UNIQUE LEARNINGS IN CREATING A 360 VIEW OF MOBILE CONSUMERS

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Introduction

The steep rise in the consumption of media and advertising content on an ever-expanding base of mobile devices has prompted a significant surge in both research and advertising dollars in the mobile arena. One of the major concerns for researchers in this venue is the predisposition to build mobile research databases in isolation from other key marketing database resources. This paper describes the pilot study phase of an initiative to develop a comprehensive database that directly combines rich mobile phone data collected from a passive mobile monitoring device with the large-scale inventory of variables available in a large nationally syndicated study.

This database synergy connects key mobile phone behaviors such as application use, website visitation, text messaging activity, GPS location and more to a panoply of product and brand use, multi-platform media preferences and attitudinal measures. Using this kind of enhanced database researchers can provide marketers with a wealth of information about the mobile phone audience and their behaviors. Marketers will be able to thoroughly profile the mobile behaviors of their customers and the customers of their competitive set. What is the best way to reach their customers using a mobile platform, is it SMS, website, streaming video? Which websites and concomitant advertisements are they accessing with their mobile phones? What brick and mortar retailers and stores do they frequent or pass near?

Researchers will also be able to provide rich profiles of different types of mobile users. Which mobile users have the highest levels of advertising receptivity? Identify mobile users who are exposed to advertising for businesses that they pass by during their day. Single out people who use mobile applications sponsored by products or services they consume. Profile individuals who consume products that are good candidates for purchase via the mobile phone.

The deployment of mobile passive metering technology also brings with it a number of measurement issues – some of them familiar to researchers utilizing passive metering systems in other media such as television and other issues that are unique to the mobile research environment. In addition, passive mobile measurement brings with it familiar privacy issues that are specific to mobile such as geo-location that will bear upon a number of key components including recruitment as well as data privacy issues.

This paper describes some of the knowledge acquired from a small, initial mobile measurement pilot study that deploys a passive monitoring application on smartphones belonging to recent Simmons National Consumer Study respondents. Working in conjunction with our agency co-authors, we describe some of the preliminary results from this pilot study to link a set of detailed and specific mobile behaviors with the breadth and depth of a large national syndicated consumer study. It is hoped that these learnings will inform the research community at large about the potential as well as the challenges of obtaining detailed mobile measurement and combining that data with comprehensive consumer databases.

Substantive Background

One of the few things that researchers can be fairly certain when it comes to the mobile marketplace is that it is emerging at an incredible, exponential rate of growth. The magnitude of mobile data traffic in 2010 was three times the data traffic volume of the entire Internet in 2000 (Cisco, 2011). Over 500,000 Android-based devices are activated every day (Google, 2011) while Apple sold 30% more iPads in the third fiscal quarter of 2011 than all of the personal computers Dell sold in the same time period (Kopytoff and Austen, 2011). The fact that Mobile advertising sales for 2011 are expected to double to 1.2 billion dollars (Walsh, 2011) coupled with the knowledge that the top 1% of mobile device users generate 20% of mobile traffic (Cisco, 2011) means that content publishers and advertisers cannot afford to ignore the mobile market any longer nor fail to deploy rigorous consumer targeting mechanisms to the mobile environment.

Market researchers have not been entirely ignoring this consumer trend towards the mobile platform but the initial progress towards measuring the mobile market has been a bit of a bumpy ride for a number of reasons. One of the reasons for this is the fact that mobile devices are a multi-functional platform. A mobile phone is a primary communications device providing voice and messaging services to consumers. Mobile devices also provide informational services such as maps and geolocation. In addition, they serve as platforms for more traditional commercially produced content in audio and video form such as television shows through web browsing and movies as well as personally produced content such as postings to social networking services. To complicate matters further, there is also some evidence that consumer use of smartphones changes as they become more experienced with mobile devices (Rahmati et al, 2011). It's not surprising that market researchers have not had an easy time understanding how consumers utilizing mobile platforms as well as how content providers and advertisers can take advantage of this new media channel.

In addition to the challenges attributable to the nature of how consumers use the mobile platform, there are significant measurement issues present for researchers in their search to develop methodologies that can measure consumer behaviors on the mobile platform. While self-report measures for the mobile platform are a necessary part of the methodological mix, it is obvious that passive measurement is going to play an important part in understanding consumer mobile behaviors. One of the biggest logistical challenges is the rapid growth and increasing technical complexity of the mobile environment itself. Mobile devices are evolving at an incredible rate and along with that so are the operating systems that enable the mobile phones to function. The rate of mobile hardware and software evolution as well as the inherent complexity of these systems has made building passive measurement tools for these platforms a very expensive and difficult endeavor. Until the mobile environment becomes more mature, market researchers are going to face a number of ever-changing challenges in their attempts to measure consumer mobile behavior.

