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Smartphones

An Emerging Tool for Social Scientists

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Recent developments in mobile technologies have produced a new kind of device: a programmable mobile phone, the *smartphone*. In this article, the authors argue that the technological and social characteristics of this device make it a useful tool in social sciences, particularly sociology, social psychology, urban studies, technology assessment, and media studies. The device is willingly carried by a large fraction of people in developed countries, integrates a number of technologies for automatic observation, can be programmed to interact with the user, and can communicate with remote researchers. This allows unobtrusive and cost-effective access to previously inaccessible sources of data on everyday social behavior, such as physical proximity of people, phone calls, and patterns of movement. The authors describe three studies in human behavior that have augmented existing methods with the smartphone, two of which the authors conducted themselves. Based on their experience, the authors critically evaluate the improvements and threats to validity and reliability of smartphone-augmented methods. These approaches are rapidly becoming feasible for the social scientist, since research software for smartphones have been published in open source, which lowers the technical and economic investment needed for their utilization in research.

Keywords: *Smartphones; data collection methods; behavioral patterns; validity; reliability*

Progress in science and technology often go hand in hand. A convincing recent example can be seen in psychology. The Decade of the Brain

Authors' Note: An online appendix is available at http://smr.sagepub.com.

(Library of Congress N.d.) would never have been possible without the preceding advancements in applied physics that led to the production of a noninvasive and affordable brain imaging technology. The revolutionary fMRI (functional magnetic resonance imaging [Casey 2002]) enabled access to the most intimate, unconscious workings of the human brain during an experiment fully controlled by the psychologist. What would be the modern correlate of fMRI in social sciences?[1] Ideally, it would provide unobtrusive yet systematic access to all social behavior while being affordable and easy to use. We believe that recent developments in mobile devices, particularly smartphones, have introduced capabilities that make them a lucrative tool for research. While not yet "the fMRI of social science," a promising future can be projected if the methodologies around the smartphone are adopted to fit the needs of various fields of social science interested in everyday activities of people.

Smartphones are, simply, programmable mobile phones. Besides programmability, which allows subtle control over events taking place in the phone, the main technical characteristics of interest are their relatively sophisticated sensing capabilities, increasing storage capacity, and built-in networking. Reliability and controllability of these characteristics has increased as the technology itself has become more mature. Moreover, the smartphone's nature as a primary communication tool should not be forgotten: People carry phones around naturally and use them in the everyday management of social relationships (Ling 2004; Katz and Aakhus 2002; Kopomaa 2000). Researchers can now access that domain of data in real time. Smartphones thus differ from related technologies, such as personal digital assistants (PDAs) (Barrett, Feldman, and Daniel 2001), not so much technologically as psychologically: Mobile phones are an accepted and integrated part of the lives of most people in Western countries. Smartphones are becoming increasingly common: According a recent estimate, 1 billion smartphones will be shipped in 2012 (Canalys.com 2006). Moreover, we have noticed that it is not difficult to persuade a person to switch to a smartphone temporarily in a research setting, since smartphones almost always contain all the functionalities of an ordinary mobile phone and since the user interfaces are in many important ways quite similar. These features combine to enable research approaches that have been either impossible or prohibitively expensive.

Programmable mobile devices such as smartphones have not been widely utilized as research tools in the social sciences but have been used in the field of human-computer interaction (HCI) for a period of some years. As a subfield of computer science, HCI is fertile for these kinds of methodological advances due to the necessary engagement with sophisticated technologies (the subject matter of the field) and the availability of high-end development skills and resources. We bring results, such as usage scenarios, from this existing body of work in addition to our methodological and practical contributions. During the past three years, we have developed a software environment called ContextPhone (Raento et al. 2005) that is suitable for certain research practices and used extensively for field studies by our research group and by several others in HCI.

The main contribution of this article is to propose and critically evaluate smartphones as tools for social science research. For this end, the state of the art of the technology and the available software are reviewed. The description and evaluation are aimed to be concrete enough for practitioners to both make decisions about the tool's applicability to their research aims as well as to guide them in actual utilizing it. We discuss the smartphone not as a replacement for current any existing methods but rather as a means to augment existing data-gathering practices in the social sciences. We believe that the main arguments to social scientists are as follows:

- *Flexible control*. As full-fledged computers, smartphones can be programmed to actively interact with subjects, record a variety of behavioral data such as movement and communication, and even send this information back to the researchers in real time.
- *Cost-efficiency*. Economically feasible large-scale and long-term study of everyday actions. A rich body of data can be gathered without the researcher's intervention, which reduces the work needed. Additionally, the devices themselves are becoming very affordable (e.g., 200 EUR for a device and 10 EUR/month for data costs in addition to normal phone bills).

Smartphones, when applicable, offer improved *ecological validity* through two factors:

- *Access*. The phone is an integrated and nonintrusive part of both the individual as well as the social life. Smartphones therefore allow observational access to domains of behavioral data not previously available without either constant observation or reliance on self-reports only.
- *Unobtrusive data collection*. Those phenomena accessible to smartphones can be studied without the researcher's being present, thus decreasing evaluation apprehension and increasing the ecological validity of the method. Modern data logging runs reliably in the background of the smartphone,

which requires less input and control from the participant. The realized level of physical obtrusiveness depends of course on how much the method relies on user interaction with the device, for example, experience sampling.

We will discuss how the smartphone can in some cases replace previously employed methods such as beepers, diaries, postevent interviews, and observation but also, more importantly, how it can augment them (we particularly do not advocate a purely behavioral approach, but the fruitful combination of behavioral and self-report data). We will also discuss in detail the problems and limitations, for example, the large granularity of movement tracking, of the smartphone and how some of these problems may be overcome with future technological developments, such as the inclusion of better positioning technologies.

The article is structured as follows. We first introduce the smartphone technology and the software we have developed. We then give three examples of field studies with smartphones. These studies are selected to represent different areas of research, different research questions, and different methodologies. The examples are followed with an in-depth evaluation of the tool's benefits, problems, and practical considerations. The article ends with an enumeration of the research fields that could be most suitable for this tool and the anticipated features of smartphones in the near future.

Technological Properties of Smartphones

With the word *smartphone*, we mean *programmable* mobile phones. Programmability is important for creating research tools flexibly. Instrumenting personal mobile phones for data collection supports unobtrusiveness and ecological validity. Smartphones typically include the features of other high-end mobile phones: high-speed data connection, color screen, camera, local connectivity (Bluetooth and Infrared), Web browsing, text and multimedia messaging, e-mail, and games. Crucially, they also provide sensing capabilities, such as positioning. It is the combination of sensing capabilities with programmability that makes them powerful tools for research. It is this combination of features that we discuss in the following text, rather than the qualities that distinguish smartphones from other mobile phones.

Smartphones are a very recent development in mobile computing. The first devices that could be called smartphones shipped in 1999, but the technology was not mature enough for general acceptance. Smartphones began to penetrate the mobile phone market in the fall of 2003 (Levin 2006) with the release of Nokia's 6600, which was small and usable enough for user acceptance (shipping 2 million units in four months [Nuttall 2004]) and had enough storage and processing capacity for research purposes. Smartphones accounted for approximately 6 percent of all mobile phone sales in 2005, which means that they are widely available but not yet used by the majority of mobile phone users (Gartner Inc. 2006; Symbian Ltd. 2006; Canalys.com 2006).

