Getting online but still living offline: the complex relationship of technology adoption and in-person social networks

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Abstract

Previous research in Kyrgyzstan has demonstrated the importance of close social networks as avenues for gathering and sharing information, assistance and goods in the country. However, the relationship between technology use and social network use has not been investigated; understanding this relationship is important when considering the design of technology applications that support existing social networks. Contrary to Robert Putnam's hypothesis that technologies have an "individualizing" force on populations, we have found that social network patterns do not appear to be negatively associated with higher technology use. In fact, the higher the level of technology use, the more face-to-face social networks were used for multiple types of information seeking.

1. Introduction

The importance of social networks and their relationship to social capital has been a well-studied concept in the social sciences for over 30 years. Originated by Bourdieu [2], social capital, in the most general sense, refers to benefits people gain by their relationships with others through their social networks [6, 14, 13]. In the discussion of social networks, many researchers have differentiated between types of relationships.

The differentiation between strong ties, those in which there is a greater time commitment and an assumed greater similarity, and weak ties is a common distinction [9, 12]. While there are many exceptions, family and friends are considered a source of strong ties whereas neighbors are more often considered a source of weak ties. Robert Putnam discusses the difference between bridging and bonding social capital; bonding capital is between homogenous groups that share common interests, for example gang membership, whereas bridging capital is between heterogeneous groups, for example choirs [5]. Bonding social capital is more often associated with strong ties whereas bridging social capital is more often associated with weak ties. Additionally, researchers have used the theory of social capital to discuss the effects of technology use on social networks [3, 7, 15].

There are differing opinions on the effects of technology use on social capital. On one side of the debate, Putnam hypothesizes that at least part of the decay in social capital and subsequent decline in civic engagement is due to the "individualizing" forces of technologies and the Internet [12]. The decrease in civic engagement in America, Putnam argues, can be seen through the decline in many types of associational institutions including church attendance, labor union membership, and parent-teacher associations. Alternatively, others argue that the Internet, especially through social network sites, has provided an increase of, at the very least, weak social ties - resulting in a net gain in one's overall social network [3, 13]. This discussion, however, is largely is focused on urban communities in Western societies.

We study the effects of technology on social capital within developing regions/emerging markets where people live in resource-constrained environments (RCE). We define a RCE as any environment with limited access or reduced availability of resources. Resources include anything from a reliable Internet connection to clean water access. Traditionally, across many societies, RCEs have demonstrated a strong reliance on face-to-face social networks for information and services [16, 11]. Therefore, if increased technology use were to imply a concurrent reduction of social ties, the implications for increased technology usage in RCE would be significant and, potentially, disruptive. In this paper, then, we set out to examine the connection between increased technology use and an individuals' reliance on social networks.

While this examination is part of an overall project to understand cultural issues related to technology use, we also have the goal of understanding the relationship between technology and social capital in order to help inform the design of appropriate technologies that support existing social networks. We are interested in looking at technology use and social capital findings through the lens of Putnam's framework to analyze if his hypothesis of the individualizing forces of technology extends to RCEs and, based on those findings, how we might address issues of technology design for RCEs. For the purpose of this paper, we are using Kyrgyzstan to represent an RCE.

Kyrgyzstan, located in Central Asia, is a post-Soviet country transitioning to a capitalist economy from the centralized Soviet system. Limited access to the Internet, low employment, and failing infrastructure are three examples of resource constraints faced by people in Kyrgyzstan. As part of the Central Asia + Information Communication Technology (CAICT) project, a multi-year investigation of technology adoption and use, we have found that the importance of face-to-face social networks is critical in Kyrgyzstan (as it is in most RCEs) [10]. Social networks serve as avenues for gathering and sharing information and goods. These social networks offset the lack of reliable and trusted information from traditional institutions found in the United States, such as the government, police and court system [10]. While the structure of existing social networks has been investigated in the region, research has not focused on the relationship between technology use and social network use; this paper addresses that void.

