**Determinants of mHealth Effectiveness: Evidence from a Large-Scale Experiment[[1]](#footnote-1)**

# Abstract

mHealth, the use of mobile technologies for healthcare management and delivery, offers great promise to promote health and improve care. However, to date, most mHealth treatments have failed to demonstrate a significant impact on clinical outcomes, and there is surprisingly little knowledge of factors that drive its effectiveness. This study examines mHealth effectiveness by investigating both mHealth design and social support. In so doing, we leverage one of the world’s largest field experiments on improving the health of expectant mothers and reducing the rate of cesarean sections. We hypothesize that 1) the combination of both self-directed mHealth and provider-directed mHealth ensures the highest mHealth effectiveness; 2) the husband, as one of the most significant social supports for expectant women, can be an important moderator in mHealth effectiveness. Our analyses show that the combined mHealth design achieved significant reduction in cesarean section use. In addition, a husband’s healthy behavior is pivotal in enabling mHealth interventions to be effective, as demonstrated by the fact that the cesarean section reduction in the strongest intervention group is four times bigger for those wives whose husbands engage in healthy behavior than it is for those whose husbands are not. Further analyses reveal that the husband’s healthy behavior has a stronger influence on mHealth effectiveness when the wife has more power in the marriage. Our findings represent the first study to examine the effectiveness of these two mHealth designs (self-directed and provider-directed) and the critical role of social support in determining mHealth effectiveness, and this research has important implications for both academic research and the practice of mHealth.

# Keywords

mHealth, Healthcare, Social support, Cesarean Section, Field experiment

**Determinants of mHealth Effectiveness: Evidence from a Large-Scale Experiment**

# 1. Introduction

Widespread adoption of mobile phones has created a promising new channel for accessing patients and improving healthcare delivery. The capabilities enabled by mobile devices are broadly referred to as mHealth, defined by the World Health Organization (WHO) as “medical and public health practice supported by mobile devices, such as mobile phones, patient monitoring devices, personal digital assistants (PDAs), and other wireless devices” (Kay et al. 2011). The growth of mobile healthcare has been remarkable. From 2010 to 2015, the percentage of smartphone owners who downloaded health applications increased threefold from 19% to 58% (Fox et al. 2010; Krebs et al. 2015). Concurrently, the number of mHealth applications has also experienced rapid growth. On the iOS platform, mHealth applications grew by 106.2% from 2013 to 2015 (Statista 2017b), and in 2017, there were more than 165,000 mHealth applications on the market (Highland 2017). The market value of mHealth is projected to reach $46 billion in 2020, almost double that of hospital and physician practice-based technologies such as electronic health records (Statista 2017a).

While mHealth has been hailed by many as a transformational innovation in healthcare because it offers the ability to directly engage patients (Rose et al. 2013; Ben-Zeev et al. 2016), outcomes associated with mHealth have left much to be desired. Empirical evidence supporting the effectiveness of mHealth is equivocal: a large-scale study of patients with chronic conditions did not detect meaningful differences when mHealth was utilized (Bloss et al. 2016). A review of mHealth randomized clinical trials (RCTs) reported that in half of the studies, mHealth interventions failed to achieve significant effects (Hamine et al. 2015). One possible explanation for the lack of significance is that these studies have typically focused on evaluating the average treatment effects of mHealth rather than exploring any underlying heterogeneity. As a result, the question of how mHealth affects patient health outcomes remains largely unaddressed.

Our study aims to advance the understanding of mHealth effectiveness. We examine two critical factors that may theoretically drive outcomes: the design of mHealth in terms of its functionality, and the environment in which it is deployed, i.e., the social support available to the user. First, reviewing and synthesizing prior literature, we consider two major types of mHealth design: self-directed mHealth that seeks to empower users to achieve good health outcomes, and provider-directed mHealth that connects users with medical resources or supports from others (e.g., doctors). While both types of mHealth have been argued to play a crucial role in health management (Howitt et al. 2012), almost all mHealth solutions in the existing literature focus only on one of the two types. Arguably, the combination of self-directed mHealth and provider-directed mHealth should exert an even bigger impact; yet little is known about how these two types and their combination lead to different outcomes.

Second, healthcare researchers increasingly acknowledge that social factors, especially family and friends, play an important role in patient behavior (Cohen et al. 2015). Substantial evidence suggests that the social environment is a significant determinant of the effectiveness of patient-directed solutions. Social support can benefit patients in multiple ways, including increasing adherence to medication and physician-recommended activities (DiMatteo 2004; Gonzalez et al. 2004), promoting self-care (Toljamo et al. 2001) and healthy choices (Janis 1983), and reducing future suicidal ideation and behaviors (Rowe et al. 2006). However, up until now there have been no studies on the role of social support in the context of mHealth, a void we aim to fill.

Our research setting is one of the largest reported field experiments on pregnant women. Women’s health is a global concern of significant magnitude, and especially so in the case of maternal health and child mortality (Craft 1997; Filippi et al. 2006). Our experiment enrolled 4,629 expectant mothers over a period of 2 years from 2013 to 2015 in China, with an overarching objective of reducing the cesarean (c-section) rate and improving infant health. While the WHO (2015) states the ideal c-section rate is 10%-15%, the world average c-section rate was 21% in 2015 (Boerma et al. 2018), and scholars consider the overuse of c-sections as a global epidemic urgently in need of resolution (Betrán et al. 2018; Visser et al. 2018) because it imposes short-term and long-term risks on women and children (Sandall et al. 2018). WHO (2015) data show that after the c-section rate exceeds 10%, maternal and newborn deaths do not decrease any more. In our study setting, China, the c-section rate is an alarming 46.2% (Lumbiganon et al. 2010), indicating the pressing need for effective interventions.

In the study, based on existing medical knowledge and local medical resources, mHealth treatments were provided to the enrolled expectant mothers via Short Message Service (SMS; see Su et al. (2016) for the study protocol). The messages covered basic information related to fetal development, reminders about prenatal preparation, and messages about seeking care and about good household prenatal practices. In addition to a control group, three different treatment groups were included, representing self-directed mHealth, provider-directed mHealth, and a combination of the two designs. Our results indicate that the combined mHealth intervention reduces c-section use more significantly than either of the individual designs.

