Research Article

Social Influence in Mobile Phone Adoption: Evidence from the Bottom of the Pyramid in Emerging Asia

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Abstract

This article attempts to quantitatively measure the various influences on mobile phone adoption at the bottom of the pyramid (BoP) in Bangladesh, Pakistan, India, Sri Lanka, the Philippines, and Thailand. Based on an existing theoretical framework, adoption is modeled by fitting a logit model to a large six-country dataset. The study finds evidence for the importance of social influence in mobile adoption in two modes: one that exerts pressure on individuals to adopt, and another that helps to generate benefits via social networks that are tied in with economic and business networks. The article elaborates on the resulting social policy implications for using mobile telephone services to fight poverty at the BoP in these and similar countries.

1. Introduction

There have been numerous studies on the positive economic impact of phone adoption. Early studies ranging from Hardy (1980) to the recent Kathuria, Uppal, and Mamta (2009) have demonstrated the significant impact of telecom services on economic growth and development. From a more microeconomic angle, Donner (2006), Jensen (2007), Abraham (2007), Aker (2008), and de Silva and Ratnadiwakara (2008), among others, have shown how phones reduce information search costs, leading to lower transaction costs. Moving beyond pure economics, others like Bayes, von Braun, and Akhter (1999), Goodman (2005), Frost and Sullivan (2006), and Kwaku Kyem and LeMaire (2006) have shown how mobile phone adoption leads to greater social cohesion and improved social relationships.

The literature generally shows that adoption of (primarily) mobile telephones has significant benefits not just to the adopter, but to the community at large. In this context, the objective of the current article is to examine, from a user perspective, the influences (as well as the interplay of these influences) on mobile phone adoption by the poor in a selected set of countries in the emerging Asian region. For this purpose, we use data from a 2008 large sample survey among the poor across Bangladesh, Pakistan, India, Sri Lanka, the Philippines, and Thailand.

2. Mobile Phone Adoption: Brief Theoretical and Empirical Background

Theoretical Background

Pedersen and Ling (2002) categorize the literature on adoption into three schools of thought: diffusion, adoption, and domestication. Pedersen

(2005) characterizes diffusion research as describing the adoption process as an S-shaped function of time that may be used to group adopters of different kinds (Kiljander, 2004; Rogers, 2003); domestication research as looking at the adoption and use of technology in everyday life with a focus on the social, cultural, political, and economic consequences (Silverstone & Haddon, 1996); and adoption research as explaining adoption decisions of individuals by applying cognitive and social theories of decision making (Davis, 1989; Fishbein & Ajzen, 1975).

Building primarily on adoption and domestication schools of thought, Van Biljon and Kotzé (2008) contextualize mobile phone adoption in an extended technology acceptance model (TAM) framework, where perceived usefulness in adoption is encompassed in a multidimensional setting in terms of sociocultural, gender, and income criteria. Originally proposed by Davis (1989), the TAM is an adaptation of the theory of reasoned action (TRA) developed by Fishbein and Ajzen (1975) using attitude and subjective norms as the two factors that affect behavioral intentions. Davis (1989) and Davis, Bagozzi, and Warshaw (1989) conceptualize TAM as focusing on the attitudinal explanations of intention to use a specific technology or service consisting of six concepts: 1) external variables, 2) perceived usefulness, 3) perceived ease of use, 4) attitudes toward use, 5) intention to use, and 6) actual use.[1] While this model is able to explain adoption well from a technical perspective, Malhotra and Galletta (1999) identify the lack of explicit accounting for social influences affecting adoption as a limitation of the TAM. Van Biljon and Kotzé's extension identifies a number of determining factors that form the basic construct influencing mobile phone adoption and use. They are social influence, expressed as the pressure exerted on the individual by the opinions of others; facilitating conditions, or the necessary infrastructure; perceived usefulness, or the extent to which a user believes that he or she will benefit from using the mobile phone; and perceived ease of use.

Besides the determining factors, the model contains a set of mediating factors that influence the determining factors toward behavioral intention; say, a person finds it beneficial to use a mobile phone (determining factor: perceived usefulness) but lack of income (mediating factor) could hold back adoption. As such, mediating factors identified in the model are personal factors, like preference and beliefs about mobile phones (including image); demographic factors like age, gender, education, etc.; and socioeconomic factors, such as occupation and income. The model postulates that actual adoption and use are the final outcome of the interplay of the mediating and determining factors.