Our hypothesis for this paper is that technology usage patterns are related to how people use face-to-face social networks. As stated above, we situate this work within an ongoing conversation related to increases in technology use and subsequent effect on social networks; however, we expand the scope of such questions beyond communities that are highly resourced. Specifically, our research questions asked: (1) Do variables that measure face-to-face social network use and trust predict whether someone is a technology user, in other words, are there differences in social network use and trust between technology users and technology nonusers? (2) Is there a difference among levels of technology users and their trust of face-to-face networks (those that represent bridging or bonding ties)? and (3) Is there a difference among levels of technology users and their utilization of their face-to-face social networks for information seeking, in other words, does there appear to be an "individualizing" association with technology use. To investigate our questions, we use data collected from a broad social survey that asked respondents questions designed to probe technology-related developments, including their attitudes and behaviors.

2. Method

The following sections first describe the survey design and deployment. We then briefly describe the demographics of the respondents, followed by a discussion of the data analysis used for this paper.

2.1. Survey design and deployment

This paper uses three years of survey data from Kyrgyzstan (2006 to 2008). Each survey included 1000 participants for a total of 3000 respondents. The survey instrument was designed by the CAICT team and was administered by the BRiF Research Group located in Kazakhstan. Rigorous methods were employed to ensure a random sample.

The BRiF research group selected households using a random walk procedure in neighborhoods. Only one respondent was interviewed in each selected household. Each respondent was chosen using the Kish grid method, a common technique to ensure a random selection of household members. Additionally, the survey sample was based on government census information on age, gender, ethnicity, and geographic location. The final sample included 50 sampling locations; 12-29 respondents were interviewed in each location.

This project encountered two methodological challenges in Central Asia: (1) creating appropriate survey content and (2) implementing the sampling approach. (Note that while this paper concentrates in Kyrgyzstan, we have also conducted this survey over the same three-year period in Kazakhstan, Tajikistan and Uzbekistan). These challenges guided our research in specific ways, requiring a departure from some traditional research approaches in the West.

First, in reference to survey content, the likert scales used in our survey for trustworthiness have no middle point reducing our overall power to observe more finite differences among groups; however, our choice of a four-point scale is not by accident. In our initial pilot studies, conducted in 2003, we found that if a neutral option was introduced, a majority of respondents would choose neutrality. This appeared to be associated with other findings in the region that suggest that citizens in post-Soviet contexts are resistant to expressing an opinion and will opt for neutrality when possible. After consultation with statistical experts at the University of Washington, we modified our survey so that all likert scales contained either four or six options.

Second, attaining a random sample was a difficult. Since there is not a communication system equivalent to the phone infrastructure found in the West, the random walk procedure was deployed. Additionally, all interviews were conducted face to face and no other household member was present in the room at the time of the interview. Strict confidentiality was guaranteed to the respondents. These sampling methods were chosen after careful pre-testing of research methods to ensure as representative a sample as possible given the cultural context.

2.2. Participants

The average survey respondent was 39.9 years old (*SD* = 17.3 years) and had 11.4 years of formal education (*SD* = 3.1 years). A slight majority, 56%, of the sample was female, and 44% lived in urban environments. In the 2006 survey, the enumerator was asked to report on socio-economic status (SES) ranging from low to high, and in the 2007-2008 surveys the participant was asked to self-report on SES using the same scale. While the methods of determining SES were slightly different, the results were largely the same: in 2006, 78% were judged middle class; in 2007, 85% judged themselves as middle class; and in 2008, 80% claimed to be middle class.

2.3. Data analysis

We first separated the respondents into two groups: (1) technology users (who reported using a mobile phone, computer, and/or Internet) and (2) technology non-users. In background modeling, we discovered that a simple model using demographic variables alone (age, gender, education, SES, and rural versus urban location), could reliably predict whether or not someone was a technology user; however, we did not know if variables that measured social network use and trust could also predict technology use after controlling for demographic variables. To investigate this question, we utilized the technology groups as the dependant variable in a sequential logistic regression to determine if the addition of social network variables would significantly predict technology use after demographic variables had been considered.