With respect to social support, we study the effects of the most proximal form of support for an expectant mother: the husband. We hypothesize that the husband’s health behavior plays an important role in determining the degree to which mHealth is effective in reducing the c-section rate, and our results affirm this expectation. Strikingly, almost all of the reduction in cesarean section rate is observed in women whose husbands actively engage in healthy behaviors. By contrast, the mHealth treatment has very little effect on reducing the c-section rate for those expectant mothers whose husbands do not regularly engage in healthy behaviors. In addition, we also find that the relatively higher power of the wife in the marriage conditions the value of husband healthy behavior in mHealth interventions.

To the best of our knowledge, this is the first study investigating the two types of mHealth and their combination. It is also the first to examine how mHealth effectiveness is influenced by partner social support. We contribute to IS research in several ways. First, while IS researchers have examined the impact of IT in healthcare (Agarwal et al. 2010), most of this work focuses on provider side technologies such as EMR and CPOE. mHealth is one of the most dynamic domains within health IT, and its importance is growing concurrently with ubiquitous adoption of smartphones. Therefore, our study extends the frontier of health IT research to the mobile and patient side.

Second, while many studies in mHealth did not achieve significant results, our findings on the two types of mHealth interventions provide potential answers to the ineffectiveness reported in the literature. Finally, IS researchers have long been interested in the effects of contextual factors in value generation from IT investment, especially in healthcare. For example, Dranove et al. (2014) find that health IT investment in hospitals does decrease costs, but only for hospitals located in IT-intensive regions. Atasoy et al. (2017) also find a significant spillover effect from neighboring hospitals in reducing operations costs. We contribute to this stream of work and add insights on how mHealth effectiveness is affected by the patient’s social factors.

The rest of the paper is organized as follows: in Section 2, we review the literature on mHealth design and social support related to mHealth and develop our research hypotheses. We also introduce the background information regarding c-sections, which serves as our research context. We then describe our research setting and the field experiment in detail in Section 3. Section 4 reports the results of this study, including the investigation of the main treatment effect and moderating effects and deeper analysis of the moderating effect. Finally, a discussion and conclusions are provided in Section 5.

# 2. Background

## 2.1 Classifying mHealth functions

In the past decade, a fast-growing smartphone market has enabled mobile technologies to proliferate and diffuse rapidly across the globe, with users availing themselves of a wide variety of applications. In the context of health management, there are about 4 million free downloads and 300,000 paid downloads of the top ten mHealth applications every day, and it is estimated that half of all smartphone users have at least one health-related application on their smartphones (Schenker 2017). The WHO heralds mHealth as a “groundswell” change in its influence on patient behavior across a broad variety of health-related domains. Behaviors examined in prior mHealth research include smoking cessation, physical activity, calorie intake, safe sexual behavior, and alcohol consumption, as well as chronic conditions such as diabetes, asthma, hypertension, and mental disorders (Ali et al. 2016; Free et al. 2013). Studies have also documented cost reductions in healthcare delivery after the adoption of mHealth (Akter et al. 2010; Thirumurthy et al. 2012).

Given the large number of instantiations of mHealth, the literature offers many taxonomies of mHealth solutions based on different dimensions such as the nature of the technology, the disease or medical condition addressed, and the functions supported. An early WHO review (Kay et al. 2011) classified mHealth applications into six categories: those that enable “communication between individuals and health services,” “communication between health services and individuals,” “consultation between health care professionals,” “intersectoral communication in emergencies,” “health monitoring and surveillance,” and “access to information for health care professionals at point of care.” As the diversity of mHealth solutions increased rapidly, the functions provided soon extended far beyond the initial list created by WHO. A more recent industry report (Research2Guidance 2017) summarized all the mHealth apps in 2017 and found the top mHealth categories to be “connection to doctor” (30%), followed by “diabetes” (27%), “heart, circulation, blood” (24%), “medication” (24%), “staying healthy/fitness” (22%), “hospital efficiency” (19%), and “mental health” (17%).

From the perspective of the technology, Sanner et al. (2012) classified mHealth applications in low-resource contexts into four categories: interactive voice response, plain-text SMS, locally installed handset and SIM applications, and browser-based solutions. Martínez-Pérez et al. (2013) divided all mHealth applications along two dimensions: the development context and the target users. mHealth applications could be developed as open source, commercial, or research, and they could be targeted at different user groups: patients or healthcare staff. Olla and Shimskey (2015) developed an mHealth taxonomy and additionally classified mHealth applications according to the medical use cases: point of care diagnostic, wellness, education and reference, efficiency and productivity, patient monitoring, compliance, behavior modification, and environmental monitoring. Stephani et al. (2016) categorized all mHealth interventions into four categories according to the relationship between interventions and outcomes, including “health promotion and awareness”, “remote monitoring and care support”, “disease surveillance and outbreak detection”, and “decision support system”. Iribarren et al. (2017) used five categories to summarize all mHealth interventions: behavior change communication, data collection, finance, logistics, and service delivery.

Our review of existing classifications suggests that although many taxonomies have been proposed, each one focuses on different dimensions of mHealth. Based on the synergy of existing taxonomies, we classify mHealth interventions at a higher conceptual level from the perspective of the core function they serve. Our classification is derived from factors identified and widely agreed upon in healthcare research as influencing the quality of healthcare: patient-related factors, provider-related factors, and environmental factors (Mosadeghrad 2014; Naidu 2009). Because environmental factors are typically beyond the scope of mHealth and have not been explicitly addressed in available applications, we further simplify the taxonomy and classify mHealth as self-directed, provider-directed, or both. Existing classifications that include mHealth targeting clinical use (e.g., connection to providers) or technological tools that increase the health empowerment of patients (e.g., health education, self-monitoring, reminders) are subsumed within our classification that further abstracts existing granular groupings.