To put smartphones' capabilities into perspective, they can be compared to a 1990s desktop PC as to memory, disk (permanent storage) and processing capacity, and network connection. The combined storage and computational horsepower provides the devices with the abilities to both collect and analyze large amounts of data. For example, a smartphone can store 250 hours of voice-quality audio or five years of sensor and interaction data logged with ContextPhone (detailed below). Smartphones cannot, however, be used for continuous processing in the same way a desktop computer can, simply due to battery life constraints. Although programmable, many smartphones need skills specific to the manufacturer's chosen platform—desktop programming skills are often not directly applicable, and there are few easy-to-use rapid software development environments available.

The smartphone interface is quite different from that of a traditional desktop or handheld computer. Most users want phones to be quite small, which necessarily means a small display and small keyboard. Screens are typically capable of showing fifteen lines of thirty to forty characters (compared to a desktop monitor's approximately forty lines by one hundred characters). Some devices have QWERTY keyboards, others touch screens or joysticks, but a vast majority have the keypad familiar from mobile phones. Many users are, however, habituated to such an input device and are capable of keying in at least small amounts of text with it (typical input speed on a mobile phone seems to be around five to eight words per minute [Butts and Cockburn 2002], compared to twenty-five to fifty words per minute with handwriting [Summers and Catarro 2003]). Obviously, familiarity with the smartphone's input capabilities and user-interface varies greatly within a population.

A significant technological difference between the smartphone and other mobile devices is the (almost) always available data network. It is quite reasonable to expect for the phone to be able to communicate with researchers at least once a day. The network speed is similar to a modem-line: adequate for many tasks, but not enough for high-bandwidth interaction or rapid transfer of multimedia. Again, battery consumption is a main limiting factor: Constantly maintaining a data network connection lowers a phone's standby time from a week to around two days. In practice, research setups with continuous data transfer force the user to charge the battery once every day; if the data transfers can be batched to occur once per one to three days, the charging has to happen every two days. Pure data collection and storage allows for near-normal use of the phone.

One of the most promising smartphone features is its sensing ability. *Current-day* devices allow for automatic gathering of the following behavioral data (Raento et al. 2005):

- Location: The position of a mobile phone can be tracked on the district-level (several city blocks). Infrastructure can be constructed for finer-grained positioning (ten-meter radius) in limited areas (Chan et al. 2003).
- Other devices in physical proximity: Bluetooth scans on the phone can identify other devices nearby, enabling the researcher to infer which people a particular subject encountered during the day.
- Mobile communications: both metadata (logs of who, when, how long) of calls and text messages, as well as the actual contents (recordings of voice, text) of such communication.
- User's commands and interaction with the device: whether the subject is playing games, surfing the Web, making calls, or not using the phone.
- Calendar: the timing and description of calendar events on the device (note that not all subjects necessarily use the device calendar).
- Device state: network coverage, battery level, charger status, alarm clock, silent/audible profile.

With additional sensors, data such as detailed location (via a global positioning system [GPS] device), physiological variables (heart rate, galvanic skin response), or activities (accelerometers can be used to distinguish walking from running or sitting) can be integrated (Korpipaa et al. 2003; Kern, Schiele, and Schmidt 2003; Strauss et al. 2005). Many of these apparatuses already have versions on the mass market that feature Bluetooth connectivity.[2] However, external devices that the user will have to remember to carry and keep charged of course sacrifice at least some of the sought-after ecological validity. In the near future, this may become less of a problem as many sensors (such as accelerometers or GPS) will most probably be available as integrated features of smartphones. The online appendix provides some technical details of past, current, and upcoming smartphones and how they relate to the ability to use them for experiments.

The smartphone is also a media capture device. All phones support audio and text capture, and most also support still images and video, which can be used for self-documentation. Smartphones can typically be programmed to allow media capture that is only limited by available storage, in comparison to the arbitrary limits on lower-end phones. Combined with networking capability, self-documentation can be made available to the researcher in near–real time. Using the programmability of the device or even simply triggers via alarms or short message service (SMS), the user can be prompted to carry out such self-documentation, similar to the experience sampling method (ESM) (Csikszentmihalyi and Larson 1987). In the original ESM study, participants carried beepers that reminded them to fill out short questionnaires about their momentary experiences, feelings, and thoughts. In contrast to beepers and paper diaries/questionnaires, mobile phone–controlled ESM provides greater control over the timing, content, and triggering logic of these questionnaires, and researchers can remotely follow participants' answers in close to real time.

More structured documentation can also be gathered via interactive questionnaires programmed by the researcher.

These capabilities are useful only if they can be harnessed by the researcher. The main barrier is posed by the difficulty of programming the phone. One step toward reducing this barrier is ContextPhone (Raento et al. 2005): a software platform for Nokia S60 devices, developed by our research group during the past three years. ContextPhone supports out-of-the-box logging of all the above-mentioned data, automatic transfer of these logs to a server, and the gathering and transfer of captured media. The software is available as open source, free of charge.[3] ContextPhone can also be extended for other uses, such as triggers and questionnaires, but such features are not available out of the box. There are also other emerging software packages suitable for research use, such as MIT's context-aware experience sampling tool (Intille et al. 2003).[4] The online appendix lists some representative software packages and their features, availability, and maturity.

Examples

The example studies in this section are meant to illustrate the advantages and limitations of smartphones in different fields of research: human-computer interaction, design ethnography, and social network studies. For each study, we present briefly the research questions, describe the methodology, and highlight the smartphone's role. We present examples of results from these studies to illustrate the *kinds* of results possible with these methods, not necessarily results that are interesting as such. The methodology in each study is compared to non-smartphone methods typically employed for the same research questions. The comparison details the gains from smartphones as well as what was not achievable.

Computer-Mediated Communication

It is well known that the success rate of mobile phone calls is low. In our studies, mirroring statistics gathered in Finland, only 45 to 75 percent (average by subject, fifteen subjects, 3,969 total call attempts) of calls reached the intended receiver. Recently, the field of HCI has witnessed the emergence of "mobile awareness systems" (e.g., Holmquist, Falk, and Wigström 1999) to mediate real-time cues of other people's current context and undertakings. Importantly, these *awareness cues*, such as another person's current location or alarm profile, can be used to infer the presence, availability, responsiveness, or interruptibility of that other person. Some have expressed pessimism about whether such inferences would actually be systematically utilized by the users to reduce the number of failed or interruptive calls (Fogerty 2004); our aim was to test this idea in a field experiment (Oulasvirta et al. 2007).

An A–B intervention methodology (from clinical medicine and clinical psychology) was utilized where a baseline of behavior is gathered in a period of time denoted by A, after which technology ("the treatment") is introduced in period B. In such a study, the effect or impact of the technology under study is defined as observed differences between the two periods. Because technology effects are often slow to emerge and depend on the interplay of social interaction and practice-related factors, longitudinal studies are necessary (Olson and Olson 1997). In our study, three groups of teenagers participated in the study for a total of 265 days. All that time, ContextPhone was running in the background, recording all available information. While our participants are always informed of what data is gathered and how, our general observation is that the monitoring did not affect their normal, everyday behavior apart perhaps from the first two to three weeks of the trials, when they were curious of the new technology.

