Main Regression Results.

	Dependent Variable								
	Chiang Rai			Salavan			Pooled Sample		
	Public care	Private care	Informal care[a]	Public care	Private care[a]	Informal care[a]	Public care	Private care	Informal care
(Model Number)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Marginalisation Index[b]	0.39	−0.34	0.10	0.07	1.86	0.19	0.08	0.16	0.36
	(0.60)	(0.63)	(1.99)	(0.49)	(1.23)	(94.13)	(0.37)	(0.52)	(0.76)
Health-related phone use[c]	0.64*	1.15***	0.26	0.96***	1.39	0.82	0.61***	1.16***	0.27
	(0.34)	(0.27)	(1.87)	(0.34)	(5.97)	(79.81)	(0.20)	(0.24)	(0.54)
Health-related social support	−0.23	0.30	1.04	−0.02	2.45	0.06	−0.07	0.67**	0.69*
	(0.36)	(0.32)	(1.30)	(0.19)	(5.25)	(35.59)	(0.19)	(0.28)	(0.41)
PHONxMARG[a]				−2.36**					
				(1.14)					
(control variables [age, gender, household size, employment status, illness severity, adult/child illness], constant term, and multi-level variance parameters omitted)									
Pseudo R^2			0.07		0.10	0.16			
Variance Component Test	0.03	0.70		0.14			<0.01	0.12	0.39
Log likelihood	−364.3	−295.9	−83.4	−334.3	−87.0	−34.9	−720.8	−388.9	−124.3
χ^2	20.89	38.48	4.96	17.77	6.80	0.02	32.62	45.85	16.80
N_1 (Individuals)	192	159	65	206	57	23	398	216	88
N_2 (Villages)	30	30		29			59	46	34
N_3 (Districts)	5	5		5			10	10	9
N_4 (Sites)							2	2	2

Notes. Coefficients reported. Standard errors in parentheses. Analysis at illness-episode level. N_1 – N_4 indicate sample sizes on the various levels, ranging from 23 to 398 on the lowest level of analysis.
*p < 0.1, **p < 0.05, ***p < 0.01.
a. Single-level models reported because multi-level models did not converge. Single-level models reported because multi-level models did not converge. Standard errors calculated with bootstrap estimation using 5000 replications and clustered at village level.
b. Marginalisation defined as multiple dimensions of disadvantage that situate people at economic, social, and spatial margins of society. Approximated through aggregate index comprising binary indicators of education (zero years), ethnic minority (<20% of village ethnicity), wealth (bottom quintile of household wealth), travel time (>30 min to nearest town), and village remoteness.
c. Phone use variable specific to type of healthcare access, e.g. "health-related phone use prior to accessing public healthcare" rather than "any health-related phone use."

Table 8
Evidence in Relationship to Research Hypotheses.

Hypothesis	Evidence
H1 Marginalised groups have fewer means to access formal treatment, driving them towards increased informal healthcare access.	**Partial support:** Informal healthcare access more common with increasing marginalisation, but no discernible link to access delays.
H1a) Marginalisation links positively to informal healthcare access and negatively to formal healthcare access.	**Consistent support:** Lower private and higher informal healthcare utilisation among marginalised groups.
H1b) Marginalised groups experience longer delays to formal healthcare access.	**No support:** Duration until healthcare access not associated with marginalisation.
H2 Social support and phone use help marginalised groups overcome constraints in accessing formal healthcare, but facilitation is directed towards private providers.	**Partial support:** Disproportionate uptake of formal healthcare among marginalised phone users/receivers of social support, but not directed towards private providers.
H2a)Facilitators like social support and phone use entail more and faster access to formal healthcare providers.	**Partial support:** Phones and social support associated with more formal access, but also with longer delays (exception: faster public access among marginalised phone users in Salavan).
H2b)Private healthcare access increases disproportionately when marginalised groups involve social support and mobile phones.	**No support:** Disproportionate uptake of public healthcare access among marginalised groups, and less private healthcare access among marginalised phone users in Salavan.
H2c)Social support and phone use are less influential among non-marginalised groups.	**Partial support:** Disproportionate uptake of formal healthcare among marginalised phone users/receivers of social support and faster access in Salavan; but also parallel patterns in which non-/marginalised groups experienced similar relationships.

