Chale, How Much it Cost to Browse? Results from a Mobile Data Price Transparency Trial in Ghana

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ABSTRACT
Mobile data usage is on the rise globally. In emerging regions, mobile data is particularly expensive and suffers from the lack of price and data usage transparency needed to make informed decisions about Internet use. To measure and address this problem, we designed *SmartBrowse,* an Internet proxy system that shows mobile data usage information and provides controls to avoid overspending. In this paper, we discuss the results of a 10-week study with SmartBrowse, involving 299 participants in Ghana. Half the users were given SmartBrowse, and the other half was given a regular Internet experience. Our findings suggest that, compared with the control group, using SmartBrowse led to a significant reduction in Internet credit spend and increased online activity among SmartBrowse users, while providing the same or better mobile Internet user experience. Additionally, SmartBrowse users who were prior mobile data non-users increased their webpage views while spending less money than control users. Our discussion contributes to the understanding of how forward-looking ICTD research in the wild can empower mobile data users, in this case, through increased price transparency.

Categories and Subject Descriptors
H5.M [**Information interfaces and presentation (e.g., HCI)]:** Miscellaneous

General Terms
Experimentation, Measurement, Human Factors

Keywords
Mobile data, Ghana, Pre-paid, Pay-as-you-go, Android, developing countries, digital divide

1. INTRODUCTION
While the individual benefits of mobile ICT use are still a topic for active research, the significance of mobile ICT *spending* is equally important. For example, a nationally-representative consumer survey in 17 countries in sub-Saharan Africa (SSA) showed that mobile phone spending was 10-26% of individual income in the lower-75% income bracket [5].

Because of the individual economic significance of mobile ICT use, we believe that enabling mobile users to make the best use of their ICT spending should be a key area for ICTD research -- and in particular, we believe that mobile *data* usage should be a key area for forward-looking research. While many ICTD practitioners rightly focus on maximizing access for the lowest socioeconomic groups by using carrier voice and messaging services, ICTD research cannot ignore the fact that mobile data usage is rising rapidly. For example, in 2012, 99.2% of all Internet traffic in Kenya was from mobile data [33]. This rise cuts across a range of socioeconomic groups because it often enables cost savings (e.g., over-the-top voice and messaging services can be substantially cheaper than the carriers' voice and messaging services) as well as new, innovative services.

Price transparency is an important barrier to making informed choices about mobile data use. A recent McKinsey study found that over 20% of mobile data non-users in major African cities cited lack of pricing information and control over monthly expenses as key factors for their Internet non-use [3]. Consumers can easily manage carrier voice and messaging costs because the units of cost and billing (minutes and messages) are relatively clear. In contrast, the cost of Internet browsing is opaque -- what is the cost to load a "web page"? What does a balance of 3MB tangibly mean? Which websites take up most credit? While there have been attempts to normalize per-page costs via content modification [6], this creates a technically brittle, second-class browsing experience. Is there a way to allow mobile users to understand their data spending without altering content?

In this paper, we present results from a 10-week study of 299 mobile Internet users in urban Ghana. We provided participants with Android phones that enabled a full Internet browsing experience, and gave half of them access to an Internet proxy system, called *SmartBrowse*. Through a variety of features, the system informed users of the cost of accessing a given Web page *prior to and immediately after incurring that cost*. We believe that the comparative browsing behavior of the participants (all participants still paid for their own data usage) provides significant evidence that price transparency for Internet browsing can be increased without rewriting content.

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The contribution of this paper is twofold. First, we describe the SmartBrowse system and its effectiveness in reducing mobile data spending without negatively affecting Web browsing behavior. To the best of our knowledge, our research is the first study that seeks to understand user behavior when mobile data usage is made transparent *while* using the Internet (as opposed to retrospective presentation of usage information), in an emerging region context. Second, we provide a detailed description of the logistics involved in running a user study that requires this degree of "new" infrastructure – studying interventions that are currently not pervasive or affordable to a majority of socio-income groups, but are steadily increasing – deployed with randomly-selected users in the wild. This is in contrast with other forward-looking ICTD interventions that focus on technologically enhancing an institutional or commercial worker's efficiency, e.g., NGO health workers or clinicians [2,23].

The paper is organized as follows. We highlight our baseline research findings on mobile data attitudes, which informed our software design on pricing information and protection. We describe the SmartBrowse system in detail, followed by a discussion on the research methods we used to measure the effect of the intervention. We then describe findings from our trial, including Internet usage and credit spend behavior, attitudes and perceptions; overall satisfaction; and the feeling of control over mobile data credit. As a mixed-methods paper that bridges qualitative with quantitative data, we organize our findings thematically with categories that emerged from the data. We follow up the findings with a discussion on price transparency, including empowerment of users, helping mobile data non-users scaffold into Internet use, conducting research with urban users, and running a forward-looking study in ICTD. We conclude the paper by describing our logistics and experience of setting up the SmartBrowse trial, focusing on the trial setup, recruitment, maintenance, incentives, and feedback tools we used.

2. BACKGROUND

2.1 The Cost of Mobile Service

The cost-sensitivity of mobile phone and Internet users in developing regions is a common concern in ICTD. For example, researchers frequently propose low-cost access services based on "alternative" connectivity models with reduced interactivity (e.g., [14,21]). However, for a growing segment of the population, the relevant question is no longer how to obtain access -- geographic access (coverage) and economic access (affordability) of commercial mobile ICTs have improved greatly over the last decade [29]. Instead, the question is how to work access into routines in both opportunistic [25] and planned [30] ways over the course of a day, or how to negotiate access from those around them [24]. A 2012 report on "base of the pyramid" (BoP) mobile use in Kenya indicated that, even in the BoP demographic, 25% of participants reported using mobile data services [10].

2.2 Buying Mobile Data in Developing Regions

It is instructive to look at what is known about how people buy mobile services, focusing on SSA where data are available.

2.2.1 Telecom and Development Indicators

While country-level statistics tell us relatively little about individual purchasing behavior, they do give us some important comparative context for those behaviors. This context comes from both supply-side and demand-side sources.

Supply-side (operator-reported) data. Supply-side data includes characterizations of the service plans offered in various markets, including prices (e.g., [9,15,20]); the number of service plan subscriptions (e.g., [29]); and the type of service plan subscriptions (e.g., [15]). This data is released by operators and collated by various methods – via national regulators and the ITU, shareholder reports, websites, etc.