Self-directed mHealth interventions provide knowledge or motivational messages to promote healthy behavior among mHealth users, with the expectation that such behaviors could lead to good health outcomes. By contrast, in provider-directed mHealth, relevant medical diagnostic knowledge (e.g., symptoms), medical resources, and access to care could be offered, all in the hopes of directing users to healthcare providers for preventive care and timely treatment. As noted in the literature (Harno et al. 2006; Kiselev et al. 2012; Logan et al. 2012; Quilici et al. 2013), both of these mHealth types can theoretically contribute to the health of a user, but the mechanisms are distinct from each other.

Self-directed mHealth aims at increasing the empowerment of an individual in achieving better health outcomes via two mechanisms: the provision of health knowledge that amplifies health literacy, and recommendations of specific customized and contextualized actions that users can take. Health literacy, defined as “the degree to which individuals have the capacity to obtain, process, and understand basic health information and services needed to make appropriate health decisions,” is important in facilitating the appropriate use of healthcare services, self-care of chronic disease patients, and overall health maintenance (Parker 2000). Johnson & Johnson estimated the annual cost of low health literacy in the US to be between $106 billion and $236 billion (Ratzan 2010). Smartphones’ ubiquitous adoption and ease of use make them a powerful tool for enhancing health literacy (Kumar et al. 2015). This is especially important in the under-resourced context of developing countries whose health systems lack the capability to adequately serve the population (Roess 2017). Our field experiment, conducted in relatively underdeveloped areas in China, thus provides a rich research context to examine the impact of mHealth.

In addition to enhancing literacy, self-directed mHealth can also recommend best practices in a timely, targeted manner (Cafazzo et al. 2012; Rabbi et al. 2015; Forastiere et al. 2016). For example, an mHealth solution for diabetes patients could suggest specific diet and exercise plans according to the progress of the disease and seasonal factors (e.g., weather) that may constrain certain types of physical activity (Dobson et al. 2015).

Provider-directed mHealth, on the other hand, focuses on directing mHealth users to healthcare providers for preventive care and timely treatment. To achieve this, provider-directed mHealth expands individuals’ self-monitoring capabilities by triggering interactions with healthcare providers in certain situations. One example of such interaction is provided in Worringham et al. (2011), where patients in a cardiac rehabilitation program are monitored by an ECG-powered mHealth system while exercising and clinicians are notified automatically if an adverse event occurs. In addition, provider-directed mHealth can improve preventive care by reminding patients to make scheduled visits. Preventive care has been proven to have substantial advantages with better health outcomes (US Preventive Services Task Force 2009) and being more cost effective (Pignone et al. 2002). Cooney et al. (2009) estimated that increased prescription of low-risk, preventive medications (such as aspirin) could save 1,861-7,452 lives per million. Given that preventive care is not yet well delivered (Lipton et al. 2007), mHealth could make huge contributions in this regard.

As self-directed and provider-directed mHealth leverage different aspects of the healthcare process, there should be synergies between the two. Self-directed mHealth could be better implemented with guidance from provider-directed mHealth. For instance, professional healthcare providers could use their expertise and equipment to better gauge a user’s status before mHealth generates a personalized intervention plan, then after the plan is generated, the provider could also evaluate and improve the plan to make it more efficient and effective. Provider-directed mHealth, on the other hand, would not be able to realize its value without users’ compliance. Self-directed mHealth can therefore facilitate the implementation of prescribed plans by enhancing empowerment.

Given the promise of mHealth, studies showing its effectiveness have attracted much attention. However, as noted, the findings are far from conclusive. Some studies have documented significant effects of mHealth in improving both adherence behaviors (Brath et al. 2013; Khonsari et al. 2015; Petrie et al. 2012) and clinical outcomes (Kiselev et al. 2012; Lim et al. 2011; Lyles et al. 2011; Seto et al. 2012). At the same time, many other studies have failed to find significant effects. For example, Arora et al. (2014) evaluated mHealth in diabetes patients and found that it did not improve self-efficacy, performance of self-care tasks, quality of life, or diabetes-specific knowledge. Similarly, researchers failed to identify a significant change in self-efficacy among patients with asthma (Ryan et al. 2012). A comprehensive review by Hamine et al. (2015) showed that improvement of adherence behaviors was only observed in 56% of mHealth Randomized Controlled Trials (RCT), while 61% of the studies failed to detect a significant effect on clinical outcomes.

This inconsistency in the empirical findings highlights the limited understanding of contingencies driving the success of mHealth. Reviewing the mHealth effectiveness studies from the perspective of mHealth design, we find that a predominant majority of the mHealth interventions in these studies use only one type of functionality (i.e., either self-directed or provider-directed). Hamine et al. (2015) summarized 41 mHealth studies aiming at improving clinical outcomes and 27 mHealth studies that sought to improve adherence. Our analysis of the mHealth designs in these studies indicated that among the 41 studies for clinical outcomes, 22 used only a self-directed mHealth intervention, 14 used only a provider-directed mHealth intervention, and only 5 included both self-directed and provider-directed functionality (Table 1). Given that patient empowerment and healthcare resources/support are both necessary components, we aim to systematically examine the impact of such a design on the effectiveness of mHealth.

To maximize its effectiveness, mHealth solutions should include inputs from both the patient and healthcare providers/supports. However, our literature review shows that most current mHealth solutions only address one aspect, which might explain the many insignificant findings. Among the studies that combine both self-directed and provider-directed mHealth, it is not clear how the combination is superior to either capability alone. Following research in healthcare indicating the importance of both patient and provider factors (Morrill et al. 2005; Nam et al. 2011) and a complementarity assumption, we propose that combining self-directed and provider-directed mHealth treatments would yield the most significant results.

*Hypothesis 1. An mHealth solution combining self-directed and provider-directed mHealth treatments will be more effective than mHealth solutions that include only a self-directed or only a provider-directed mHealth treatment.*

We note that since the design of mHealth interventions is quite diverse, the above conjecture is not easily testable by simply comparing results across findings in the literature. We rigorously examined this hypothesis in a large field experiment where the effectiveness of mHealth was evaluated for a self-directed intervention, a provider-directed intervention, and a combination of the two.

