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The Smartphone Psychology Manifesto

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Abstract

By 2025, when most of today's psychology undergraduates will be in their mid-30s, more than 5 billion people on our planet will be using ultra-broadband, sensor-rich smartphones far beyond the abilities of today's iPhones, Androids, and Blackberries. Although smartphones were not designed for psychological research, they can collect vast amounts of ecologically valid data, easily and quickly, from large global samples. If participants download the right "psych apps," smartphones can record where they are, what they are doing, and what they can see and hear and can run interactive surveys, tests, and experiments through touch screens and wireless connections to nearby screens, headsets, biosensors, and other peripherals. This article reviews previous behavioral research using mobile electronic devices, outlines what smartphones can do now and will be able to do in the near future, explains how a smartphone study could work practically given current technology (e.g., in studying ovulatory cycle effects on women's sexuality), discusses some limitations and challenges of smartphone research, and compares smartphones to other research methods. Smartphone research will require new skills in app development and data analysis and will raise tough new ethical issues, but smartphones could transform psychology even more profoundly than PCs and brain imaging did.

Keywords

mobile computing, telecommunications, digital sensors, GPS/GIS, behavioral informatics, human subjects/IRB issues

Smartphones such as the iPhone, Blackberry, and Android are not just new communication technologies. They are an occasion to rethink what psychology could be. If psychology had no history—if it was invented today and had no methodological inertia—what research methods would we use for gathering behavioral data? I think that we would use smartphones, because they are ubiquitous, unobtrusive, intimate, sensor-rich, computationally powerful, and remotely accessible. Smartphones offer huge potential to gather precise, objective, sustained, and ecologically valid data on the real-world behaviors and experiences of millions of people where they already are, without requiring them to come into labs (Dufau et al., 2011; Kwok, 2009; Rachuri & Mascolo, 2011; Raento, Oulasvirta, & Eagle, 2009). Smartphones can also run controlled but perceptually and behaviorally rich surveys, tests, and experiments. Downloadable software applications for smartphones (which I will call "psych apps," though they can be used in any behavioral science) could become our central way of recruiting, obtaining consent from, observing, experimenting on, and debriefing participants—anyone, anytime, anywhere. This manifesto argues that if we start taking smartphones seriously now as research tools, psychology could become much more powerful, sophisticated, international, applicable, and grounded in real-world behavior. Smartphones could revolutionize all fields of psychology and other behavioral sciences, if we grasp their potential and develop the right research skills, psych apps, data analysis tools, and human subjects protections.

How could such humble little devices have such power to advance our science? A $700 iPhone doesn't look like much compared with a $2 million MRI brain scanner. Yet smartphones are becoming very common, powerful, and multifunctional—an all-in-one lifestyle technology, a sort of electronic Swiss Army knife (Barkhuus & Polichar, 2011). Worldwide, mobile broadband users (who typically use smartphones) numbered about 370 million in 2009, 720 million in 2011, and will reach 1.8 billion in 2014; worldwide sales of new smartphones were about 175 million in 2009, 350 million in 2011, and will reach 700 million in 2015 (Portio Research, 2011). By 2025, when most of today's psychology majors are in their mid-30s (with some who entered academia just going up for tenure), most of the projected eight billion people in the world will carry smartphones. Each smartphone will have more computing power and memory, faster connectivity, better sensors, more input–output options, and more software apps than any

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current desktop computer. For many users, smartphones have already replaced a huge range of other devices: landline phones, digital cameras, photo books, video recorders, MP3 music players, radios, voice recorders, GPS navigators, handheld game consoles, watches, alarm clocks, calendars, and calculators. In psychology, smartphones could also replace a wide range of conventional research methods: paper-and-pencil surveys, mail surveys, phone surveys, and, if connected to the right peripherals, many lab studies, field studies, and Internet studies.

There is a lot of money driving smartphone developments that can benefit psychology. Global mobile telecoms service revenue (excluding hardware sales) is expected to reach about \$1.7 trillion by 2015 (Portio Research, 2011). By contrast, global annual revenue is about \$1.5 trillion for the auto industry, \$600 billion for the pharmaceutical industry, and \$400 billion for the arms industry. (Except where otherwise noted, all telecoms market data, smartphone specs, and technical details throughout this article are from Wikipedia, the International Telecommunications Union, or company websites). Annual research and development (R&D) spending is around \$9 billion by Samsung, \$8 billion by Nokia, and \$2 billion by Apple, and much of that goes to smartphone development. By contrast, the National Science Foundation spends around \$250 million a year on all of the social, behavioral, and economic sciences. Even including applied psychology spending (e.g., \$1.5 billion per year by the National Institute of Mental Health, \$1.0 billion per year by the National Institute on Drug Abuse, \$450 million per year by the National Institute on Alcohol Abuse and Alcoholism), total U.S. federal spending on behavioral research is less than what the top three manufacturers are spending on smartphone research. This corporate R&D is a great scientific windfall: It saves psychologists from having to win billions of grant dollars to develop the hardware and software ourselves.

Psychology's history is largely a story of new research technologies sparking not just new findings but new research areas, theories, courses, journals, applications, statistical methods, career tracks, and funding sources. The key examples are familiar. Brass-instrument psychology led to perception and memory research in the late 1800s. Computers led to cognitive psychology in the 1960s and 1970s. Brain imaging led to cognitive, affective, and social neuroscience from the 1990s onward. How will psychologists be collecting behavioral data in 2025, when more than five billion people are using smartphones with powerful sensors, processors, memories, and connectivity, plus virtually unlimited memory and processing power through cloud computing? It would border on scientific malpractice if we were still giving paper-and-pencil questionnaires to a few hundred local college students, recruiting a few dozen people to participate in laboratory tasks, or running Internet studies for people just sitting at desks. I think we can do better by doing some hard thinking now about the future of our research methods.

Previous Research Using Mobile Electronic Devices

For about 20 years, some researchers have been using mobile electronic devices to gather behavioral data. Rather than exhaustively reviewing this literature (see Kjeldskov & Graham, 2003; Mehl & Conner, 2011), I outline four existing types of studies that give a context for future developments in smartphone research.

In the first type of study, researchers persuade telecoms service providers to share aggregated call-routing records of each call's time, length, number dialed, and location (inferred from which cell towers handle the call). This allows tracking the movements and social connections of many users—up to hundreds of millions for some studies (Calabrese et al., 2011; Gonzalez, Hidaldo, & Barbasi, 2008; Song, Qu, Blumm, & Barabási, 2010). Such studies can apply sophisticated analysis methods from social network theory and physics to very large samples, but they are restricted to the anonymized call-routing data already gathered by telecoms providers, so cannot exploit the full sensor, connectivity, and interactive power of mobile devices.