For our purposes, the key takeaway from the supply-side data is that pre-paid mobile service plans, sold in small increments, have increased affordability of mobile service in developing regions (e.g., [17]). In 2012, an estimated 87% of mobile subscriptions in developing regions were pre-paid [15]. The logic here is essentially the same as that for sachet marketing of physical goods [22]: availability in smaller sales units increases product affordability for customers who cannot easily obtain credit or save larger amounts of cash. There is not as much research on mobile data usage, but the same logic would be expected to apply [11] and the limited operator data available suggests that consumers do prefer smaller units for pre-paid data (see, e.g., [27]).

Demand-side (consumer survey) data. Demand-side data is generally obtained through surveys that assess what subscribers are actually paying for mobile services (e.g., [5]), typically as a fraction of income as well as in absolute terms, and what services they are actually using (e.g., [4,10]).

For our purposes, the key takeaway from the demand-side data is that, in spite of dramatic affordability (and adoption) gains over the last decade, mobile service is still a large fraction of the disposable income for many SSA consumers. Mobile service costs in SSA represent double-digit percentages of income for all but the top income quartiles, unlike the low-single-digit percentages typical in developed economies [5]. Even in highly competitive telecom markets like Kenya, surveys reveal that the poorest subscribers still often cut back on necessities (e.g., food) to access those services [10].

2.3 Studies of ICT Consumption in Local Markets

As one asks increasingly specific questions about mobile user purchasing patterns, data is generally only available for specific countries (or cities and regions within countries).

Pre-paid credit balances for mobile service (usable for voice call "airtime," SMS, etc.) are generally "topped up" by purchasing "scratch cards" or by using a mobile payment service balance from a ubiquitous network of informal traders. Naturally, both technical mechanisms and informal practices (e.g., [18,24]) for balance-sharing are used throughout the developing world. Balances can also be used to pay for mobile data at a "pay as you go" (PAYG) usage-based rate. PAYG blurs the boundaries between airtime and data, since the same resource is used for both and notifications systems do not present usage information in an easy-to-understand fashion to users [24].

Pre-paid data can also be purchased at a discounted rate in bundles – a given allowance (in megabytes) with an expiration period (typically 1, 7 or 30 days, depending on the bundle size). Bundles are expected to be "topped up" like regular balances. For our purposes, the key takeaway from the limited studies of mobile purchasing is that a minority of subscribers uses the discounted bundles, even the small sachet-like bundles that are aimed at lower-income users. For example, a 2011 survey of public venue Internet users in Cape Town found that 37% of teens and 32% of adults had used mobile data bundles [28], despite bundles being typically cheaper than PAYG. (This is consistent with Vodacom's estimate that one-third of their mobile data subscribers in South Africa purchased bundles in 2011-12 [27].) A 2012 survey of low-income mobile phone users in Kenya found that only 1% had any knowledge of data bundles at all, even though a quarter of them used mobile data [10,23].

2.4 Usage Transparency

To date, researchers have explored ways to allow users to retrospectively view and manage Internet bandwidth usage (see [7] for a study on usage practices around bandwidth caps among residential Internet subscribers in South Africa and [8] for a bandwidth management tool). More broadly, researchers have explored ways to effect behavior change around resource consumption, like water and electricity, in the forms of information, prompts, incentives, goal-setting, and social comparison (see [12] for an overview of feedback technologies). Our research contributes to the understanding of changes in decision-making when pricing and usage transparency are made available in context, while using the Internet, by showing current balance information and providing actionable controls, specifically on a mobile phone.

3. BASELINE RESEARCH

3.1.1 Mobile Data Survey in Kenya

In February 2012, we conducted an exploratory survey in Nairobi, Kenya to understand user attitudes towards mobile data pricing and usage [16]. Eighty-two participants (19 mobile data non-users) were surveyed in mixed-income sites (income screening cut-offs were USD120-1200), such as a shopping mall, a supermarket, and a university.

Our findings show that respondents who understood the relationship between the size of a webpage and the associated cost reported spending less money on mobile data. The same respondents were willing to pay less per MB than those who did not understand this relationship.

3.1.2 Mobile Data Survey in Ghana

As a follow-up to the Kenya survey, we conducted a more comprehensive survey on mobile data practices and attitudes with a larger sample size (798 mobile data users and 194 mobile data non-users) in Ghana in June 2012 [16]. Participants were screened from mixed-income sites (USD152-1020) in Accra and Sunyani.

Most mobile Internet users (48%) spent less than USD2.5 per week on mobile data, while 28% spent less than USD2.5 per week on voice calls. Mobile data users and non-users did not have an accurate understanding of mobile Internet costs and many believed they were billed by time. Only 19% of users were able to correctly identify which mobile data activities were most expensive. Fewer users monitored mobile Internet spending, compared to voice/SMS balances. Seventy-five percent of users kept track of their voice/SMS balances, compared to 38% who tracked their mobile Internet balance. One-third of data users had accidentally spent more money than they intended on mobile data.

4. SMARTBROWSE: PRICE TRANSPARENCY FOR MOBILE DATA

Guided by the findings from the Kenya and Ghana surveys, our motivation was to improve price transparency through three different methods:

Increase awareness of mobile data spending among users: Allow users to constantly keep track of their credit balance and learn about web page costs as they browse.

Protect users from unexpected spending: Alert users before browsing expensive websites to prevent unexpected overspending, to allow them to make a decision on whether or not to continue to visit the website.

Allow users to top-up easily: Provide a standalone on-screen element to easily check and top-up credit balance, avoiding the difficult-to-use balance check through USSD (short code).

4.1.1 System Design

Android devices were selected for ease of control over the OS and installed apps. A dual-SIM phone was chosen to allow setup of one SIM provided by our team solely for data access and for a separate SIM for the user's personal voice calls, to encourage usage of the phone without separating their main SIM from the study SIM. Phone software was preconfigured with a customized browser and home screen web shortcuts. Mobile device management software was used to restrict user access to apps and direct all Internet usage through the browser, with the exception of Whatsapp, which was used to collect user feedback.

