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Divide and diffuse: Comparing digital divide and diffusion of innovations perspectives on mobile phone adoption

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Abstract

Integrating digital divide and diffusion of innovations approaches, this study analyzes individual-level and market-level influences on the 8-year cumulative adoption of the mobile phone in one developing country. Considering each year separately, as tests of the typical digital divide model, age, education, economic condition, Internet access, and household size were significant divides in all years; employment, marital status, and urbanness were so only in about half the years, and sex in none of the years. However, a diffusion of innovations approach revealed some differences in demographic influences on mobile phone adoption across three adoption categories. Changing mobile phone market conditions were associated with varying adoption levels, and gross domestic product (GDP) per capita correlated with percent adoption except during the global economic crisis.

Keywords

Adoption categories, Armenia, diffusion of innovations, digital divide, ICTD, mobile phone, new media adoption

Many studies have used the digital divide or the diffusion of innovations theoretical orientations for understanding mobile phone adoption (Annafari, Axelsson, & Bohlin, 2013; Vishwanath & Goldhaber, 2003; Wei, 2001). The digital divide approach emphasizes

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individual sociodemographic differences on either side of a divide or gap, and associated social inequities, but does not propose different influences across different time periods. The diffusion of innovations approach explicitly acknowledges variations in influences on individuals' time of adoption and also considers the role of innovation clusters, though it does not generally focus on the social inequalities associated with divides (though see Rogers, 2003, Chapter 11). Both approaches refer to social and/or economic forces, but most studies apply either an individual or a macroeconomic approach.

This study extends prior digital divide analyses of mobile adoption (especially in developing countries; Rouvinen, 2006) by examining variations in sociodemographic and economic influences within different adoption categories across 8 years in one high-poverty, high-literacy developing country, using individual-level survey data, which are usually unavailable in developing countries. This study represents two of Donner's (2008) six categories of research on mobile phone use in the developing world: the non-development (diffusion, adoption, market liberalization) and the development (digital divide, universal access) aspects of mobile adoption (2008, p. 144, Table 2). Castells, Fernandez-Ardevol, Qiu, and Sey (2007) also distinguish studies emphasizing mobile use in everyday life, and those focusing on economic development. We also draw from the rich literature on information and communication technologies for development (ICT(4)D; Toyama, 2010) and mobiles for development (M4D; Donner, 2015). Finally, we note Pearce's (2013) and Pedersen and Ling's (2003) call for more theoretically driven studies of mobile phones in developing countries, and Wei's (2001) call for over-time surveys to identify changing influences on cell phone adoption.

Theoretical framework: Digital divide and diffusion of innovations

Digital divide

The *digital divide* or *digital inequality* originally described the socioeconomic gap between those with and without access to computers in the US. The digital divide is now a central focus of information and communication technology (ICT) studies generally. The digital divide concept has been expanded to include any gap between groups (including nations) across divides of awareness, adoption, knowledge, skill, social capital, devices, language and literacy, use, activities, and outcomes of ICTs (Hargittai & Hsieh, 2013; Hilbert, 2011; Pearce & Rice, 2013; van Deursen & van Dijk, 2013, 2014; van Dijk, 2005). Here, we focus only on the basic and most common divide: nonadoption versus adoption, although adoption by itself is often insufficient for true inequality reduction. Unequal adoption of communication/information technologies generally relates to differential participation in social, informational, and economic activities, as influences and as outcomes (Helsper, 2012; Katz & Rice, 2002; van Dijk, 2005).

The adoption of a mobile phone and its affordability, portability, and potential for privacy affords greater opportunities for communication, civic engagement (Neumayer & Stald, 2014), livelihood improvement (Duncombe, 2014), safety and access to health-care (Gonzales, 2014), and educational resources (Velghe, 2014), to name a few. Mobile phones are less associated with central digital divide factors than is Internet use (Rice &

Katz, 2003), raising the possibility of "leapfrogging" the more expensive and material-based technology (i.e., computers and landlines) (James, 2009), and thus reducing some digital divides (Stump, Gong, & Li, 2008). However, mobile phone and especially smartphone use seems associated with lower levels of functionality, content availability, information seeking, content creation, and social capital-enhancing activities, than is personal computer-based Internet use (Donner, 2015; Napoli & Obar, 2014; Pearce & Rice, 2013), thus possibly fostering other kinds of divides, even after adoption. Thus, understanding who *is* and who is *not* adopting can increase understanding of how mobile phones can potentially reduce inequalities.

Diffusion of innovations

Diffusion of innovations theory proposes how, why, and at what rate new ideas, products, and services spread (or are rejected) through social systems over time, and with what consequences (Rice, 2009; Rogers, 2003). Because messages about an innovation constitute novel information, and the innovation and its attributes are subjectively interpreted, uncertainty surrounds a potential adopter's decision-making. Diffusion of innovations theory describes a broad set of factors that affect this uncertainty and thus adoption. Those include psychological (e.g., innovativeness, dogmatism), individual (e.g., sociodemographics, location, adopter category, finances), relational (social networks, opinion leaders), innovation attributes (relative advantage, compatibility), communicative (mass media, online discussions), group and community (social influence, norms), technical (usability, access), organizational (voluntariness, training), industry (research and development, market, standards, pricing), national (culture, policy), and historical (interdependence with prior innovations, social trends) factors. The present study considers only individual-level and national influences—particularly those common to both the digital divide and diffusion literature. Further, the dependent variable is adoption versus nonadoption, though there are of course a variety of other indicators of adoption (i.e., simple use, duration and frequency, activities, discontinuance, reinvention, etc.; see Rice, 2009; Rogers, 2003). Further, we focus on adopter category, as that is one primary distinction between the digital divide and diffusion approaches.

Using the somewhat arbitrary boundaries of standard deviations in the normal adoption-time distribution, Rogers (2003) identifies five adopter categories. Influences on adoption supposedly vary somewhat across the five adopter categories (as Wei, 2001, found in his analysis of cell phone adoption).