From the studies, we gathered 370 megabytes of raw data, including short recordings from 667 calls, 56,000 movements, 10,000 activations of the phone, 560,000 interaction events with our applications, 29,000 records of nearby devices, and 5,000 instant messages. ContextPhone logs these in text files on the phone, one line per event. The text files were automatically transferred to our server nightly. For analysis we transferred the data into a relation database, using one table for each kind of events (e.g., movement, interaction event, call), and allowing the use of standardized language for making queries in the phase of data analysis. An anonymized version of the data set has been made available online (Raento 2004).

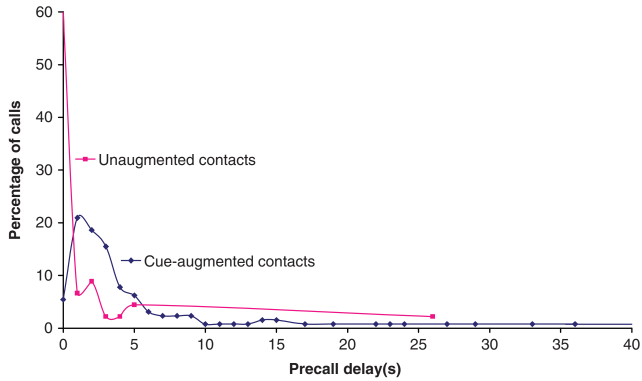
Besides introduction and two postperiod interviews, the researchers were not interacting with the participants during the study. Automatic logs of contextual data and interaction covered between 53 and 93 percent (average 73 percent, $SD = 14$ percent) of the study period. Reasons for missing data include running out of battery and turning off the phone as well as faults in the ContextPhone software. Yet, this data-gathering method afforded a set of sophisticated high-resolution analyses, such as how often the cues were looked at in the phone (i.e., highlighted on the user interface), how their access was distributed between different locations such as school and home (as interpreted from location information of ContextPhone), how long they were looked at just before placing a call (and after a rejected call), and how they referred to locations in the beginnings of phone calls (as manually coded from over six hundred phone call recordings).

In the analysis phase, we separated the different variables, such as location, interaction, and proximity, and loaded them into a relational database. Current values of variables could then be queried for any single point in time, by allowing them to be correlated with calls, which were our main analytical unit. The call recordings were used as focal points of interviews, and the recordings together with interview data were used to gain a qualitative understanding of the situations represented by the values of observed variables. We often resorted to additional, more ad hoc, views of the history of the variables around particular events, rather than just single points in time.

Concerning the impact of the awareness system to communication practices, the main findings of that study were as follows. Only one of the groups exhibited an increase (12 percentage points) in the success rate of within-group phone calls during period B when the awareness application was used, and this turned out to be statistically significant. Both groups looked at the phone book significantly more during B periods than A periods just before the phone call (Figure 1). The most frequent utilization of the cues was associated with the participants being mobile, that is, moving in the city. Moreover, one user group learned to systematically relate location information in the beginnings of their phone calls at a higher level of granularity in phase B than phase A (Arminen 2006).

Overall, the participants' subjective experiences concerning the use of the system agreed with the conclusions that were made on the basis of the log data. For example, we concluded from the logs that the access

Figure 1
Distribution of Frequencies of Precall Delays in the Three Trials



Note: Those contacts with cues available were watched longer just before placing the call.

of the contact book increased when the awareness cues were introduced. The participants agreed with this conclusion. They reported keeping the contact book foregrounded in the phone in order to be able to spot changes in others' state. One participant told about her monitoring another user, which was also salient in the logs. Some of the participants reported being interested in the awareness cues to the extent that they had to deliberately refrain from repeatedly looking at them. The participants also confirmed our observation that the cues are mostly used when on the move; they told of using the system in a bus or when waiting for somebody to arrive. Importantly, they gave various reasons for why they looked at the cues before placing a call, reasons such as being better able to predict if the other will receive the call, if the other is interruptible or not, and so on.

Utilizing ContextPhone was a highly cost-efficient way to gather rich data with high fidelity and resolution. The teenagers expressed no major technical or usability problems when changing from using their ordinary phones to the smartphones for the period of the study. A possible biasing factor was posed by the fact that we paid the cost associated with using a data connection on the phone, which most likely directed the group's communication to the smartphone and invited them to use the communications more regularly than they would have normally. An alternative to smartphone-based logging would have been paper-based questionnaires or diaries asking the participant to mark how frequently they did something during a period of time. On the other hand, the studied activity itself took place at and through the phone, so utilizing it as the data collection tool was natural. In the following two examples we look at cases where the locus of activity resides beyond the phone.

Mobile Probes

Hulkko et al. (2004) described two studies using programmable mobile phones for design ethnography—the study of user behavior as a part of participatory design (a design methodology including stakeholders throughout the design process). The study's goal was to produce ideas for new information services and artifacts. They called the method "Mobile Probes." We focus here on the second of those studies, which used the phones for experience sampling (Csikszentmihalyi and Larson 1987) of mobile workers' needs. It is also notable that this example does *not* rely on programmability but can be carried out on any mobile phones capable of capturing images and sending multimedia messages.

The study comprised three stages: focus groups interviews; a one-week period of experience-sampling-like self-documentation; and a final workshop where the documentation gathered was analyzed jointly by the researchers, the subjects, and representatives from the company the study was for.

In the self-documentation stage participants were sent questions with SMS, which they were meant to answer with media captured on the phone. The questions had been formulated based on the focus group interviews and were sent from a central server. The participants could use text or the combination of text and images to respond (via multimedia messaging service [MMS]). The responses were gathered on a media server and could be perused by the researchers as the study was running. Although this study of workers' needs did not use the programmable features of phones, the other study in the article did, in that the authors used interactive questionnaires in place of the simple textual questions and text + image answers.

The method described by Hulkko et al. (2004) can be contrasted to computerized experience sampling (ESMc) (Barrett et al. 2001). In non-smartphone–based computerized ESM the questions are posed by and answered on handheld computers (such as the HP IPAQ). Technologically, the main advantage of the camera-equipped smartphone are the always-available networking, enabling *flexible posing of questions* and monitoring of the answers as well as the *ability to use images* and other media to both document the surroundings and to trigger memories in later

Figure 2
Example Question Posed via Short Message Service (SMS) and Multimedia Answer from Mobile Probes

User J
Wed, 21 Jan 2004 11:39
What kind of information do you need at the moment?

Where's my car?

Source: Hulkko et al. (2004). Copyright 2004 Association for Computing Machinery, reprinted with permission.

analysis sessions. Figure 2 shows an example question-answer pair from the study.

Computerized ESM has of course in general advantages over, for example, beepers and paper questionnaires: the subject does not have to accurately note answering times (and so the times tend to be more accurate), the ability to generate dynamic questionnaires, and the digital nature of the resulting material. These are inherited by smartphone-based ESM, with stricter limitations on screen size and input modalities. The main advantage of smartphones is then not the technical capabilities as such, but the ability to bring these capabilities to new settings, where people are unwilling or unable to carry additional devices or where such devices would affect the phenomena under study more; for example, taking out a mobile phone can be quite invisible and acceptable in social settings, whereas a handheld computer will likely bring extra attention to the subject.