4.1.2 Architecture

Every web request from these devices was routed to the proxy server. Before fulfilling the request, the proxy evaluated historical sizes for the requested URL to generate an estimate of expected size. Prior to this trial, we had established a byte-cedi conversion rate via an analysis of historical sizes. We used this data to calculate the cost to the user for the requested web page. Based on the cost, the user's balance, and their settings, the proxy would first alert the user if the size exceeded the alert threshold or would warn the user that their balance was too low to load the page. When the page was retrieved, the proxy also measured the total number of bytes trafficked to the user. These sizes were stored for later analysis. The user was always billed for the original cost estimate, even if it was found to be inaccurate after the page was loaded. For this experiment, we opted not to pre-render, cache, or compress web page data. These are all possible for future trials, and each may affect user perception of cost, latency, and freshness of data.

We created a billing system that managed balances for each mobile device. All balances and usage were indexed by device ID, so the proxy could both query a device's balance and perform subsequent billing for usage. A web service was built to provide a top-up page (discussed under "features").

4.1.3 Features

SmartBrowse consisted of four main features:

Balance bar: A persistent balance bar displayed current data balance over all webpages, allowing users to check their balance with no effort on their part. The balance bar provided a link to the top-up page (see below).

www.X.com Search Results Page Costs: The estimated page cost of each X.com search result was shown in the local currency. Costs were displayed below the web snippets (see Figure 1). Our motivation was to educate the user about the costs of various search results.

SmartAlert interstitial: As a protective barrier to overspending, the "expensive page SmartAlert" appeared before browsing expensive webpages (set by default at USD0.015), allowing the user to continue or go back. Additionally, the user could customize the SmartAlert threshold.

The "top-up SmartAlert" appeared when the balance was too low to visit the requested page, allowing the user to top-up or go back. The default threshold was determined from the Ghana survey and publically available data from Opera Software: 85% of respondents in the survey used PAYG for data. The a la carte rate in July 2012 was USD0.035 per MB in Ghana. Opera Mini mobile file compression was 59% in 2010 [34]. Conseqently, the default rate was set to USD0.015 per MB.

Top-up page: An online top-up page, reachable through the balance bar and home screen, allowed the user to check their balance without relying on USSD. The top-up page allowed the user to top up by entering custom scratch codes (more details in the "running a trial" section). The page was zero-rated (free of charge to use).

Webpage shortcuts: In addition to the features above, shortcuts to top websites (based on analysis of most-visited websites from Ghana) were added to the home screen, including a link to the top-up page.

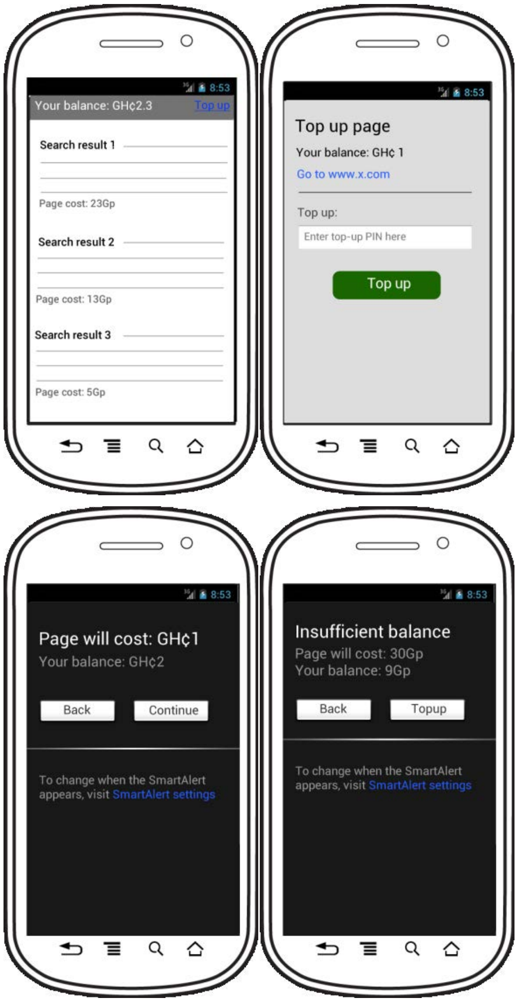

Figure 1. Clockwise. (Top left) X.com page costs for search results and Balance bar [wireframed for anonymity]. (Top right) Online Top-up page. (Bottom left) Expensive page SmartAlert. (Bottom right) Top-up SmartAlert.

5. RESEARCH DESIGN

The research trial lasted for 10 weeks, between mid-September to mid-November 2012. For our participants, we aimed for 300, to be split into control and treatment equally. All participants were given a free GH¢2 starter credit scratch card. The *control* group could use regular Android phone features and view the top-up page. The *treatment* group could, in addition, view and use SmartBrowse features (balance bar, web page costs, and SmartAlert). The participant mix was balanced with prior mobile data users and non-users (also called as "new mobile data users" from here on) but skewed towards users (primary screening criterion); predominantly low- to mid-income; a mix of students and non-students but skewed towards students; of equal gender ratio; and distributed across different departments and years of study. In total, we recruited 299 participants (see table 1). The research trial is described in detail towards the end of the paper.

5.1 The Ghanaian Context

With a population of 24.65 million and a literacy rate of 67.3% [32], Ghana is one of West Africa's most promising and peaceful democracies. Accra, a coastal city, is the national capital. Ghana has an estimated telecom penetration of 88.9% [31], with an Internet penetration of 14% and mobile broadband penetration of 23% (according to ITU, Ghana occupies the first place in mobile broadband penetration in Africa) [15]. Ghanaian currency notations, GH¢ and Gp, are used throughout the paper. At the time of writing the paper, a GH¢ (Ghana Cedi), was valued at 0.51 USD. A Gp (Ghana Pesewa) is 1/100th of a GH¢ [35].

Table1. Breakdown of recruited participants

Control (n = 148)	Treatment (n = 151)
Mobile data users: 106 Mobile data non-users: 42	Mobile data users: 117 Mobile data non-users: 34
Students: 106 Non-students: 42	Students: 121 Non-students: 30
Male: 72 Female: 76	Male: 73 Female: 78
Low-income: 50 Mid-income: 77 High-income: 21	Low-income: 56 Mid-income: 79 High-income: 16

Participant count at the end of the trial: 282. Seven phones were stolen and 10 participants dropped out for various reasons.