7. Discussion

7.1. Limitations

Our interpretations and conclusions are subject to three main sets of limitations. The first set related to the survey sample. On the one hand, our representative samples spoke specifically to the living conditions of the rural populations during the dry post-monsoon season, when accessibility especially to remote and mountain villages was easier and safer. Together with harvest cycles, seasonal outmigration, and changing epidemiological patterns (Greer et al., 2018; Haenssgen et al., 2018), this could mean that marginalisation and constraints in healthcare access materialise differently during other seasons and that our results may therefore be relatively conservative. On this basis, we could speculate that the monsoon season introduces more constraints and risks, thereby amplifying the role of health-related social support and mobile phone use. On the other hand, as a rural survey in Chiang Rai and Salavan, we could not make claims about health behaviours in urban areas or other regions of the world.

Secondly, the static analysis of cross-sectional data could shed only very little light on causal relationships and on the evolving and bi-directional link between marginalisation and health behaviour. From a static perspective, we could argue for instance that longer healthcare episodes may prompt patients to use a mobile phone in order to find more viable healthcare solutions. However, most of the incidences of health-related phone uses occurred early in the process: 48% of all health-related mobile phone use took place in the first illness step; 77% in the first two steps.[15] Over the long term, the relationship between healthcare access, mobile technology diffusion, social networks, and marginalisation could be recursive: If mobile phones and social support helped people manage their health better, then they might be less subject to catastrophic health expenditure/outcomes and thus less likely to enter a process of marginalisation, which would in turn affect their relationship to health-related social support and mobile phone use. The current data only enabled a glimpse at this network of relationships, underlining the need for longitudinal research on the multidimensional implications of mobile phone diffusion and social support.

Lastly, even if a causal relationship could be established, facilitated healthcare access (be it through mobile phones or social networks) is not automatically beneficial for individuals. Further research will be necessary to establish whether any such consequences have tangible outcomes on people's health or the operation of health systems.

7.2. Main findings

We summarise our findings in Table 8. Our results provided support for Hypothesis H1a that marginalisation linked positively to informal healthcare access and negatively to formal healthcare access, in particular private healthcare providers. We did not find evidence in support of Hypothesis H1b that marginalised groups experienced longer delays to formal healthcare access. The evidence was therefore moderately consistent with the overarching Hypothesis H1 that marginalised groups had fewer means to access formal treatment, driving them towards increased informal healthcare access.

The evidence relating to Hypothesis H2 was more mixed. Hypothesis H2a stated that facilitators like social support and phone use entailed more and faster access to formal healthcare providers. The evidence presented in this paper was consistent with this hypothesis insofar as that, broadly speaking, mobile phone use and social support were associated with more access to formal healthcare (also see Appendix Table A4 for models not presented in the main results). However, we observed little indication that these factors contributed to faster access – rather the opposite!

Hypothesis H2b posited that private healthcare access increased disproportionately when marginalised groups mobilised social support and mobile phones. Our data suggested that marginalised groups had instead relatively more access to *public* healthcare if they were aided by phones and social support, and the evidence in Salavan even hinted at substitution away from private towards public healthcare – in accordance with people's reported preferences for public over private healthcare. Although mobile phone use appeared to coincide with increased private healthcare access more generally (based on results from the pooled sample), this relationship was similar for marginalised and non-marginalised groups.

Finally, according to Hypothesis H2c, social support and phone use should have been less influential among non-marginalised groups, for which we find partial support in our data. In terms of healthcare utilisation, especially the rate of public healthcare access was higher among marginalised phone users and people receiving social support, whereas private healthcare access was more likely to be independent of either factor. In the low-income context of rural Salavan, mobile phone use was also associated with faster public healthcare seeking among marginalised groups.