Next we separated technology users into two separate groups by examining three of the survey questions: (1) Do you own or use a mobile phone? (2) Do you ever use a computer, at least occasionally? and (3) Do you ever use the Internet, at least occasionally? In our initial scale, one point was given for an affirmative answer to each question, resulting scores ranged from 0-3. We eliminated 225 respondents who scored one point for only using a computer for two reasons: (1) because composition of the low level user group changed radically over the three years of the survey, comprising 43% mobile users in 2006 to 98% mobile users in 2008, in other words, grouping all respondents who scored one point in the low level user group created a radically different group composition for each year of the survey; and (2) it can be reasonably argued that as technologies, mobile phones and computers often function much differently in social networks. In other words, mobile phones often function as a facilitator of social interaction and computers serve as facilitator of information. The resulting groups were defined as (1) technology non-users; (2) low level technology users (only used a mobile phone); and (3) high level technology users (used a mobile phone and a computer and/or the Internet). We collapsed our top two groups (Internet users and computer users) because fewer than 15% of the survey sample used the Internet. Our analysis first looked at how these user groups had changed across each year of the survey.

We then examined social network use and trust through the lens of our three user groups by analyzing 15 social network related variables in the survey. For three of the variables respondents were asked questions regarding trust; respondents judged family, friends and neighbors on a scale of 1-4, from very untrustworthy to very trustworthy. We used ANOVAs to investigate differences in trust levels among the user groups.

Additionally, respondents were asked about six categories of information and what sources they used in the previous week to gather information about those categories. For these questions, family was considered one source, and friends and neighbors were grouped as another source; additional sources included television, newspapers and radio. The information categories were (1) something you wanted to buy; (2) elected official or government representatives; (3) official services; (4) religious news; (1) health issues; and (5) local news. Through Chi-square tests we investigated differences among user groups of their utilization of face-to-face user networks as information sources.

3. Results

The results section first discusses the sequential logistic regression model we used to investigate our first research question: are the variables measuring social network use and trust reliable predictors of technology use after controlling for demographics? Next, we describe the composition of the three technology user groups that we utilized to answer the second and third research questions. These questions analyzed (a) if there are difference in the level of face-to-face network trust among the different levels of technology users, and (b) if there are differences in the utilization of their face-to-face social networks for information among the different levels of technology users.

3.1. Do variables that measure social network trust and use predict technology use?

Of the 3000 respondents, about half (N=1572) were defined as technology users. Sequential logistic regression was employed to investigate if social network variables predicted technology use after controlling for demographic variables.

A test of the model using the five demographic predictors against the null model with no predictors was significant, $\chi^2(5, N = 2693) = 729.00, p < .001$, indicating the set of demographic predictors reliably distinguishes between those who use technology and those who do not. The approximate variance in technology use status accounted for by the set of variables was .316 (32%) using Nagelkerke's formula. Model sensitivity (classification of technology non-users) was 66%, and specificity (classification of technology users) was 74%, with an overall hit rate of 70%, which was an improvement from the null model's hit rate of 52%. In other words, demographics do reliably predict technology use status.

After the addition of the 15 social network variables, the model improved, $\chi^2(20, N = 2693) = 782.00, p < .001$. The approximate variance in technology use status accounted for increased to .336 (34%) using Nagelkerke's formula. Additionally, comparison of the log-likelihood ratios for models with and without the social network variables showed a statistically significant improvement, $\chi^2(20, N = 2693) = 53.63, p < .001$. Model sensitivity increased to 69%, and specificity increased to 75%, with an overall improved hit rate of 72%.

In summation, these results indicate that variables that measure social network use and trust predict a small but significant variation in technology use after controlling for demographic variables. The social networking variables accounted for an additional 2% of the variance in technology use (using Nagelkerke's formula). The improvement was most noticeable in the prediction of technology non-users (model sensitivity) which increased by 3%.

3.2. Differences among technology usage groups

Of the 3000 respondents, 225 were eliminated from the second set of analysis because they scored only one point for computer use, (but did not use a mobile phone), for a final sample of 2775 respondents. In our final three technology user groups, a score of 0 was a technology non-user (N = 1428), a score of 1 was a low level technology user (N = 772) and a score of 2 or 3 was a high level technology user (N = 575). Figure 2 shows that over the three years of the survey, the number of technology non-users decreases, while the numbers of high and low level users increase. Figure 3 demonstrates that this is primarily due to the increase in mobile phone use. Additionally, this change in technology groups over the years was significant, $\chi^2(4, N = 2966) = 257.93, p =< .001$.