5.2 Research Methods

5.2.1 Qualitative Methods

5.2.1.1 Baseline Data Collection

All participants filled out a baseline survey before getting their phones. Questions focused on device ownership and use (mobile phone ownership and usage, Internet access methods and usage, mobile data use, Internet activities and attitudes); airtime and mobile data spend (top-up amounts, and attitudes towards data spend); cost awareness (for a text-lite site, a text+images site, and an image-only site). Questions were largely divided into discrete measures, such as ownership and use, and continuous measures, such as cost awareness and attitudes towards Internet.

5.2.1.2 Mid-trials 1 and 2

To compensate users for their participation, incentive payments were provided to participants in the mid-trials and exit trial (more detail in the "running a trial" section). In weeks 3 and 7, participants came to collect the first set of incentives after filling out a survey. Mid-trial survey questions focused on overall and feature-level satisfaction and usefulness, understanding of SmartBrowse, top-up behavior, perceptions of management of credit, and cost awareness. In addition, we pre-selected 30 participants for interviews based on their attributes, like new mobile data users, control/treatment, and non-students. Interview questions focused on phone tours and SmartBrowse features. Interviews were conducted in Twi, a regional language, for non-English speaking participants.

5.2.1.3 Exit Trial

In week 10, when participants came to collect their final incentive, we followed the same process of survey and handing out incentive as mid-trials. Exit trial survey questions were focused on satisfaction, perceptions of management of credit, future phone purchases, and cost awareness. Similar to mid-trials, we conducted focus groups with 25 participants in both groups.

5.2.1.4 Follow-up Survey

Three months after the end of the trial, we conducted a follow-up survey to understand how SmartBrowse had impacted ex-participants, especially around new phone purchases, mobile data plans and usage, and cost awareness. Using e-mail, phone calls, and SMS, we reached out to our ex-participants. We received 126 responses (63 control and 63 treatment) out of the 299 contacted.

5.2.2 Quantitative Methods

5.2.2.1 Logs Analysis

In addition to attitudinal measures, we collected and analyzed usage logs (anonymized by removing login and network address information) for actual behavior changes across the control and treatment groups. Table 2 shows the metrics derived from the usage log data.

Table 2. Metrics computed from log data.

Per-user metrics, control and treatment	
Fraction days active	Frequency of user activity during the study
Daily pageviews	Number of web pages viewed per day
Daily sessions	Number of browsing sessions per day ("session" = page view sequence w/o 5min break)
Session length	Number of pages per browsing session
Page cost	Cost (GH¢) per pageview
Session cost	Cost (GH¢) per browsing session
Total money spent	Total spend (GH¢) during the study
Per-user metrics, treatment only	
SmartAlerts seen	Total number of pages w/SmartAlerts raised
Total SmartAlert price	Total projected page costs, SmartAlerts seen
Total SmartAlert savings	Total projected page costs, SmartAlerts declined
Per-website metrics	
Number of visits	Used to compute popularity ranking during study

To measure the treatment effect, we computed the ratio of the mean metric values (mean of observations for treatment vs. mean for control) within each of five demographic (sub-)groups of the participants (Table 3). Significance (*p*-value) of this treatment/control ratio was tested using a resampling-based permutation test (see, e.g., [13], Sec. 16.5) with 10,000 resamples. (Such permutation tests are straightforwardly applied to statistics such as ratios, and require fewer assumptions about the underlying distribution than parametric tests.) Findings reported as significant remain significant with the false discovery rate (FDR) controlled at 0.05 [26] ($m=63$, $\lambda=0.20$).

5.2.3 Caveats and Limitations

Our trial experienced a few caveats. First, due to a software bug, www.X.com web page costs were shown to the control group for the first two weeks. These costs positively influenced the cost awareness of the control group (explained in detail under "findings") to an extent. Second, due to a bug, we underpriced web page costs by 1Gp (we charged 2Gp/MB instead of 3Gp/MB). We noticed the bugs after the first two weeks and rectified them. Both bugs have some effect on user behavior. At the same time, they helped highlight aspects of Internet usage; such as how influential page costs were in driving cost awareness and how sensitive participants were/became to web pricing.

Table 3. (Sub-)groups analyzed for treatment effect.

All users	**All study participants**
Prior mobile data user	"prior" = had used mobile data prior to study "new" = had not used mobile data prior to study
Gender	female, male
Life-stage	student, non-student
Income bracket	GH¢/month - low (x), medium (y), high (z)

It is also important to note the limitations of our trial. While we tried to include non-students, our trial remained largely focused on students because of the university environment. We placed limitations on the types of content accessible through the phones because of technical implementation and security constraints. Our participants could browse all webpages, but access to apps, viewing videos, and downloading files were disabled. Apps and videos are not discrete resources and can continuously pull data; hence the size and length information cannot be known before streaming or downloading. Downloading files placed a security risk on the phones. Therefore, our findings are not completely reflective of organic mobile data usage.

6. FINDINGS

Overall, from our satisfaction surveys, we learned that treatment users were slightly more satisfied than control users (see figure 2) while using SmartBrowse features. The terms "SmartBrowse users" and "treatment users" are used interchangeably.

6.1 Mobile Data Usage Logs

6.1.1 SmartBrowse Users Went Online More Often than Control Users

Over the 10-week period, both control and treatment users, including new mobile data users, used their phones regularly without major dips in usage (see figure 3). We measured the number of users that effectively dropped out of the experiment by not using their phones on a regular basis. To track drop-off rates, we measured, for each user, the fraction of days when they went online with their phone at least once (an "active day"). Over the 10-week experiment, on average, a user in the control group was active 70% of days, while a treatment user was active 75% of days. A treatment user was active on an average of 7% more days than a control user (significant to the 99% level).

6.1.2 SmartBrowse Users Spent Less on Internet Credit

Users in the treatment spent an average of 19% less than overall population during the trial (GH¢4.1 treatment versus GH¢5.06 control) significant to the 99% level. This result was largely constant across subpopulation (age, gender, etc.).