Empirical Background

While some researchers have concentrated on theorizing technology adoption, others have focused on using empirical models to explain technology adoption by fitting mathematical models to the data. The widely cited Rice and Katz (2003) paper and the recent Chabossou, Stork, Stork, and Zahonogo (2009) paper are two of several papers approaching the question from such an angle, and they are most useful in predicting behavior. There are many ways in which data can be modeled, but at the outset, it must be noted that linear regression models are not appropriate for modeling adoption (a dichotomous outcome) as the dependent variable; thus, logit or probit models that use exponential functions and allow for a dependent variable between 0 and 1 explaining the probability of adoption, or discriminant analysis that classifies a set of observations into predefined classes are generally used. Rice and Katz (2003), based on a nationally representative sample of 1,800 adults in the United States, used a logistic regression model to explain three types of digital divides in phone and Internet use: owner vs. non-owner divide, veteran vs. recent divide, and continuing vs. dropout divide. The paper demonstrated that different factors influenced each of these three kinds of Internet and mobile phone divides. For instance, compared to mobile phone owners, non-owners were found to have lower incomes, less education, more likely to not have been married, not have children, not work full-time, and belong to fewer community organizations. Chabossou et al. (2009) used a probit model to analyze factors that contribute to the probability of an individual adopting mobile telephony based on a

1. Although the TAM is mainly applied to explaining the adoption of technology within organizations, the constructs of the model are meant to be fairly general (Davis et al., 1989).

nationally representative 22,000-respondent study across 17 countries in Africa.[2] This paper showed that income and education vastly enhance mobile adoption in these countries, but that gender, age, and membership in social networks have little impact. The last finding is interesting from the theoretical construct of earlier analyzed adoption models, including Van Biljon and Kotzé (2008), where social influence is an important determining factor, which perhaps Chabossou et al. (2009) implicitly attempted to measure through membership in various social networks and clubs.

The debate on the social influence and impact on mobile adoption as separate from economic pressures and benefits has been longstanding. But the debate is taking a new twist with adoption in developing country scenarios, where mobile phones are seen as a potential way out of poverty.[3] In this context, finding social uses of the phone as the main use of phones among low-income earners is an important finding, as opposed to business and entrepreneurial uses, as much of the "ICT4D" hype seems to highlight. De Silva and Zainudeen (2007) question why such (social) uses should be considered "frivolous." Similarly, Donner (2009) criticizes overemphasis of the development angle of mobile phone adoption by questioning how the value of social calls can be ignored when evaluating the drivers of demand. There are two interrelated issues here. One is the benefits of mobile phone adoption from a social angle, described in Van Biljon and Kotzé (2008) as perceived usefulness; as benefits measured by social relations in de Silva and Zainudeen (2008); or as the "blurred" social and business communication implied by Zainudeen, Samarajiva, and Abeysuriya (2006), as well as by Donner (2009). The other issue not explicitly stated is the societal influence applied by social or business networks toward mobile adoption.

Related to these concepts of social influence and perceived usefulness is the concept of network externalities. Network externalities are said to be present where the number of consumers of a good has a direct effect on the quality of that good/service, and therefore, on the utility derived from its consumption (Katz & Shapiro, 1985). In the case of a telephone network, the size of the network has a positive impact on the value of the "goods" in the network: in the simplest case, phone calls, or connections between two subscribers. For every additional subscriber, the number of potential connections that can be made increases by an increasing factor (Katz & Shapiro, 1986); thus, the value of the network to an individual increases as her contacts become a part of that network. This means that people are more likely to get connected in groups, an argument that this paper also supports. Katz and Shapiro (1985) show that there are three sources of consumption externalities, the direct source being relevant in the case of mobile phone adoption, where the number of consumers of that particular good/service have a direct effect on the quality of that good/service and, therefore, on the utility derived from its consumption. They find that "consumption externalities give rise to demand-side economies of scale, which vary with consumer expectations." In this case, interconnection between competing operators' networks becomes key, determining the size of the network effect. Much research has been done on the implications of network externalities on competition and the market structure (Bental & Spiegel, 1994; Economides, 1993; Economides & White, 1994).

3. Methodology

This article is based on data from a 2008 representative study among poor, or "bottom of the pyramid" (BoP) in Bangladesh, Pakistan, India, Sri Lanka, the Philippines, and Thailand. The study was conducted using quantitative and qualitative research methods among those who had used, but not necessarily owned a telephone to make or receive voice calls in the previous three months.[4]

2. This study was conducted by Research ICT Africa. The 17 countries were Benin, Botswana, Burkina Faso, Cameroon, Cote d'Ivoire, Ethiopia, Ghana, Kenya, Mozambique, Namibia, Nigeria, Rwanda, Senegal, South Africa, Tanzania, Uganda, and Zambia.

3. Nobel Laureate Prof. Muhammad Yunus told the author that mobile phones were going to change the world as we knew it. "We have not seen the real power of the technology yet," he said, and added that a "digital genie" will appear from the "Aladdin's lamp" (mobile phone) to "empower the poor." Available at http://www.youtube.com/watch?v=9O4BvXG_btI

4. Phone use in the previous three months included making or receiving a telephone call (but not SMS) on any phone whether owned or not.

Table 1. Sample Size and Composition.

	Respondents	Margin of error at 0.95 confidence level
Bangladesh	2,050	2.8%
Pakistan[a]	1,814	2.3%
India	3,152	1.7%
Sri Lanka[b]	924	3.3%
Philippines[c]	800	3.1%
Thailand[d]	800	3.5%
Total	9,540	

Notes: a. Excludes tribal regions; b. Excludes conflict regions; c. Excludes SEC D; d. Sample excludes Bangkok because the SEC D and E population in Bangkok is small.