[15] These patterns followed the more general distribution of steps in the treatment-seeking process. Across all illness episodes in the sample, health-related mobile phone as a share of each step was relatively constant with between 11% and 15% of each step (between Steps 1 and 6, after which no phone occurred any longer).

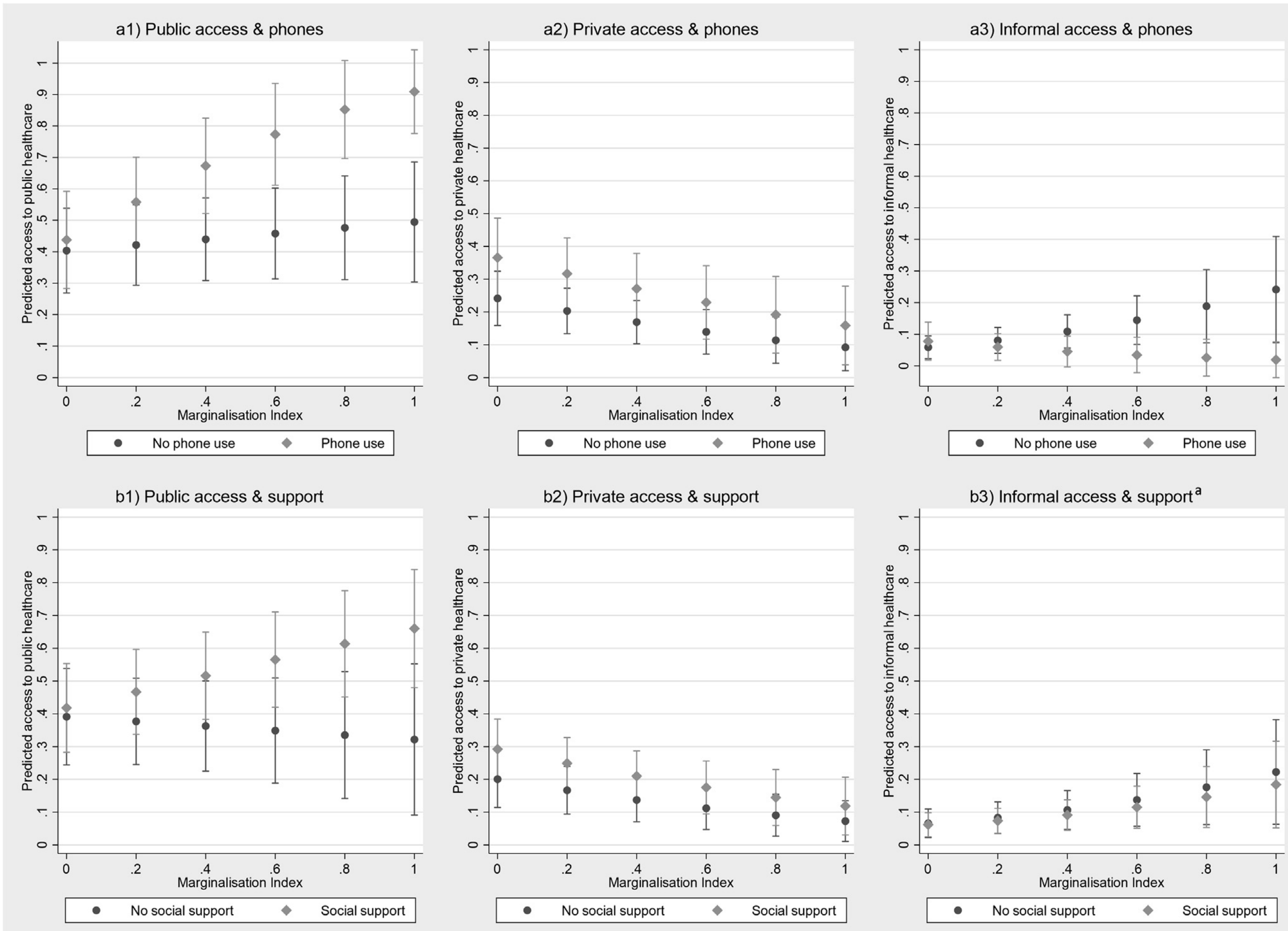

Fig. 6. Predicted Access to Healthcare as a Function of Marginalisation, Health-Related Mobile Phone Use, and Social Support; Pooled Sample. *Notes.* Illness-episode level. $n = 964$. Predicted results of Models 8, 9, 10, and 11 in Table 6, whereby private healthcare access models have been estimated as 3-level models with site-fixed effect to enable calculation of numerical derivatives for predicted results. Error bars indicating 95% confidence interval. Marginalisation defined as multiple dimensions of disadvantage that situate people at economic, social, and spatial margins of society. Approximated through aggregate index comprising binary indicators of education (zero years), ethnic minority (<20% of village ethnicity), wealth (bottom quintile of household wealth), travel time (>30 min to nearest town), and village remoteness. [a.] Results are not statistically significant at $p < 0.1$ and included for illustration only.

We can therefore conclude that the evidence was partly consistent with H2: the patterns support the notion that social support and phone helped marginalised groups overcome constraints in accessing formal healthcare, but they were not specifically directed towards private providers.

8. Conclusion

Speaking to the practice of mHealth and to the development literature on the diffusion of digital technologies, this article asked, "*How do mobile phone use and social support networks influence rural treatment-seeking behaviours among marginalised groups?*" We framed our research within the theme of marginalisation, using representative health behaviour survey data from the relatively resource-constrained contexts of rural Chiang Rai and Salavan. We hypothesised that marginalised groups are driven into informal healthcare utilisation, and that health-related phone use and social support help overcome some of the underlying constraints yet with a bias towards private healthcare providers. Our analysis provided partial support for these hypotheses, whereby the disproportionate uptake of public healthcare among marginalised groups with social and mobile phone support was especially notable. Social support had weaker associations with healthcare access, but it was also distributed more equitably than phone use.