## 2.2 Social support and mHealth effectiveness

As discussed in Section 2.1, optimal healthcare quality is a function of three sets of factors: patient-related, provider-related, and environmental. Environmental factors include aspects of the healthcare system such as insurance policies and the healthcare market structure, as well as the social environment of the target patient, including friends and family. Among these environmental factors, the healthcare system and market are not directly amenable to change through patient-directed interventions and are relatively invariant across patients in a specific setting. Social support, however, can exhibit significant heterogeneity across patients; yet its role in facilitating mHealth effectiveness has not been addressed in prior work.

Social support is the support accessible to an individual through social ties to other individuals (Lin et al. 1979). The subcomponents of social support include emotional support, informational support, and instrumental support (Barrera 1986; House 1981; Tilden et al. 1987). Emotional support occurs when one individual emotionally buffers some stress for another and provides empathy, concern, affection, love, trust, acceptance, intimacy, encouragement, or caring to that person (Langford et al. 1997). Informational support is the provision of relevant information, including suggestions and guidance (Wills 1991). Instrumental support involves the provision of direct and tangible resources, such as financial or material support or companionship and service (House 1981).

Numerous studies have confirmed that social support plays a crucial role in patient outcomes via many pathways. First, social support increases people’s immunity to physical illness. One study has found that lower social support is associated with more physical and mental health issues (Cornwell et al. 2009){Berkman, 1995 #257}. In fact, social isolation itself is a recognized health risk factor (House et al. 1988). Second, social support is believed to play a complementary role by enhancing the effects of medical treatment. Medical studies have even connected social support with the functioning of specific biological mechanisms, with one notable study examining inflammatory processes (Uchino 2006). Coussons-Read et al. (2007) observed lower cesarean reactive protein levels (a blood test marker for inflammation in the body) among expectant mothers who have better support.

Finally, by providing a buffer for stress and serving as an additional channel of information, social support also optimizes decision making. For example, making an individual feel loved increases their level of perceived emotional support, which in turn may cause that individual to be more motivated to engage in health-enhancing behaviors (Harvey et al. 2012). Other behavioral changes that can be linked to the availability of social support include a healthier diet, reduced risk of weight gain, and increased physical activity (Ainsworth et al. 2003; Brunt et al. 2000). Even in online health communities, virtual relationships among users are a source of social support and, through both emotional support and informational support mechanisms, have significant benefits on mental health (Yan et al. 2014) and other outcomes (Goh et al. 2016).

We suggest that social support can be especially influential in mHealth efficacy. Unlike standard treatments such as medication or surgery, where patients play a relatively passive role, mHealth motivates patients to be proactive by changing their daily behaviors, such as diet and exercise, and seeking medical help. Given the human tendency towards inertia (Kelly et al. 2016; Marteau et al. 2015) and heterogeneity in health information use (Wimble 2016), informational and emotional support can be pivotal by providing the “nudge” necessary for the patient to take action and, therefore, for the mHealth intervention to be effective. At the same time, instrumental support is also essential in enhancing patient health empowerment in response to mHealth interventions.

Our work presents the first exploration of the role of social support in mHealth effectiveness. Specifically, we examine the role of the husband in the effectiveness of the mHealth solution for pregnant women. During the 40-week period of pregnancy, expectant mothers experience significant physical and mental changes. Symptoms such as fatigue, headaches, sore breasts, and mood swings are common (Knapp 2017). Weight gain and decreased agility also become major lifestyle constraints. These ongoing changes give rise to worries and anxieties on a daily basis, which cannot be addressed by the standard, infrequent visits to doctors’ offices (Johnson 2016). This is especially important in rural China, where access to care is costly and limited (Dummer and Cook 2006; Hu et al. 2008). Our mHealth intervention is designed to provide much-needed health information to pregnant women. As previously mentioned, the treatment takes the form of SMS messages that introduce basic medical knowledge to help women understand their current status, to provide necessary guidelines for seeking care when unusual symptoms are observed, and to suggest best household practices.

In implementing an mHealth treatment such as this, there is always considerable uncertainty about whether and to what degree individuals will react, as a response will often require the participant to overcome human inertia and make behavioral changes (Norman et al. 2007). As a result, some of the expectant mothers may not fully utilize the mHealth intervention due to limited awareness, attention, or resources. It is precisely in such circumstances that social support can play a central role (Mayberry et al. 2016).

During pregnancy, the husband is arguably the expectant mother’s most important social tie. The importance of the husband as a source of social support has been widely recognized in the clinical literature (Helzer et al. 1991; Mastekaasa 1994). Forde (2017) identified husbands as providing emotional and tangible forms of support. While husband support is important in general, it becomes even more pivotal during pregnancy, when the wife is under stress and vulnerable to pressure from healthcare providers and therefore has a much higher need for support. Previous studies involving pregnant women have found an association between the husband’s support and the woman’s health outcomes, such as emotional distress (Røsand et al. 2011).

 Better social support from the husband can be the catalyst for mHealth to promote better decision making. When provided with tangible or informational support, an expecting mother may be capable of better judgment and therefore make wiser decisions for her baby’s and her own health. With more emotional support, the expecting mother can make medical decisions unclouded by depression or anxiety and may therefore be more resistant to supply-induced, unnecessary treatments. In these ways, social support from the husband should lead to better efficacy of our mHealth intervention in curbing the cesarean section rate. We therefore test:

*Hypothesis 2: Support from the husband enhances the effectiveness of mHealth in terms of reducing the c-section rate.*

## 2.3 Cesarean section decisions

The cesarean section was initially designed as a medical procedure to save babies. However, this potentially life-saving intervention also poses potential harm: studies find c-sections without medical necessity are strongly and significantly associated with severe maternal morbidity (Souza et al. 2010), readmission (Thompson et al. 2002), persistent pain (Kainu et al. 2010), reduction of future fertility (Gilliam 2006), fetal wastage and stillbirth (Gilliam 2006; Visco et al. 2006), and risk of uterine scar dehiscence or even uterine rupture (Gilliam 2006).

Given the risks of the procedure, the global healthcare community estimates that the cesarean section rate should be between 10% and 15% (World Health Organization 2015). In China, deviating sharply from these guidelines, the c-section rate is extremely high. According to data from the WHO’s Global Survey (Lumbiganon et al. 2010), the 2007-2008 rate in China was 46.2%. Betrán et al. (2016) estimate that the average annual rate of increase in China from 1990 to 2014 has been about 10%.