The second type of study yields richer behavioral data from much smaller samples: Researchers buy, program, and distribute limited-capability devices such as personal digital assistants (PDAs) or electronically activated recorders (EARs) to local samples, to gather a few types of behavioral data. For example, PDAs and EARs have been distributed to run conversation sampling studies (Mehl, Pennebaker, Crow, Dabbs, & Price, 2001), diary studies (Bolger, Davis, & Rafaeli, 2003), experience sampling studies (Hekter, Schmidt, & Csikszentmihalyi, 2007), and studies on the psychological correlates of ambient sound environments (Mehl, Gosling, & Pennebaker, 2006; for an overview, see Mehl & Robbins, in press). The Mobile Sensing Platform from the University of Washington and Intel is a more sophisticated wearable device for recognizing what activity the user is doing, with a slightly wider range of sensors than current smartphones have (Choudhury et al., 2008). The MyLifeBits project (Gemmell, Bell, & Lueder, 2006) recruited participants to wear head-mounted displays with forward-pointing webcams, for continuous recording of all visual input. Such devices are usually expensive, bulky, unfamiliar, intrusive, and embarrassing and must be physically distributed to local participants; for almost all purposes, they have been superseded by smartphones (Amft & Lukowicz, 2009).

The third type of study is much like the second except for the hardware: Instead of a limited-capability PDA or EAR, researchers distribute a particular model of smartphone preprogrammed with a psych app. Such work has been the cutting edge of studying behavior with mobile phones, but it is has been done mostly by computer scientists rather than psychologists, it focuses on developing software rather than analyzing behavior, and it appears in journals such as *IEEE Pervasive*

Computing and *Personal and Ubiquitous Computing* and in the proceedings of conferences such as Pervasive Computing, Ubicomp, CHI, MobileHCI, MobiSys, and SenSys. Table 1 presents some highlights from this type of research, in which computer science lab groups have developed and pilot tested apps to gather behavioral data from smartphones. However, very few groups have run large-scale validation studies, and only the MyExperience project made its app development tools user-friendly for researchers with limited programming expertise, such as most psychologists.

The fourth type of study acknowledges that the smartphone hardware is already out there in nearly a billion hands, so we just need to distribute the software: psych apps that participants can download remotely, with the app managing the whole study autonomously, including consent, data gathering, data upload, debriefing, and payment. Only a few studies so far have used this method—notably, Oliver (2010), Killingsworth and Gilbert (2010), Dufau et al. (2011), and the mappiness.org.uk project at the London School of Economics (see Table 1). As the next section explains, current research lags far behind what current smartphones can do and is very primitive compared with what smartphones will be able to do soon.

What Smartphones Can Do Now and Will Be Able to Do in the Near Future

Smartphones are not just cool cell phones with e-mail. They are powerful computers small enough to hold up to your head

Table 1. Examples of Research Using Smartphone Apps to Gather Behavioral Data, in Rough Chronological Order

Project or App	Notes	Citation
ContextPhone	Platform for developing context-aware smartphone apps for gathering behavioral data	Raento, Oulasvirta, Petit, and Toivonen (2005)
Reality Mining Project	Pioneering; collected diverse data on 100 MIT students/staff for 10 months	Eagle and Pentland (2006, 2009)
SocioXensor	Presented surveys, recorded audio diary entries, logged phone calls, tracked GPS signals, monitored ECG signals from heart monitors	Ter Hofte (2007)
MyExperience	Useful open-source platform for developing psych apps; allow context-triggered surveys and user experience sampling, passive logging of device usage, user activities inferred from calendar apps, GPS data, and sensor readings	Froehlich, Chen, Consolvo, Harrison, and Landay (2007)
Personal Environmental Impact Report	Combined GPS and GIS data to track users' location and transportation mode, for a running estimate of carbon impact, smog exposure, and fast food exposure	Mun et al. (2008)
BeTelGeuse	Gathered data from biosensors via Bluetooth, for telemedicine and remote physiology research	Kukkonen, Lagerspetz, Nurmi, and Andersson (2009)
SoundSense	Used microphone input to analyze a wide range of ambient sounds and infer the user's social context and behavior	Lu, Pan, Lane, Choudhury, and Campbell (2009)
EmotionSense	Did speaker recognition and emotion recognition from microphone input	Rachuri et al. (2010)
Blackberry usage study	Collected data on device usage patterns from 17,300 Blackberry users	Oliver (2010)
Trackyourhappiness.org	Collected over 250,000 happiness and mindfulness reports from over 5,000 people in 83 countries	Killingsworth and Gilbert (2010)
LiveLab	Collected a wide range of data from 25 iPhone users for a year, including calls, text messages, e-mails, address book usage, web browsing history, GPS, accelerometer, app usage, network usage, and local Wi-Fi and Bluetooth devices	Shepard, Rahmati, Tossell, Zhong, and Kortum (2011)
Psycholinguistic study	Collected experimental data from over 4,000 people in 7 languages doing lexical decision tasks with millisecond timing using iPhone app	Dufau et al. (2011)
Mappiness project	Collected over 3 million mood reports plus GPS locations and ambient noise levels from over 45,000 people through an iPhone app	Mappiness.org.uk

Note. MIT = Massachusetts Institute of Technology; ECG = electrocardiogram; GIS = geographic information system.

when you want to make phone calls. Since IBM introduced the first smartphone ("Simon") in 1993, they have evolved from being "phone-centric" (mobile phones that can run some limited software) to being "data-centric" (general-purpose computers valued mainly for their software, media record/play functions, sensors, and Internet access, that can also be used to call people). This shift in function was exemplified by Apple's introduction of the first-generation iPhone in 2007 and by release of the open-source Android operating system in 2008. Thus, current smartphones differ from older mobile phones in having their own general-purpose operating systems that can run diverse apps created by software developers—perhaps including psychologists.

To understand the full potential of smartphones for psychology, we should consider the features typical of current state-of-the-art smartphones, the likely improvements in those features up to around 2025, and the utility of each feature for research. (Smartphone technology is the fastest changing sector of consumer products, so the cutting edge now, as of writing in February 2012, will be outdated by next year's Mobile World Congress.)

Size

Unlike tablets, laptops, and desktops, smartphones fit in hands and pockets, so people tend to carry them around throughout the day, allowing continual background data gathering, for example, of GPS location. Their smallness, cuteness, proximity, familiarity, frequent use, social importance, and customized cases also make smartphones unusually intimate, personalized, and trusted pieces of technology, so users may reveal thoughts and feelings through psych apps that they would not feel comfortable revealing through other research methods. With rapid advances in nanoelectronics and the nano-electro-mechanical systems used for smartphone sensors, the small size of smartphones should not constrain their future capabilities very much.

Processors

Current smartphones (e.g., with dual-core 1.4 GHz processors) have more computing power than most dusty PCs in faculty offices. Moore's law (that transistor densities on microchips double every two years) has been accurate for the last four decades and should remain valid for at least a few more, given emerging technologies such as 3D integrated circuits and optical computing. If so, smartphones in 2025 will include at least eight 200 GHz processors, yielding about 10 teraflops—making them ten times faster than the first teraflop supercomputer in 1997, the $50 million, 9,600-processor Intel ASCI Red that filled a whole room. Such powerful smartphones could run complex psych apps continually in the background (e.g., running emotion detection algorithms on voice input or combining GPS and geographic information system (GIS) data into measures of daily movement patterns), without disrupting other apps and annoying participants. Future smartphones—basically handheld supercomputers—will be able to run psych apps of nearly limitless complexity. Further, given fast connectivity, smartphones can recruit cloud computing to do remotely whatever they cannot do onboard.