Although these findings might seem encouraging overall, the relatively widespread health-related mobile phone use and its behavioural consequences are – in our assessment – not necessarily good news for mHealth practitioners. While widespread use signifies a degree of technological readiness (Hampshire et al., 2015; Khatun et al., 2015), it is also evidence that the "vessels" for technological solutions to healthcare are no longer empty (Polgar, 1963). New solutions are likely to stand in competition with existing ones. Given the growing evidence base on "informal mHealth," researchers and practitioners can therefore no longer assume that digital healthcare solutions are implemented in a vacuum. We recommend that mHealth interventions targeting the general population should always be preceded by a people-centric analysis of existing solutions to solve the (healthcare) problem in question as part of feasibility studies and subsequent evaluations.

More generally, our study contributes to the empirical understanding of emerging health-related phone use and complements the recent WHO guidance on digital interventions for health system strengthening (WHO, 2019b). By shedding light on the local adaptation of diffusing technology and its social consequences, we also contribute to the broader body of work on ICT and development. And yet, our research raised more questions than it asked. The perhaps most important point is whether the opportunity to use mobile phones excludes marginalised non-users from healthcare access in the long term. Based on the existing literature (Riley, 2018), we would assume that phone-facilitated support crowds out community-level social support, leaving already marginalised rural dwellers in yet more precarious circumstances. Detecting any such trends would require further longitudinal micro-level panel data that consider long-term changes and inter-relationships of treatment seeking, technology use, social network composition, and multidimensional poverty. Another question is whether and how the existing patterns of informal health-related phone use and social support shape the implementation process and success of formal mHealth interventions. Lastly, it is not clear whether neighbouring fields like "mEd" (the use of mobile phones to improve educational attainment) or mobile-phone-based governance may experience similar complications as the ones raised in our study, which promises a lively research agenda in the years ahead.

CRediT authorship contribution statement

Marco J. Haenssgen: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Supervision, Visualization, Writing - original draft, Writing - review & editing. **Nutcha Charoenboon:** Data curation, Formal analysis, Investigation, Methodology, Project administration, Supervision, Validation, Writing - review & editing. **Giacomo Zanello:** Conceptualization, Formal analysis, Funding acquisition, Methodology, Validation, Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A

Table A1
Variable Description.