The BoP was defined as the two lowest socioeconomic groups (SEC),[5] D and E, with the exception of the Philippines where only SEC group E was considered.[6]

The quantitative component comprised 9,540 face-to-face interviews among those who had used, but not necessarily owned a telephone in the previous three months.[7] Both households and respondents were randomly selected. The sample was designed to represent the BoP in each country.

With the exception of India (where the majority of states were covered), all regions of each country were covered. The researchers used a multistage stratified cluster sampling by probability proportionate to size (PPS) to select the target number of urban and rural centers. After determining the number of centers to be selected from each cell (strata in respective provinces), urban and rural areas were selected again, using PPS on a constant population interval on geographically ordered centers within each cell. Within selected urban and rural centers, a common place such as a road, park, or hospital was designated as the starting point for contacting households using either the right-hand rule or the left-hand rule. A fixed number of interviews were conducted around each starting point. The number of starting points selected from each center was determined in proportion to the population of the selected center. After a completed interview, three[8] houses were skipped in urban areas[9] to minimize neighborhood bias.

One respondent was selected per household; in households with more than one eligible respondent, the Kish grid (random number chart) was used to randomly select the respondent. Within each country, data were weighted by gender, province group (or zone), and urban–rural proportions to correct over- or undersampling in certain areas and socioeconomic groups. See Table 1 for an overview of the sample size and composition.

A survey was administered among selected respondents. It featured general ICT access and ownership questions, as well as more detailed questions on mobile use inter alia.

5. SEC categorizes people into groups A to E based on the education and occupational level (as well as a few other parameters in certain countries) of the chief wage earner of the household. SEC is closely correlated to an income level of around US$2 a day in five of the six countries studied, thereby allowing for cross-country comparisons. SEC (rather than income levels) was used to define the BoP due to the problems generated by spatial and temporal cost of living adjustments, which would make cross-country comparisons difficult. In addition, problems of over- or under-reporting could affect the correct classification of BoP respondents. In rural India and Pakistan, the R2–R4 groups were considered as equivalent to SEC D and E.

6. The SEC D and E population of the Philippines constitutes 92% of the population, whereas the SEC E population, corresponding with the population living on US$2 per day, comprises 38%.

7. Phone use in the previous three months included making or receiving a telephone call (but not SMS) on any phone, whether owned or not.

8. Four houses in India.

9. Due to the large distances between houses in some rural areas, the skipping procedure was not always followed; instead, the next house was visited.

The qualitative module consisted of 60 protocols in the six countries (not equally distributed) of respondent mini-ethnographies, home visits cum media mapping exercises, and focused group discussions.[10]

4. Statistical Model for Mobile Phone Adoption

Logistic Regression Model for Mobile Adoption

As alluded to earlier, Van Biljon and Kotzé (2008) explain that adoption and use of mobile phones will be the result of the complex interplay among a number of factors within the determining and mediating categories. In reality, these factors are different for each individual and cannot be observed. What can be observed is whether a person has a mobile phone or not; as Chabossou et al. explain,

> One individual might neither be able to afford nor be interested in a mobile phone while another might just be close to getting one and still saving money towards it. For both individuals it can only be observed that they do not have a mobile phone. (2009, p. 395)

The process leading to the adoption decision is unobservable, and the factors used to model the adoption decision are referred to as the determining and mediating factors. Logit models (as well as probit models) tie the determining and mediating factors to the latent variable (i.e., mobile adoption) through contributions to the probability of the latent variable taking a value above or below a threshold that would lead to the observable outcome: adoption or not. Therefore, the logit model assigns a probability of adoption of mobile phones based on the various determining and mediating factors postulated in the theoretical model.

The general formula of the logit model is:

$$Probabilit(Y) = \frac{1}{1 + \exp\left(-\alpha - \sum_{i=1}^{n}\left[(\beta_i X_i)\right]\right)}$$

where Y is mobile adoption (a dichotomous variable taking the value 1 if the respondent owns a phone and 0 if the respondent does not), and X_i are the factors that impact such adoption (also referred to as determining and mediating factors or influential factors). β_i values are factor sensitivities of each influential factor, X_i. Influential factors, $X_{i,}$ can be quantitative or qualitative variables; dummy variables are used to represent the "states" in the case of qualitative variables. The influential variables, X_i, used in the study are given in Table 2, as are their expected signs.

The influential variables are self-explanatory, and the expected signs are logical. Country dummies capture the unique characteristics in each country, such as policy, culture, perception, different needs, etc. The variable "number of top five contacts that own a phone" and the emergency, social, and economic "perceived benefit indices" are introduced for the first time in this article and explained below.