The first 2.5% of adopters (three standard deviations below the mean of the total normal curve adoption distribution) are *innovators*. They are more venturesome, and have greater knowledge and resources to manage uncertainty. They are more likely to be males, have higher education, and, for some technological innovations, be younger. The next 13.5% (two *SD*s) are *early adopters*. Early adopters often include opinion leaders, those who help identify/shape social groups' attitudes toward the innovation, and influence others. The first two categories are also likely more urban, because of greater accessibility to, infrastructure for, and exposure to innovations in general. They also are more likely to have greater economic resources necessary for the higher costs of early innovations. For transformational innovations, there is a chasm between the second and third categories (Moore, 2002) because members of the first two adopter categories like to experiment with new things that may not have established reliability or widespread adoption, are interested in experimentation with new/untested features, willingly pay more for the innovative experience, and are less susceptible to social influence. Mobile phones or smartphones may or may not be transformational, but our analyses focus on the next three categories beyond the chasm.

The next 34% (one *SD* below) are the *early majority*. These are more deliberative, less prone to fads, unlikely to be opinion leaders, and more likely to adopt an innovation that has reached substantial market penetration due to influences and role-modeling of other adopters, easy accessibility in the marketplace, lower price, and stable features. Age and education have less influence on this category. Urbanness may still matter given the increased density of possible contacts providing social influence, and, in the case of mobiles, more people available in denser calling areas.

The following 34% (one *SD* above the mean) are the *late majority*. They are skeptical and cautious, interested in stable products at commodity prices by reliable brand-name producers, more likely to adopt due to economic/social necessity and peer influence, and have fewer resources to risk on high-involvement innovations. For technological innovations, they are likely older and less educated. This and the next category are slower to become aware of innovations, and in adopting even after awareness. The final 16% (two *SD*s) constitute the *laggards* (including nonadopters). They are more locally oriented and rural, have few resources to risk, and are noninnovative.

Influences on adoption

We hypothesize about influences on mobile adoption, in terms of the digital divide, and then the diffusion adopter categories. We consider primary individual influences on adoption to include demographics (age, sex, education), economic status (employed, relative economic condition), social environment (urbanness), family context (marital status and household size), and technology cluster (Internet access, color TV). We also consider two country-level economic factors (mobile market changes and GDP per capita).

Demographics

Age. Although age is not a strong correlate of innovativeness generally (Rogers, 2003), younger people have the highest adoption rate and levels of use of communication media due to earlier exposure and training, peer use, and greater psychological and physiological comfort with new technology (Annafari et al., 2013; Katz & Rice, 2002; Rice & Hagen, 2010). H1a. Age correlates negatively with mobile phone adoption. As laggards tend to be the oldest demographic group (Rogers, 2003), H1b. Age is more negatively influential in later mobile phone adoption stages.

Sex. During initial years of diffusion, due to expense, size, and functionality, mobile phones were businessmen's domain. Earlier adoption by men is supported empirically in other contexts (Castells et al., 2007). However, as more people adopt, there are proportionally more women adopting, and in some contexts sex disappears as a digital divide. H2a. Being male associates positively with mobile phone adoption. H2b. Being male is less positively influential in later mobile phone adoption stages.

Education. Educational attainment relates positively to mobile ownership (Annafari et al., 2013; Rice & Katz, 2003). This is due to not only increased innovativeness, but also to awareness, cognitive skills, and knowledge necessary to use technology (Rogers, 2003; van Dijk, 2005), perhaps especially so for smartphones (Stump et al., 2008). However, education would be more influential early on while awareness and familiarity are still somewhat low, but would likely diminish in influence over time. H3a. Education is associated positively with mobile phone adoption. H3b. Education is less positively influential in later mobile phone adoption stages.

Economic status

Employment and relative economic condition. Economic wellbeing relates positively to mobile phone ownership (Annafari et al., 2013; Rice & Katz, 2003; Wareham, Levy, & Shi, 2004). This stems from the basic issues of affording the device and services, and increased innovativeness and social connectedness associated with more resources (Rogers, 2003). Although innovators are less concerned about the economic costs than are early majority adopters, they experience higher product costs in the earlier adoption stages. As innovations become more popular and there is more competition, production/sales costs reduce, lessening the economic impact. Regardless, typically laggards experience economic obstacles to adoption. Central to perceived economic wellbeing is whether one is employed or not, which is related to Internet and mobile adoption (Rice & Katz, 2003). H4a. Employment associates positively with mobile phone adoption. H4b. Employment is more positively influential in later mobile phone adoption stages. H4c. Relative economic condition is associated positively with mobile phone adoption. H4d. Relative economic condition is most influential in early and late (compared to middle) mobile phone adoption stages.

Social environment

Urbanness. In developing countries generally, and in former Soviet countries particularly, the division between capital cities, regional cities, and rural areas is stark (Buckley, 1998). Rural areas have less telecommunications infrastructure and are the last to have access and maintenance services. There also may be a motivational divide due to the slower rural life pace, and less communicative need due to greater access to, and frequency of, communication with local relations. However, mobiles may overcome many infrastructural differences between urban and rural settings, and developed and less-developed regions, as wireless connectivity requires far less infrastructure (Loo & Ngan, 2012), thus reducing the influence of urbanness. H5a. Urbanness relates positively to mobile phone adoption. H5b. Urbanness is less influential in later mobile phone adoption stages.

Marital status and household size. Being married and cohabitating with more people would simultaneously increase mobile phone necessity (Allen, 1988), while also changing economic pressures in already impoverished situations. These factors are not much discussed in either the digital divide or the diffusion literature, so we include these as research questions. How do (RQ1a) marital status and (RQ1b) household size influence mobile phone adoption, and do those influences change over the adopter categories?

Technology cluster

Because mobiles are objectively and perceptually considered part of a communication technology cluster (or functionally similar innovations; Rogers, 2003; Wei, 2001), and those who adopt technologies within a cluster are more likely to be more innovative and thus adopt subsequent technologies in that cluster (Vishwanath & Goldhaber, 2003), we expect adopters of other media—here, *Internet* and *color TV*—to be more likely to adopt mobiles. H6a. Having access to the Internet, or (H6b) owning a color TV, will associate positively with mobile phone adoption. Again, however, there is little research on cluster effects over time. Do the influences of (RQ2a) Internet or (RQ2b) color TV change over time?