Unfortunately, the obstacles to better understanding mobile behavior do not stop there. Even when there is a stable passive measurement system in place, the operational definitions, the meaning and value of mobile metrics are not yet substantially clear. While there has been an industry effort to standardize mobile metrics for mobile advertising by a collaboration between the Internet Advertising Board, the Mobile Marketing Association and the Media Ratings Council (2011), there are still a very large number of questions and unresolved issues in the area of mobile metrics. As will be seen in following section, the development of rigorous mobile metrics is a challenge that still faces the market research industry.

Mobile Metrics: A Melee in the Making

Mobile Metrics Environment

An examination of the measurement milieu of the current mobile marketing arena reveals the effects of a convergence of factors that resembles the approach of the elements of a perfect methodological storm. Most obvious of these factors is the incredible speed at which the mobile phone environment is changing. On a weekly basis consumers are presented with an ever-changing selection of smartphones with competing or different capabilities, features and functions. This makes identifying, investigating and constructing the appropriate mobile metrics a task with a rather fast moving target.

In addition to the pace of innovation in the smartphone industry, market researchers are still in the early stages of building an understanding of how individuals are using these devices and how these devices are shaping the attitudes and consumer behavior of their users. One particular characteristic that complicates this undertaking is the fact that smartphones are true multi-dimensional media and communications devices. Rather than having the task of building an understanding of how individuals use a device with multiple functions within a single dimension – such as understanding how individuals interact with a simple DVD player for example – researchers must contend with constructing an understanding of how individuals utilize a device that provides many different communications, social, entertainment, information and commerce functions among others.

Further, many of the functions of smartphones are open rather than closed operational systems that are ripe for deployment in new and novel ways by their owners. One historical example is emergence of the iPhone "flashlight" app. Some of the early adopters of the iPhone noticed that its touch screen gave out a copious amount of light during the night, especially when the screen was nearly all white. iPhone application developers jumped on this phenomenon and wrote numerous iPhone flashlight applications that turned your iPhone into a usable flashlight. Being aware of new and emerging applications for sometimes unintended "features" of smartphones is one of the hazards of developing meaningful metrics.

The nature of passive measurement also gives rise to complexity of mobile metrics through the sheer number of metrics available. Bypassing the need to enlist the moment to moment cooperation of respondents to self-report their behaviors and utilizing the programming characteristics and functionality of smartphones means that there is often a very large number of metrics that can be passively collected and analyzed. As an example, Table 1 below reveals some of the metrics that were collected during just the pilot study described in the paper.

Table 1

Selective High-Level List of Metrics Collected

Class	Description
Application usage	Foreground application usage
Voice usage	Voice calls made and received
Location	Time spent in different locations during a day
Messaging	SMS, MMS and emails sent/received
Music	Music played, music info at artist level
Application installation	Applications installation actions and installed application scans
Browsing	Accessed web pages aggregated and categorized
Http-data	http based traffic generated by browser and other applications

The actual number of mobile metrics when aggregated across time collected for each smartphone in the pilot study exceeded 100. The issue becomes one of which metrics are meaningful and important to collect and analyze and which ones are not as meaningful. This decision of course depends upon the nature of the objectives of the analyst. Analysts looking to improve connection service, such as one might find at a large mobile service provider such as Verizon, would have a very different take which mobile metrics are important than would a mobile marketing analyst at an advertising agency.

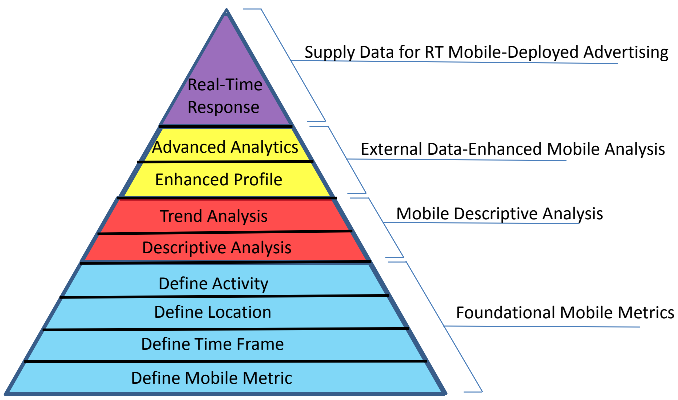
A Mobile Metric Heuristic

While there have been some initial attempts by industry organizations to develop a standard set of metrics – such as is the case with the Mobile Marketing Association specifically in the area of mobile advertising metrics (2011) and the establishment of a mobile analytics best practices committee in 2011, there is much left to be done in the area of providing a better understanding of mobile metrics, the nature of their value and the development of standards and best practices for mobile metrics and analytics.

One of the ways in which this dilemma of mobile metrics[1] can be managed is to develop some basic heuristics around the foundational measures, basic metrics and enhanced analytical metrics that can arise out of this environment. Figure 1 below details one such heuristic device for mobile metrics.