The use of a c-section procedure is typically driven by two forces: 1) medical necessity; and 2) women’s misconceptions about the procedure. Medically, under certain conditions, such as a breech presentation, it is safer to use a c-section than vaginal delivery (Hannah et al. 2000). However, a significant proportion of cesarean sections are performed when no such medical condition exists, sometimes driven by women’s misconceptions about the procedure. The expectant mother is the one who makes the final decision, so in the absence of obstetrical factors, maternal choice can boost the use of cesarean section (Christilaw 2006). The reasons women make this choice may be nonmedical ones, such as a misunderstanding of pain management. Beyond the medical conditions and patient preferences, physician factors have also been implicated in c-section use. For example, a study found that physician convenience incentives are stronger indicators of c-section use than physician training, suggesting that in some cases the procedure is unnecessary (Burns et al. 1995).

Accordingly, to reduce the c-section rate among participants, our mobile messages are designed to 1) promote maternal (and fetal) health; and 2) educate participants about cesarean sections and when they might be necessary. As noted, we used self-directed mHealth, provider-directed mHealth, and the two in combination. The self-directed mHealth intervention aims to change the expecting mother’s behaviors so that she can benefit from both improved health and medical knowledge. The provider-directed mHealth intervention provides information about diagnostic symptoms, routine checks, and low-cost local medical resources, seeking to promote both preventive care and timely treatment. While both the mHealth solutions should be beneficial to the users, they take effect through different routes. Self-directed mHealth relies on the daily behaviors of the users, while provider-directed mHealth, on the other hand, focuses on the medical side and targets more serious problems. Therefore, a combination of the two types should be able to leverage both the proactiveness of the user herself (self-directed) and the strong medical support (provider-directed).

Regarding social support, as discussed above, a husband’s support will help the women respond to these messages, as a husband’s proactive actions can substantially improve the expectant mother’s overall health by removing stressors, providing assistance, aiding her in exercise and healthy eating, etc. Another channel by which a husband can support a natural delivery is by the atmosphere created in the family: husbands who consider health more important and have more knowledge about health can substantially improve their partners’ health education outcomes. Improved knowledge of c-sections in particular and childbirth in general can then significantly prevent many misconceptions and protect the expecting mother from misleading information. As a result, husbands who are more health-conscious should improve mHealth effectiveness in reducing c-section rates.

Furthermore, the power dynamics of the couple may also influence the conditioning effect of the husband’s behavior. Studies have found that people with different relative power in their conjugal relationships differ strongly in the direction and extent of their influence on their partners regarding health and health decision making (Chapagain 2006; Gubhaju 2009). If the wife has more power in the relationship, she should be more able to utilize the support. On the other hand, if the wife carries no weight in the relationship, the support may not be fully utilized. Thus, to provide more granular insights into the moderating effect, we also examine the relationship between the husband and wife regarding their relative positions of power.

# 3. Research setting and experiment design

To examine the effects of mHealth in promoting healthy pregnancy and reducing cesarean section rates, we conducted a large field experiment from September 2013 to October 2015 in a rural region of China. Researchers enrolled 4,629 expectant mothers during the two-year period. At enrollment, a baseline survey interview was utilized to collect general information from each participant, including demographics, basic health conditions, attitudes, etc. The healthy behavior information (including exercise frequency and drinking frequency) of the husbands was collected in the baseline in a construct we label “husband healthy behaviors.” Then, the participants were randomly assigned to four groups who received different versions of the mobile messages, which were developed from a message bank maintained by Apricot Forest, Inc.[[2]](#footnote-2) The treatment period lasted until the birth of the new babies. Finally, a follow-up survey was conducted within one week after baby delivery. Information on c-section use and infant health information was collected at this stage.

The mHealth treatments were delivered via SMS message sent to the participating women’s mobile phone. Among the four groups, Group 1 is a control group that received only basic messages containing general fetal development information and basic reminders for prenatal visits and hospital delivery. For example, at Week 24, a reminder message was sent to all groups saying “make a baby shopping list: ask friends who have given birth to a baby for advice. This can save you a lot of time.” Group 2 is the provider-directed (PD) mHealth group, who received all the messages in the control group plus information about how to identify health issues and seek care so as to better utilize healthcare resources. Group 3 is the self-directed (SD) group, who received all the messages in the control group plus guidelines about healthy behaviors during pregnancy. Finally, Group 4 is the full messages (FM) group, where participants received all messages used for Group 2 and Group 3. The messages were sent based on gestational age of the fetus, intending to provide timely interventions.

Sample messages for each group are displayed in Table 2. Any messages explicitly mentioning c-section reduction were not sent to the control group, while all other treatment groups received several messages specifically targeted to reduce c-section use. Overall, 148 messages were sent out during the treatment period. Of these, 25 messages were sent to Group 1 (control group), 82 to Group 2 (PD), 91 to Group 3 (SD), and 148 to Group 4 (FM). For more details of the message design and the full messages see Su et al. (2016).

## 3.1 Measurement

Our primary outcome, c-section use, is a binary variable collected directly from the new mother after delivery (within one week). We use three dummy variables to represent the three treatments, with the control group as the baseline comparator. Social support is measured by a composite score of healthy behaviors performed by the husband: exercising regularly and not drinking. This score is computed as the average of two dummy variables, one for each behavior. The broad range of demographic and socio-economic variables, medical conditions, and lifestyle factors included in the pre-treatment survey were included as controls in our models.

## 3.2 Randomization check

We conducted a randomization check on the 4,629 participants at the beginning of the experiment. They are well randomized on all the 49 variables except for gender preference, where there is a marginally significant difference between the control group and the PD group but no significant difference between the control group and the SD group. Given that we are comparing 49 variables across four groups, it is quite expected that some variables will show minor differences in a large field experiment (Bloom et al. 2014). Therefore, the sample is well-balanced, indicating successful randomization.