Country-level economic factors

Donner (2008) recommends increasing integration between general ICT adoption studies and those emphasizing national development issues. There are many country-level factors on ICT adoption, in four general categories: socioeconomic, political, cultural, and technological/structural (Adhiarna, Hwang, & Rho, 2011). Physical constraints (e.g., infrastructure, pricing, battery charging, interface language, topography, and signal range/strength, etc.) affect mobile phone access, adoption, and use (Marsden, 2007). Higher GDP per capita fosters innovation demand and purchase ability (Beise, 2004). Yamakawa, Rees, Sala, and Alva (2013) concluded that market concentration, population, regulated interconnection tariffs, and GDP per capita best predicted the growth of mobile adoption in Peru from 1994 through 2010.

Mobile phone market changes and entrants. Many national telecommunication services' policies trend toward regulatory liberalism (privatizing services, allowing competition, increased broadband access), and the accompanying price reductions and feature increases, alter the cost–benefit ratio of innovations, and therefore the adoption rate (Yamakawa et al., 2013). H7. Increased mobile phone providers and services correlate positively with mobile phone adoption.

GDP per capita. As the national economic condition changes, so should individuals' economic conditions and mobile phone adoption. H8. Greater per capita GDP correlates positively with mobile phone adoption.

Method

Context: Armenia and mobile phones

Armenia, a post-Soviet country facing external conflict, internal instability, and political strife (Heritage Foundation, 2008), has great economic and social inequality. Thirty-two percent of Armenians do not have enough money for food; another third (36%) can buy food but do not have enough for clothing (Pearce & Rice, 2013). GDP per capita in 2000 USD$ ranged from $975.05 in 2004 to $3,076 in 2011, recovering after the global financial crisis from its maximum of $3,606 in 2008 (http://knoema.com/atlas/Armenia/GDP-per-capita). Armenians are highly dependent upon labor migration remittances and are more vulnerable to economic changes (Grigorian & Melkonyan, 2011). Unusually for an impoverished country, Armenia has high education (86.5% of the population has secondary school education and over half have completed postgraduate work) and near-universal literacy (the adult literacy rate is 99.4%; World Bank, 2009). Thus education's influence on adoption may be muted in Armenia because of near-universal literacy and high levels of education.

In 1998, the Armenian government sold the newly privatized telecommunications infrastructure to the Greek company OTE with a 15-year exclusivity right in fixed line and a 5-year one in mobiles. However, the Armenian government detested the performance of the telecommunications system under OTE, locally known as Armentel, and attempted to cancel the exclusivity rights in 2004. OTE filed suit against the Armenian government; it was settled out of court in late 2004, leading OTE to relinquish its monopoly (Valderrama, 2011). Consequently, new telecommunication companies entered the market, increasing the number of firms, and adoption rate. 2004 was the last year with a mobile phone monopoly. 2005 was an important year for the Armenian telecommunications industry because a second provider, VivaCell, entered the market offering prepaid cards; thus, individuals without the ability to pay a deposit for a mobile contract were able to use mobile services. Although 2008 was the beginning year of the global economic crisis, Armenian per capita GDP was again strong. Moreover, the state telecommunications monopoly Armentel was sold to Russian-owned Beeline, which had savvier marketing, less expensive plans, and 3G service, making adoption cheaper and more attractive. In 2009, the first sign of the global economic crisis appears as decreased per capita GDP, indicating less disposable income for telecommunications; however, a third mobile provider, Orange, entered the market, resulting in price competition again and lower costs. Per capita GDP improved slightly in 2010.

Because of Armenia's high poverty, high educational attainment, increasingly competitive mobile phone market, fairly recent and rapid adoption of mobiles, and annual survey data covering early majority through laggard years, it provides a novel context for testing hypotheses about influences on the digital divide, by year, overall, and by adoption category.

Respondents and sampling

Respondents were adults from households in Armenia answering a face-to-face survey the Caucasus Research Resource Centers administered (n.d.), in each year from 2004 through 2011. Thus these are eight sets of cross-sectional data, from a different representative sample in each year. The methods and results are publicly available via its website. Survey participation was voluntary and anonymous. The sampling universe was adult (age 16+) residents in November of each year. The design used multistage area probability sampling. Primary sampling units were electoral precincts. The sampling frame was divided into three "macrostrata" by settlement type: capital, urban region, and rural. The secondary sampling unit was electoral districts, the third was households (via a random route method), and the final was individual respondents (the next-birthday method). Response rate varied across these years from 70% to 90%. Such (high) rates are typical for Caucasus countries, with multiple adults in a household, high unemployment, and a norm of children staying at home until age 4 or 5, so that someone is usually home.

Measures

Table 1 provides the item stems, response choices, and descriptive statistics for each measure (a correlation matrix is available from the authors).

Demographics

Age. Respondents reported their birth year, which was transformed into age by subtracting from the survey's year.

Sex. Interviewers noted the participant's sex (0 = male, 1 = female).

Education. Respondents reported their education (1 = no primary to 8 = postgraduate).

Economic status

Employment. In years 2004–2006, respondents selected from 11 employment statuses. We grouped "unemployed looking for work," "unemployed no longer looking for work," "student," "pensioner," and "housewife" as unemployed (= 0), and all others as employed (= 1). In 2007–2011, the interviewer asked only if they were not employed (= 0) or employed (= 1).

Relative economic condition. Although many studies use income as a single indicator of socioeconomic status, income is not a complete, direct, or reliable measure of total economic wellbeing (Falkingham, 1999; Ringen, 1988). It is also difficult to measure income in the former Soviet Union because of mixed income sources from multiple household members, secondary employment, and outside-of-the-market transactions (Falkingham, 1999; Kandiyoti, 1999). Thus respondents were asked their perceived relative economic condition (from 1 = very poor to 5 = very good).