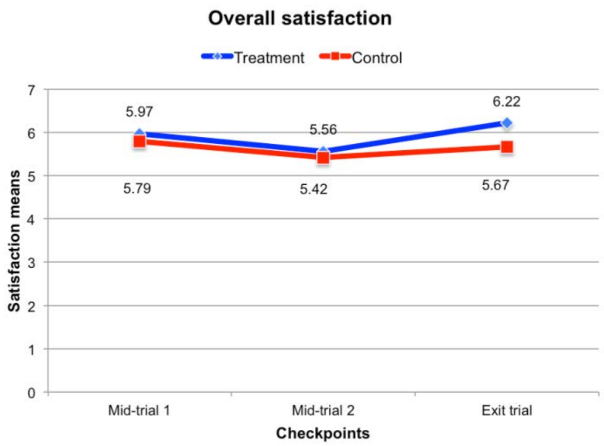

Figure 2. Overall satisfaction across checkpoints (1: extremely dissatisfied to 7: extremely satisfied)

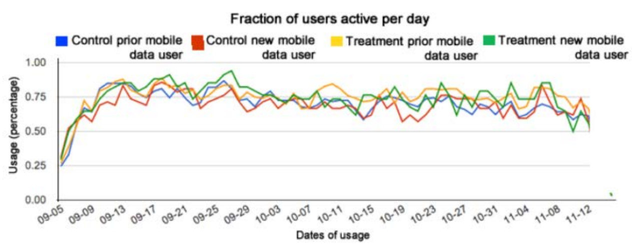

Figure 3. Fraction of users active per day over 10 weeks, broken down by C vs. T, mobile data user vs. new user

6.1.3 SmartBrowse Users Actively Responded to SmartAlert

About half (55%) of the money saved by treatment users is explained by users avoiding expensive pages via SmartAlert. Recall that SmartAlert is a warning page that asks a treatment user to confirm before loading an expensive page.

Control users spent about GH¢ 450 total, while treatment users spent GH¢360 total. When we add up the costs of all pages that triggered SmartAlerts where the user chose to "Go Back" (avoid loading it) instead of "Continue" (pay and load the page), this amounts to GH¢50. In other words, users potentially would have spent about GH¢50 more if we simply took away the SmartAlerts. While this is not a perfect conclusion, since it is possible that users went back and loaded an alternative page instead (see the section, "user strategies for saving credit", below), it is indicative of the perceived usefulness of SmartAlert. See figure 4.

During the course of the experiment, treatment users saw a total of about 2000 SmartAlerts. On about 1200 of these, the user hit "Continue" and paid to load the page. These pages had an average cost of 4.5Gp (max: 27Gp). On 800 SmartAlerts, the user hit "Back" or navigated elsewhere. These pages averaged 6Gp (max: 42Gp). Declined pages were about 33% more expensive than accepted pages, showing that the more expensive the page, the more likely a treatment user is to decline to pay for it.

6.1.4 Treatment Users Went to Cheaper Web Pages Overall

SmartBrowse users spent 21% less than control on average on session costs (significance >99%). Recall that a session is when a series of webpages are viewed without a >5-minute break.

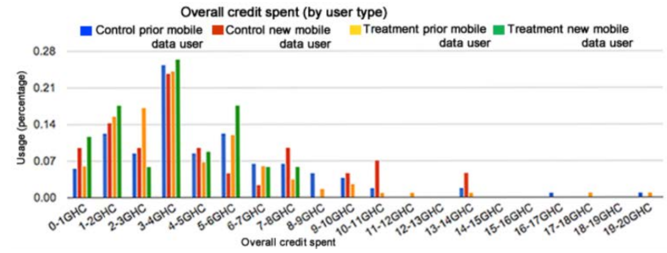

Figure 4. Overall credit spent over 10 weeks, broken down by C vs. T, mobile data user vs. new user

Table 4. Raw values of control and treatment metrics

	Control raw values (n=148)	Treatment raw values (n=151)	Treatment effect on sub-population	Significance
Fraction days active	0.70	0.75	7%	99%
Average session cost	0.01	0.01	-21%	100%
Money spent Cedis	5.06	4.10	-19%	99%

6.1.5 New Mobile Data Smartbrowse Users Experienced Greater Benefits

If we restrict our measurements to new mobile data users – subjects who did not use the mobile Internet on their phones before the experiment, we get more dramatic results. Non-users in the treatment visited 53% more web pages than non-users in the control group (96% significance), while also spending 27% less money (99% significance). This result could be interpreted to imply that cost-related information is especially useful for new users. New mobile data control users (see figure 4), spent a lot more money on credit, since most had no prior conception of Internet pricing.

Table 5. Raw values for non-user metrics

	Control raw values (n=148)	Treatment raw values (n=151)	Treatment effect on sub-population	Significance
Average daily pageviews	22.11	33.83	53%	96%
Average page cost	0.00	0.00	-27%	99%
Average session cost	0.01	0.01	-34%	100%

6.1.6 Male Users Spent More than Females

In accordance with previous research and expectations, men visited webpages that were 50% more expensive on average. Men went online slightly more often, but visited fewer pages than women in a given browsing session. The result is that men spent about 25% more money on average. Male users visited a lot more data-heavy sites, such as football websites, than female users.

7. COST AWARENESS

7.1.1 SmartBrowse Users had Greater Cost Awareness

During the course of the trial, both control and treatment users became closer to the original cost estimates. However, more treatment users were in the correct cost estimate categories than control users (see table 7). Interestingly, most control participants had noticed the page cost labels on www.X.com within the first two weeks and revised their estimates of how much webpages cost. For self-assessed cost awareness, control users were ambivalent whereas treatment users rated themselves much higher (57% control participants noted they were more cost aware since SmartBrowse compared to 91.5% in treatment). Several treatment users had discovered that some of the websites were more expensive than they originally assumed. For example a participant discovered buybay.com cost him 46Gp instead of 10Gp. Conversely, some users discovered that some websites that they had originally assumed to be expensive were actually cheaper. For example,

> *"I used to think Facebook was very costly, especially for photos. After I started SmartBrowse, I realize it is not costing so much. I am on Facebook always and it costs only 1-2Gp."*

The calibration of the cost of a regular website was revised to a much smaller number (for some participants from 50Gp in baseline to as low as 2Gp during the trial). After starting SmartBrowse, several treatment users mentioned they hit "back" at about 10-15p, compared to the 50Gp average estimate from the baseline, which alludes to a revision of "expectation of cost".

7.1.2 SmartBrowse Users Reported being Better at Management of Data Credit

In the exit trial, 72% of treatment users reported they were making better decisions at managing their Internet credit (28% noted they were making same or worse decisions compared to pre-SmartBrowse), whereas only 43% of control users felt they were making better decisions.