For a field experiment on this scale and of such a long duration, it is common to have high dropout rates. In healthcare clinical trials, the average dropout rate can be up to 30% (Tointon 2016). Bull (2009) summarized the dropout rates in 42 clinical trials of antipsychotics. With an average duration of 24 weeks, the average dropout rate in these studies was 49% and 27 studies had a dropout rate higher than 50%. In our context, given the fact that the duration of pregnancy is much longer than 24 weeks and that the duration of our intervention lasted beyond the baby’s birth, we also found dropout rates to be a challenge. We categorized a participant as a dropout if any of the following occurred: the mother had a miscarriage (i.e., the choice of delivery method did not need to be made), the participant discontinued the mHealth treatment program (i.e., withdrew voluntarily), or the participant failed to complete the follow-up survey (i.e., the outcome could not be observed). In total, 2,115 (45.69%) new mothers completed the follow-up survey and reported their delivery method. However, some participants failed to receive the SMS messages, due to either technical or network glitches or because of the selected privacy settings on their phones. After excluding those who missed the messages (23.7%), our final dataset includes 1,613 mothers: 394 in Group 1, 382 in Group 2, 382 in Group 3, and 455 in Group 4.

To ensure balance across the four groups and confirm the validity of randomization we further conducted joint t-tests on all the 49 variables in our final dataset. The variables included the following categories: (1) demographic and other basic information, (2) birth and delivery, disease history and lifestyle, (3) information about the current pregnancy, and (4) psychological factors. Given the large number of variables, it is not unusual for some variables to show minor differences in the means (Bloom et al. 2014). Among the 49 variables, 45 pass the randomization check, with the exception of number of pregnancies, number of miscarriages, attitude toward pregnancy, and perceived susceptibility to health problems. Among these variables, the number of pregnancies and number of miscarriages are highly relevant to this study. When comparing the control group and the FM group, we observe that the average number of pregnancies and the average number of miscarriages are both higher in the FM group. In other words, participants with higher numbers of both pregnancies and miscarriages were more likely to stay in the program if they were in the FM group as opposed to the control group. This suggests that the effect of the mHealth treatment could potentially be stronger than our results indicate.

Importantly, we find that the key moderator, husband healthy behavior (*HHB*), is well randomized across the groups. We coded the husband as having *healthy* behavior (*HHB* as 1) if the participant indicated on the baseline survey that their husband exercises and does not drink. We then deem those husbands who drink and do not exercise as *non-healthy* with a score of 0. The rest (with {exercise, drinking} or {not exercise, not drinking}) are classified as *medium healthy* behavior with a score of 0.5. As shown in Figure 1, among all the 1,613 mothers, 34.0% of the respondents on average indicated that their husbands engaged in healthy behavior. Across the four groups, this percentage is 35.3% for the control group, 32.5% for PD, 34.0% for SD and 34.3% for FM. A t-test was conducted between the control group and each of the treatment groups, with no significant difference observed (p>0.1).

# 4. Results

## 4.1 Model-free evidence

Overall, we observe a reduction in c-section rate in all the treatment groups in comparison with the control group. The c-section rate is 29.9% for the control group, 24.9% for PD, 25.6% for SD, and 22.2% for FM. Compared to the control group, the c-section rate in PD and SD is lower by 5.0 percentage points and 4.3 percentage points, respectively. However, a t-test reveals that neither of the reductions is significant (p>0.1). Finally, for the FM group, we find a significant reduction (p<0.1) with a bigger effect size (7.7 percentage point). This represents a sizable 25.8% drop compared to the control group. We therefore observe that the mHealth intervention has a significant impact on the c-section rate only when both self-directed and provider-directed mHealth treatments are combined and not when either treatment is used independently, suggesting preliminary support for Hypothesis 1.

We next provide visual, model-free evidence for the Hypothesis 2, which states that husband healthy behavior moderates the efficacy of the mHealth intervention in reducing c-section rates. Figure 2 depicts the c-section rates across the four groups. Among the 1,613 mothers, 412 c-section cases occurred (approximately 25%). We further split each group based on the value of *HHB* and make several observations. First, it is interesting to note that in the control group, the c-section rate of those whose husbands engage in non-healthy behavior is 27.7%, while those whose husbands engage in healthy behavior (i.e., HHB equals 1) have a higher rate of 32.1%. This difference preliminarily suggests that husband healthy behavior is an important factor relevant to c-section use. In the absence of the mHealth intervention, the natural occurrence of c-section is more frequent among wives whose husbands engage in healthy behavior. However, in the FM group we see a greater reduction of c-section use (from 32.1% to 17.3%) among families where the husband engages in healthy behavior, which is four times larger than the reduction (from 28.9% to 25.1%) we observe in the remaining families. Our model-free evidence clearly shows the moderating effects of husband healthy behavior, providing initial support for Hypothesis 2.

## 4.2 Regression results

To confirm the patterns indicated in the model-free analysis, we conduct a series of formal analyses that include a broad range of controls. We use the following logistic regression models to investigate the main effects of mHealth design (Equation 1) and the moderating effect of husband healthy behavior (Equation 2).

|  |  |
| --- | --- |
| $$CSection\_{i}= β\_{0}+β\_{1}PD\_{i}+β\_{2}SD\_{i}+ β\_{13}FM\_{i} + control variables + e\_{i}$$ | (1) |

|  |  |
| --- | --- |
| $$CSection\_{i}= β\_{0}^{'}+β\_{1}^{'}PD\_{i}+β\_{2}^{'}SD\_{i}+ β\_{3}^{'}FM\_{i} + β\_{4}^{'}HHB\_{i}+ β\_{5}^{'}PD\_{i}× HHB\_{i}+ β\_{6}^{'}SD\_{i}× HHB\_{i}+ β\_{7}^{'}FM\_{i}× HHB\_{i}+ control variables + e\_{i}$$ | (2) |