Social environment

Urbanness. Urbanness represents a range from less to more urban (see Cossman, Cossman, Cosby, & Reavis, 2008). Interviewers determined if the household was located in a rural area (= 0), an urban city/region (= 1), or the capital (= 2). Urban regions in post-Soviet countries are a settlement with more than 10,000 residents and the majority must not be employed in agriculture (Buckley, 1998).

Family context: Marital status. Respondents selected from seven categories, grouped into not married (0 = never, divorced, separated, widowed) and married (1 = cohabiting, married).

Table 1. Descriptive statistics, by year and adopter category.

	Early majority			Late majority			Laggards	
Year	2004	2005	2006	2007	2008	2009	2010	2011
N	1,500	1,500	2,065	2,458	2,082	1,877	1,908	2,365
Age								
M	47.3	46.7	46.2	45.7	48.1	47.3	47.1	48.5
SD	17.3	16.5	17.1	17.1	17.7	17.9	17.6	17.9
Range	19–95	17–92	17–95	17–95	16–96	18–98	18–92	18–92
Sex (0 = M; 1 = F)								
M	.63	.66	.65	.68	.66	.59	.51	.55
SD	.48	.48	.48	.47	.47	.49	.50	.50
Education (1 = none; 8 = postgrad)								
M	5.40	4.98	4.80	4.86	4.79	4.69	4.92	4.92
SD	1.46	1.46	1.41	1.43	1.52	1.45	1.48	1.48
Employed (0 = N; 1 = Y)								
M	.40	.34	.51	.38	.34	.43	.38	.39
SD	.49	.47	.50	.49	.48	.50	.49	.49
Econ cond (1 = v. poor; 5 = v. good)								
M	2.44	2.40	2.56	2.74	2.77	2.79	2.82	2.84
SD	.90	.91	.84	.77	.76	.81	.76	.66
Urbanness								
0 Rural	–	23.1%	33.4%	11.2%	36.8%	37.3%	39.8%	38.8%
1 Urban	–	27.0	32.0	29.1	30.4	31.5	29.1	31.6
2 Capital	100%	49.9	34.6	59.7	32.8	31.2	31.1	29.6
M	–	1.73	1.99	1.52	2.05	2.06	2.09	1.91
SD	–	.81	.82	.69	.83	.83	.84	.82

(Continued)

Table 1. (Continued)

	Early majority		Late majority			Laggards		
Marital (0 = N; 1 = Y)								
M	.59	.68	.65	.65	.63	.62	.66	.66
SD	.49	.47	.48	.48	.48	.49	.48	.47
Hhold size (1–7 or more)								
M	3.80	4.24	4.20	3.89	3.78	3.85	4.04	3.83
SD	1.66	1.71	1.73	1.81	1.77	1.80	1.73	1.75
Internet (0 = N; 1 = Y)								
M	.07	.04	.04	.04	.48	.21	.32	.37
SD	.26	.20	.19	.20	.50	.41	.47	.48
TV (0 = N; 1 = Y)								
M	.94	.93	.94	.91	.94	.96	.98	.98
SD	.25	.25	.23	.29	.24	.20	.15	.15
Mkt 2005	0	1	1	1	1	1	1	1
Mkt 2008	0	0	0	0	1	1	1	1
Mkt 2009	0	0	0	0	0	1	1	1
GDP 2000 USD	975.05	1,109.03	1,253.81	1,424.19	1,520.03	1,302.46	1,326.71	1,384.09
Adopters	22%	25%	47%	70%	76%	81%	92%	93%

Note. Mobile phone adoption measured whether one owned a mobile phone (0 = no 1 = yes).

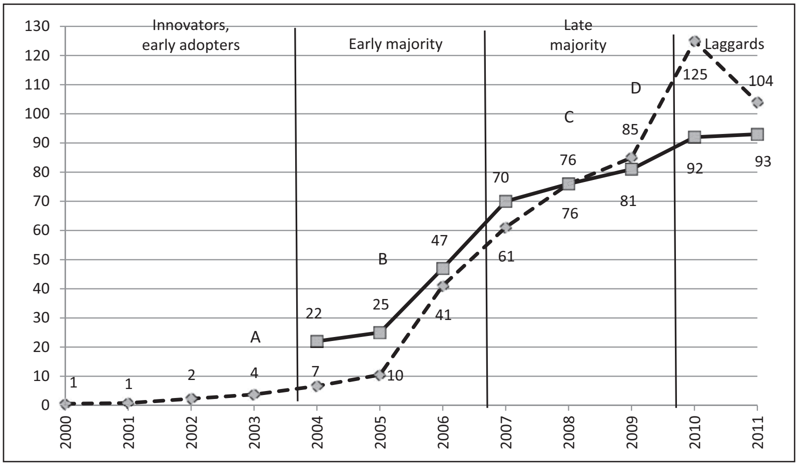

Figure 1. Cumulative adoption (percent) of mobile phone adopters in Armenia by adopter category and by year (2000–2011), and year of new market entries.
Sources: Continuous line is based on data from Caucasus Research Resource Centers (n.d.); dashed line is based on data from International Telecommunication Union (2011).
A = 2003, Armentel network upgrade complete; Wireless Application Protocol (WAP) available.
B = 2005, 2nd provider VivaCell enters market; prepaid cards become available.
C = 2008, Armentel sold to Beeline; Armentel/Beeline launch 3G.
D = 2009–2010, 3rd provider Orange enters market.

Family context: Household size. This question asked how many people resided in the household. Answers above 7 (infrequent) were recoded into 7.

Technology cluster. For 2004–2006 and 2009–2011, respondents were asked if they and/or their family had *Internet access* (0 = no, 1 = yes). For 2007 and 2008, the question was constrained, asking if they had Internet access from their home computer. Only a small number answered in 2008, so we dropped that year's measure. All years' surveys also asked if they had a color TV (0 = no, 1 = yes).

Country-level economic factors

Mobile phone market changes. The market changes in providers/services 2005, 2008, and 2009 were represented by three dummy variables with a 0 for each year up to the implementation year, and 1 for the first year of their appearance and each following year.