Understanding social influence or social pressure in technology adoption has a long history. As previously pointed out, Malhotra and Galletta (1999) found the lack of accounting for social influences explicitly to be a limitation of the TAM, which subsequently resulted in the unified theory of acceptance and use of technology (UTAUT) model of Venkatesh et al. (2003), which placed social influence as a key construct that determines usage intention and behavior. Van Biljon and Kotzé (2008) innovated further by segmenting social influence into human nature influences (inherited) and cultural (learned) influences. At an empirical level, Rice and Katz (2003), implicitly examining this phenomenon in explaining digital divides, did not find that belonging to various social groups has any uniform influence on adoption and use of mobile phones and the Internet. Similarly, Chabossou et al. (2009), implicitly attempting to assess the importance of this factor through memberships in any "social network" (church groups and sports clubs, etc.) in their model, found that belonging to such networks contributes positively to the probability of mobile adoption in seven of the 17 study countries, but not the others. How does the social pressure influence adoption? Chen and Sutano (2007) propose "social coercion, social imitation, and social normalization" as key processes by which social pressure is applied. Others have also explained this process (Chen & Wong, 2003; Segrest et al., 1998). Goldstein (2009), explaining how to harness social pressure, shows that people are more likely to adopt if others who are like them also adopt.

10. Further details can be found at http://lirneasia.net/wp-content/uploads/2008/04/qualitativereport.pdf

Table 2. Influential Variables for the Mobile Adoption Model.

Variable	Hypothesized sign	Remarks (Van Biljon & Kotzé model factor)
Gender		Male = 0, female = 1; expect no gender difference (demographic)
Age squared[a]	−	Technology is usually adopted faster by younger people (demographic)
Ln (monthly personal income)[b]	+	Natural log of the monthly personal income; lack of income is key barrier to adoption (socioeconomic)
Primary Education		If highest educational level attained = 1, if not highest educational level attained = 0 (demographic)
Secondary Education		If highest educational level attained = 1, if not highest educational level attained = 0 (demographic)
Tertiary Education		If highest educational level attained = 1, if not highest educational level attained = 0 (demographic)
Number of top five contacts that own a phone	+	The more people in one's close network with phones, greater will be the social (social-economic-business) pressure to adopt (social influence; social pressure)
Emergency Perceived Benefits Index (PBI)	+	Phone enables emergency communication (perceived [safety] usefulness and/or personal)
Social PBI	+	Phone helps to maintain and improve social relationships (perceived [social] usefulness and/or personal)
Economic PBI	+	Phone brings economic benefits through lower transactions costs such as less need to travel to obtain business information (perceived [economic] usefulness and/or personal)
Fixed phone in household	−	Yes = 1, no=0; mobile phones are substitute for fixed phones at the BoP (facilitating condition)
Walk time to nearest town	−	Proxy for urban and rural indicator; rural adoption is lower than urban (demographic factor)
Access to electricity in household	+	Yes = 1, no=0; electricity as a facilitating condition for mobile adoption (facilitating condition)
Television in household		Yes = 1, no=0; impact of having a television in household on mobile adoption (socioeconomic)
Radio in household		Yes = 1, no=0; impact of having a radio in household on mobile adoption (socioeconomic)
Pakistan		Country dummy for Pakistan
Sri Lanka		Country dummy for Sri Lanka
Thailand		Country dummy for Thailand
Bangladesh		Country dummy for Bangladesh
Philippines		Country dummy for the Philippines
Constant		

Notes: a. Age-squared is used, as it has a higher explanatory power compared to Age, as the former magnifies the marginal differences in the age variable and will have better predictive power. As Tegegne (1999) and Chabossou et al. (2009) point out, differences of the impact of the age in mobile adoption can be better modeled by using Age-squared instead of Age; b. Natural log of monthly income better explains the impact of monthly income on mobile adoption.

Therefore, the question we have is how to model social pressure or influence in mobile phone adoption in a way that provides some useful and comparable quantitative explanations. Instead of the previously used membership in social or community group proxies, we use a new measure: the adoption status of the respondent's closest circle of contacts (friends, family, business contacts, etc.). We postulate that the more people in one's circle who have adopted, the greater the social influence or social

Table 3. Perceived Benefits.

Category	Disaggregated benefit aspects
Emergency	1. Ability to act in an emergency 2. Ability to contact others in an emergency
Social	1. Ability to maintain relationships with family and friends 2. Social status/recognition in the community
Economic	1. Ability to make more money (generally, and not via sale of calls) 2. Ability to make more money through the sale of calls 3. Ability to find out about work opportunities 4. Ability to access price or market information 5. Ability to save money 6. Ability to save on travel costs 7. The efficiency of your day-to-day work

pressure toward his or her adopting will be. Thus, the expected sign for "number of top five contacts having a phone" is positive. The thinking is along the same lines of Valentene (1996), who creates a social network threshold model based on adopter categories to show how external influence and opinion leadership channel the diffusion of innovation. While Valentene (1996) demonstrates the differences from low-network-threshold individuals (those who adopt before many others in their network do) to high-threshold individuals (those who adopt after most of their network have adopted), and also the level of innovativeness with respect to their "personal networks" or with respect to the "social system," our objective is to ascertain the importance of social pressure or influence of "personal networks" on adoption of mobile phones.