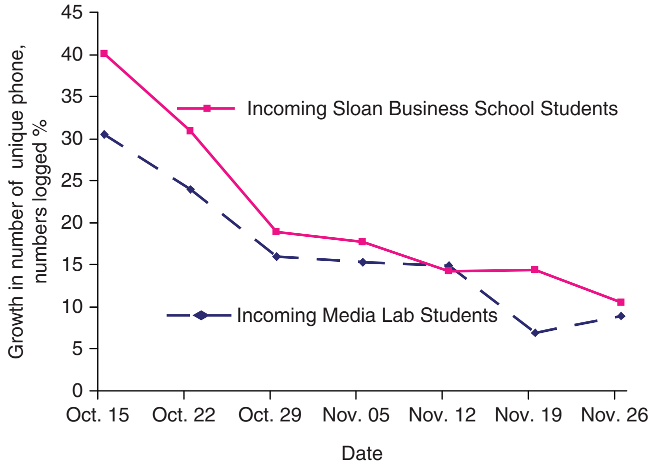
In Mobile Probes, the data gathered by the experience sampling was not aimed at providing facts about the social world *as such*. Instead, it was used as a "brainstorming" tool, where the validity of the method was linked to whether the ideas thus produced could be used in the workshop to further generate product concepts together with the participants. Since the data set was purely self-reports, it agreed on a trivial level with how the subjects perceived the situations. The workshop allowed the subjects to participate in the interpretation of the documentation produced.

Social Network Analysis

The very nature of mobile phones makes them an ideal vehicle to study social networks: people habitually carry a mobile phone with them and use the phone as a medium through which to do much of their communication. The Reality Mining experiment (Eagle 2005) consisted of one hundred Nokia 6600 smart phones preinstalled with ContextPhone. Seventy-five users were either students or faculty in the MIT Media Laboratory, while the remaining twenty-five are incoming students at the MIT Sloan Business School adjacent to the laboratory. The information collected includes call logs, Bluetooth devices in proximity, cell tower IDs, application usage, and phone status (such as charging and idle). The study has generated data collected by one hundred human subjects over the course of nine months and represents over 450,000 hours of data on users' location, communication, and device usage behavior. This data set has been downloaded and used in the research of over thirty academics from all over the world. In addition, interest in the data set seems to have spanned traditional academic disciplines. The Reality Mining data set has been used to inform projects involving urban planning, machine learning, organizational behavior, ad hoc networking, sociology, and pervasive computing, along with many others.[5]

In return for the use of the Nokia 6600 phones, students have been asked to fill out Web-based surveys regarding their social activities and the people they interact with throughout the day. Comparison of the logs with survey data has given us insight into our data set's ability to accurately map social network dynamics. Through surveys of approximately forty senior students, we have validated that the reported frequency of (self-report) interaction is strongly correlated with the number of logged nearby devices ($R = .78$,

Figure 3
The Social Network Growth of Two Demographics of Incoming Graduate Students during the First Two Months of the School Year



Note: In this case, a subject's social network is approximated by the communication logs. The number of new people the incoming Media Lab students call decreases dramatically after two months, while growth of the typical business school student's social network does not appear to have slowed down significantly.

$p = .003$) and that the dyadic self-report data have a similar correlation with the dyadic proximity data ($R = .74$, $p < .0001$). The surveys were not significantly correlated with the proximity logs of the incoming students, which we do not know the reason for. Additionally, a subset of subjects kept detailed activity diaries over several months. Comparisons revealed no systematic errors with respect to proximity and location, except for omissions due to the phone being turned off or left at home or work.

The Reality Mining data has enabled us to build statistical models on different scales of the social system, ranging from the individual to the aggregate. In particular, discriminative and generative probabilistic graphical models, as well as models based on eigendecomposition, were used to classify and predict an individual's behavior, relationship with others, and affiliation to specific groups. Moving from individuals to groups of people, it was shown that the dynamics of an organization can be reflected in its proximity network. We were able to uncover unique patterns in the collective behavior of the subjects that were indicative of major externalities such as weekends, finals week, organizational deadlines, major sporting events, and holidays. (for an example, see Figure 3).

To receive human subjects approval, it was necessary to explicitly describe each type of data collected from both participants and nonparticipants. It was needed to be made clear that participants have the option to delete any data they are not comfortable submitting to the study, as well as the ability to disable the logging application at their discretion. Particular emphasis was placed on the data captured from people who were not participants in the study. This data includes the Bluetooth hardware addresses, as well as phone numbers logged by the subjects. We made the point that the Bluetooth hardware address is an anonymous identification number that does not provide any information about the identity of an individual. However, this argument does not hold for the communication logs, which include the phone numbers and (if available) the individuals' names from the phone's address book. To be able to capture this data, we used the precedent of ongoing e-mail studies within academia. Similar to call logs, e-mail headers provide the identity and contact information of individuals not in the study. As with the e-mail studies, we made the point that these phone logs were the property of the participants in the study and were submitted with their approval. Prior to starting the experiment, each subject had to read and sign a detailed consent form listing the type of data to be gathered, providing sample data, detailing how the data would be treated, and describing what it would be used for. A sample of this consent form is available on the project's Web page.[6]

Traditionally, social network analysis has relied on self-report network data, making it difficult to collect extensive longitudinal data, largely due to the time-soncuming and burdensome nature of collecting data (Freeman, Romney, and Freeman 1987). Besides traditional self-report surveys or observational data to quantity social networks, the advent of the Internet has enabled a method of collecting extremely large social network data. Today, physicists are now deeply involved in the social network analysis by applying tools such as statistic mechanics on extremely large-scale social networks extracted automatically from digital information such as e-mail (Albert and Barabási 2002). These networks can represent the connections of millions of people and have a variety of interesting properties, yet the rich interpersonal relationship information that was traditionally collected by surveys or the human observer has been lost. The suite of rich, continuous behavioral data that can be logged by today's smartphones fall in between traditional observational data and analysis of very large networks from digital communication such as e-mail. While the resulting data may lack the subtle details of a subject's social interactions as recorded by a human observer, smartphones provide a platform to continuously collect behavioral data that can scale to a large group of subjects and contains much more depth than simply one medium of communication.

Evaluation

The previous sections have given a concrete introduction into the capabilities of smartphones and their potential to augment social scientific research methods. Here, we generalize the opportunities for improved validity and reliability, as well as threats to them.

Strengths

Smartphones can significantly reduce the costs required to record and log mundane everyday activities of an informant and do not require an observer to be present in the activities. Improvements in ecological validity should be possible, since the automatic data collection can be done throughout the subject's everyday life and with minimal intrusion. The already available sensors can be used to infer many interesting aspects of an individual's everyday activities, such as movement at the macro level (basic global system for mobile communications [GSM] cell ID recording), meetings and encounters with identifiable and unidentifiable people (Bluetooth presence), communications (phone calls and SMS), contents and use of contact book and calendar, and audio scenes (microphone recording). The basic sensors can be in principle supplemented with more sophisticated ones, such as accelometers and geographic positioning systems (GPS) for keeping track of movements at the micro level, physiological sensors for measuring emotions, and body-worn microphones for recording conversations. Analysis of the data can concentrate on individual events or more systematic patterns occurring over time. Depending on the population studied, the analysis can look at emergent patterns at the level of a social group, community, or geographical area. Thus, when applicable, smartphone-based data collection may augment self-report methods, offer in some cases a transition from self-report to observation, and extend the reach of experience-sampling, thus reducing the well-documented threats to validity of methods like diaries, interviews, and questionnaires (Bernard and Killworth 1977; Bernard et al. 1985).