GDP per capita. Gross domestic product per capita in constant year 2000 USD$ for each survey year was obtained from the World Bank (data.worldbank.org/data-catalog) for each year.

Results

Before 2004, International Telecommunication Union (2011) data indicate adoption was below 5% (Figure 1). In the 2004 survey it was 22%, growing to 93% by 2011.

Results from four analyses follow. (a) Applying a typical digital divide approach, we run logistic regressions for each year; (b) then, we run a regression on the combined years. (c) Applying a diffusion approach, we run regressions on groups of years matching the respective three adoption categories; (d) then, we assess moderation effects of adoption category on the influence of the variables on mobile phone adoption.

Digital divide relationships yearly and combined

The separate binary logistic regressions explaining mobile phone adoption for each year (table available from the authors) is a "traditional" approach in the sense that we could imagine a survey taken in any one of those years, at whatever adoption level existed at the time, and use data from that year to test for influences of the proposed variables on adoption (except for market changes and GDP influences, being single values for each year.)

Separate years. Across the separate year results, age (H1a), education (H3a), and relative economic condition (H4c) were all associated positively with mobile phone adoption in each of the 8 years (2004–2011). Internet access was significant in 6 of the 7 years measured (supporting H6a), color TV in only 2 years (rejecting H6b), employment in 5 years (supporting H4a), urbanness in 3 (not supporting H5a), and sex in none of the years (not supporting H2a). Being married was significant in 5 of the years (RQ1a), and household size in all 8 years (RQ1b). Variances explained by the logistic regressions were 32%, 34%, 34%, 45%, 45%, 39%, 36%, and 41%.

So a typical digital divide analysis in any of those years finds support for the traditional age, education, economic condition hypotheses but only somewhat for employment and urbanness, and not for sex, with somewhat more or less support in particular years. Thus, depending on the particular year analyzed, digital divide influences varied somewhat. However, as noted earlier, the digital divide approach provides no theoretical rationale for such variations.

Combined years. An alternative to analyzing separate years of a traditional digital divide approach (perhaps depending on feasibility of a survey in a given year or timing of a study, and thus presuming results would apply to other, unsurveyed, years) is to analyze data combined from all of a study's available years (not distinguishing among adoption categories). So, we combined the data from all years 2004–2011 (but analyzed a 34% random sample to match sizes with the category sizes; see note in Table 2). As there are multiple years, we can now include market change dummies and per capita GDP.

Columns 2–4 (for 2004–2011 combined) of Table 2 show that except for sex, all the demographic, economic status, and social environment variables were significant influences, as predicted from the general digital divide literature (supporting H1a, H3a, H4a, H4c, H5a). The first mobile phone market change was associated with decreased adoption, the second one was not associated, and the third one was associated with increased adoption (mixed results for H7).[1] GDP was also very slightly but significantly associated with mobile phone adoption in all adopter categories (supporting H8). Here, 61% of the variance was explained.

Digital divide relationships by diffusion of innovation adopter categories

Logistic regression analyses by adopter category. Taking the diffusion approach requires that we group the yearly data into respective adoption categories (2004–2006 = early majority, 2007–2009 = late majority, and 2010–2011 = laggard) based on the range of yearly adoption percentages appropriate to each category (see Figure 1), and conduct regressions for each category. Columns 5–13 of Table 2 present those results.

We again note that Rogers's categories presume measures of when a respondent adopted, that the respondents are placed in mutually exclusive categories on the basis of their adoption time, and that near-complete adoption has occurred. Given that the surveys only asked whether the respondent owned a mobile phone in the year of the survey, and not the year in which the respondent adopted, the categories used here are only general estimates. For the most extreme mismatched case, someone reporting owning a mobile phone in 2011 (and thus placed in the laggard category for explanatory purposes) could in fact have adopted way back in 2004 (thus at the time been in the Early Majority category).

The variables' coefficients and significance differ somewhat across the categories. Age remains a consistent slight negative influence. Sex disappears as a factor by the late majority. The influence of education declines across the categories, but remains significant. Employment was influential throughout, but became a major factor by the laggard category, reflecting the economic changes during that period, as well as the hypothesized increased concern with costs by laggards; however, relative economic condition remained a consistently strong influence. The effect of urbanness varies considerably across the categories, possibly reflecting changes in mobile phone transmission access associated with the market changes. Marital status disappears as an influence, though the influence of household size increases, in the laggard category. Having Internet declines as an adoption cluster stimulant across the categories, but remains strong. Conversely, having a color TV changes from having no influence in the early majority to having an increasingly strong explanatory contribution by the laggard category.

These adoption category analyses treat the market changes somewhat differently than in the combined approach. As changes in the year 2008 and 2009 are grouped together into the late majority category, the 2009 market dummy variable was not entered into that regression. And, as values for all three change variables are the same (i.e., 1) in the laggard category, none was included in that regression. The market changes have very little variation, but nonetheless the 2005 change was associated with less adoption in the early majority while the 2008 change was associated with more adoption in the late majority.[2]

Moderation analyses by adoption category. Instead of only verbally comparing simple effects across the three regressions, we can test for interactions of the variables with (or moderation by) adopter category (see Table 3). Moderation analysis (using PROCESS; Hayes, 2013) tests for this, using a dummy = 1 for each adoption category of interest, compared to a dummy = 0 for the two other adoption categories. The three values in each cell of Table 3 are the effects (coefficient) of the variable for dummy = 0 (the other two adoption categories), dummy = 1 (the specific adoption category in the column heading),

Table 2. Binary logistic regressions on mobile adoption by all years combined, and by adopter categories.