> *"We are college students. We don't have much pocket money. I buy GH¢1-2GH¢ credit from our Hall shop every 2-3 days. Now I am learning how to be careful with my small amount. Earlier I did not notice, but now I know which websites are cheap and my balance is OK. It lasts 4-5 days now."*

7.1.3 Being in Control with Carriers

Many treatment users mentioned they felt they were in better control of carrier pricing after using SmartBrowse. By learning the costs of webpages and setting new expectations around what various types of content should nominally cost, users mentioned they now had a better grasp of prices that could be applied to future carriers. However, some participants felt SmartBrowse was inexpensive compared to their carrier and mentioned they would verify and compare prices for future carriers.

> *"Now I know how much to pay for which website. I will not get cheated by any phone company in the future."*

7.2 User Strategies for Saving Credit

7.2.1 Becoming Cost-Conscious

Qualitatively, across control and treatment, several participants noted that they spent more time online since starting SmartBrowse. Increased online browsing was attributed to perceived cheap prices of SmartBrowse and ease of use of a touch phone. Downloads and watching videos were carried out on other devices. Many participants reported going online more during the first two weeks of the trial to explore the phone, visit various websites and to get a sense of the pricing of SmartBrowse.

> *"Wednesday to Monday, I spent my first GH¢2. I finished the second GH¢2, which I bought, in a week. I used my own money in the second week, so I was careful with browsing. First GH¢2 was an incentive to use, so I visited pages I was not supposed to visit."*

Some users were motivated enough to verify the SmartBrowse pricing by comparing it to their carrier's prices, painstakingly, by loading multiple webpages and checking their credit before and after, to ensure SmartBrowse was not overpriced.

Several treatment users reported becoming more aware of their credit spend since starting SmartBrowse. The visual foregrounding of usage information by SmartBrowse was cited as a huge influence in becoming more conscious of credit.

> *"Earlier I did not think so much about credit for data. I used to just buy small amounts to control how much I spend, but it would run out so soon and I did not know where I spent the money, on which websites. But now I see the balance bar all the time. It is showing my how my balance is reducing as I am browsing. I think more about my credit now, which I did not earlier. It has helped me save money."*

Table 6. Cost awareness exercise results. (Top to bottom) text-lite, images+text, and image-heavy sites. Correct intervals are highlighted in green. Responses with majority numbers are highlighted in orange.

Value	Baseline	C (MT1)	T (MT1)	C (MT2)	T (MT2)	C (exit)	T (exit)
<1Gp	3	18	6	9	10	13	10
1 - 5Gp	36	61	66	80	115	94	133
6 - 15Gp	60	22	27	25	13	16	8
16 - 50Gp	111	25	20	25	4	16	6
51Gp - GH1	25	10	4	2	0	0	0
1.1 – GH5	28	3	6	0	0	0	0
>GH5	4	2	0	0	0	0	1
Value	**Baseline**	**C (MT1)**	**T (MT1)**	**C (MT2)**	**T (MT2)**	**C (exit)**	**T (exit)**
<1Gp	7	12	9	4	13	13	12
1 - 5Gp	16	41	59	66	106	84	111
6 - 15Gp	45	23	19	24	24	23	18
16 - 50Gp	141	44	40	21	9	14	12
51Gp - GH1	32	15	8	0	1	0	0
1.1 – GH5	28	4	0	0	0	0	0
>GH5	2	0	3	1	0	0	0
Value	**Baseline**	**C (MT1)**	**T (MT1)**	**C (MT2)**	**T (MT2)**	**C (exit)**	**T (exit)**
1 - 5Gp	42	61	62	82	111	98	121
6 - 15Gp	62	26	26	29	13	16	10
16 - 50Gp	120	27	25	26	4	7	5
51Gp - GH1	27	11	5	1	1	0	0
1.1 – GH5	11	3	3	0	0	0	0
>GH5	6	0	1	0	0	0	0

> *"Ghanaleaks.com amount of credit is so high. Within 2-3 minutes, about 80Gp-GH¢1 will be gone. I did not know it costs so much. Now I know. I don't open that site anymore."*

7.2.2 Finding Cheaper Alternatives to Websites

With SmartBrowse, many prior mobile data users in treatment found cheaper alternatives to the websites they wanted to visit, by finding substitutes in the same content category. For example, one participant noted,

> *"I used to go to soccernet.com everyday to check football scores. But then I realized it costs 18Gp from the pop-up [Smartalert]. So I stopped going there and now I go to goal.com instead, which also shows me football scores but it costs only 5-6Gp."*

New mobile data users did not have a strong conception of favorite go-to websites on the phone (some participants had used the Internet on their laptops or in cybercafés). They were generally more cost-conscious in their decisions to browse websites (as noted earlier in "usage logs").

Many treatment users mentioned they would visit a website regardless of cost if it provided the information they wanted, such as Facebook.com and MyJoyOnline.com. The most visited websites [facebook.com, google.com, ghanaweb.com, myjoyonline.com, and twitter.com] redirected to their mobile versions automatically. When users were not particular about visiting a certain website, then they would choose a cheaper option, such as for dictionary sites or research sites. Control users were less vigilant of credit spend as compared to treatment, but still reported using the top-up page to check balance more frequently than their previous USSD experiences.

7.3 Using SmartBrowse Features

7.3.1 Balance Bar

The balance bar was generally perceived to be necessary. For many treatment participants, the balance bar served as a way to check their balance, swinging between knowing credit in aggregate (determining whether credit had dropped too low or not) and knowing individual page costs when the web page cost labels were not shown or when SmartAlert would not pop up (for webpages below SmartAlert threshold or non-X.com pages).

> *"Before I start browsing, I have to know amount of credit on the phone. So I will check my balance on the bar. After visiting a page, I will check my balance again. Within 5 minutes, I will check the credit deducted. Once in a while to see if credit is OK, to make sure it is not jumping from GH¢2 to GH¢1.5 suddenly."*

7.3.2 Top Up Page

Participants found the visual display of balance to be convenient and simple. The page was found to be more reliable than USSD balance checking, which usually resulted in "network error" and "timeout" messages. Many users liked the ease of inputting the short scratch code. Some control users reported checking their balance more often on the online top-up page as compared to USSD. Several control users mentioned they checked their balance less on SmartBrowse because they felt "safe" that it was cheap and they were not going to be cheated. Many noted that they checked balance a lot initially and then stopped checking as much once they started trusting the system. A majority of the treatment users checked their balance through the balance bar and opened the topup page only for adding credit.