The data collected automatically in the background—basically actions of people in time and space—correspond to "observations" as they are done in natural sciences. Therefore, we see them useful for behavioral social sciences. However, if the researcher is interested in a more interpretative analysis, the experience sampling method can be tied to events and activities. Intille et al. (2003) described a system where the researcher can specify rules defining when questions are asked, and which questions, based on contextual variables such as location. This limits the sampling to the times when a subject is performing a particular activity rather than burdening the subject with a very high question rate. Answering ESM questionnaires while mobile may task the available cognitive and attentional resources. The programmability of the smartphone opens up avenues of *optimized questionnaires*: Kurhila et al. (2001) showed that modeling the reasons underlying answers to questions allows the questionnaire to be adapted, so that a minimum number of questions will be answered while maintaining the level of information gained. However, care should be taken in the experiment design to ensure the results are not fully determined by the hypothesized model of activities or reasons.

The automation of observations about activities and encounters allows for a high granularity of data. For example, we have shown that the sampling interval defines the "observed" structure of social networks (Eagle 2005:82). With very frequent observations we can begin to understand how the network appears at different time scales. The rapidity can be extended to the researcher's ability to follow and control the study: Because data can also be transferred without human intervention, it is possible to get the data almost immediately as events occur or questions are answered. Should the experiment not be running according to expectations, it can be modified as soon as this is noticed.

Smartphones provide a number of attractive features at a relatively low cost. The automation of observation greatly reduces the amount of work required of the researcher, as the Reality Mining study demonstrated how a single researcher can observe one hundred subjects. The artifacts produced by self-documentation are digital, reducing the effort needed for analysis. The technology itself, although not free, is not very expensive. The low-end smartphones cost at the time of writing around 200 EUR. These smartphones are quite capable of carrying out the tasks described in this article. If real-time monitoring of the experiment is wanted, data connections are required for the participants. Data connectivity can be acquired for 10 to 20 EUR per month in many countries, but may be significantly more costly in some.

Threats to Validity and Reliability

The main criteria for evaluating any method are its validity and reliability. Given the characteristics reviewed above, smartphones have the potential to play an important role in improving the validity and reliability of data-gathering methods in the fields of social scientific inquiry interested in everyday activities. However, there are inherent technical and practical concerns that can pose threats and limitations to the smartphone's validity and reliability as a data collection device. This section reviews the most typical limitations that have emerged in our efforts at field studies.

Technical. Existing smartphones already have interesting data sources, such as movement and proximity sensors, that create new possibilities for research. These sensors, however, are hardly adequate for monitoring all physical or social activities: what the subjects are working on, what they are saying, and how they feel. The nature of available sensors obviously determines the domain of possible constructs that can be studied with the phone. However, in many cases, the currently limited sensory data can augment other methods. Automatically gathered data, especially recordings of phone calls together with contextual cues, can be very helpful for interviews: They can trigger memories and help the subject relive the situation.

Some of the data sources that do exist are quite noisy. The Bluetooth-based detection of other subjects nearby is inherently stochastic. The absence of a phone from a Bluetooth scan cannot be used as proof positive that the person in question was not present. Noise per se is threat only to statistical conclusion validity, given that the introduced noise is random. This noise in Bluetooth scanning is tentatively identified as random and should not correlate with any behavioral phenomena (Eagle 2005:49).

A more serious problem is caused by various inaccuracies. GSM-cell–based positioning, with city- and district-level tracking, may not give accurate enough location. It is, for example, not accurate enough to distinguish between home and the shop nearby, or office and the lunch café. These inaccuracies can be systematic and thus should be accounted for in the analysis of data. On the positive side, foreseeable technological advances may help to overcome this problem. For example, it is possible to augment such location with Bluetooth beacons set in appropriate locations (Chan et al. 2003).

Studying communication patterns via the mobile phone will give strong insights into a subject's relationships, especially since we can collect both the occurrence of communication as well as the content of it. However, not all communication is through the phone, not even all technologically mediated communication. E-mail and instant messaging can be used even predominantly in some relationships. If comprehensive studies of communication are to be made, the e-mail and messaging data should be collected as well. It is quite easy to gather the e-mails sent and received by a subject, but detailed knowledge of the context in which a message was read or written may not be possible.

Studies conducted with the assistance of technology are of course susceptible to failures of technology. We have experienced nonworking data connections, corrupted memory cards, crashing software, and broken phones. The most fragile link is often the data connection, which may be unavailable for even days at a time due to failures of the phone software or lack of network coverage. Any study should take into account the possibility that remote real-time observation is not always possible. Even if remote data collection can be unreliable, so can local collection. Software problems and hardware failure may result in losing locally stored data. In our experience, it is more reliable to gather data remotely, because the duration of a potential failure decreases significantly. If remote collection is not possible, data should be collected from the participants quite frequently, while accounting for the possibility of data loss in the sample size and sampling strategy. The most extensive figures on the reliability of data collection come from the Reality Mining study, where overall collection coverage was 85.3 percent on average (Eagle 2005:50).

Finally, when the study relies on self-documentation, the limits of the device should be taken into account. The small screen and fairly difficult text input may limit the amount and expressiveness of answers that can be gathered from the user, compared both to pen-and-paper ESM and computerized ESM. On the other hand, interactive questionnaires can be used to reduce the amount of text input needed, and photos and audio recordings may be used in conjunction with text.

Human factors. While mobile phone technology is increasingly familiar to people in the developed world, not all users are comfortable or familiar with smartphones. Many mobile phone subscribers only use the most basic functionality and simple phones. Switching to a more complicated phone, or switching to a different manufacturer's phone, may scare some and will most certainly influence the way people use the device. If the subjects are not familiar with the smartphone, any measurements relying on phone use (communications, self-documentation, interaction logs) from the beginning of the study should be used with care. The data from the Reality Mining experiment suggests that the use of the phone reaches a stable level in about two weeks (at two weeks the 75th percentile of the number of functions used during the day has fallen to 6, from the initial 12. The 75th percentile falls further to 5 after about two months, which suggests lingering effects). It may be prudent to allocate some observation time to gauge how familiar the users have become with the device. At any rate, individual differences in the ability to use the phone pose a threat to validity that should be considered at the outset of research.

Although the phone is carried extensively by the user, it may be left behind by choice or accident. We have shown (Eagle 2005:50) that detecting such situations is possible when the phone is forgotten for a longer period but becomes significantly harder for short periods, for example, leaving the phone in the office when going to lunch. In general, it should not be assumed in the analysis of the results that all data gathered on the device correspond to the activities of the user, and observation may be needed to estimate how this affects statistical inference.