Variable		Description
Controls	Female	Binary variable: Sex of respondent (R); [1] if female.
	Age	Continuous variable: Age in years.
	Household size	Continuous variable: Number of household members
	Employment status: unemployed	Binary variable: [1] if occupation of R was coded as "unemployed," "retired," or "student" without indication of additional income-generating employment
Marginalisation	Education	Binary variable: [1] if R reported not having completed at least one year of formal education.
	Ethnic Minority	Binary variable: [1] if R ethnic group reported by R represented<20% of the population in R's respective village.
	Wealth	Binary variable: [1] if R falls into the bottom wealth quintile of the rural provincial population. Calculated separately per field site, based on average of 17 household assets and amenities.
	Travel time	Binary variable: [1] if travel time between R's village and nearest town exceeded>30 min by car (based on *Google Maps* and survey team travel to village)
	Remoteness	Binary variable: [1] village was classified as "remote" in a semi-quantitative assessment comprising categories "*peri*-urban," "rural," and "remote." (Consensus assessment among survey team members)
	Marginalisation index	Continuous variable: Sum of all five individual marginalisation indicators, normalised to scale from [0] to [1].

(*continued on next page*)

Table A1 (*continued*)

Variable		Description
Healthcare preferences	Shops selling medicine Traditional healers Pharmacies Private clinics/ hospitals Public primary care Public hospitals	Binary variable for each type of healthcare provider: [1] if R reported considering the respective type of healthcare provider for consultation/treatment, advice, medicines, or other form of health service provision (e.g. check-ups).
Characteristics of illness episodes	Illness episode of child	Binary variable: [1] if illness episode was experienced by child under R's supervision.
	Self-rated severity	Ordinal variable: [1] if illness is reported as "mild;" [2] as "moderate;" [3] as "severe."
	Duration	Continuous variable: Total duration of illness episode in days, calculated as sum of duration of individual steps in illness episode. (note: minimum unit per step is one day)
	Process steps	Continuous variable: Total number of discrete healthcare steps in illness episode.
	Public healthcare	Binary variable: [1] if R reported accessing health centre or hospital during illness episode.
	Private healthcare	Binary variable: [1] if R reported accessing private clinic, hospital, or pharmacy.
	Informal healthcare	Binary variable: [1] if R reported accessing grocery store or traditional healer (excluding self-care and care from family and friends).
	Health-related phone use	Binary variable: [1] if R reported any phone use related to the illness (excl. general conversations), carried out by R or any other person at any step.
	Health-related social support	Binary variable: [1] if R reported that any of R's personal contacts was involved in the illness by providing advice or help.
Public access	Duration until access	Continuous variable: Duration in days until R accessed public healthcare provider.
	Steps until access	Continuous variable: Number of discrete healthcare steps until R accessed public healthcare provider.
	Phone use before/during access	Binary variable: [1] if R reported health-related phone use in steps before or while accessing public healthcare provider.
Private access	Duration until access	Continuous variable: Duration in days until R accessed private healthcare provider.
	Steps until access	Continuous variable: Number of discrete healthcare steps until R accessed private healthcare provider.
	Phone use before/during access	Binary variable: [1] if R reported health-related phone use in steps before or while accessing private healthcare provider.
Informal access	Duration until access	Continuous variable: Duration in days until R accessed informal healthcare provider.
	Steps until access	Continuous variable: Number of discrete healthcare steps until R accessed informal healthcare provider.
	Phone use before/during access	Binary variable: [1] if R reported health-related phone use in steps before or while accessing informal healthcare provider.

Table A2
Pairwise Correlation of Marginalisation Dimensions, by Field Site.