Memory

Current smartphone memory sizes (e.g., 1 GB RAM, plus 80 GB flash memory) mean that users can store large numbers of photos, songs, and videos that could be content analyzed if accessed through a psych app, given informed consent. Assuming Moore's law and Kryder's law (that storage cost per information unit halves every two years), smartphones in 2025 will have over 100 GB RAM and 8 terabytes total memory, enough for 2,000 high-definition movies. Future smartphone users may store any personal records on their smartphones that could be useful to release to emergency doctors (e.g., medical records, complete genomes and genealogies, full-body CT and MRI scans), retailers (e.g., purchase histories, consumer preferences, credit score), governments (e.g., voter registration, tax records), potential employers (e.g., validated SAT scores, college transcripts, and employment histories), or potential mates (e.g., validated marital status, recent STD tests, church attendance records). Given informed consent, psych apps could analyze such records for studies in, respectively, health psychology, behavior genetics, or brain structure; consumer psychology or behavioral economics; political psychology; intelligence research or occupational psychology; and sex research or psychology of religion.

OS and usage logging

Smartphones run a general-purpose operating system (OS; such as Android, BlackBerry OS, or Symbian) that can run diverse apps (e.g., about 400,000 now available for Android). Most OSs allow multitasking, which is crucial for psych apps running in the background while people use their phones. No current OS is ideal for smartphone research (Oliver, 2008), but market competition is pushing fast OS development to support more flexible apps that can reach deeper into the guts of the smartphone's hardware, which is what psychologists need. Unlike Internet studies, smartphone apps can present stimuli and record responses with millisecond timing, allowing reaction-timed perceptual and cognitive experiments (Dufau et al., 2011). Current smartphones allow apps to track what phone functions, Internet connections apps, and other apps are being used, as well as the content of those communications and apps. This includes call logs of voice calls; text messages; address book usage; and Internet logs of e-mail use, web browser history, and Facebook activity (Do, Blom, & Gatica-Perez, 2011). These patterns of communication can reveal the size and structure of the user's social network (Eagle, 2008). Given informed consent, psych apps could also record the actual contents of messages for psycholinguistics, social psychology, psychiatry, and so forth.

Connectivity

Current smartphones can communicate with other devices through up to seven kinds of connections: wires plugged into HDMI or Micro USB ports and radio waves at five different frequencies and ranges—near-field communication (a few centimeters' range, for example, for waving near a credit card reader), Bluetooth (around 10-meter range, for example, for connecting to laptops and heart rate monitors), Wi-Fi (around 100-meter range, for broadband access through local routers), cellular broadband (up to 50-km range, for fast Internet access through cell towers), and cellular voice (up to 50-km range, for talking and texting). Nielsen's law says that Internet connection speed grows 50% per year; this is proving accurate for cellular broadband speeds. This will soon allow experiments in which participants stream high-definition (HD) video from smartphones for display on any local screen. It will be important to recruit only participants with unlimited data plans, as some service plans charge high fees on "excess" use (e.g., U.S. Verizon charges $10 per gigabyte), such that a participant in a perception experiment streaming 30 min of HD video (7 GB per minute) could, at today's rates, face a surprising Verizon bill for $2,100.

Onboard sensors

Smartphones now incorporate a surprising number of sensors that will be useful in psychology, such as ambient light sensors (to control screen brightness and photo flash), proximity sensors (to turn off the screen when holding the phone to the head), magnetometers (working as a digital compass), 3-axis accelerometers (to detect linear acceleration in all directions), 3-axis gyroscopes (to detect changes in orientation around all axes), and barometers (to detect altitude and predict weather; Lane et al., 2010). Accelerometers can reveal whether people are standing still or walking, exercising or dancing, feeling calm or nervous, and so on (Ermes, Parkka, Mantyjarvi, & Korhonen, 2008; Miluzzo et al., 2008); barometers (now sensitive to about ±0.5 m in altitude) can reveal whether people are walking up stairs or down. Sensor data can be logged passively as participants behave normally, but psych apps could also ask them to rig the smartphone in a secure standardized position (e.g., belt-clipped to a hip) while doing certain things that are hard to study in labs (e.g., learning to ride a motorcycle, canoodling in a night club), to give precise, objective measurements of those activities. Though designed for connectivity, Bluetooth is a potent onboard sensor in its own right: It routinely scans the identity codes of all other Bluetooth devices nearby; as most people now carry a Bluetooth-enabled mobile phone, the density of local Bluetooth devices is a good proxy for the number of people nearby (Do et al., 2011; Eagle, 2008). Combining Bluetooth scans and call log data allows accurate inference of friendships and social networks (Eagle, Pentland, & Lazar, 2009). Future smartphones could easily incorporate digital sensors for temperature, humidity, infrared light, ultraviolet light, ionizing radiation, carbon dioxide, and pollution, giving more insight into how such environmental variables influence, and are influenced by, behavior (Choudhury et al., 2008; Honicky, Brewer, Paulos, & White, 2008). Further, smartphones will soon incorporate radio-frequency identification (RFID) tag readers (Want, 2006), so once RFID tags get small and cheap enough to be incorporated into every product and possession, psych apps will be able to record what participants are buying, wearing, eating, reading, and driving, which could revolutionize consumer psychology.

External sensors

Powerful connectivity means that smartphones can link to a fast-growing range of external sensors that could give useful psychophysiological data. Consumer electroencephalogram (EEG) headsets have already been used to drive mobile phone apps (Campbell et al., 2010) and could allow neuropsychologists to study high-temporal-resolution brain activity in large samples of smartphone users doing requested tasks or everyday activities. (Consumer fMRI headsets are unlikely, given the 4,000 kg magnets required.) More than 240 companies in the Continua Health Alliance are developing Bluetooth biosensors for mobile health care (Alemdar & Ersoy, 2010; Krishna, Boren, & Balas, 2009). These will range from ultrasound imagers (e.g., the MobiSante MobiUS) and heart electrocardiogram (ECG) monitors (Worringham, Rojek, & Stewart, 2011), to optofluidic fluorescent cytometry devices that are too complicated to explain but that would allow a smartphone camera to do cell counts from blood samples taken in people's own homes (Zhu, Mavandadi, Coskun, Yaglidere, & Ozcan, 2011). Progress in the biological micro-electro-mechanical systems (or BioMEMS) underlying these biosensors is very fast (Liu, 2011). By 2025, many people will have a set of wireless biosensors that are wearable, implanted, or injected, to monitor not only basic vital signs (temperature, blood pressure, pulse, respiratory rate, pulse ox, and ECG) but also blood glucose, blood alcohol, hormone levels, immune system activity, inflammation, and ovulation (Jovanov, Poon, Yang, & Zhang, 2009), allowing powerful forms of remote psychophysiology and health psychology. Bluetooth connections to control units and sensors in appliances, vehicles, and homes would further broaden the scope of smartphone research from people's bodies to their possessions.