Any ESM-like method has to take into account that people are not equally capable or willing to answer questions in all situations. If the user is actually mobile at the time of a sample, he or she may have extremely limited attentional and cognitive resources (Oulasvirta et al. 2005) to allocate to answers. Even when not mobile, it may be awkward to fill out a questionnaire in a social situation. In these cases, the answering may either be postponed to a later time, with a decrease in accuracy, or not done at all, with a bias in the sampling. These error sources are particularly relevant, since they may well correlate with the phenomena under study.

As with any research that requires an intervention into the subject's life, the intervention itself may affect the phenomena studied (sometimes called the "Hawthorne effect," even if the original study has come under criticism [Kompier 2006]). There seems to be no reason to assume that this effect is larger with smartphones than it is with other methodologies, and it may be significantly smaller when smartphones are used as purely observational tools (in comparison to, e.g., video recordings). A relevant way to combat the effect of the intervention is to increase the length of the study to allow for habituation, which the lower cost of smartphone-based methods should allow. A specifically relevant way in which this may happen is an increase in communication activity if the researcher is paying the phone costs. Especially for younger users, the cost of calling is the limiting factor to the amount of calls they make. We recommend that the users pay for the normal use of the phone, while the researcher only pays for extra costs incurred by the study.

Practical. Although there are emergent software packages for the types of research outlined in this article, most of these tools still require some level of familiarity with the underlying technology. In practice, it has proved necessary to have a technician involved in the research effort. The technician should be familiar with issues like mobile phone hardware, subscriptions, mobile data connection, installing of software on phones, and transfer of data from them. Additionally, contractual aspects of mobile phones, such as the ability to switch phones or the cost of data connections, vary a great deal between countries, which requires some time to learn the local protocols.

If the feature set of existing software does not meet a particular research need, programming the smartphone can be daunting task. A mobile phone programmer does not need to be allocated full-time to one study, however, but can be either employed part-time or shared between different studies. Finding suitable personnel should be given enough time and funding, and programming should be approached as a medium-difficulty software engineering effort, even if the changes would seem trivial on the requirement level. For example, changing the ContextPhone software to support memory cards and some additional data sources for the Reality Mining study took approximately two weeks of work time and maybe four weeks of calendar time, with an experienced programmer.

Tools to support the analysis of data gathered with smartphones are not widely available. In all three studies described in the previous section, the data were analyzed with proprietary tools developed either by the researchers or within the same institute. Although off-the-shelf software, such as database management systems, can be used to solve parts of the problem, representation and presentation of high volumes of multidimensional timeline data remains a difficult information visualization task.

It is crucial for many measurements (communications, usage patterns) as well as for ecological validity that the smartphone used for data gathering is the subject's *main* phone. Having a subject carry around two phones does not provide many advantages compared to traditional computer-aided ESM with handheld computers. However, we have found that a new smartphone may be enough motivation for many participants to switch from their existing phones.

The studies described here prove that smartphones can be used for medium-term longitudinal studies (on the order of months). There is nothing that indicates that new subject-related problems would specifically arise from extending the study period with smartphoenes in general. On the technology side, the devices used last for a maximum of a couple of years, and subjects may also have expectations on upgrading phones every year at least. Thus, the researcher would need to have resources to maintain the software so that it can be used on upcoming phones and so that the functionality of the new phone/software combination is comparable enough to enable comparisons on the data.

The efficiency of using smartphones for data gathering is not fully clear. The amount of effort in producing a robust gathering process with programmable devices may outweigh the benefits in some cases where, for example, pen-and-paper experience sampling would also be appropriate. In such cases, the researcher will have to evaluate the options specifically for their goals, subject population, and available resources. For the kinds of studies exemplified in the Reality Mining case, the smartphone is the only method currently capable of producing the described data. Hence, if such data is of interest, the method is efficient.

Ethical. An ethical issue in the use of emerging technological artifacts is *informed* consent. Although the researcher may explicitly describe each type of data collected from both participants and nonparticipants, the subject may have trouble realizing what this actually means. The sheer quantity of data produced can create a situation where neither the subject nor the researcher may be fully aware of what lies within the information collected. The use of data analysis tools may uncover unforeseen patterns or models. As subjects may not fully comprehend the data collected, the researcher needs to be specific about the goals of the research and may have to limit the reuse of the data to preserve informed consent.

The unobtrusiveness of the smartphone hinges on habituation to the presence of the phone. In principle, the less aware the subject is of the presence of the observing device, the less its presence should affect the study. Being unaware of course conflicts with informed consent. We feel that in many cases, it is ethical to carry out a study if the subject has after consideration given willing permission, even if he or she is not constantly aware of participating in the study after the permission has been given. If the topic of study or the subjects studied are deemed so sensitive that continuous awareness is mandatory, the obtrusiveness of the phone can be increased, either in a way that aids in data collection, such as by posing questions, or even purely for the reason of notifying the user of the ongoing observation. In our studies, for example, the recording of phone calls has always been accompanied by a beeping sound to remind the subjects of the recording, and in several cases, they have altered their conversation with that knowledge.

The methods described here have been used to gather data not only of the explicit subjects but also of others they interact with. This holds of course for other methods where subjects are asked to describe their interactions with other people. However, the ease of collection and the amount of data do create a difference from, say, diary studies. In all of the cases described here, it is possible to limit the amount and kinds of data gathered of others (for example, the physical proximity data could be gathered of consenting others only, and the same for call logs). The researchers will need to apply restraint appropriate to their goals in the use of the smartphone.

Finally, there is a larger risk in the use of digital data in comparison to physical artifacts. The smartphone may be stolen or the data transmissions eavesdropped upon; the technical nature of the method means more personnel are involved in the study, and it is easy to accidentally set inappropriate permissions on computer files. These issues need to be addressed by researchers in relation to the nature of the data they choose to gather and perceived risk. For example, the subjects may be required to have passwords for their phones, the transmission of the data may be protected with encryption, and all personnel involved in the studies may need to be specifically trained in the privacy issues involved.

Conclusion

This article has proposed and illustrated smartphones as a research tool for social scientific research. Thus far, smartphones have been mainly used in applied interdisciplinary areas like HCI and computer-supported cooperative work, mainly because of high development costs and the specialized skills needed for their utilization, but the technology clearly has potential beyond these applied settings. Emerging research software packages are rapidly changing the cost of using smartphones. Both the methods and research questions of HCI are often close to those of other behavioral and social sciences. The smartphone's promise of cost-effectively enabling new kinds of observational studies, allowing long-term ecologically valid observation of daily activities, and providing rich self-documentation possibilities should be relevant to any research involving human field studies.

The previous section has reviewed many threats and limitations to validity and reliability for methods utilizing smartphones as a data-gathering tool. To summarize, the main technical threat against validity of methods based on smartphone data is the (currently) limited set of sensors. Although current phones feature several relevant sensors, such as location and proximity of other devices, it is a fact that the basic sensors do not yet support access to a very broad range of everyday activities. In the near future, the number and breadth of sensors available to smartphones is expected to increase significantly. Similarly, present-day technical factors such as restricted battery life and limited network coverage affect the reliability of smartphone-based methods, but improvements are foreseeable in these areas as well. A more serious threat is posed by the nature of the phone as integrated into everyday life of the participants. While the willingness of people to carry phones is the key argument for using them for data collection, it also introduces threats that are particular to the skills and practices of using the phone. Due to people's practices of carrying and controlling the phone, the validity of data collection may suffer. Systematic demographic differences in ownership and skills using the phone may introduce selection and other biases. Of course, many of these threats can be countered with careful research design and implementation.