The other exploratory feature of our work is the attempt to disaggregate and capture the perceived benefits of mobile adoption in terms of emergency, social, and economic factors. Perceived usefulness has been at the base of technology adoption models since the early days of TAM as the extent to which a person believes using the system can enhance his or her job performance,[11] later generalized to mobile adoption by others (Kleijnen et al., 2004; Kwon & Chidambaram, 2000). Following this logic, Van Biljon and Kotzé (2008) place perceived usefulness at the center of their model. The model also refers to users' beliefs about the benefits of mobile phones (including, inter alia, image and trust) under personal factors. Once again, we consider an alternative approach to the previous models and disaggregate perceived benefits of mobile phone adoption into emergency (or safety[12]), social, and economic-business categories. Respondents evaluated 11 aspects belonging to the three groups on a five-point Likert scale, with 1 indicating the phone worsening that particular aspect for the respondent, 3 indicating no change, and 5 indicating that it had improved. The categorization is given in Table 3.

Three indices were created to reflect each category of benefits: Social Perceived Benefits Index (SPBI), Emergency PBI (EmPBI), and Economic PBI (EcPBI). SPBI and EmPBI indices reflect the number of benefit aspects (0, 1, or 2) that the respondents perceived to have improved (score of 4 or 5 in the scale for each aspect) as a result of using (whether owned or otherwise) a phone; i.e., SPBI would take the value 2 if the respondent perceives benefits have accrued to both aspects in that category. EcPBI has four levels. The first level is when the respondent sees either no aspects as having improved or only one aspect as improved; the second is when the respondent perceives that two or three economic aspects have improved; the third is if four or five aspects have improved, and finally, the fourth level is when the respondent perceives that six or all seven aspects have improved.

The item reliabilities for each of the indices, tested using the Cronbach's alpha test, are presented

11. The original paper focused on technology adoption in organizations.
12. Katz and Aakhus (2001) have shown that safety is the primary motive for women to acquire a mobile phone (in Rice & Katz, 2003).

in appendix A. This is a statistical procedure to check whether the data used (e.g., "Ability to act in an emergency"; "Ability to contact others in an emergency") are measuring the same construct (Emergency perceived benefits). Generally, a Cronbach's alpha of above 0.6 is acceptable. Except for the Social PBI, all other PBIs have Cronbach's alphas greater than 0.6. SPBI has a Cronbach's Alpha of 0.5; however, since the study is an exploratory one, the authors decided to proceed with the analysis.

5. Findings and Discussion

Table 4 provides a breakdown of the sample showing the characteristics of mobile phone adopters vs. non-adopters (who are users nevertheless, using others' phones).[13] The chi-square value given in the table indicates where there are significant associations between the two variables.[14] The significance level established in chi-square significance tests, with probability of 0.05 or less, is commonly interpreted as justification for rejecting the null hypothesis that variables are not related in some way.

The table shows that, at a high level, mobile phone adaptors (or owners) at the BoP in the study countries are more likely to be younger males, with higher relative income[15] and usually a secondary education, and with most of their closest contacts already having phones of their own. They perceive that their phones have improved the social and economic aspects of their lives and helped their capabilities to communicate in emergencies. They also live somewhat closer to a town with relatively better access to electricity and in a household with a television. The profile for non-adopters, in contrast to adopters, is mainly younger females with relatively lower incomes and only a primary education living somewhat further away from town. Fewer of their closest contacts have their own phones. In terms of perceived benefits, we find non-adopters not very different from adopters in terms of placing value on benefits from mobile phones. While emergency benefits seem to be the same, there is a slight drop in perceived social and economic benefits. This is perhaps due to the fact that they have access to phones even though they do not own their own.

We now consider the results of the logit model to assign probabilities of adoption of mobile phones to correspond, as much as possible, to the mediating and determining factors postulated in the theoretical model in Van Biljon and Kotzé (2008). (Expected signs for the variables, along with brief remarks for the same, were provided in Table 2.) The logit model showed a good fit with an R-square (Nagelkerke R-square) value of 0.34. The signs of the coefficients of the variables are as expected, except in the case of gender, where we presupposed no gender difference.[16] Coefficients of variables in a logit model can have either positive or negative values; a positive value indicates that the particular variable has a positive impact on adoption and vice versa. From each coefficient, a corresponding odds ratio is computed by taking the exponent of each coefficient,[17] as the coefficients cannot be directly interpreted. The odds ratio is a way to present the probability of an event. The odds of an event happening (mobile adoption) indicates the probability that the event will happen (mobile adoption) divided by the probability that the event will not happen (non-adoption).

The odds ratio implies that, for each unit increment of the independent variable, the odds of the concerned dependent variable (in this case, mobile adoption) changes by a percentage of *odds ratio − 1,* given in Column 3 of Table 5. For exam-

13. Rice and Katz (2003) present a similar table wherein they dichotomize almost all variables to make it easier to interpret the otherwise complex data.

14. A significant chi-square value indicates the existence of a relationship between the concerned variable and mobile adoption.

15. The mean is US$47.75 per month. The adoption profile is the same, even when dichotomized at US$50 per month: adopters at less than US$50, 48.6%; more than US$50, 51.6%; non-adopters at less than US$50, 73.3%; more than US$50, 26.5%.