GPS

Smartphones can receive signals from multiple navigation satellites to track location and time pretty accurately (±10 m for latitude and longitude, ±15 m for altitude, ±10 nanoseconds for time). GPS location data integrated over time yield accurate heading and speed (Townshend, Worringham, & Stewart, 2008). However, current GPS does not work indoors, and it works better in Assisted GPS, where satellite signals are combined with signal strengths to nearby cell towers ("multilateration") and records from onboard accelerometers and gyroscopes (Farrell, 2008). GPS data are most powerful when cross-referenced to GIS digital maps, which can reveal where participants live, work, study, eat, and play and how they are affected by local weather, traffic, social interactions, and community events (Wolf & Jacobs, 2010). GPS coverage will improve this decade as Europe, China, India, and Russia launch about 60 more navigation satellites to supplement the 31 current U.S. satellites. Given likely technical progress, GPS accuracy should increase to about ±1 m by 2020 and to the centimeter range some time thereafter. Centimeter-accuracy GPS, combined with high-resolution GIS and onboard sensor data, could reveal whether smartphone carriers are calmly looking out the northeast window of a coffee shop, sprinting toward Gate 12 in Heathrow Airport's Terminal 5, or burping a baby on their back porch—raising new privacy and human subjects issues for institutional review boards (IRBs; Gasson, Kosta, Royer, Meints, & Warwick, 2011; King, 2011; Krontiris, Freiling, & Dimitriou, 2010; Shilton, 2009).

Visual output

Smartphones can now offer bright color touch screens with high definition (around 1280 × 800) and glasses-free 3-D. Smartphones also include HDMI ports that can drive nearby 3-D HDTVs and other displays, allowing much larger images, for example, for perception studies. Also, some smartphones now include tiny built-in digital projectors ("picoprojectors"), which can project an image on any nearby surface and could present video stimuli to small groups of participants for field studies in social psychology or communication research. Future smartphone users will access a succession of head-mounted displays, electronic glasses, and electronic contact lenses, which will overlay digital information on the real visual environment, delivering "augmented reality" and allowing new kinds of real-world experimental research.

Visual input and recording

High-end smartphones now include three high-resolution digital cameras and video recorders: two pointed away from the user (for binocular 3-D photos) and one pointed toward the user for webcam or video calls. Participants could be asked to do some "media capture": take photos or videos of certain things (themselves, others, objects, or environments) under certain conditions. For example, psych apps could run eye-tracking studies if the participant holds the smartphone up just under eye line so that the forward camera records what is seen and the rearward camera records the user's face, with onboard software detecting gaze direction. Several companies are already supplying fish-eye, macro, and microscopic lens attachments for smartphone cameras, allowing panoramic recording of physical and social context, close-ups of nearby objects, or home analysis of biomarkers under psychophysiological influence, such as sperm counts. Given willing participants, psych apps could record much more of people's lives, both what they see and how their faces look in response, at much higher spatial and temporal resolution than psychologists have ever seen before. Soon, the sensors for digital cameras will become so small and cheap that they can be incorporated into most eyeglasses frames, bike helmets, and cars, continually streaming users' visual experiences into their smartphone memories, in case they want to share a clip with friends, family, Facebook, insurers, or police. At that point, researchers with enough bandwidth and data storage could upload continual HD video of all the visual input that every participant is seeing.

Audio output

Smartphones typically include a medium-quality speaker (for holding up to the ear) and a headphone jack (for music listening through higher quality stereo earbuds or headphones). The HDMI port can output much higher quality 8-channel digital audio that can drive multispeaker home theater systems. Thus, psychologists interested in auditory perception or music cognition can already present lab-quality audio through smartphones, if participants connect them to good headphones or speakers.

Audio input and recording

Smartphones include dual midquality microphones pointed to the user's mouth that can record the user's voice, nearby people, and ambient sounds in stereo, revealing much about the user's context and behavior (Lu, Pan, Lane, Choudhury, & Campbell, 2009). Speech recognition is improving quickly (as in the Siri app for the iPhone 4S), which will allow participants to give verbal rather than typed or tapped responses to many behavioral tasks, making it easier for the young, the old, and the mobility impaired to participate in studies. Near-future models will include microphones directed away from the user, registering ambient noise for active noise cancellation; given participant permission, psych apps could potentially record sound from both microphones continually, giving auditory perception researchers, psycholinguists, and ecological psychologists better samples of the real-world soundscapes that people encounter.

Haptic and motor output

Current smartphones include only a weak internal vibrator for silent call alerts or simple haptic (touch) feedback in games. However, Bluetooth or USB ports could drive external devices with much more elaborate haptic and kinematic (movement) output, including current force-feedback devices, and future technology for gamers, virtual reality, and telepresence. By 2025, full-body suits with haptic and kinematic feedback and wireless smartphone connections will be popular with gamers (see MacLean, 2009), who would be ideal recruits for studies of touch perception, proprioception, and motor control.

Haptic and motor input

The main input for current smartphones is a touch screen. Touch screens are ideal for surveys that have one question and answer per screen and for experiments based on simple movement tasks, but they are poorly suited for sustained typing (e.g., studies of expressive writing) or for registering fine motor control or large limb and body movements. Devices for full-body gaming, such as the Xbox 360 Kinect, are bringing gesture-control and motion-capture technology to consumers and will soon be connectable to smartphones, opening the way for remote studies of nonverbal behavior, motor skill learning, couple dynamics, human–animal interaction, and so forth. Future clothing will likely incorporate piezoelectric transducers at key joints to convert body movements into recharge power for smartphones, and they could easily provide body-motion information as well, allowing smartphones to record limb and torso movements continually.

Summary of smartphone capabilities

In general, smartphones will become ever more versatile and powerful ways to run psychology studies, especially when combined with various peripherals. Their capabilities encompass and surpass most existing research methods: They can run surveys, questionnaires, field observations, and interactive experiments. Although their built-in screens and speakers are small, they can drive high-quality output to HDTVs, headphones, and speakers. Likewise, although their built-in touch screens and keyboards are small and fiddly, smartphones can receive Bluetooth input from full-sized keyboards, tablets, touch screens, game controllers, force-feedback devices, and even EEG headsets. Thus, through connections to external devices that many potential participants already own, smartphones can already emulate much of the lab equipment used in most branches of psychology, including perceptual, cognitive, cross-cultural, educational, evolutionary, health, and clinical psychology. Smartphones uniquely combine a capacity to gather precise, objective, sustained, ecologically valid field observations of real-world behavior by very large numbers of people and a capacity to run perceptually and behaviorally rich experiments with those same people. Apart from psychology, smartphones could revolutionize empirical research in economics, political science, anthropology, sociology, geography, communication, education, medicine, management, and public policy. They also offer new possibilities for diagnosis, treatment, interventions, applications, and training, for example, in clinical, educational, health, military, organizational, and sports psychology and also in psychiatry (see Krishna et al., 2009). To illustrate the potential of smartphones in psychology, the next section gives a hypothetical example of how a smartphone study could work given current technology.

How Smartphone Psychology Research Could Work

Suppose an evolutionary psychology lab group wants to study ovulatory cycle effects: how women's sexual strategies, mate preferences, and attractiveness change adaptively as fertility waxes and wanes each month (Thornhill & Gangestad, 2008). Existing studies have been done mostly on young-adult college students, typically unmarried and childless. Will the findings generalize to women who are older but still fertile—and are typically married with at least one child? This section explains how one smartphone study by one research team with a few hundred participants could test and extend many of the existing findings among such older married mothers.

First the team identifies several cycle effects that they aim to replicate and that could be investigated through five distinctive smartphone capabilities by programming a psych app.