	Chiang Rai					Salavan				
	Education	Ethnic Minority	Wealth	Travel time	Remote-ness	Education	Ethnic Minority	Wealth	Travel time	Remote-ness
Education	1.00					1.00				
Ethnic Minority	0.13***	1.00				−0.06	1.00			
Wealth	0.36***	0.13***	1.00			0.33***	−0.08	1.00		
Travel time	0.11***	0.03	0.22***	1.00		0.02	0.07	−0.12***	1.00	
Remoteness	0.29***	0.13***	0.40***	0.59***	1.00	0.06	0.04	−0.01	0.58***	1.00

Notes. Hypothesis tests with Šidák adjustment for more conservative estimates, taking into account the number of hypothesis tests performed in the pairwise comparison. Population-weighted statistics, accounting for complex survey design.
*p < 0.1, **p < 0.05, ***p < 0.01.

Table A3
Overlap Between People who use Mobile Phones and Involve Others During Illness.

		Health-related phone use			
		Chiang Rai		Salavan	
		No	Yes	No	Yes
Other people involved	No	27.4%	3.9%	27.9%	2.0%
	Yes	46.5%	22.3%	56.7%	13.5%

Notes. Illness-episode level. Population-weighted statistics, accounting for complex survey design. Chiang Rai: n = 608; Salavan: n = 356.

Table A4
Access to Healthcare: Regression Results.

	Chiang Rai									Salavan									Pooled Sample								
	Public Care			Private Care			Informal Care			Public Care			Private Care			Informal Care[a]			Public Care			Private Care			Informal Care		
	NoInt	IntA	IntB	NoInt	IntA	IntB	NoInt	IntA	IntB	NoInt	IntA	IntB	NoInt	IntA	IntB	NoInt	IntA	IntB	NoInt	IntA	IntB	NoInt	IntA	IntB	NoInt	IntA	IntB
(Model Number)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)	(27)
Marginalisation Index[b]	0.79	0.43	−1.25	−0.79	−0.93	−0.67	0.86	1.20*	1.21	0.59	0.19	0.60	−2.71**	−2.10*	−2.93	3.12*	3.42**	2.05	0.91*	0.50	−0.41	−1.35***	−1.31**	−1.34	1.41**	1.78***	1.70*
	(0.52)	(0.56)	(1.00)	(0.55)	(0.60)	(0.90)	(0.60)	(0.64)	(0.92)	(0.92)	(0.95)	(1.44)	(1.13)	(1.17)	(2.03)	(1.60)	(1.65)	(2.37)	(0.50)	(0.52)	(0.79)	(0.50)	(0.53)	(0.84)	(0.63)	(0.65)	(0.90)
Health-related phone use	0.46*	0.13	0.45*	0.45**	0.35	0.45**	−0.25	0.19	−0.24	1.43***	0.14	1.43***	−0.02	1.36**	−0.02	−0.27	1.42	−0.21	0.67***	0.19	0.67***	0.43**	0.46*	0.43**	−0.27	0.32	−0.27
	(0.24)	(0.30)	(0.24)	(0.22)	(0.28)	(0.22)	(0.33)	(0.42)	(0.33)	(0.45)	(0.62)	(0.45)	(0.47)	(0.64)	(0.47)	(0.91)	(1.24)	(0.91)	(0.20)	(0.27)	(0.21)	(0.20)	(0.25)	(0.20)	(0.31)	(0.41)	(0.31)
Health-related social support	0.45*	0.42*	−0.05	0.38	0.37	0.41	0.10	0.12	0.22	0.61*	0.66**	0.61	0.86**	0.94**	0.81	−0.38	−0.53	−0.95	0.55***	0.53***	0.15	0.55***	0.55***	0.55**	−0.02	0.00	0.10
	(0.25)	(0.25)	(0.31)	(0.24)	(0.24)	(0.29)	(0.30)	(0.30)	(0.39)	(0.32)	(0.32)	(0.51)	(0.42)	(0.43)	(0.58)	(0.59)	(0.61)	(1.12)	(0.19)	(0.19)	(0.26)	(0.21)	(0.21)	(0.26)	(0.26)	(0.26)	(0.37)
PHONxMARG		1.86*			0.57			−2.54			9.20***			−16.99**			−9.49			2.81***			−0.18			−3.28*	
		(1.10)			(1.02)			(1.78)			(3.45)			(6.60)			(6.67)			(1.06)			(0.98)			(1.75)	
SUPPxMARG			2.68**			−0.16			−0.54			−0.01			0.27			1.47			1.74**			−0.01			−0.43
			(1.06)			(1.00)			(1.10)			(1.46)			(2.06)			(2.46)			(0.80)			(0.89)			(0.97)
(control variables [age, gender, household size, employment status, illness severity, adult/child illness], constant term, and multi-level variance parameters omitted from reporting)																											
Variance Component Test	<0.01	<0.01	<0.01	0.03	0.03	0.03	0.07	0.05	0.07	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	0.08	0.06	0.08
Log likelihood	−325.1	−323.6	−321.4	−333.1	−333.0	−333.1	−197.6	−196.3	−197.4	−191.6	−187.0	−191.6	−130.7	−124.6	−130.7	−67.6	−66.2	−67.5	−526.9	−523.1	−524.4	−475.7	−475.7	−475.7	−279.0	−276.8	−278.9
X^2	78.91	79.98	81.51	24.28	24.44	24.36	14.05	16.32	14.38	28.14	30.46	28.14	16.54	22.11	16.45	9.05	10.46	9.24	102.80	105.34	105.24	31.82	31.91	31.84	18.46	22.46	18.72
N_1 (Individuals)	608	608	608	608	608	608	608	608	608	356	356	356	356	356	356	339	339	339	964	964	964	964	964	964	964	964	964
N_2 (Villages)	30	30	30	30	30	30	30	30	30	30	30	30	30	30	30	30	30	30	60	60	60	60	60	60	60	60	60
N_3 (Districts)	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	10	10	10	10	10	10	10	10	10
N_4 (Sites)																			2	2	2	2	2	2	2	2	2