16. While, theoretically, that may be the case, many studies have found that males are more likely to adopt mobile phones over females (Chabossou, 2009; Katz, 2003).

17.

$$Probabilit(Y) = \frac{1}{1 + \exp\left(-\alpha - \sum_{i=1}^{n}[(\beta_i X_i)]\right)}$$

$$Odds\ Ratio = \frac{Probabilit(Y)}{1 - Probability(Y)} = \exp\left(-\alpha - \sum_{i=1}^{n} \beta_i X_i\right)$$

Table 4. Mobile Adopter vs. Non-Adopter.

	Mobile adopter (% of sample)	**Non-adopter (% of sample)**
Overall	45.9	54.1
N	4,382	5,158
Gender (Chi-Square=401.30)***		
Male	63.9	43.4
Female	36.1	56.6
N	4,382	5,158
Age (Chi-Square=33.32)***		
Less than 35 yrs	65.3	59.6
More than 35 yrs	34.7	40.6
N	4,381	5,158
Monthly Personal Income (Chi-Square=363.16)***		
Less than the median [USD 26.25]	37.7	60.9
More than the median [USD 26.25]	62.3	39.1
N	4,277	4,901
Education (Chi-Square=291.0)***		
Primary	35.1	51.1
Secondary	52.0	43.7
Tertiary	12.9	5.2
N	4,123	4,245
Number of top five contacts that own a phone (Chi-Square=801.52)***		
0	0.9	2.7
1	6.4	11.9
2	12.2	23.5
3	15.3	24.0
4	14.7	13.1
5	50.5	24.8
N	4,381	5,155
Emergency Perceived Benefit Index (PBI) (Chi-Square=20.49)***		
0	2.5	3.0
1	9.9	12.6
2	87.6	84.3
N	4,318	4,800
Social PBI (Chi-Square=176.15)***		
0	4.0	6.2
1	30.9	46.2
2	65.1	51.3
N	4,230	4,720
Economic PBI (Chi-Square=197.76)***		
1	10.1	18.1
2	27.6	33.1
3	30.8	23.4
4	31.5	25.4
N	4,256	4,693
Fixed phone in household (Chi-Square=23.09)***		
Yes	7.9	10.8
No	92.1	89.2
N	4,382	5,158
Walk time to nearest town (Chi-Square=125.76)***		
Less than the median [20 minutes]	57.1	46.6
More than the median [20 minutes]	42.9	53.4
N	4,469	5,071

Table 4. (Continued)

	Mobile adopter (% of sample)	Non-adopter (% of sample)
Access to electricity in household (Chi-Square=569.14)***		
Yes	91.8	77.3
No	8.2	22.7
N	4,382	5,159
Television in household (Chi-Square=569.14)***		
Yes	80.9	57.1
No	19.1	42.9
N	4,381	5,158
Radio in household (Chi-Square=284.11)		
Yes	48.3	31.4
No	51.7	68.6
N	4,382	5,158

*Note: *** Chi-Square is significant at 95%.*

Table 5. Logit Model Results.

Variable	Coefficient (1)	Odds Ratio (2)	Change in odds (%) (3)	P-value (4)
Age^2	−0.03	0.97	−3	0.03
Gender	−0.43	0.65	−35	0.00
Ln (monthly personal income)	0.48	1.61	61	0.00
Primary Education	0.34	1.41	41	0.00
Secondary Education	0.80	2.23	123	0.00
Tertiary Education	1.40	4.06	306	0.00
Number of top five contacts who own a phone	0.32	1.37	37	0.00
Emergency Perceived Benefits Index (PBI)	0.20	1.22	22	0.07
Social PBI	0.16	1.18	18	0.01
Economic PBI	0.10	1.10	10	0.00
Fixed phone in household	−0.63	0.54	−46	0.00
Walk time to nearest town	0.00	1.00	0	0.01
Access to electricity in household	0.38	1.47	47	0.00
Television in household	0.90	2.46	146	0.00
Radio in household	0.29	1.33	33	0.00
Bangladesh	−0.05	0.65	−35	0.96
Pakistan	−0.42	0.00	−100	0.66
Sri Lanka	−0.82	0.00	−100	0.44
Philippines	−0.23	0.12	−88	0.80
Thailand	1.27	0.00	−100	3.58
Constant	−4.21	0.02	−98	0.00

ple, the odds ratio of 1.37 for the number of phone-owning contacts variable implies that, for each unit increment in the variable while fixing the value of other independent variables, the odds of mobile phone adoption increases by 37%.

It is observed that age is likely to have a negative impact on mobile adoption, with the squared value of the respondent's age having an odds ratio of 0.97; younger people are more likely than older people to purchase a mobile phone. The gender

Table 6. Influences of Personal Network on Mobile Adoption.