Call logging and context-aware surveys

Lieberman, Pillsworth, and Haselton (2011) reasoned that women near peak fertility in their cycle should reduce contact with male kin to minimize the risks of incest and genetic inbreeding. Analyzing itemized cell-phone bills from female college students who retrospectively reported the sex, age, relationship, and emotional closeness of each caller, they found that women at peak fertility talked less (in call number and duration) with their fathers but more with their mothers, consistent with incest avoidance. The psych app for this new study could prompt women to complete a brief survey after each voice call and text message to or from a previously unidentified person, reporting the same information. Combined with call log and text log data, this could replicate the incest-avoidance finding. Further, after each call or text with an unrelated adult male other than the husband (e.g., coworker, neighbor, friend), the psych app could ask women to rate that man's sexual attractiveness; this context-aware survey could check whether peak-fertility women are more attracted to men other than their husbands (Haselton & Gangestad, 2006) and measure their sexual proceptivity (making calls, sending texts) versus receptivity (receiving calls and texts). Call logs could also give objective data on whether husbands are doing more mate guarding—for example, calling and texting their wives—when they are most fertile (Haselton & Gangestad, 2006).

Media capture

Women's cycle effects are stronger if their long-term partners have lower body symmetry (Gangestad, Thornhill, & Garver-Apgar, 2005) or are rated as less attractive (Haselton & Gangestad, 2006). The psych app could ask each participant to take some photos and video clips of the husband, including face and full-body shots, and short video recordings of the husband answering a few thought-provoking questions, acting out certain emotions, or telling funny stories. After upload to the team, these could all be measured, coded, and rated to assess each husband's physical attractiveness, masculinity, symmetry, intelligence, personality, sense of humor, expressiveness, and other traits, yielding an index of the husband's mate value that might modulate the woman's cycle effects. The psych app could also prompt women each day after dressing to photograph themselves in a mirror—face and full-body—to check whether higher fertility makes women's faces and bodies more attractive (Roberts et al., 2004; cf. Bleske-Rechek et al., 2011) and leads women to wear more stylish and revealing clothing (Durante, Li, & Haselton, 2008). The app could also prompt women to record themselves each day saying a standard sentence that allows some emotional expressiveness (e.g., "I may be married with kids, but I'm also a woman with my own needs and desires"); these audio clips could reveal whether peak-fertility women show higher voice pitch (Bryant & Haselton, 2009) and could be rated by men to track fertility effects on vocal timbre, attractiveness, and sexual receptivity.

Running experiments

Studies presenting video clips and computer animations of men to women show that higher fertility increases women's attraction to behavioral dominance (Gangestad, Garver-Apgar, Simpson, & Cousins, 2007) and flirtatious facial movement (Morrison, Clark, Gralewski, Campbell, & Penton-Voak, 2010) but not to intelligence (Gangestad et al., 2007; Prokosch, Coss, Scheib, & Blosiz, 2008). To replicate such studies, the psych app could present similar video clips of men and ask for attractiveness ratings at high and low fertility phases in each cycle, whenever convenient for participants. Videos and ratings of male musicians, dancers, and comedians could also reveal cycle effects on preferences for musical talent, dance ability, or sense of humor and clarify whether these traits evolved as signals of good genes (Fitch, 2006; Greengross & Miller, 2011; Hugill, Fink, & Neave, 2010). Further, peak-fertility women are faster to categorize faces by sex (Macrae, Alnwick, Milne, & Schloerscheidt, 2002) and show higher racial prejudice, stereotyping, and sexual wariness, as measured by Implicit Association Tests (Navarrete, Fessler, Fleischman, & Geyer, 2009); the psych app could easily be programmed to run these types of reaction-timed social cognition tasks (Dufau et al., 2011).

GPS tracking

Theory predicts that females at peak fertility should do more mate search, and they do express more interest in going out to dance clubs and parties to meet new men (Haselton & Gangestad, 2006) and more willingness to dance with attractive male strangers (Gueguen, 2009). GPS and GIS data could reveal whether peak-fertility women go out more often to areas with bars and clubs, and Bluetooth scans could reveal whether they go more often to places with a lot of people; after such excursions, the psych app could ask whether the woman was out with her husband, whether she talked or danced with any other men, and so forth. One old pedometer study (Morris & Udry, 1970) showed that women walk more miles per day at peak fertility, consistent with more (unconscious) mate search, but the finding needs replication; GPS data could reveal women's distances walked and driven per day and also rates of taking new routes and visiting new places across the cycle. Further, GPS input can give apps the context awareness to run surveys when and where they are most useful. For example, fertility influences tip earnings by lap dancers (Miller, Tybur, & Jordan, 2007) and might also influence earnings by waitresses, telemarketers, saleswomen, and others; women working in such jobs could be prompted to report their tips or sales commissions when GPS shows that they have left their place of work and arrived somewhere else, when their earning amounts are still fresh in mind.

Sensor data logging

Women's gait varies across the cycle, as shown by video analysis of reflective markers worn by women walking (Provost, Quinsey, & Troje, 2008). If each participant agrees to wear her smartphone in a belt holster on either hip throughout most of each day, data logged from the onboard accelerometers, gyroscopes, and magnetometers may also reveal cycle effects on gait, for example, hip sway. These sensors could also measure overall activity level and energy expenditure per day, to see whether peak-fertility women invest more energy in body-movement displays of health and mate value (Hugill et al., 2010).

Practicalities and logistics

Given the research goals above, the team considers inclusion–exclusion criteria for recruitment. They will recruit only heterosexual women ages 25–40 who are married and living with their husband, have at least one child, and are not pregnant or using hormonal contraception. The team also restricts participants to those using the team's language (to simplify the psych app) and living in the team's country (to limit the number of GIS databases their geography collaborators need to access). Finally, participants must have just one smartphone with certain specs that the psych app can check and be willing to keep it on, charged, and worn throughout each day.

The team turns to the practicalities of app development. They will develop a psych app for the Android OS because it is the market leader (now on about 50% of new smartphones), and they hire some local computer science postdocs who have app-writing experience. They also find a couple of geographers with GIS expertise, so they can plan how the GPS data can be cross-referenced with digital maps of roads, workplaces, schools, nightspots, and other places of interest (see Wolf & Jacobs, 2010). The app needs some simple programming for context awareness (Chalmers, 2011; Hong, Suh, & Kim, 2009; Soylu, De Causmaecker, & Desmet, 2009) to optimize data gathering and minimize power consumption in different contexts, for example, reducing Bluetooth sampling rate when the clock, accelerometers, and GPS records suggest the participant is home asleep. Also, the app must not cause a system crash during an emergency call or a security breach allowing a virus to wipe the smartphone's contact list. To increase the psych app's reliability, safety, security, and usability, the team gets several rounds of feedback from beta testers before the final version is ready for release to participants (see de Sá, Carriço, & Duarte, 2008; McMillan, Morrison, Brown, Hall, & Chalmers, 2010). The researchers also get some corporate sponsorship from a telecoms service provider keen to understand female customers, so they can offer 500 women $200 each through PayPal after completing the study.