Notes. Coefficients reported. Standard errors in parentheses. Analysis at illness-episode level. N_1 – N_4 indicate sample sizes on the various levels, ranging from 356 to 964 on the lowest level of analysis.
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.
a. 17 observations dropped due to collinearity.
b. Marginalisation defined as multiple dimensions of disadvantage that situate people at economic, social, and spatial margins of society. Approximated through aggregate index comprising binary indicators of education (zero years), ethnic minority (<20% of village ethnicity), wealth (bottom quintile of household wealth), travel time (>30 min to nearest town), and village remoteness.

Table A5
Duration Until Healthcare Access: Regression Results.

	Chiang Rai									Salavan								Pooled Sample								
	Public Care			Private Care			Informal Care[b]			Public Care			Private Care[a,b]		Informal Care[b]			Public Care			Private Care			Informal Care		
	NoInt	IntA	IntB	NoInt	IntA	IntB	NoInt	IntA	IntB	NoInt	IntA	IntB	NoInt	IntB	NoInt	IntA	IntB	NoInt	IntA	IntB	NoInt	IntA	IntB	NoInt	IntA[a]	IntB
(Model Number)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)	(27)
Marginalisation Index[c]	0.39	0.39	0.21	−0.34	−0.27	−1.35	0.10	0.17	1.80	−0.25	0.07	0.96	1.86	1.75	0.19	0.82	−2.12	0.08	0.18	0.23	0.16	0.26	−1.30	0.36	0.08	1.58
	(0.60)	(0.65)	(1.14)	(0.63)	(0.70)	(1.26)	(1.99)	(1.63)	(13.22)	(0.46)	(0.49)	(1.01)	(1.23)	(34.39)	(94.13)	(52.00)	(343.54)	(0.37)	(0.39)	(0.73)	(0.52)	(0.57)	(1.22)	(0.76)	(0.87)	(1.31)
Health-related phone use[d]	0.64*	0.64	0.64*	1.15***	1.21***	1.15***	0.26	0.53	0.21	0.42*	0.96***	0.43**	1.39	1.39	0.82	2.54	1.39	0.61***	0.75***	0.61***	1.16***	1.24***	1.16***	0.27	0.54	0.22
	(0.34)	(0.46)	(0.34)	(0.27)	(0.35)	(0.27)	(1.87)	(4.33)	(2.26)	(0.22)	(0.34)	(0.22)	(5.97)	(6.30)	(79.81)	(46.38)	(83.83)	(0.20)	(0.28)	(0.20)	(0.24)	(0.31)	(0.24)	(0.54)	(2.42)	(0.55)
Health-related social support	−0.23	−0.23	−0.27	0.30	0.30	0.10	1.04	1.02	1.68	−0.03	−0.02	0.40	2.45	2.42	0.06	0.19	−1.78	−0.07	−0.07	−0.02	0.67**	0.67**	0.40	0.69*	0.68	1.19**
	(0.36)	(0.36)	(0.43)	(0.32)	(0.32)	(0.39)	(1.30)	(1.55)	(3.58)	(0.20)	(0.19)	(0.38)	(5.25)	(8.64)	(35.59)	(33.05)	(206.70)	(0.19)	(0.19)	(0.28)	(0.28)	(0.28)	(0.35)	(0.41)	(0.44)	(0.59)
PHONxMARG[d]		−0.02			−0.30			−2.40			−2.36**					−164.23			−0.57			−0.51			−4.85	