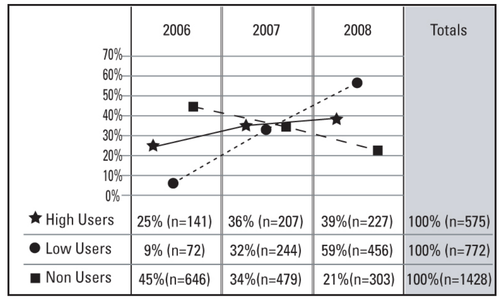

Figure 1. Trends in user groups

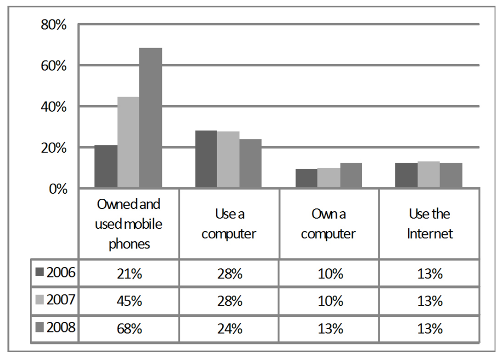

Figure 2. Trends in technology use

3.3. Demographics of the three user groups

Since demographics were a significant predictor of technology use, we first wanted to understand demographic differences among our three technology user groups. To account for family-wise type one error inflation on the demographic construct, we used Bonferroni's adjustment (.05/5) reducing the alpha level to .01 for each demographic group comparison.

The high level technology user group was younger, had more years of education, and a slightly higher SES score. See Figure 3. Additionally, through ANOVAs, we found that all of these differences were statistically significant: Age, $F(2, 1591.72) = 289.26, p < .001$; Years of schooling, $F(2, 2772) = 257.61, p < .001$; and SES, $F(2, 1541.26) = 80.66, p < .001$. [1]

We also found the high level technology user to be more likely to live in an urban location, and surprisingly, to be female, see Figure 3. Location differences were significant

[1] Levine's test of homogeneity was not met for many ANOVAs, common for uneven group sizes; therefore we reporting Welch's F in cases that have not met the test of homogeneity, which has been shown to be more robust [8].

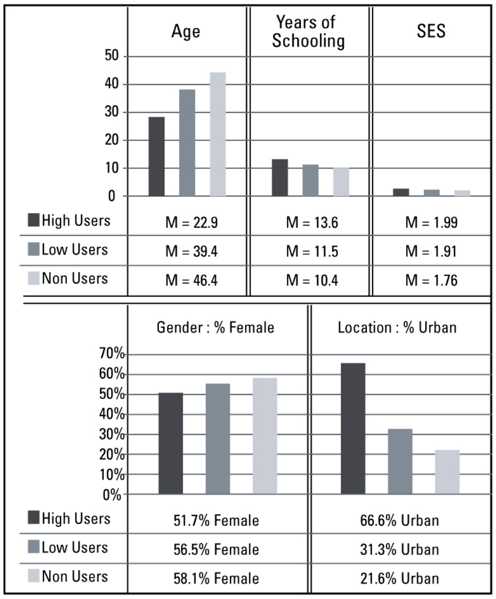

Figure 3. Demographics of user groups.

through Chi-square tests, $\chi^2(2, N = 2775) = 375.10, p < .001$; however, with the adjusted Bonerroni alpha level differences between gender were not significant, $\chi^2(2, N = 2775) = 6.84, p = .03$.

3.4. Face-to-face social network trust patterns among technology user groups

While clearly the demographic composition of the user groups is important, the sequential logistic regression established that social network use and trust contributed a unique variation to technology use after controlling for demographics. To explore our second research question, (trust differences among levels of technology users) we utilized three survey questions that asked respondents to judge on a scale of 1-4 how much they trusted family, friends and neighbors, from very untrustworthy to very trustworthy. We used ANOVAs to analyze this data. Again, to account for family-wise type one error inflation on the trust construct, we used Bonferroni's adjustment (.05/3) reducing the alpha level to .017 for each comparison.