The team recruits through the Android app store, *Psychology Today*, and Internet sites for psychological research, plus word of mouth through e-mail, Facebook, and other media. Each participant downloads the free psych app whenever convenient, wherever she is. Upon launch, the app presents a video explaining the study, checks the inclusion criteria, and asks for a touch screen signature as informed consent. The app asks participants to complete several initial surveys, pausing and resuming whenever they like, with one item per screen, and touch screen responses. These include questionnaires about demographics, background, marriage, children, sexual experiences, sexual attitudes, personality traits, and ovulatory cycle patterns. The psych app uploads these responses via Internet to the team's lab computer and switches into data logging mode for 2 months. The first few days, participants are fairly busy getting used to wearing the smartphone in a belt holster, setting up call logging by identifying their relationships with different callers and texters, labeling GPS points of interest (home, work, children's schools), and taking the photos and videos of husbands. Shortly though, the psych app grows less demanding, mainly running surveys and experiments about once a week when convenient and prompting for the daily self-photos and audio recordings, for reporting tip or commission earnings if job-relevant, and for rating the attractiveness of some male callers and texters. After the app has run for 2 months, it thanks the participant, who watches a well-produced debriefing video and gets paid through PayPal.

Within a few months, the team has many terabytes of data and starts data analysis and paper writing. The longitudinal design, with two full ovulatory cycles from each of 500 women, gives formidable power to detect cycle effects (or reject their existence with high likelihood), with tight confidence intervals on their effect sizes. This one study could address at least the following 16 research questions, concerning cycle effects on (a) calls and texts with male versus female kin; (b) calls and texts with male nonrelatives other than the husband; (c) husbands' mate guarding through calls and texts; (d) spending evenings outside the home in places with other men; (e) distances walked and driven per day; (f) rates of visiting new places and taking new routes; (g) tips and commissions earned by service workers; (h) walking gait; (i) preferences for dominance, flirtatiousness, and intelligence; (j) preferences for musical talent, dance ability, and sense of humor; (k) speed of categorizing sex from photos; (l) sexual wariness of men from other ethnicities; (m) face attractiveness; (n) body attractiveness; (o) clothing attractiveness; and (p) voice pitch and attractiveness. These last four would require many attractiveness ratings (about 120,000), but these could be farmed out to Mechanical Turk (Buhrmester, Kwang, & Gosling, 2011) for just a few thousand dollars. Papers from this study could also examine how cycle effects are modulated by the husband's mate value and by the women's sexual attitudes and personality traits. A couple of years after starting the project, the team is flourishing, developing new hypotheses to test, new data analysis methods, and new psych apps for further studies.

Limitations and Challenges

The example above gives a rosy picture of smartphone research, but smartphones have some important limitations as research platforms (Raento et al., 2009).

Technical limitations

Current smartphones have several technical constraints (Oliver, 2010; Rachuri & Mascolo, 2011). Volatile memory can cause data loss, and other apps may interfere with the psych app (Oliver, 2010). Limited battery power may constrain how many hours per day a psych app can gather data, especially for energy-hungry GPS sampling, so psych apps need to maximize energy efficiency through context-aware sampling rates and logging intervals and through piggybacking on data already logged by the smartphone's native software (Chalmers, 2011; Shepard et al., 2011; Wang et al., 2009). Limited-accuracy sensors were designed not for gathering behavioral data but for common phone functions (e.g., microphones for making calls, gyroscopes for flipping from landscape to portrait view). Different smartphone models include sensors and displays with different hardware specs and software drivers, so psych apps may need to target a specific model or cleverly adapt to different hardware. Heat dissipation is a problem when you pack a lot of computational power into a small enclosed device without a cooling fan, so smartphones that are working hard get quite warm, and participants might not want to hold them very long. Nonetheless, manufacturers are prioritizing these problems—battery life, sensory accuracy, hardware compatibility, heat dissipation—and they are likely to be resolved within a few years. For example, Koomey's law states that the number of computations possible per joule of energy dissipated doubles every 1.6 years and has held since the 1950s, so heat dissipation problems should resolve as processors become smaller and more energy efficient.

Challenges in participant recruitment

Smartphone research can only reach potential participants who have smartphones. That is now more than 500 million people globally, and the number is growing very quickly, greatly increasing the scope for cross-cultural research and reducing overreliance on college subject pools (Henrich, Heine, & Norenzayan, 2010). However, smartphone adoption is probably slower among people who are poor, closed-minded, introverted, neurotic, less intelligent, mentally ill, or living in countries with poor telecoms infrastructure (e.g., Devaraj, Easley, & Crant, 2008; Lane & Manner, 2011). Also, certain kinds of people will avoid studies that are intrusive, demanding, and privacy threatening, imposing other selection biases in recruitment. Still, by 2025, when most people in most countries will have a smartphone, recruitment biases in smartphone research will be much less severe than with any other research method. However, the potential for global recruitment raises new challenges, such as creating multilanguage interfaces for psych apps.

Smartphones also extend the demographic reach of recruitment. Older adults, who are hard to recruit with traditional methods, will adopt smartphones quickly when their lives start to depend on mobile health systems and biosensors, such as accelerometers that detect falls and ECGs that detect heart attacks prompting smartphones to summon help automatically. At first glance, smartphone research seems ill suited for developmental studies of children, since children may not follow directions from psych apps; however, their parents, who have to give consent anyway, could run certain kinds of studies as the researcher's proxy. Smartphones will force us to take seriously the idea that the people we study are not just passive "subjects" but active "participants," as studies may ask them to take sensor readings of their environments; to record photos, video, or sound; or to run experiments on themselves or others (see Mehl & Conner, 2011). When most participants in psychology studies are college students, and researchers are older, brighter, and better educated than most students, there seems a big status gap between participant and researcher. However, when we start recruiting participants who may be older, brighter, richer, and/or better read than we are—for example, Hong Kong millionaires or science fiction novelists—we will need a serious attitude adjustment that acknowledges a genuine continuum between participant and collaborator.

Challenges from participant behavior

Smartphone research will also be constrained by participant behavior. Participants may forget to recharge smartphones or to carry them, interrupting data gathering. Participants may lose the phone or upgrade it to a new model during the study. Some people have one phone for the workday (e.g., a corporate-leased Blackberry that prohibits downloading apps) and a second for outside work (e.g., a personal Android), and this may restrict data gathering to evenings and weekends. Participants may lend phones to family or friends, so the psych app does not know whose behavior it is tracking. Malicious participants may give bad data (Oliver, 2010). Participants may change their behavior because they know they are being studied. Researchers will need to anticipate such problems and write psych apps that minimize their impact.

Programming psych apps

Another big problem is that very few psychologists know how to program smartphone apps at the moment. Smartphones manufacturers do offer substantial support for app developers in the form of software development kits ("devkits"; Lane et al., 2010), but those app developers are typically expert in Java, Objective-C, C#, or other common app programming languages. Also, many market research companies sell online survey software, but only one so far, Confirmit Mobile Solutions, has developed downloadable survey apps for all major smartphone OSs (which were used to run 15 million surveys in 55 countries in 2010). Although corporate market research is a huge business compared with psychology, it has been no faster to embrace smartphones as part of its research methods. So, for the first few years, smartphone researchers will need to collaborate with expert app developers and/or computer science lab groups already using smartphones as research platforms. Smartphone manufacturers put a high priority on studying how users interact with phones ("user experience research"; Hassenzahl & Tractinsky, 2006), which will push for devkits that make it easier to program apps for gathering behavioral data. To promote open-source psych app development, psychology journals should accept smartphone research papers only if authors upload clean, modular, well-documented source code for both their psych apps and their data analysis tools to a public online registry. Some psychology PhD programs may start offering courses on psych app development—and their graduates may be in high demand, just as early fMRI experts were in the 1990s.