7.3.3 SmartAlert

SmartAlert was used in impromptu browsing, when the user did not have a particular site in mind. Users made decisions about whether or not to visit the webpage when they were explicitly presented with cost information. SmartAlert seemed less useful when a decision to visit a website was already made. A few treatment users mentioned they would get annoyed if the SmartAlert popped up over their favorite websites.

> *"Cosmo is my favorite site! I have to check it everyday. But the alert pops up every time I visit it. Its quite annoying."*

However, users were reluctant to change the SmartAlert settings to a lower threshold (among the ones who had discovered the link) fearing that there will not be an alert for expensive but "fun" webpages that they would not necessarily visit if they knew the cost. Intelligent, learning systems can help mitigate this issue.

7.3.4 Web Page Costs

www.X.com page costs were perceived as "good to know". As evidenced in the increased cost awareness for control due to the bug, X.com page costs were heavily influential in educating users about costs. Decisions on which X.com search results to visit were highly contextual, i.e., content influenced most visit decisions and cost influenced some decisions. Web page costs were largely purposeful for education.

7.4 New Behaviors and Changes

7.4.1 Shortcuts were Key to Defining Browsing Behavior

The shortcuts we placed on the home screen of Android introduced new browsing patterns. Several participants noted that they visited new websites simply because there was a shortcut to the site, such as MyJoyOnline and Goal.com. Most websites visited by users seem to be within the scope of the shortcuts (note that we chose shortcuts from top website traffic in Ghana). The home screen shortcut for the Opera browser was the most common entry point. In addition, shortcuts on the Opera home page were heavily used. Similar to the home screen, these shortcuts introduced participants to new websites.

7.4.2 Going Online on a Phone for the First Time

In the case of new mobile data users with prior Internet experience in cybercafés and PCs, many participants reported enjoying the smart phone Internet experience and that it had changed their assumptions about phone browsing being difficult. Some participants mentioned they had gained awareness of webpages costs in general, which they did not consciously think about otherwise:

> *"Before SmartBrowse, I did not think much about how much websites cost. Now I know. I will avoid some sites even in café."*

Note that page sizes and data costs may vary across access media. New data users that had no prior experience with Internet (predominantly low-literate workers) had some difficulty with using the Internet because of literacy constraints. Some participants reported that they sought the help of friends and family members to browse. Those with sufficient literacy mentioned they learned how to browse Internet for the first time.

7.4.3 Getting Used to a Smart Phone

All participants who were interviewed responded positively to using the phone, with varying levels of enthusiasm depending on whether or not they were prior smart phone users. Most smart phone non-users did not have a clear sense of what the Android operating system was, but identified the phone qualities, such as the touch screen, large screen size, ability to zoom ("*it has life*!", in the words of a participant), and portability as highly enjoyable and convenient. Prior smart phone users were less enthusiastic about the phone. New mobile data users reported enjoying not having to visit a cyber café and being able to instantly retrieve information on the Internet anytime, anyplace.

Participants paid a lot of attention to network speeds, looking for network strength bars and page loading speed. Speed was perceived in binary as "fast" and "slow" and appeared to be a major determinant of satisfaction.

7.4.4 Post SmartBrowse

Roughly half of the follow-up survey respondents (n=126 in total) had purchased a new phone since the end of the trial. Out of these, 86% from control and 78% from treatment had purchased a smart phone. Most up-conversions were from mid-range feature phones to smart phones. Half of the participants attributed the decision to purchase a smart phone to the SmartBrowse experience. 36% on average had converted to mobile data since SmartBrowse (54% already had mobile data and 10% did not). Roughly half had moved to the mobile phone as a primary Internet browsing device.

We conducted a cost estimation exercise in the follow-up survey. Both ex-control and ex-treatment participants were mostly accurate in their correct estimates, possibly suggesting building of *knowledge* of webpage costs that persisted beyond the trial. Participants noted that SmartBrowse changed their Internet usage by making them cost-conscious when using the Internet and made them appreciate browsing the Internet on the phone.

> *"I now know which site to visit and not to visit. I now spend little time to browse cos of cost involved. That is, I try to save credit."*
>
> *"[Changed my Internet usage] Because am very much conscious with page charge when using a friend's phone to browse."*

8. DISCUSSION

What are broader learnings from our price transparency trial that can be applied to ICTD?

8.1 Empowerment through Usage Transparency

Our study, while not entirely authoritative, shows a positive indication that usage transparency, when applied to an opaque and expensive resource, can bring about economic efficiency. By providing a balance of usage information with actionable prompts before appropriate cost thresholds, SmartBrowse created a sense of empowerment among users by helping them stay in control of spending. By design, we provided cost information and not data information (KB or MB) to help users make sense of their usage in their micro-decisions. Educating users about costs, with an intuitive set of controls to avoid overspending, led to increased cost awareness and better decision-making for website browsing, and, even, making more informed choices about carriers.

On the flipside, price transparency could lead to users becoming extra conscious of web page costs, negatively influencing their decisions to visit websites. While our trial showed no degradation in treatment user experience, we were limited to mostly students for a relatively short period of 3 months. Longer-term studies with other user groups could lead to a finer understanding of the implications of behavior change through price transparency.

8.2 Easing in the Novice User's Experience of Mobile Data

With new mobile data users, we found that price transparency led to a better understanding of the Internet, which is often perceived as expensive and out of reach, among other perceptions, by low-income mobile users. Price transparency allowed non-users to get what they wanted from the Internet, by scaffolding their cost understanding of the Internet and creating a feeling of control in their hands. With friends and family using mobile data price transparency, mobile data non-users may get introduced to an Internet that sets expectations for being more manageable.

8.3 The Emerging Urban User

Our study points to high-tech interventions with emerging, urban users as a promising area of ICTD research. With rising rural-to-urban migration rates in many emerging regions, the urban low-income groups are increasingly interfacing with technology. Dropping prices, extensive distribution channels, and increased familiarity with technology have led more and more urban consumers to adopt high-tech ICTs, like smart phones. African cities are experiencing rapid increases in phone penetration, particularly in the youth demographic. Smartphones can be purchased for as low as USD75 and already constitute 25% market share in Nigeria and 18% in Ghana [19]. As high-end phones become cheaper, the experience we presented will quickly become more representative of what middle and lower income groups see.