	Digital divide			Diffusion of innovations categories								
	2004–2011 (n = 4,416[a])			Early majority 2004–2006 (n = 4,664)			Late majority 2007–2009 (n = 4,193)			Laggards 2010–2011 (n = 4,287)		
Variable	B	*SE*	Odds	B	*SE*	Odds	B	*SE*	Odds	B	*SE*	Odds
Age	−.02***	.003	.98	−.02***	.00	.98	−.03***	.00	.97	−.05***	.01	.96
Sex	.06	.10	1.06	−.10	.08	.91	.07	.10	.93	−.03	.16	.97
Educ	.28***	.04	1.32	.29***	.03	1.34	.22***	.03	1.24	.15**	.05	1.16
Empl	.45***	.10	1.56	.33*	.08	1.40	.24**	.10	1.28	.94***	.20	2.55
Econ	.69***	.06	2.00	.67***	.05	1.95	.88***	.06	2.42	.55***	.09	1.74
Urban	.11*	.06	1.12	.51***	.06	1.66	−.16**	.06	.85	−.03	.09	.72
Marital	.41***	.10	1.50	.39***	.09	1.48	.30***	.09	1.35	−.06	.16	.71
HH size	.28***	.03	1.32	.20***	.03	1.22	.28***	.03	1.32	.56***	.05	1.75
Internet	1.97***	.25	7.16	1.98***	.19	7.22	1.48***	.29	4.39	.81**	.27	2.24
Color TV	.70***	.20	2.00	−.12	.19	.89	.70***	.16	2.01	.92**	.30	2.50
Market 2005	−.61**	.22	.54	−.60***	.16	.55	–	–	–	–	–	–
Market 2008	.50	.55	1.64	–	–	–	1.17***	.21	2.13	–	–	–
Market 2009	1.6**	.55	4.87	–	–	–	–	–	–	–	–	–
GDP US 2000	.01***	.00	1.01	.01***	.00	1.01	.004**	.00	1.00	.005*	.00	1.01
Constant	−14.7***	.68	0.0	−15.2***	.77	0.0	−8.75***	–	–	−7.17*	–	–
Nagelkerke R2	.61	–	–	.37	–	–	.41	–	–	.39	–	–
$X^2/(df)$	2603.1 (14) ***	–	–	1427.3 (12)***	–	–	1421.5 (12)***	–	–	718.2 (11)***	–	–
Correct	84.4%	–	–	77.3%	–	–	79.2%	–	–	59.7%	–	–

Note. [a]This dataset uses a 34% random sample of the combined dataset, with a resulting size of 4,416, similar to the sizes of each adoption category's data.
*p < .05. **p < .01. ***p < .001.

Table 3. Moderation effect of adopter category and explanatory variables on mobile phone adoption.

	Category dummy	Early majority (2004–2006) B	Early majority (2004–2006) SE	Late majority (2007–2009) B	Late majority (2007–2009) SE	Laggards (2010–2011) B	Laggards (2010–2011) SE
Age	0	−.05***	.00	−.02***	.001	−.03***	.001
	1	−.03***	.00	−.05***	.002	−.07***	.004
	Interaction	.02***	.00	−.03***	.002	−.04***	.004
Sex	0	−.54***	.05	−.43***	.04	−.25***	.04
	1	−.16**	.06	−.43***	.06	−.42***	.12
	Interaction	.38***	.08	−.00	.08	−.17	.12
Education	0	.38***	.02	.18***	.01	.24***	.04
	1	.35***	.02	.39***	.02	.35***	.04
	Interaction	−.03	.03	.20***	.03	.11**	.04
Employment	0	1.01***	.06	−.79***	.05	−.28***	.04
	1	.83***	.06	.94***	.07	1.68***	.18
	Interaction	−.17*	.09	1.73***	.08	1.96***	.18
Economic condition	0	1.09***	.04	.96***	.03	1.06***	.03
	1	.89***	.04	1.17***	.04	.98***	.07
	Interaction	−.20***	.06	.21***	.05	−.08	.08
Urbanness	0	−.14***	.03	−.29***	.03	−.18***	.02
	1	.09**	.04	−.12***	.04	−.01	.06
	Interaction	.23***	.05	.17***	.05	.17*	.07
Marital	0	.81***	.05	.40***	.04	.53***	.04
	1	.47***	.06	.82***	.06	.85***	.12
	Interaction	−.34***	.08	.42***	.07	.32**	.12
Household size	0	.53***	.02	.15***	.01	.23***	.01
	1	.20***	.02	.50***	.02	.79***	.05
	Interaction	−.33***	.03	.35***	.02	.55***	.05
Internet	0	2.74***	.18	3.21***	.13	2.66***	.14
	1	2.39***	.17	2.71***	.26	2.25***	.24
	Interaction	−.35	.24	−.49	.29	−.41	.28
Color TV	0	2.05***	.09	1.34***	.11	1.34***	.08
	1	.90***	.15	1.93***	.11	1.74***	.23
	Interaction	−1.15***	.18	.59***	.15	.41	.24
Market 2005[a]	0	–	–	–	–	–	–
	1	–	–	–	–	–	–
	Interaction	–	–	–	–	–	–
Market 2008[a]	0	–	–	3.19***	.06	–	–
	1	–	–	.50***	.06	–	–
	Interaction	–	–	−2.69***	.09	–	–
Market 2009[a]	0	–	–	3.19***	.06	–	–
	1	–	–	.45***	.07	–	–
	Interaction	–	–	−2.74***	.09	–	–

(Continued)

Table 3. (Continued)

	Category dummy	Early majority (2004–2006)		Late majority (2007–2009)		Laggards (2010–2011)	
		B	*SE*	B	*SE*	B	*SE*
GDP US 2000	0	.00***	.00	.01***	.00	.01***	.00
	1	.00***	.00	.00***	.00	.00	.00
	Interaction	.01***	.00	−.01***	.00	.00	.00

Note. Results were computed using PROCESS (Model 1; Hayes, 2013).
The three values in each cell are effects (coefficient, significance, and standard error) of dummy = 0 (the other two adoption categories); dummy = 1 (the adoption category of interest, in the column heading); the interaction between the adoption category dummy and the explanatory variable, that is, the effect of the dummy adoption category (= 1, respectively for either EM, LM, or LG) for that sociodemographic variable, compared to the other two combined (e.g., = 0 for EM/LG, EM/LG, or EM/LM).
As respondents from each adoption category's years are included in each moderation test, the sample size for all years combined is larger than for individual yearly analyses, and the standard errors are much smaller, so the effects are more likely to be significant within any adopter category than in separate years. However, the sample size for each category is about a third of the combined sample size, so the effects are less likely to be significant than in the combined sample.
[a]Not analyzable for years with dash due to insufficient variance of the measure.
*p < .05.**p < .01.***p < .001.

and of the interaction (moderation) between the adoption category dummy and the explanatory variable (not centered), respectively.