Data management and analysis

We will need to develop new ways of recording, organizing, analyzing, interpreting, and protecting the huge volumes of data that will be produced by psych apps (see Lazer et al., 2009). Most psychology studies have collected rather small amounts of behavioral data: Participants make marks on paper or press buttons a few hundred times, and an undergrad research assistant can type the results into a spreadsheet in a few minutes. Brain imaging and genotyping studies yield large data sets, but most of those data concern the neural or genetic correlates of behavior, not behavior itself. By contrast, a moderate-sized smartphone study (Kiukkonen, Blom, Dousse, Gatica-Perez, & Laurila, 2010), tracking 168 participants for an average of 4 months each, yielded 15 million Bluetooth scans, 13 million wireless LAN scans, 5 million GPS records, 4 million app usage records, 500,000 accelerometer readings, 220,000 audio samples, 130,000 voice calls, 90,000 text messages, 28,000 photos taken, and 2,000 videos shot—a formidable data analysis challenge. If a smartphone study recorded 1 hr of HD video (400 GB) per day from each of 70 participants, that would equal the raw data output (300 MB per second) from CERN's Large Hadron Collider, which is handled by 200,000 processors and 150,000 terabytes of disk space across 34 countries. Other sciences and industries are used to heavy informatics challenges: The Allen Brain Atlas of mouse brain gene expression yielded 600 terabytes of data; Facebook tracks the activity of over 800 million active users. Smartphone researchers will have to develop informatics skills that can cope with comparable volumes of behavioral data, including more expertise in signal processing, feature extraction, pattern recognition, and machine learning (e.g. Peebles, Lu, Lane, Choudhury, & Campbell, 2010), so that we can, at least, collaborate well with computer scientists and informatics experts. The demands of smartphone research may initially require a Big Science approach, with large multidisciplinary networks of collaborators. However, after a decade or so, when psych app devkits and data analysis tools become more standardized and user-friendly, it will be possible for small lab groups or even individual researchers to run very large and sophisticated studies.

Human subjects and IRB issues

Smartphone research raises many IRB problems about consent and privacy (King, 2011; Shilton, 2009). Indeed, the problems are so severe that either smartphone research will make current IRB systems obsolete and force their replacement with better systems (my preferred option), or the current IRB systems will stifle academic smartphone research in some countries, allowing other countries and corporations with more liberal rules to pull far ahead. One nightmare scenario is that IRBs in the United States and Europe impede their psychology departments from running large-scale cross-cultural smartphone studies, leaving researchers in China, India, and elsewhere to do all the cool, global, data-rich smartphone studies that will dominate twenty-first-century psychology—and that will reach participants in the United States and Europe anyway. Meanwhile, the informatics geniuses of Google and Facebook will be working their data-mining wizardry on exhaustive data from billions of people, who currently give no real informed consent and enjoy no IRB protection. By 2025 or so, if human subjects protection does not change for both academia and industry, such companies will know vastly more about human behavior than psychology does. However, their corporate insights will be trade secrets, and their researchers will be laughing as quaint old academic psychology falls further and further behind.

What are these severe IRB problems with smartphone research? First, informed, thoughtful consent is tricky to obtain for smartphone studies: Most smartphone and Internet users do not read software licensing agreements before clicking "I agree" to the download, and they do not worry about the huge volume of personal data that Facebook, Amazon, and Netflix routinely log without clear warning or consent. For example, there was only a brief outcry following recent reports that iPhones and Android phones regularly transmit location data to Apple and Google (Angwin & Valentino-Devries, 2011).

Second, anonymity will gradually become impossible in data-rich smartphone studies (King, 2011). Although most participants in mobile phone studies do not want researchers to record the contents of their voice calls, text messages, and e-mails, they are surprisingly comfortable with detailed logging of sensor, call log, and GPS data (Gasson et al., 2011; Krontiris et al., 2010; Shilton, 2009). Such data would probably allow inference of a participant's identity, sex, life stage, marital status, social status, home address, health, sex life, and religion, even if those were not self-reported (Gasson et al., 2011; King, 2011). Researchers running such studies could not in good conscience promise anonymity. Psych apps can also threaten the privacy of third-party bystanders, for example, if their texts messages to participants are content analyzed or if participants are asked to record a lot of photos and video in public.

Third, even with encrypted data uploads and privacy-preserving data analysis, a participant's confidentiality will be vulnerable to authorities. Given totalitarian governments, fundamentalist regimes, or national-security panics, smartphone data could be commandeered to hunt down dissidents, apostates, or pacifists (see Dobson & Fisher, 2003; Shilton, 2009). Also, if police arrest someone for possible restraining-order violations, meth-lab visits, or hit-and-run vehicular manslaughter, and they discover that the suspect's smartphone is running a psych app from a particular university, a court might subpoena the GPS records that could put the participant at the crime scene (Shilton, 2009). (However, National Institutes of Health Certificates of Confidentiality can offer U. S. participants and researchers some protection against such forced disclosure.) Further, the most powerful way of protecting data confidentiality—encryption during data upload and storage—would be vulnerable if quantum computing becomes practical. The cryptography-obsessed U.S. National Security Agency will likely be able to crack sophisticated encryption methods long before psychologists know about it. The moral dilemmas here are very tricky. It may be reasonable for psych apps to allow participants to change data-management settings flexibly, precisely, context sensitively, and even retroactively, for example, data recorded during a previous night's drag race, embarrassing hookup, or ill-judged political rally speech.

Fourth, IRB approval is problematic given the potential for global collaboration and global recruitment. Suppose a team of 20 researchers from 10 universities in 5 countries designs a smartphone study, collecting data globally. For convenience, they store and analyze the terabytes of data by using a cloud computing system, so the data may be spread across hundreds of servers in many countries. The notion of protecting participant data by locking it in a lab filing cabinet or on a password-protected lab computer will be ludicrously outdated. The U.S. rules (e.g., federal policy 45 CFR 46) about multisite studies are ambiguous and in flux: do all 10 universities need to approve the study, or one, or none? The international rules are also a mess: The 2011 International Compilation of Human Research Protections lists over 1,000 rules from 101 countries—do all apply, if a study is run globally? Another problem is that children, prisoners, mentally ill people, people from indigenous tribes, and other "vulnerable groups" are quickly adopting smartphones and could participate in studies that were not designed to protect their distinctive interests. Until there is a global IRB system with clear rules and procedures, researchers could try to protect smartphone data according to a high international standard such as the European Union's Data Protection Directive (95/46/EC) and Fair Information Practice Codes, but those are too abstract and outdated to serve as best-practice guidelines. Quite soon, psychologists will need updated guidelines that replace, for example, 45 CFR 46, which was first written in 1991 (when mobile phones were brick-sized and only seven million Americans used them) and never revised to address technologies for remote data collection. Ideally, the new rules would apply equally to corporate researchers and academic researchers, holding Facebook to the same standard as Harvard.