ICTD has predominantly focused on rural socio-economic groups, but these emerging urban segments are not only relevant to cities, but are also spurring economic growth back in villages. Many families in Africa are split rural and urban for an indefinite period of time to diversify income [1]. Rural-to-urban migration has led to increased economic and social ties back to villages, in the form of remittances and circulation of used phones back to the villages. It is likely that the rural populations will also interface with mobile data and smart phones soon.

8.4 The Promise of Phone Trials

As evidenced in our follow-up survey, a forward-looking technology trial can heavily influence future purchase and usage decisions, provided the devices are within affordable reach of the user. We note that deploying with students could have influenced smart phone uptake positively. More research on smartphone trials can help us understand what skills and capabilities they engender and what shortcomings they pose. Smart phone trials may provide a great mechanism for communities to get introduced to mobile data. Well-thought shortcuts may steer traffic towards development content, such as Khan Academy or Wikipedia.

8.5 Forward-Looking Research in ICTD

Our trial presents forward-looking research wherein users are exposed to the next generation of technologies. Traditionally ICTD research has focused on existing device infrastructure, like voice calls and SMS for cost, scalability, and implementation reasons. As we have shown, it is informative to conduct forward looking trials to provide a glimpse into the problems that low and middle income users will encounter in the near future and point to directions to proactively solving them.

On the other hand, research with new technology also involves practical challenges that must be planned for. Giving out currently expensive devices (phones used in the trial were priced at USD150 each, which was more than the average monthly pocket money of student participants) in the wild for 10 weeks involves its own set of unique challenges -- users may need training, users may need help solving technical issues, phones may get lost, and so on.

In the next section, we describe how we set up the trial – how we screened and recruited participants, the role of a physical location in the trial success, how we designed appropriate incentives to motivate users, mechanisms we put in place to ensure phones would be returned, and the role of Whatsapp in building community among participants.

9. RUNNING THE SMARTBROWSE TRIAL

9.1 Trial Preparation

The trial was conducted at the University of Ghana, Legon, a few kilometers outside of Accra city. The university environment helped us bind participants to an ID card for handing out Android phones for 10 weeks in the wild (although no action was taken when phones were actually reported lost during the trial).

Our Ghana ground team comprised a research coordinator, a research assistant, and six interns to help run the study. A dedicated room, called the SmartBrowse Hub, was set up in a central location. The room had basic infrastructure for the trial, including Wi-Fi, laptops, printers, and storage. The Hub was manned between 9am to 5pm on weekdays and for half a day on weekends. Interns were constantly available to troubleshoot phone issues, sell scratch cards, and answer questions. The Hub was hugely instrumental in making the trial work, allowing users to walk in with issues on their way to classes or offices.

Motorola Dual-SIM XT685 Android phones were chosen as the final deployment phones, pre-loaded with an MTN SIM card exclusively for mobile data. Stickers were placed on the back plates of the phones with our ground team's phone number for trouble-shooting and to report lost or stolen. Custom scratch cards with recharge codes (on an MTN post-paid account) were designed for the top-up page. These top-up cards, in denominations of GH¢1, GH¢2, and GH¢5, were sold at the Hub.

Each participant received a bag with the phone; a SIM; a charger; an instruction booklet on using the phone; a campus map with directions to the Hub; and a free starter GH¢2 scratch card.

9.2 Trial Recruitment

Invitation: Interns visited various locations on campus to invite students and staff to the Hub. Screeners with questions on mobile data usage, gender, income, year of study or profession, and department were handed out. In addition, posters were put up on walls and notice boards in various strategic locations on campus.

ID check: Once a potential participant came to the Hub, their ID was checked to verify their university affiliation. As word got out virally about "free phones" and "GH¢200". At 8am on day three, we had ~250 participants lined up outside the building. Following this incident, we modified our procedure to hand out sign-up sheets and pre-screened participants to invite them.

Screening desk: Next, the research coordinator checked against her current tally and breakdown of participants to place the participant. Participants were alternated into the control and treatment groups (see table 1).

Paperwork: The participant then filled out the baseline survey, following which, the phone bag was handed to them.

Orientation: A phone orientation was conducted to set up security PINs, top up, make test calls, and load webpages.

Table 7. Incentive structure for participants

Week	Phase	Amount
1	Baseline	-
3	Mid-trial I	30GH₵
7	Mid-trial II	30GH₵
10	Exit trial	140GH₵

9.2.1 Incentives

In order to keep our participants motivated to use the phones for 10 weeks and later return them, we provided a monetary incentive of GH¢200 (~100USD). We distributed the incentives into three checkpoints to collect survey data from participants every month and to ensure that their phones were working smoothly (see table 8). We set checkpoint incentives high enough for participants to visit the Hub, yet the final incentive was the highest amount to motivate our participants to persist through the trial. Due to customs restrictions, we could not provide the phone as an incentive. At the end of the trial, many participants expressed they would rather keep the phone and give up their incentive.

9.3 Whatsapp Groups

We used Whatsapp for participants to coordinate and report issues. Groups of treatment and control, with 10 members each were created. Every intern moderated five groups. Logs were analyzed every two weeks. Whatsapp was a great tool to receive instant feedback, both for participants and their concerns, such as slow speeds or proxy outage, and for our team to post queries, like their experience with the features, which was otherwise difficult to elicit (such as "how is SmartBrowse today?" and "how do you feel about how much you are charged on SmartBrowse?"). Participants interacted with each other and reported problems live. Group members shared jokes, greetings, and information about Ghana politics. A strong sense of community evolved, with some participants exchanging phone numbers during the exit trial.

10. CONCLUSION

In this paper, we presented our findings from a 10-week study on enabling price transparency for mobile data with 299 participants. Our findings point to an increase in Internet usage with a decrease in credit consumption, especially among new mobile data users, and higher cost awareness among treatment users. We discussed our logistics of running a trial with new infrastructure in the wild in an emerging region context.

Price transparency is important to the access and usage of the Internet. As more lower-income user groups encounter the Internet on the phone for the first time, providing ways to be aware of and control data expenditure is important for their economic efficiency. While our trial focused on data spend on the phone, it can easily apply to bandwidth management in general. Conducting forward-looking research on technologies that are slowly but steadily rising in emerging regions can help preemptively reduce barriers to technology usage and help millions of new and existing users experience a safer, more manageable, and less erratic Internet.

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