Sociological and social psychological studies often assign the subjects to a passive role and give few benefits for participation. The data collected from the smartphone can be seen as a form of automated diary and could be used by the subjects for self-reflection; memory augmentation; or, if media capture is used, as a way of organizing media and telling stories about them (examples include Nokia's LifeBlog,[7] Microsoft's MyLifeBits research effort [Gemmell et al. 2002], as well as our Merkitys–Meaning[8] software). One of the authors experimented with some subject-viewable representations of the data. Most of them were not very engaging to the subjects, but the game-like aspect of comparing social network sizes with other subjects was important to some. Care must of course be taken if such tools are used during a study, especially if they expose critical variables under study.

Despite these limitations, there is a potential for the technology. To conclude the article, we return to assess the idea that the smartphone could be "the fMRI" of the social sciences. We believe that its main strengths as a data collection tool are related to its natural integration into people's mobile phone–related practices. The most significant strength of smartphones is that they can make feasible and augment longitudinal, process, and context-sensitive investigations that transform the whole logic of investigation. This enables researchers to unobtrusively peek into aspects of social interaction—not unlike fMRI allows peeking into an individual's psyche.

However, as in the case of fMRI, there is no unambiguous mapping between the data a smartphone can automatically collect and everyday social behavior. Similar to fMRI, which is largely based on a hypothesis on the relationship between blood circulation and brain activity, the development of the smartphone methodology requires careful basic studies of how the log data maps to everyday social behavior. We are only in the beginning stages of such endeavors. The first case example reported in this article presented an intervention study where vast amounts of sensor data were collected and analyzed—over 370 megabytes of raw data. Obviously, the researcher's interpretation of such data, devoid of the subject's own interpretation of the recorded events, relies on information that can be supplied by other methods.

However, since experience sampling can be easily applied in smartphones to complement background logging, smartphones themselves can provide a partial solution for the need for triangulation. Indeed, smartphones provide three modes of data collection: (1) automatic data logging in the background, (2) experience sampling as a way to collect subjective data, and (3) integration of the two.

Described like this, we believe that smartphones can be useful as the main tool or as a supplementary tool for many of the primary methods of social sciences, like observation, longitudinal studies and case studies, interview, and content analysis. The invention of a new method may in a sense "create" the phenomena that scientists study. The validity of many traditional methods are constrained by retrospective and unreliable data collection with associated numerous biases. What smartphones offer is a relatively inexpensive way to collect high-fidelity data that may reveal the processual and contextual facets of the studied phenomenon.

We anticipate that the rapid development of new sensor and interface technologies soon will change this situation. Nevertheless, there are fundamental social limitations to the domain of applicability. Just like fMRI presumes a controlled laboratory context for conducting experiments, smartphones presume a context of mobile phone usage for data collection, which reduces the tool's applicability in studying those aspects of everyday situations where mobile phones are not naturally present. To make this speculation more concrete, four speculative examples are given below, complementing the three real cases and differing in the technical sophistication of the smartphone application assumed. First, instead of beepers and diaries (Csikszentmihalyi and Larson 1987), most experience sampling can be done on handheld devices (Barrett et al. 2001). Intelligent context-dependent triggering rules can be utilized to alert the participant to fill in an interactive questionnaire. For the participants, this implies that a single-purpose, specialized tool would no longer have to be carried. Second, as opposed to diaries and questionnaires, everyday mobility patterns of urban residents could be studied by recording the location information available to smartphones (see, e.g., Laasonen 2005). Third, conversational patterns of people could be studied by smartphones recording contents of the phone calls. Our own attempts have looked at the utterance of location in the beginning of phone calls (following Arminen 2006), but the potential of smartphones extends beyond that. For example, we imagine that the question of in what situations and contexts people make phone calls is of interest to communication studies. Or a conversation analyst could sample everyday discussions of people by utilizing the background external audiorecording capabilities of the phone. Fourth and finally, the Bluetooth connectivity could be utilized to augment the existing sensors with a range of external sensors that the participant can wear elsewhere (within about a ten-meter range). Such might include heart rate monitors, galvanic skin response sensors, pedometers, accelerometers (for activity recognition), external cameras, and microphones. For example, psychophysiological sensors combined with activity recognition based on microphone input could be utilized to study emotions in social interaction. We believe that the success of the smartphone as a research tool will depend on our innovativeness in integrating new sources of data.

From a wider perspective, we foresee a significant potential for this tool in different fields of social scientific inquiry. Two distinct modes may characterize the tool's utilization in different fields: passive and active. For example, sociologists are most likely to use it for analysis of phenomena like social networks, diffusion, and social behavior. We tend to believe in its usefulness also in many other areas of sociology, for example, those looking at demography, collective behavior, rural and urban sociology, migration, sociometry, social network analysis, conversational practices, leisure studies, interpersonal relationships, the practices of social organizations such as families, and social movements. Such studies would rely on the assumption that the phone, passively collecting data on movement and encounters of participants, does not itself affect the phenomena under scrutiny. On the other hand, behavioral scientists may be more interested in utilizing the smartphone as a tool in controlled field experiments and as a way of actively probing the participants for information. Economists may find useful the new possibility to compare objective data on consumer behavior to subjective reports, and the same aspect may be of interest to psychologists looking at the ecological validity of psychological constructs like personality or working memory span. Educational and organizational sciences may find new ways to study an individual's or an organization's practices at the micro level. Studies utilizing this mode must take a stance toward the question of how this method of data collection changes the participants' behavior.

Notes

1. We will in this article use the generic term "social sciences" for compactness. We foresee a promising avenue for research utilizing smartphones in various fields in the social sciences, but particularly sociology, social psychology, urban studies, technology assessment, and media studies.

2. http://www.brainquiry.com/.

3. http://www.cs.helsinki.fi/group/context/.

4. Available from http://web.media.mit.edu/~intille/caes/.

5. Data set available from http://reality.media.mit.edu/download.php.

6. http://reality.media.mit.edu/pdfs/consent.pdf.

7. http://www.nokia.com/lifeblog/.

8. http://meaning.3xi.org/.

References

Albert, R. and A. L. Barabási. 2002. "Statistical Mechanics of Complex Networks." *Reviews of Modern Physics* 4:47-97.

Arminen, I. 2006. "Social Functions of Location in Mobile Telephony." *Personal and Ubiquitous Computing* 10:319–23.

Barrett, L., B. Feldman, and J. Daniel. 2001. "An Introduction to Computerized Experience Sampling in Psychology." *Social Science Computer Review* 19(2):145-185.

Bernard, H. R. and P. D. Killworth. 1977. "Informant Accuracy in Social Network Data II." *Human Communications Research* 4:3–18.

Bernard, H. R. P. D. Killworth, D. Kronenfeld, and L. Sailer. 1985. "The Problem of Informant Accuracy: The Validity of Retrospective Data." *Annual Review of Anthropology* 13:495–517.