Liability issues

Smartphones are so central to people's lives that bad psych apps could cause real damage to participants, through negligence or malice. Programming bugs could be dangerous if they squander battery power, prevent an emergency call, or make a neurosurgeon's smartphone suddenly vibrate during a delicate operation. Malevolent researchers could defraud or blackmail participants by programming psych apps to capture participants' credit card numbers or call logs. Considering both human subjects issues and liability issues, smartphone research will reach into people's private lives as never before, and we will need to develop whole new systems of safety, privacy, accountability, and law to protect everybody.

Smartphones Versus Traditional Research Methods

Smartphones offer distinctive strengths and weaknesses compared with traditional research methods. Table 2 presents some key comparisons between six research methods, explicated here:

1. Paper-and-pencil survey: questionnaires or mental tests printed on paper, asking participants to write responses; distributed either in person (e.g., lab or classroom) or through mail (allowing national recruitment and higher convenience but less contextual control);
2. Lab study: interactive tasks in a research lab, run individually or in groups, face to face (e.g., interviews, focus groups) or on a computer (e.g., perceptual, cognitive psychology), sometimes with observation by video recording, motion capture systems, brain imaging, or with biosampling (e.g., blood draws, DNA swabs);
3. Field study: researchers bring video cameras, GPS navigators, and other equipment out into some field site to record natural behavior there and/or run a field experiment through display screens and speakers brought to the site, with possible biosampling;
4. Internet study: participants recruited online (e.g., through Mechanical Turk) for an interactive study using their PC or laptop at home, work, or elsewhere, with tasks and responses similar to lab computer studies, sometimes running tasks requiring common peripherals such as a joystick or full-size headphones and audio or video capture through microphone and webcam;
5. Smartphone study using psych app: as with the ovulatory cycle example in this article, participants are recruited to download a psych app onto their own smartphones; they then do surveys, tests, structured tasks, or experiments (sometimes requiring connections to common peripherals such as a full-sized keyboard, joystick, HDTV, headphones, or motion capture system like Kinect), usually combined with some passive data logging from onboard sensors and GPS and some media capture;
6. Smartphone study also using special peripherals: like the previous method, but researchers recruit participants who already own some peripherals that allow more powerful remote data gathering but that are likely to remain rare and expensive for a while, such as EEG headsets, heads-up display visors, or more advanced biosensors.

Most of these six methods allow both correlational and experimental studies and can be used once or repeatedly, with one participant or many, and with twins or adoptees, so I do not list correlational studies, longitudinal studies, case studies, or behavior genetics studies separately.

Table 2 rates these methods on 16 dimensions The entries in Table 2 suggest that the main advantages of smartphones over other psychology research methods are

1. potential for global recruitment and very large samples;
2. high convenience, ecological validity, and unobtrusiveness for participants;
3. easy video and audio capture, motion sensing, and location tracking;
4. potential for high-quality video and audio display given common peripherals (e.g., home HDTV and speakers);
5. potential for remote biosampling when biosensors and Bluetooth biomedical peripherals become more common and sophisticated.

The main disadvantages of smartphones are

1. substantial study preparation work in writing, debugging, pilot testing, and field-testing the psych app, at least until useful open-source libraries of psych apps and user-friendlier devkits are available;
2. low contextual control over participants' physical and social environments during the study;

Table 2. Comparing Smartphones to Six Other Research Methods on 16 Criteria

Capability	Paper-and-pencil survey	Lab study	Field study	Internet study	Smartphone study using psych app	Smartphone study also using special peripherals
Ease of running study						
Ease of study prep work (writing surveys, setting up field sites, programming app)	↑	↔	↔	↔	↓	↓↓
Ease of recruiting from wide geographic area	↑	↓↓	↓	↑↑	↑↑	↑↑
Convenience to participants (running where/when they want)	↔	↓↓	↑	↑	↑↑	↑
Scalability (ease of running each additional participant once study is set up)	↑	↓↓	↓	↑↑	↑↑	↑↑
Contextual control (over physical/ social environment)	?	↑↑	↑	↓	↓↓	↓↓
Potential to automate data entry	↓	↑	↓↓	↑↑	↑↑	↑↑
Ease of data analysis (given likely amount of data)	↑↑	?	?	↑	↓	↓↓
Data quality and amount						
Audio-video quality presentable and recordable	↓↓	↑↑	↔	↑	↑↑	↑↑
Movement quality recordable (from video camera, webcam, motion capture, or sensors)	↓↓	↑↑	↑	↔	↑↑	↑↑
Potential for sustained location tracking (e.g., GPS)	↓↓	↓↓	↔	↓↓	↑↑	↑↑
Potential for biosampling (e.g., ECG, EEG, DNA)	↓↓	↑↑	↑	↓↓	↓	↑
Potential amount of data gathered per participant	↓↓	↑	↑	↔	↑↑	↑↑
Ecological validity (potential for naturalistic stimuli, intuitive responses)	↓↓	↔	↑	↔	↑↑	↑
Unobtrusiveness (participants forgetting they are being observed)	↓↓	↓↓	↑	↓↓	↑↑	↔
Ethical issues						
Ease of getting truly informed consent	↑↑	↑	↔	↑	↓↓	↓↓
Freedom from liability risks: physical danger, fraud, blackmail	↑↑	↑	↑	↑	↓	↓

Note. In each case, higher is better for the researcher and/or participant. ↑↑ = very high; ↑ = high; ↔ = medium; ↓ = low; ↓↓= very low; EEG = electroencephalogram.

3. potentially very large and complex sets of data that require sophisticated data analysis;
4. ethical challenges in obtaining truly informed consent, protecting participant privacy and anonymity, reducing liability risks, and determining which IRBs and rules apply to a study given global recruitment.

Despite these disadvantages, smartphones can do almost everything that the other methods can do and more. They render paper-and-pencil studies, mail surveys, and traditional Internet studies largely obsolete. For some research questions, lab and field observations will remain more useful than smartphone studies for a while. For perception and cognition experiments that demand high contextual control, lab computers will remain better than smartphones. Otherwise, psych apps for smartphones could become the default research method for most of psychology.

Conclusions

Manufacturers and telecoms service providers are flooding the world with billions of smartphones that have ever greater capabilities. Individually, they will be the most powerful, versatile, and intimate tools routinely carried by ordinary people. Collectively, they knit together into a pervasive, unified, global, context-aware system for sensing, storing, sharing, and analyzing information about human behavior. The smartphone industry is spending hundreds of billions of dollars to drape a data net over our world, and we would be foolish not to take advantage of it. The scientific possibilities are limited only by our imaginations and by the technology—which will keep advancing faster than our imaginations can keep up.

The question is not whether smartphones will revolutionize psychology but how, when, and where the revolution will happen. Which will be the first nations, universities, lab groups, disciplines, research consortia, scientific societies, journals, and grant agencies to promote smartphone research? How will manufacturers, telecoms service providers, app developers, user experience researchers, and consumer behavior researchers contribute financially, practically, and intellectually to smartphone research? Which universities and countries will first realize that current IRB systems, including traditional notions of anonymity and privacy, are woefully outdated and need to be completely reengineered? How can older researchers grow comfortable with such a futuristic technology—one that is, to all intents and purposes, indistinguishable from magic? Given Moore's law, Kryder's law, and Nielsen's law, with the dizzying rates of technical progress they describe, how can researchers of all ages stay current with new developments in technology, apps, and data analysis? Most important, what will you do to help psychology advance into this smartphone future?

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