Demographics. Age was a slightly, but significantly and increasingly more negative influence (e.g., being younger) across the periods (supporting H1a), and these differences were significant. Sex was a significant influence in early majority, but not during late majority or laggard, and confirmed by the moderation effect (H2b). Education was positively associated with adoption in all categories, but more so in the late adoption categories (counter to H3b).

Economic status. Employment was a significant and strong influence in all categories, and a significantly increasingly positive influence at each subsequent adopter category (supporting H4b). Perhaps more companies were requiring employees to have mobile phones, and economic condition became less of a factor as the economy was rebounding and more people were employed. Relative economic condition was also a positive significant influence in all adoption categories in the logistic regression, spiking just before and during the economic crisis, but was moderated by early majority and late majority, with less positive effect at early majority, more positive at late majority, and no significant difference compared to the laggard period (somewhat opposite of H4d). This is likely due to the extreme consequences of the fiscal crisis in a country already economically poor.

Social environment. The influence of urbanness varied widely across the three categories: strongly positive in early majority, weakly negative in late majority (when adoption was associated with being more rural) and nonsignificant in laggard (supporting H5b).

Living in more urban areas does represent a divide as to who adopts early on, with implications for early advantages and structural inequalities, but perhaps disappears as more powerful and accessible wireless services become available in more rural areas. The effect of marital status decreases from a moderate positive influence in early majority and late majority to essentially zero by laggard, with significant differences across all the category pairs (RQ1a). This may mean that with broader diffusion and lower costs, individuals were more able to own their own phones. Household size was slightly but significantly positive in the first two categories, but doubled in effect by laggard, and all the moderations were significant (RQ1b). Perhaps as more mobile phones are adopted by others over time, and for those with larger families and thus more close network members to communicate with, the positive network externality becomes stronger, and adoption is increasingly more valuable.

Technology cluster. The effect of having Internet access was strong and positive throughout all categories, and decreasingly so across the categories, though none of the differences across the categories was significant (RQ2a). Owning a color TV jumped from nonsignificant influence in early majority to a strong effect in late majority and laggard, though the final increase was not significant (RQ2b). Possibly early adopters, being more innovative, are less influenced by traditional technology cluster elements, whereas later, more reluctant, adopters need the uncertainty-reducing familiarity with a prior, more traditional, media technology.

Market changes and GDP. The 2008 and 2009 market changes show a moderation effect of the late majority dummy. Both effects are "negative" because the growth in adoption (11%) is relative to the combined high growth in early majority and the nearly flat growth in laggard (26%). Moderation effects of adoption category on GDP's association with mobile phone adoption are very small, largely because of having only one value per year and thus very low variance. They are significantly positive in the first category and negative in the second (relative to the respective two other categories) as both GDP and adoption first rose, then adoption rose while GDP declined, and finally both changed very little in the laggard category.

Visual summary of variations in individual-level influences across the adoption categories. Figure 2 plots the odds ratios within their 95% confidence intervals of the primary sociodemographic variables, showing the changing levels of influence across the three adoption categories.

Discussion

Main results

The general result is that the central digital divide argument maintains validity even in this unique (high-poverty, high-literacy) context, as there is minimal variation in influence across neighboring years. However, there are more (and significantly so in many cases) variations across larger spans such as the adoption categories identified by diffusion of

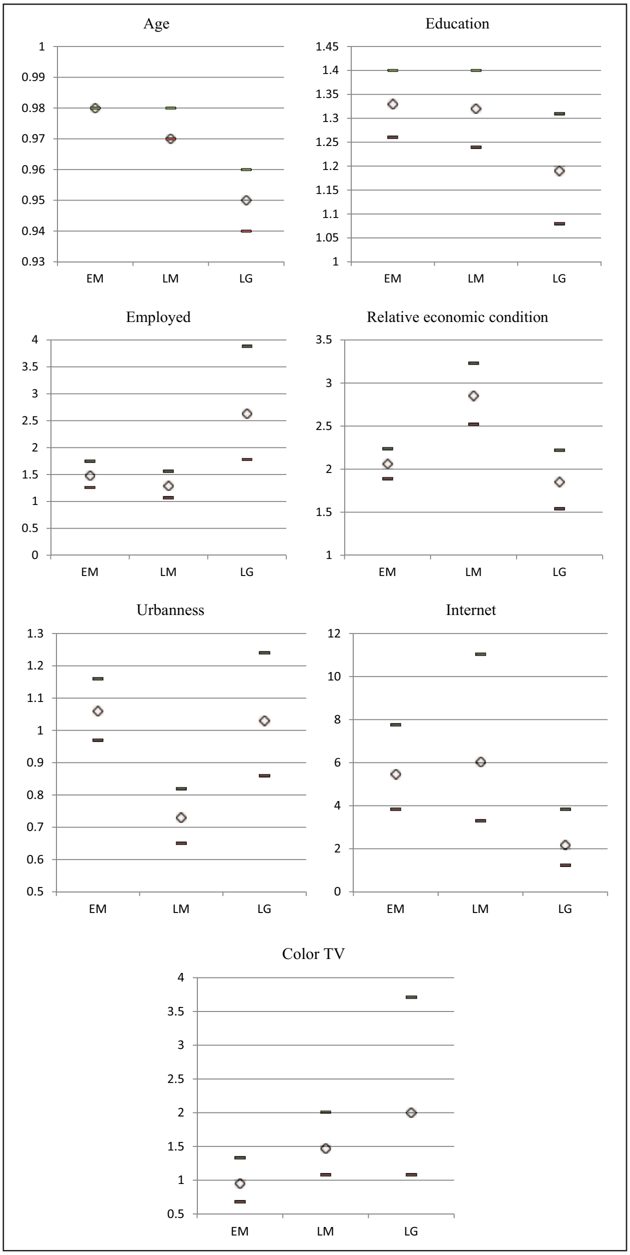

Figure 2. Variation of odds ratios, with confidence intervals, of primary influences across the three adoption categories (early majority/EM, late majority/LM, laggard/LG) on mobile phone ownership in Armenia.