Butts, L. and A. Cockburn. 2002. "An Evaluation of Mobile Phone Text Input Methods." Pp. 55–59 in *CRPITS '02: Proceedings of the Third Australasian Conference on User interfaces*. Darlinghurst, Australia: Australian Computer Society, Inc.

Canalys.com Ltd. 2006. *EMEA Smart Mobile Device Market Growth Slows in Q1*. Retrieved May 29, 2006 (http://www.canalys.com/pr/2006/r2006044.pdf).

Casey, B. J. 2002, "Windows into the Human Brain." *Science* 296(5572):1408–9.

Chan, A. T., H. V. Leong, J. Chan, A. Hon, L. Lau, and L. Li. 2003. "BluePoint: A Bluetooth-Based Architecture for Location-Positioning Services." Pp. 990–95 in *Proceedings of the 2003 ACM Symposium on Applied Computing (Melbourne, Florida, March 09—12, 2003). SAC '03*. New York: ACM Press.

Csikszentmihalyi, M., and R. Larson. 1987. "Validity and Reliability of the Experience-Sampling Method." *J Nerv Ment Dis.* 175(9):526–36.

Eagle, N. 2005. "Machine Perception and Learning of Complex Social Systems." PhD thesis, Program in Media Arts and Sciences, Massachusetts Institute of Technology, Cambridge.

Fogerty, J. 2004. "Connecting versus Calming: Interruptibility, Presence, and Availability." In *Proceedings of the Workshop on Forecasting Presence and Availability, CHI, 2004*. Retrieved June 16, 2006 (http://www.cc.gatech.edu/fce/ecl/chi-ws-presence/fogarty.pdf).

Freeman, L., A. K. Romney, and S. Freeman. 1987. "Cognitive Structure and Informant Accuracy." *American Anthropologist* 89:310–25.

Gartner Inc. 2006. *Gartner Says Top Six Vendors Drive Worldwide Mobile Phone Sales to 21 Percent Growth in 2005*. Retrieved May 29, 2006 (http://www.gartner.com/press_releases/asset_145891_11.html).

Gemmell, J., G. Bell, R. Lueder, S. Drucker, and C. Wong. 2002. "MyLifeBits: Fulfilling the Memex Vision." Pp. 235–38 in *Proceedings of the Tenth ACM international Conference on Multimedia (Juan-les-Pins, France, December 01–06, 2002). MULTIMEDIA '02*. New York: ACM Press.

Holmquist, L. E., J. Falk, and J. Wigström. 1999. "Supporting Group Collaboration with Interpersonal Awareness Devices." *Personal Technologies* 3(1-2):13–21.

Hulkko, S., T. Mattelmäki, K. Virtanen, and T. Keinonen. 2004. "Mobile Probes." Pp. 43–51 in *Proceedings of the Third Nordic Conference on Human-Computer interaction (Tampere, Finland, October 23—27, 2004). NordiCHI'04*. New York: ACM Press.

Intille, S. S., J. Rondoni, C. Kukla, I. Ancona, and L. Bao. 2003. "A Context-Aware Experience Sampling Tool." Pp. 972–73 in *CHI '03 Extended Abstracts on Human Factors in Computing Systems (Ft. Lauderdale, Florida, USA, April 05–10, 2003). CHI'03*. New York: ACM Press.

Katz, J. E. and M. Aakhus, eds. 2002. *Perpetual Contact: Mobile Communication, Private Talk, Public Performance*. Cambridge, United Kingdom: Cambridge University Press.

Kern, N., B. Schiele, and A. Schmidt. 2003. "Multi-sensor Activity Context Detection for Wearable Computing." *Lecture Notes in Computer Science* 2875:220–32.

Kompier, M. A. 2006. "The 'Hawthorne Effect' Is a Myth, but What Keeps the Story Going?" *Scandinavian Journal of Work, Environment & Health* 32(5):402–12.

Kopomaa, T. 2000. *The City in Your Pocket: Birth of the Mobile Information Society*. Helsinki, Finland: Gaudeamus.

Korpipaa, P., J. Mantyjarvi, J. Kela, H. Keranen, and E. J. Malm. 2003. "Managing Context Information in Mobile Devices." *Pervasive Computing* 2(3):42–51.

Kurhila, J., M. Miettinen, M. Niemivirta, P. Nokelainen, T. Silander, and H. Tirri. 2001. "Bayesian Modeling in an Adaptive On-Line Questionnaire for Education and Educational Research." Pp. 194–201 in *Proc. 10th International PEG2001 Conference, June 2001*, University of Tampere, Finland.

Laasonen, K. 2005. "Clustering and Prediction of Mobile User Routes from Cellular Data." Pp. 569–76 in *PKDD 2005, LNAI 3721*. Amsterdam: Springer-Verlag.

Levin, D. 2006. *Symbian Press Conference*. Retrieved May 29, 2006 (http://www.symbian.com/files/rx/file3054.pdf).

Library of Congress and the National Institute for Mental Health, Project on the Decade of the Brain. N.d. Retrieved May 20, 2006 (http://www.loc.gov/loc/brain/).

Ling, R. 2004. *The Mobile Connection: The Cell Phone's Impact on Society*. San Francisco: Morgan Kaufmann.

Nuttall, C. 2004. "High Spirits Abound but 3G Ship Is Yet to Sail." *Financial Times*, February 28.

Olson, J. and G. Olson. 1997. "Research on Computer-Supported Cooperative Work." Pp. 1433–56 in *Handbook of Human-Computer Interaction*, 2nd ed., edited by M. Helander, T. Helander, and P. Prabhu. New York: Elsevier.

Oulasvirta, A., R. Petit, M. Raento, and S. Tiitta. 2007. "Interpreting and Acting on Mobile Awareness Cues." *Human-Computer Interaction* 22(1&2):97–135.

Oulasvirta, A., S. Tamminen, V. Roto, and J. Kuorelahti. 2005. "Interaction in 4-Second Bursts: The Fragmented Nature of Attention in Mobile HCI." Pp. 919–28 in *Proceedings of the 2005 Conference on Human Factors in Computing Systems CHI 2005*. New York: ACM Press.

Raento, M. 2004. "Mobile Communication and Context Dataset." In *Proceedings of the Workshop towards Benchmarks and a Database for Context Recognition, International Conference on Pervasive Computing*. Zürich, Switzerland: ETH. Available from (http://www.cs.helsinki.fi/group/context/data/).

Raento, M., A. Oulasvirta, R. Petit, and H. Toivonen. 2005. "ContextPhone—A Prototyping Platform for Context-Aware Mobile Applications." *IEEE Pervasive Computing* 4(2):51–59.

Strauss, M., C. Reynolds, S. Hughes, K. Park, G. McDarby, and R. W. Picard. 2005. "The HandWave Bluetooth Skin Conductance Sensor." *Lecture Notes in Computer Science* 3784:699–706.

Summers, J. and F. Catarro. 2003. "Assessment of Handwriting Speed and Factors Influencing Written Output of University Students in Examinations." *Australian Occupational Therapy Journal* 50(3):148–57.

Symbian Ltd. 2006. *Symbian OS Shipments in Q4 2005 Reach 10.9m 2005 Shipments Total 33.9m*. Retrieved May 29, 2006 (http://www.symbian.com/news/pr/2006/pr20063419.html).

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