Neighbors: representing weaker/bridging ties

Significant differences were found among the technology user groups when considering the trust level of neighbors as sources of information, $F(2, 1257.77) = 18.85, p < .001$. Trust in neighbors is also generally high although there are different patterns among groups. In general, technology non-users are more likely to rate their neighbors more trustworthy than high or low level technology users. The higher level of technology use, the less trust reported in neighbors. See Figure 4.

Family: representing strong/bonding ties

Significant differences were found among the technology groups when considering the trust level of family as sources of information, $F(2, 1376.42) = 4.07, p < .017$. Whereas technology non-users are much more likely to rank their family as simply trustworthy; high and low level technology users were more likely to give their family the higher rating of very trustworthy. See Figure 4. Together, the tests of trust in neighbors and family suggest that technology non-users have more trust in bridging ties (neighbors) while higher level tech users have more trust in bonding ties (family).

Friends: representing strong/bonding ties.

No statistically significant differences were found among the technology groups when considering the trust level of friends as sources of information, $F(2, 2664) = 1.60, p > .017$. Like family, trust in friends is also high, where at least 61% of all groups report a trustworthy score and 26% report a very trustworthy score.

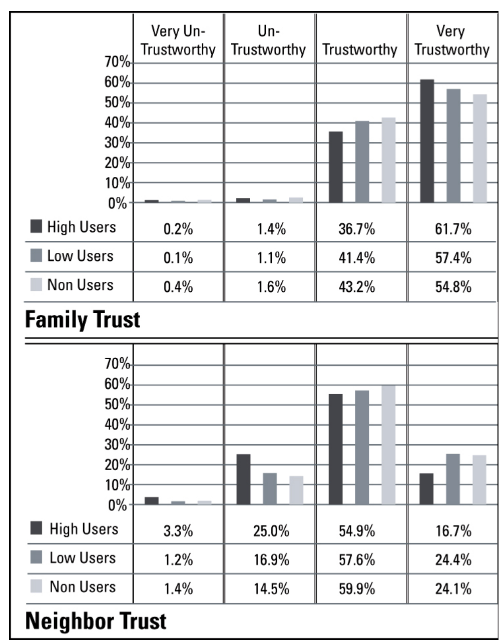

Figure 4. Trust of family and neighbors.

3.5. Face-to-face social network use (information seeking) patterns among the three groups

The survey asked respondents 12 questions about categories of information and what sources they had used the previous week for that information. The purpose of these questions was to determine what information sources were used most often. The questions not only asked about face-to-face social networks, but also about other sources including newspapers, television and radio. When considering the face-to-face social network, in these questions friends and neighbors were grouped as one source. The information categories were (1) something you wanted to buy; (2) elected officials or government representatives; (3) official services; (4) religious news; (5) health issues; and (6) local news. Chi-square tests were employed to investigate differences. To account for family-wise type one error inflation on the information seeking constructs, we used Bonferroni's adjustment for each information seeking category (.05/2) reducing the alpha level to .025 for each category.

Something you want to buy.

There were significant differences found among technology user groups when considering the use of family, ($\chi^2(2, N = 2726) = 16.80, p < .001$), and friends/neighbors, ($\chi^2(2, N = 2727) = 26.28, p < .001$), as sources of information for something they wanted to buy. As shown in Figure 5, high level users were much more likely to consult their face-to-face social network concerning purchases. However, the differences between low level users and non-users were less dramatic.

Elected official or government representative.

There were significant differences found among technology user groups when considering the use of family, ($\chi^2(2, N = 2742) = 9.87, p < .025$); and friends/neighbors, ($\chi^2(2, N = 2742) = 13.34, p < .025$), as sources of information about elected officials or government representatives in the previous week. As shown in Figure 5, high level users were more likely to consult both family and friends/neighbors.

Official services.

There were significant differences found among technology user groups when considering the use of family, ($\chi^2(2, N = 2736) = 7.69, p < .025$) as sources of information about official services in the previous week. However, using the adjusted Bonferroni alpha level of .025, the differences among and the use of friends/neighbors was not significant, ($\chi^2(2, N = 2736) = 6.71, p = .035$). As shown in Figure 5, high level users were more likely to consult their face-to-face social network about official services.