Number of members of top five contacts who own phone	Mobile adopter (% of sample)	Number of respondents	Non-adopter (% of sample)	Number of respondents
0	21.9	40	78.1	141
1	31.5	281	68.5	612
2	30.6	535	69.4	1,213
3	35.1	669	64.9	1,235
4	48.9	644	51.1	673
5	63.3	2,212	36.7	1,281

variable has a significant impact on adoption; being a woman decreases the odds of owning a mobile phone by 35%. As expected, income increases the odds of adoption, with the natural log of monthly personal income having an odds ratio of 1.61. The results also show that assumptions about education can be accepted, with the odds ratio of mobile adoption increasing significantly with more years of completed education.

Social pressure or influence on mobile adoption was found to be an important factor in increasing the probability of adoption, with an odds ratio of 1.37. This means that the likelihood of a respondent's adoption of a mobile phone increases with each additional member (at the margin) among the closest five members of his or her personal network owning a phone. More specifically, holding other influential variables fixed, the odds of adopting a mobile phone increases by 37% for each additional member in the network having adopted a phone. It was also found that the likelihood of adoption increases dramatically, with an odds ratio of 4.86, when the number of persons owning a phone among the closest five contacts increases from none to five. Table 6 depicts the relationship between the top five contacts owning a phone and the respondent's mobile adoption status.

Another significant finding is that, as per Valentene (1996), the poor in emerging Asia seem to belong to high to very high threshold categories where adoption is taking place after most of the others in the personal network have adopted. It may also be the case in terms of the social system, but data for outside SEC D and E are not available for such a comparison.

Considering the contribution of the perceived benefit indices toward the probability of mobile adoption, all three indices are significant; as expected, each exerts a positive impact on adoption, indicating a higher likelihood of mobile adoption by the people who perceive a higher level of benefit from phone access in terms of emergency, social, and economic criteria.[18] The odds ratios are 1.22, 1.18, and 1.10, meaning that, when holding other influential variables fixed, odds of adopting a mobile phone increases by 22%, 18%, and 10%, for every one unit increase in the perceived emergency, social, and economic benefit index, respectively. Perceived usefulness has been considered an important influence in mobile adoption since the earliest technology adoption theories and models. This desegregation of perceived benefits into the above three categories, along with measuring their impact on the probability of adoption of mobile phones among the BoP in this manner, now adds flavor to the discussion on how best to leverage this aspect to further enhance adoption.

Tables 7 through 9 provide category-wise disaggregated data on the respondent's adoption status by the number of perceived benefits accrued from a mobile phone.

These results indicate that adoption is linked to the level of perception of benefits (or usefulness as in the theoretical adoption literature) accrued due to use of mobile phones, particularly with social and economic factors; the higher the perceived benefits, the higher the adoption. While the adopter percent-

18. Emergency perceived benefit index is significant at 90%, while social and economic perceived benefits indices are significant at 95%.

Table 7. Emergency Perceived Benefits Index and Mobile Adoption.

Level of perceived emergency benefits accrued due to use of mobile phone	Mobile adopter (% of sample)	Number of respondents	Non-adopter (% of sample)	Number of respondents
0	42.1	106	57.9	145
1	41.4	428	58.6	607
2	48.3	3,784	51.7	4,048

Table 8. Social Perceived Benefits Index and Mobile Adoption.

Level of perceived social benefits accrued due to use of mobile phone	Mobile adopter (% of sample)	Number of respondents	Non-adopter (% of sample)	Number of respondents
0	36.8	169	63.2	291
1	39.4	1,308	60.1	2,010
2	53.2	2,753	46.8	2,419

Table 9. Economic Perceived Benefits Index and Mobile Adoption.

Level of perceived economic benefits accrued due to use of mobile phone	Mobile adopter (% of sample)	Number of respondents	Non-adopter (% of sample)	Number of respondents
1	34.5	466	65.5	885
2	45.6	1,256	54.4	1,498
3	54.3	1,175	45.7	988
4	52.8	1,296	47.2	1,157

age is higher than the non-adopter percentage at the highest level of perceived benefit (highest index number) for social and economic benefit categories, it is not so for the perceived emergency benefit category (although the perceived emergency benefit category is significant at a lower [10%] level of significance). Perhaps the importance of emergency benefits (ability to contact others in an emergency) is subsumed in the "blurred" social-economic network and cannot be easily isolated. On the other hand, it could be due to the low level of variation in the numbers of adopters and non-adopters whose emergency PBI is 0, 1, or 2 (see Table 8).

The country dummy variables are insignificant, indicating that the odds of mobile phone adoption are not affected by the country of the respondent within this BoP market. The country dummies are used to account for country-level differences (e.g., pricing,[19] policy, culture, etc.); therefore, it is somewhat surprising that the coefficients of these variables are not significant. Perhaps it may be because, at the BoP, other factors, such as income, education, social pressure, etc., are more important, and the consumers in the six Asian countries studied are in fact similar at the BoP; as incomes and socioeconomic statuses improve, the country-level factors may start to play out. Individual country models were also estimated. However, the R-squared values (interpreted as the predictive power of the model) of the individual models were all lower than that of the combined model (34%); therefore, the combined model has a higher predictive power compared to the country-level models. Still, it is interesting to note that the social influence variable (the number

19. It is important to note that the total costs of ownership (TCO) for a mobile in the six countries studied were all below the average among 70+ emerging economies for which TCO was calculated in 2008–2009 (Nokia, 2009).

of top five contacts who own a phone) is consistently significant and positive in all six country models, with the largest impacts coming in Bangladesh and Pakistan.