$β\_{1}$, $β\_{2}$, and $β\_{3}$capture the treatment effects of the three interventions: *PD*, *SD*, and *FM*. $β\_{5}^{'}$, $β\_{6}^{'}$, and $β\_{7}^{'}$ indicate the moderating effect of *HHB* on the impact of *PD*, *SD*, and *FM*. We include a number of control variables in the model to exclude variance attributable to other factors that may influence c-section use. The first control variable is the gestational age (in weeks) at the time the participant was admitted to the experiment. Since there is variation in when expecting mothers became aware of their pregnancy, the starting point, the length of treatment, and even the treatment itself can be different. Gestational age at baseline was a key consideration because the messages were created to address issues encountered at specific points during pregnancy. The second control variable is singleton or twins (categorical: singleton, twins and above, don’t know), which we control for because medically, it is an important factor influencing the use of c-section delivery. Other control variables include wife healthy behaviors, marital status, number of pregnancies, number of miscarriages, number of births, resident location (village, town, county city, province city), occupation (farmer, private business, government worker, migrant worker, local worker, and homemaker), education level, husband education level, phone owned by the wife, health status change since pregnancy (improvement or not), insurance, endometriosis, health information resources (health institution, internet, TV, books, friends, family), planned pregnancy, gender preference, gender preference of the family, same gender preference as other family members, and preference regarding vaginal delivery or c-section (vaginal, c-section, don’t know).

We first examine the effect of the three treatments without any moderator; results are in Column 1 of Table 3. Compared to the control group (basic messages), a self-directed mHealth (SD) treatment yields a non-significant change (p>0.1) in the c-section rate, while both PD and the FM treatments significantly (p<0.05 for PD and p<0.01 for FM) reduce the c-section rate. These results indicate that the individual SD treatment is not powerful enough to cause a significant reduction even though it is the dominant design in existing mHealth solutions. Comparing the impact of PD and FM, FM shows stronger (significance) and larger (magnitude) effects, supporting Hypothesis 1. The coefficient of FM is -0.47, indicating that after adjusting for a robust set of controls, moving a participant from the control group to the FM group decreases her chance of opting for a cesarean section by a substantial 62.5%.

In Column 3 of Table 3, we add the variable *HHB* and the three interaction terms. We find the moderating effect of HHB on FM is positive and significant. In other words, a greater reduction in c-section rates is detected among wives whose husbands exercise regularly and do not drink. By comparison, in the control group the reduction of c-section rates is only 3.8% when HHB is 0 and 14.8% when HHB equals 1. It is also interesting to note that after adding HHB as the moderator, the variable FM is no longer significant. This indicates that the reduction in c-section rate is mainly driven by the subgroup of wives whose husbands have healthy behaviors.

One surprising finding comes from the comparison between social support (husband healthy behavior) and personal factors (wife healthy behavior). As reported in Column 2 of Table 3, when we use wife healthy behavior rather than husband healthy behavior as the moderator, no significant moderating effect is observed. This implies that the influence of social support in mHealth might be even stronger than individual user factors.

Given the significance of husband healthy behavior on c-section rates, we further examine how the SD, PD, and FM mHealth interventions influence c-section rates among the subsample for whom HHB equals 1 and check whether Hypothesis 1 still holds. As reported in Column 4 of Table 3, only FM is statistically significant (p<0.01), which again supports our previous finding of complementarity between SD and PD.

## 4.3 Additional analyses

**Robustness tests**

We conduct robustness checks to rule out alternative explanations and address potential threats. First, as aforementioned, there are four unbalanced variables (attitude toward pregnancy, perceived susceptibility to health issues, number of pregnancies and number of miscarriages) across the four groups in our final dataset. To ensure that our findings are not driven by any potential imbalance across groups, we include them in the main regression model (Columns 1 and 2 of Table 4). We obtain consistent results; both the main treatment effects and the moderating effect of husband healthy behavior are robust and significant. Second, family income is an important variable reflecting both the socio-economic environment of the family and the expectant mother’s access to resources. To verify that our findings are not driven by underlying heterogeneity in income, we add this variable to the model. Note that this was not included as a control in the main analysis because of the lower response rate to the income question on the baseline survey. While this sample size is significantly reduced due to this, all the results of the FM intervention hold (see Columns 3 and 4 of Table 4).

**Mechanism of mHealth in c-section reduction**

Finally, we present evidence that sheds light on the mechanism underlying how mHealth reduces c-section rates. The drivers of c-section use can be categorized as medical necessity or misconceptions. Our main analyses do not support an understanding of which one of these drivers was affected by mHealth; we conduct further analyses to address this question. During our follow up survey, women who elected a c-section were asked about their reasons for doing so. Of the 412 new mothers, 348 answered this question. Of those who answered, an overwhelming majority, 344 (98.8%) replied that they chose a c-section because of medical reasons, 3 (0.9%) were afraid of pain, and 1 (0.3%) indicated that she chose a c-section out of preference. These data indicate that medical necessity alone is the respondents’ motivation for c-section use. In other words, misconception is not a significant reason for c-section use in this study. We therefore investigate the effects of our mHealth interventions on the underlying medical conditions.

The medical necessity for a c-section could be due to the health condition of the mother or of the baby. One of the most common conditions is macrosomia of the new baby (Parks and Ziel 1978; Spellacy et al. 1985). Here we report the rate of macrosomia in the four study groups. As presented in Figure 3, there are 23 (6.3%) macrosomia cases in the control group, 21 (6.0%) in the PD group, 20 (5.6%) in the SD group, and 20 (4.6%) in the FM group. Since the lowest rate of macrosomia was observed in the FM group, we observe that the mHealth intervention contributed to cesarean section reduction by improving the expectant mother’s health condition.

## 4.4 Husband support and power in marriage

The significant moderating effect of husband healthy behavior indicates the importance of this source of social support for the effectiveness of mHealth in the maternal health domain. If, then, the husband indeed plays a critical role in the effectiveness of the mobile intervention, this effect should be stronger if the wife can better leverage the husband’s support, which may happen especially if the wife plays an influential or leading role in the marriage. We therefore characterize marital relationships in terms of the relative power of the wife and investigate the interplay with the husband’s healthy behavior.