		(1.20)			(1.22)			(26.54)			(1.14)					(413.25)			(0.79)			(1.15)			(22.73)	
SUPPxMARG			0.23			1.31			−2.54			−1.41		0.12			4.01			−0.19			1.76			−1.68
			(1.22)			(1.40)			(13.06)			(1.05)		(34.21)			(322.02)			(0.78)			(1.32)			(1.43)
(control variables [age, gender, illness severity, household size, employment status, adult/child illness], constant term, and multi-level variance parameters omitted from reporting)																										
Pseudo R^2							0.07	0.07	0.08				0.10	0.10	0.10	0.16	0.20								0.08	
Variance Component Test	0.03	0.03	0.03	0.70	0.71	0.61				0.12	0.14	0.15						0.00	0.00	0.00	0.12	0.12	0.10	0.39		0.47
Log likelihood	−364.3	−364.3	−364.2	−295.9	−295.9	−295.5	−83.4	−83.3	−82.5	−336.5	−334.3	−335.5	−87.0	−87.0	−87.0	−34.9	−33.1	−720.8	−720.5	−720.7	−388.9	−388.8	−388.0	−124.3	−122.1	−123.6
X^2	20.89	20.89	20.91	38.48	38.57	39.23	4.96	4.73	4.57	13.24	17.77	15.11	6.80	6.61	2.58	0.02	0.01	32.62	33.16	32.75	45.85	46.38	47.04	16.80	12.70	17.75
N_1 (Individuals)	192	192	192	159	159	159	65	65	65	206	206	206	57	57	23	23	23	398	398	398	216	216	216	88	88	88
N_2 (Villages)	30	30	30	30	30	30				29	29	29						59	59	59	46	46	46	34		34
N_3 (Districts)	5	5	5	5	5	5				5	5	5						10	10	10	10	10	10	9		9
N_4 (Sites)																		2	2	2	2	2	2	2		2

Notes. Coefficients reported. Standard errors in parentheses. Analysis at illness-episode level. N_1 – N_4 indicate sample sizes on the various levels, ranging from 23 to 398 on the lowest level of analysis.
*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.
[a.] Single-level models reported as multi-level models did not converge.
[b.] PHONxMARG interaction model omitted because interaction term predicted failure perfectly.
[c.] Marginalisation defined as multiple dimensions of disadvantage that situate people at economic, social, and spatial margins of society. Approximated through aggregate index comprising binary indicators of education (zero years), ethnic minority (<20% of village ethnicity), wealth (bottom quintile of household wealth), travel time (>30 min to nearest town), and village remoteness.
[d.] Phone use variable specific to type of healthcare access, e.g. "health-related phone use prior to accessing public healthcare" rather than "any health-related phone use."

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.worlddev.2020.105156.

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