6. Concluding Thoughts

This article attempts to determine and measure the influences on mobile phone adoption at the BoP in Bangladesh, Pakistan, India, Sri Lanka, the Philippines, and Thailand. Based on the Van Biljon and Kotzé (2008) theoretical framework, adoption was modeled by fitting a logit model to a six-country dataset. In addition to several other important variables, evidence for the importance of social influence in mobile adoption was found in two modes: one that exerts pressure on individuals to adopt, and another that helps to generate benefits via social networks tied in with economic and business networks.

Mobile phones, now increasingly affordable and widespread in the developing world, have significant potential to extend social policy initiatives to the most rural and/or excluded groups in society, and thus have a direct impact on poverty and inequality. Mobiles provide a direct channel to provide services (for example, telemedicine, election information, hazard warnings, etc.) directly to BoP-type markets that can further social policy objectives.

This paper shows that social influence plays a key role in mobile adoption; those with a larger share of their closest contacts who already have a mobile are more likely to adopt, which means that people tend to get connected in groups. From a social policy perspective, policies that encourage network marketing by operators (which could include "friends and family"–type packages and promotions, or offering benefits to users who bring others onto the network) will therefore help to further social policy objectives. While, from a competition policy perspective, network marketing is not seen as desirable (making customers "sticky"), one could argue that such marketing only reflects consumer behavior.

Further research is needed to ascertain whether such network effects also play a role in the adoption of individual services. However, it is likely that the same "groups" that come onto a network together will encourage service adoption within their networks, too.

The study, however, has a several limitations; particularly, it only models adoption and not usage, and it does not attempt to link the social pressure with the three benefit categories, for instance, or to opinion leadership and the Katz (1957) two-step flow hypothesis of adoption influence. Further research could also help to fill these gaps. Another weakness was that the social perceived benefits index constructed was not as strong a measure of the social perceived benefits compared to the economic and emergency perceived benefits indices. Notwithstanding these drawbacks, this study has been able to isolate what seem to be some very powerful influences on mobile adoption that will be useful in understanding and influencing the adoption process of more-than-voice services among this population. ■

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Appendix

Item Reliabilities: Perceived Benefits Indices (SPSS Outputs)

1. All 11 Benefit Items

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	No. of Items
.827	.817	11

Summary Item Statistics

	Mean	Minimum	Maximum	Range	Maximum/ Minimum	Variance	No. of Items
Item Means	4.084	3.526	4.531	1.005	1.285	.124	11
Item Variances	.890	.410	1.420	1.010	3.465	.142	11
Inter-Item Covariances	.270	.007	1.002	.995	146.496	.053	11
Inter-Item Correlations	.288	.009	.728	.719	81.190	.029	11

Scale Statistics

Mean	Variance	Std. Deviation	No. of Items
44.92	39.519	6.286	11

2. Economic Perceived Benefits

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	No. of Items
.828	.820	7

Summary Item Statistics

	Mean	Minimum	Maximum	Range	Maximum/ Minimum	Variance	No. of Items
Item Means	3.918	3.528	4.359	.831	1.236	.087	7
Item Variances	1.063	.603	1.432	.829	2.373	.096	7
Inter-Item Covariances	.434	.152	1.010	.858	6.627	.058	7
Inter-Item Correlations	.394	.181	.728	.547	4.014	.023	7

Scale Statistics

Mean	Variance	Std. Deviation	No. of Items
27.43	25.670	5.067	7

3. Emergency Perceived Benefits

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	No. of Items
.704	.704	2

Summary Item Statistics

	Mean	Minimum	Maximum	Range	Maximum/ Minimum	Variance	No. of Items
Item Means	4.611	4.597	4.624	.027	1.006	.000	2
Item Variances	.395	.382	.409	.027	1.071	.000	2
Inter-Item Covariances	.215	.215	.215	.000	1.000	.000	2
Inter-Item Correlations	.543	.543	.543	.000	1.000	.000	2

Scale Statistics

Mean	Variance	Std. Deviation	No. of Items
9.22	1.220	1.105	2

4. Social Perceived Benefits:

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	No. of Items
.407	.429	2

Summary Item Statistics

	Mean	Minimum	Maximum	Range	Maximum/ Minimum	Variance	No. of Items
Item Means	4.251	4.010	4.492	.482	1.120	.116	2
Item Variances	.764	.495	1.033	.538	2.087	.145	2
Inter-Item Covariances	.195	.195	.195	.000	1.000	.000	2
Inter-Item Correlations	.273	.273	.273	.000	1.000	.000	2

Scale Statistics

Mean	Variance	Std. Deviation	No. of Items
8.50	1.919	1.385	2

a. When using 0, 1, 2 Recoded Social PBI

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	No. of Items
.501	.507	2

Scale Statistics

Mean	Variance	Std. Deviation	No. of Items
2.6189	1.421	1.19197	2