According to Blood and Wolfe's (1960) resource theory, spouses’ decision-making power is greatly regulated by their relative resources, which could be education, occupation, income, etc. We proxy the power dynamics by creating a composite score using several variables: the expectant mother’s employment status, residency location, phone ownership, education, and gender preference. A wife as a homemaker in northwestern China usually has less power within the family. A homemaker role may be connected to isolation, a shortage of information, lower contributions to family income, and a smaller social network (Herr 1962; Ajrouch et al. 2005). Furthermore, China is traditionally a patriarchal society, with male power being stronger in rural areas of China, suggesting that residing in a village could be an indicator of lower wife power (Matthews and Nee 2000). We also assume that the power of the wife is higher if she owns the cell phone used for this study (an indicator of relative economic status), if she is better educated than her husband, or if the rest of the family shares her gender preference for her new child. Our operationalization of high wife power in marriage is thus computed as the composite score (average) of the five variables: not a homemaker, not living in a village, owning the phone, higher education than husband, and same gender preference (average of the five dummy variables).

To investigate how high wife power in the marriage can influence the moderating effects of husband healthy behavior, we estimated a three-way interaction model (Brownell and Hirst 1986; Dawson 2014).

|  |  |
| --- | --- |
| $$CSection\_{i}= β\_{0}^{''}+β\_{1}^{''}PD\_{i}+β\_{2}^{''}SD\_{i}+ β\_{3}^{''}FM\_{i} + β\_{4}^{''}HHB\_{i}+ β\_{5}^{''}PD\_{i}× HHB\_{i}+ β\_{6}^{''}SD\_{i}× HHB\_{i}+ β\_{7}^{''}FM\_{i}× HHB\_{i} + β\_{8}^{''}WifePower× HHB\_{i} + β\_{9}^{''}WifePower× PD\_{i}+β\_{10}^{''}WifePower× SD\_{i}+ β\_{11}^{''}WifePower× FM\_{i}+ β\_{12}^{''}WifePower× PD\_{i}× HHB\_{i} + β\_{13}^{''}WifePower× SD\_{i}× HHB\_{i} + β\_{14}^{''}WifePower× FM\_{i}× HHB\_{i}+ control variables + e\_{i}$$ | (3) |

 Here, $β\_{12}^{''}$ , $β\_{13}^{''}$ , and $β\_{14}^{''}$ indicate the three-way interactions for the three mHealth interventions. The result is reported in Column 1 of Table 5. The coefficient of “*HusbandHealthyBehavior X PD X WifePower*” is not significant (p>0.1), suggesting that the higher power of the wife does not influence the moderating effect of husband healthy behavior on a provider-directed mHealth intervention. The coefficients of “*HusbandHealthyBehavior X SD X WifePower*” and “*HusbandHealthyBehavior X FM X WifePower*” are both statistically significant (p<0.1 and p <0.05 respectively). The significance demonstrates that the wife’s power is important to realizing the value of the husband’s support: the more power she has, the more she can benefit.

To further confirm this finding, we conducted subgroup analyses. We divided all participants into groups based on the five variables indicating the wife’s power. We report the results for subgroups where wives have higher power in the marriage in Columns 2-6 of Table 5. The moderating effect of husband healthy behavior on FM is consistently significant across all these high-wife-power groups. In a more comprehensive analysis, the moderating effect is insignificant for lower-wife-power groups (i.e., homemakers, living in a village, wife not owning the phone, education not higher, not same gender preference; these results are not reported due to space limitations).

# 5. Discussion and conclusion

The potential promise of mobile health technologies for improving healthcare delivery and health outcomes is substantial. Yet there is limited understanding of the specific drivers that make an mHealth solution effective. We examined how the nature of mHealth intervention design and the social support of mHealth users influences health outcomes. Based on one of the largest field experiments with the goal of reducing cesarean sections among expectant mothers, we find that combining self-directed and provider-directed mHealth (the FM treatment) significantly increases the overall effectiveness. Furthermore, the effect of the mHealth intervention critically depends on the extent to which the husband engages in healthy behavior. The FM treatment yielded significant effects only for the subgroup where husbands exercise and do not drink. Further analyses show that the mHealth treatment has a stronger influence when the wife is in a relatively higher position of power in the marriage.

Our findings offer implications for both mHealth application development and research on appropriating value from mHealth, thus making important contributions to the emerging literature on mobile technologies (Andrews et al. 2015; Fang et al. 2015; Fong et al. 2015; Ghose et al. 2012; Sun et al. 2015). Our evidence suggests that the combination of both self-directed and provider-directed mHealth produces superior outcomes. Providers of mHealth solutions could use these results as a foundation for designing functionality. Our findings about the importance of partner social support could potentially be generalized to other types of social support or even other environmental factors that are necessary in achieving the target user’s healthcare goals. For example, for an individual managing a chronic condition such as diabetes where exercise is a recommended course of treatment, social support from a partner is likely to play a critical role in motivating the patient. Future research could consider additional environmental factors that may be relevant to achieving the full potential of mHealth.

Our findings also contribute to the IS research on the social determinants of IT payoff. Health IT researchers have pointed out the importance of non-clinical factors in determining health outcomes (Ayabkan et al. 2016). The social factors studied in prior research include geographic location, local environment (Luo et al. 2013), friends (Bapna et al. 2015), social norms (Burtch et al. 2017), and social network structure (Venkatesh et al. 2016). We extend this stream of literature by examining social support in the marriage relationship, which has not been much explored in the IS literature.

We acknowledge some imitations of our study that also represent opportunities for further work. First, the experiment was conducted in China, so readers should be cautioned that some of the cultural factors and dynamics may be specific to this research setting. Similar studies in other cultural settings may add further nuance to our understanding of social support. Regardless, our findings provide solid evidence for the urgent need to consider social factors in mHealth effectiveness. Second, we proxy social support based on husband healthy behavior. It would be ideal to capture the husband’s social support directly, which could be a fruitful venue for future research. Finally, since the interventions are based on mobile messaging technology, it would be valuable to examine a richer media format such as mobile apps.

1. [↑](#footnote-ref-1)
2. Apricot Forest Inc. is the leading and biggest medicine reference platform in China, who also offers an all-in-one patient service system. The users of Apricot Forest cover 37% of physicians in China. [↑](#footnote-ref-2)