Note. The value indicated by the diamond is the odds ratio for each adoption category; upper and lower dashes are 95% confidence intervals. These show the variation *within the variables across the three adoption categories.* If any of the sets of dashes includes the vertical axis value of 1.0 in a given adoption category, the odds ratio for that year is not statistically significant at $p < .05$ (e.g., urbanness for EM and LG; color TV for EM).

innovations theory. Traditional digital divide studies report results either as of the particular year, from a small set of specific years, or in some unspecified combination of years. And they reasonably capture much of the influence of traditional digital divide influences, such as demographic, economic, social context, and related media use. However, a diffusion of innovations approach argues that another, complementary factor is the general adoption category, and that some variables should have different relationships with adoption within each category. Thus, specific digital divide results may be qualified or complemented by the overall adoption category of respondent for the year in which such studies are conducted. Complementing the typical digital divide single year analyses, the adoption category approach in combination with macrolevel and market factors gives greater insight into how ICTs diffuse in a society with great economic and social inequality.

The current study also shows a slight varying impact of market liberalization and national economic status (both national-level factors) on adoption (an individual-level behavior). Adoption bumps were never as strong as after the 2005 market change, while either the 2008 or 2009 market change affected adoption, depending on the analysis, perhaps due to lowered price and increased service due to multiprovider competition. Increasing GDP per capita in general provides a positive environment for mobile phone adoption, but its effect here is muted because of the drop in GDP in 2009 associated with the global economic crisis.

Limitations

The binary measure of (non)adoption is, of course, a specific, and limited, digital divide indicator, as noted before. Nonetheless, adoption does represent the primary initial challenge after awareness and access, and studies typically find greater differences in influences at the adoption divide than across subsequent divides (Katz & Rice, 2002; Pearce & Rice, 2014). We also noted that mobile phone use itself is much more complex and diverse than simple adoption. And the forms of use, regulatory implications, and design features can vary widely across countries and cultures (Donner, 2008). The survey data do not distinguish between regular mobiles and smartphones (available only in the latter years of the study), which may be differentially predicted by factors such as finances and education.

The distinctions between the adopter categories are a somewhat arbitrary convention using the standard deviations along the cumulative adoption curve. In contrast, Adhiarna et al. (2011) developed a stage-scale model of adoption and diffusion in developing countries. Thus, different conceptualizations of differences in adoption stages may simplify or generate different results.

Future research

There are of course other factors that affect adoption. Beyond psychological and relational factors, these may include disability, strict religious adherence, living in areas with no or poor cellular reception, or cultural values. It is also possible that users borrow phones from others if they need them (Burrell, 2010) or have multiple SIM cards (Donner, 2015), which can impact official adoption rates. Lee and Kim's (2014) analysis of mobile phone adoption in Korea also identified significant influences of innovativeness and competence on different kinds of mobile phone use, in turn affecting outcomes such as life management, resource use, network management, and personal identity display.

Digital divide and diffusion approaches integrate the individual level of sociodemographic influences with the social level of adopter category characteristics. Other approaches can and should be integrated with these two. For example, Pedersen and Ling (2003) summarize four approaches to studying mobile services adoption: diffusion research, adoption research, uses and gratification research, and domestication research, varying in level (micro, macro) and focus (explanation, description, consequences; and influences, behavior, effects).

While the total percent of adoption each year does allow for categorizing sets of years by adoption category (except for the low-percentage innovators and early adopters), the data in each year have, as adopters, respondents who may have already adopted during any of the prior adopter categories (though not the same individuals). In this sense the adopter category hypotheses tests in this particular study are conservative, by masking some true differences between categories. Digital divide studies could use and compare several analytical approaches to identifying adopter categories. In the typical method of having just one survey year, analysis could group respondents by the number of years since they first adopted (if that was measured), and test for differences in influences by individuals' adoption category based on the distribution of all adopters. Alternatively, with a long enough series of years, from early in the overall adoption curve through to near saturation, surveys should ask, in each year, what year the respondent adopted the mobile, and then place each respondent in one of the adopter categories based on the cumulative adoption curve across the years. One could also then compare digital divide influence results based on each yearly adoption report, and retrospectively from the last year, to test for differences in those two approaches. An even more specific approach would be to identify all those who said they adopted in the past year within each yearly dataset, group those into adopter categories based on the cumulative diffusion curve across the years, and combine and analyze only those in one dataset. Finally, following Stump et al. (2008) and their review of multicountry studies, this approach could be applied by categorizing each country by its cumulative adoption levels, and comparing influences across country-level adopter categories. Nishida, Pick, and Sarkar (2014) provide an example of a multidimensional approach that also includes spatial aspects.

Conclusion

In summary, there is a natural complementarity between the digital divide and diffusion of innovations approaches, more macrolevel measures should be included, and diffusion adoption categories can provide additional conceptual and empirical insight into the influences on mobile phone adoption and related divides.

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Notes

1. It is not clear why the 2005 market change is negatively associated, as adoption rose substantially (to 47%) compared to the 2004 level of 22%, and, as the correlations show, all three market changes were positively associated with adoption in the combined data. There is only moderate correlation between the 2005 dummy variables and the 2008 and 2009 dummies (.35 and .27, respectively, both *p*s < .001), so multicollinearity and thus highly unstable coefficients are not likely. However, there are potential problems due to low variance, and mixing country-level measures with individual-level measures. Moreover, country-level indicators from developing countries are notoriously difficult to validate.
2. Again, it is not clear why the 2005 market change is negatively associated, as adoption nearly doubled by the third year in early majority.

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