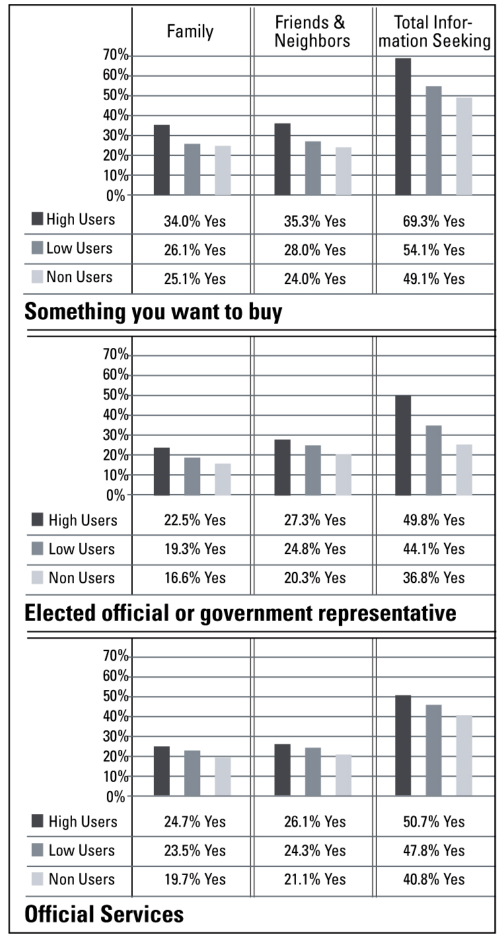

Figure 5. Network use for information.

Religious news.

There were significant differences found among groups when considering the use of family, ($\chi^2(2, N = 2734) = 7.49, p < .025$), and the use of friends/neighbors, ($\chi^2(2, N = 2731) = 25.35, p < .001$), as sources of information about religious news in the previous week. As shown in Figure 6, religious news takes on the opposite pattern as other topics, where non-users are more likely to consult their face-to-face social networks than both levels of technology users. We hypothesized that technology non-users might simply attend religious services more often; however analysis on religious attendance demonstrates no clear patterns associated with technology use level and religious attendance, see Figure 6.

Local news and health Issues.

There were no significant differences found among groups when considering the use of family or friends/neighbors as

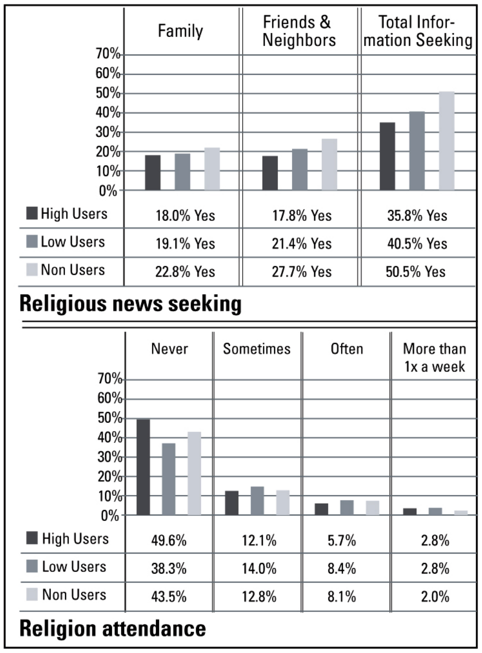

Figure 6. Religious news and attendance.

sources of information for local news or health issues in the previous week. Approximately 40% of all user groups said they had consulted their family about local news in the previous week while approximately 43% said they had consulted friends/neighbors. Approximately 30% of all user groups said they had consulted their family about a health issue in the previous week while 28% said they had consulted friends/neighbors.

In summation, our analysis suggests that the use and trust of face-to-face social networks is associated with technology use. First, variables that measure face-to-face social network and trust patterns are reliable predictors of technology use after controlling for demographic variables. Second, trust patterns for face to face social networks were found to be significantly different among levels of technology users. Finally, people who differ in their levels of technology usage also differ in how they use their social networks for multiple types of information seeking. Additionally, in most cases the highest level of technology use was associated with significantly greater reliance on face-to-face social networks as sources of information.

3.6. Discussion

In this case study of Kyrgyzstan, we found that all technology user groups found their face-to-face social networks trustworthy, although slightly different, but statistically significant, patterns emerged. A technology non-user was less likely to trust family than technology users; whereas the technology user groups displayed less trust in neighbors. There were no significant differences found in trust among user groups when considering friends. This finding suggests that technology use is associated with bonding/stronger ties but does not have the same association with bridging/weaker ties. Additionally, for most information topics, this pattern of trust could also be seen in actual network use when respondents were asked if they had used family or friends/neighbors as a source of information in the previous week.

Contrary to Putnam's hypothesis, social network use patterns do not appear to be negatively associated with higher technology use. In fact, the higher the technology score the more likely the respondents were to use their face-to-face social network for multiple types of information seeking including learning about elected officials, official services and purchasing decisions. The one exception to this pattern was religious news, for which higher level users did not actively rely on their face-to-face social network as much as technology non-users. As a whole, these findings suggest that technology use reinforces most types of face-to-face network use for most sources of information.

It could be argued that higher technology users are simply greater information omnivores and in most cases will search for more possible avenues for information [1]. However, when we compared the use of other sources including newspapers, radio and television for the same types of information we found mixed results. For health information, elected officials and official services the higher level technology users showed statistically greater reliance on newspaper sources, but they did not use radio or television at higher rates. For purchases and local news information, higher level technology users relied more on all sources. Finally, for religious news, technology non-users were statistically more likely to use all sources of information. In summation, while for most types of information, higher technology users were more likely to consult multiple sources, the information omnivore argument was not confirmed. Instead, we found that higher level technology use was statistically significantly associated with greater use of one's face-to-face network.

In conclusion, our findings here indicate that technology use appears to support face-to-face social networks in Kyrgyzstan. Our findings also suggest that research seeking to understand how increased technology usage affects face-to-face social networks needs to consider more diverse populations, including resource-constrained populations.

3.7. Future work

The work in this article is part of a larger, longitudinal project that studies technology usage patterns in diverse regions in order to generate creative ideas for appropriate hardware, software, and services design. To that end, our findings that technology users also rely on face-to-face social networks and that increased use of technology does not necessarily mean a concurrent dip in the use of in-person networks can inform design.

Indeed, our findings suggest that technology applications that support existing social networks would be adopted by our study population and other users who share similar characteristics. Additionally, the large increase in mobile phone use, when compared to other technologies, suggest mobile phones are a specific technology that can be leveraged to productively build upon already robust patterns of face-to-face social network use. However, it is important to note the high prevalence of older, non-Internet ready phones in the region, suggesting that appropriate applications should also utilize simpler technologies such as SMS. We believe that in Kyrgyzstan, and other RCEs, mobile phones and SMS can be leveraged to create applications that support and expand social networks, thereby increasing social capital. Online and offline behaviors can, in fact, productively inform and support one another.

As we move forward in our investigations in the Central Asia region, we are interested in observing how technology actually supports face to face social networks in everyday life. Additionally, we are interested in developing technologies to help support these usage patterns. In this quest, we have developed a prototype application that acts as a directory and recommendation system that users can access through SMS.[2]

The system also allows users to create their own private directories where they can post messages and control who is allowed to make recommendations. Initial usability on the prototype was performed in Bishkek, Kyrgyzstan in late March 2009.

Such design work comes directly from studies such as the one presented here, which urge us to reconsider assumptions about how offline and online interactions connect to one another. Clearly, looking at more diverse populations and their usage of social networks and technologies is necessary in order to generate a nuanced understanding of the larger effects that increased technology use has on society.

Acknowledgments

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[2] We discuss our initial user requirements for this prototype in a separate conference paper: Putnam, C., Kolko, B.,Rose E. Walton, R. Mobile phone users in Kyrgyzstan: A case study of identifying user needs and requirements. In *Proceedings of International Professional Communication Conference*, IPCC 09, Honolulu, Hawaii, July 20-22, 2009.

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