[1] One of the research staff members working on this pilot study coined the term “melee of metrics” to describe this phenomenon.

Figure 1
Mobile Metrics Heuristic Diagram



Mobile measurement and its subsequent applications can be divided into four general components. The first component consist of foundational mobile metrics. The basic traditional media metrics of reach, frequency and duration hold true here in the mobile environment as well. In defining basic mobile metrics some of the basic questions that researchers and marketers are going to want to ask are 1) who and how many people could we or did we reach 2) how many times did this happen and 3) how long did they spend on an activity where content and/or advertising was present.

The next parameter deals with defining the time frame of the metric. Are the basic mobile metrics just discussed framed temporally in terms of hours, days, weeks, months or some other time frame? One of the characteristics that must be kept in mind is that because this is panel data that is continuously being passively recorded, every data record has a date and time stamp. Thus in order to construct metrics, temporal time frames for those metrics must be designated. While the time series nature of the observations within a mobile panel present some of the usual complexities of behaviors measured across time, the temporal nature of the data also provides researchers and analysts with the opportunity to investigate trends across days, weeks or months. In addition they provide fertile ground for those analysts interested in examining mobile behaviors from an econometrics perspective.

The next basic mobile metric is defining location metrics. In its very simplest form, any activity, event or other notable data point occurs at some specific terrestrial point on the globe as represented by the latitude and longitude of the smartphone at the time the event or activity is recorded. The dimension of physical location at the moment of observation – usually not available for most market research data – may take on significant importance in mobile advertising strategies as mobile marketers look to push geo-relevant messages in real-time to smartphone users.

In addition to simply locating an event or activity geographically, geo-location information extracted from smartphones can be used for other types of metrics. For example, by comparing the location of the mobile device over a period of time, one can calculate a travel or distance activity metric that measures the distance that the mobile device user has traveled during the measurement period. Some individuals are likely to be very active in changing locations and others may be not so active. It should also be pointed out that this distance metric may have some interpretation conundrums. How do you compare someone who spent the day traveling all over town running errands with someone who hopped on a plane and traveled across the country? Who was the most distance active of these two individuals? Is it measured by miles traveled alone or by some other measures such as time/resources expended traveling?

Finally, there is the potential metric of proximity classes. Physical proximity is important because even with online shopping and ecommerce, a significant proportion of retail purchase and service acquisition activity still involves a personal visit to a physical storefront. Because physical proximity is likely to increase the propensity to shop a particular brick-and-mortar establishment, knowing how close individuals carrying mobile devices such as smartphones are to a specific retailer or type of retailer can provide the marketer with information necessary to efficiently target those individuals who are within a distance that suggests they are likely to make the effort to travel or detour to that retail establishment. Mobile marketers are already using concepts such as geofencing to market to mobile users that are within a specific radius of a brick-and-mortar storefront (Himsel, 2011). One future example scenario utilizing this promixity class metric might be the situation where a "mobile customer herder" for a specific large department store might monitor potential nearby customers in real time, noting through the geo-location and profile information where there are "herds" of high value customers moving in the general direction of the store and advising the store merchandising employees to put a certain product into the display window, sending a coupon or discount code to these individuals or quickly change the outdoor on-site advertising message to be tailored to the oncoming high value customer herd.

The final fundamental mobile metric is that of activity. Smartphones not only deliver content and advertising from web pages accessed through browsers but also through email and text messages as well as in-application messages. Because most smartphone activity is application based and the number of smartphone applications available to a platform might number in the tens of thousands, a simple taxonomy of applications will probably be useful to researchers and marketers. For example, one type of taxonomy in use is a <Source><Category><Class> taxonomy. Source would refer to the origin of the application – was it a native application that came with the operating system of the phone or was the application downloaded to the smartphone. Category here refers to general type of application that it might be – perhaps it is a social networking application for example. Class could refer to a specific class of application such as a facebook-based application that manages details and communications of the smartphone owner's facebook account.

Building upon the foundational mobile metrics just discussed, the next class of elements in the heuristic revolves around mobile descriptive analyses. Here a researcher or marketer might envision constructing a number of different metrics that only utilize data collected from the smartphone. Examples of these kind of metrics and analyses include such things as aggregating data across time to construct a "typical day" profile that describes for a target subpopulation the composition of the type, frequency and duration of applications used, number of SMS messages sent and received, types of websites visited, number of advertisements served, duration of streamed video, amount of music played and distance traveled. Similarly, the researcher might be interested in dividing a day up into dayparts and profiling the most frequent activities or applications used for each daypart or hour of the day for a target population.

Mobile descriptive analysis might also involve trending analyses. Trending mobile behaviors through time can help analysts identify and characterize shifts in how smartphone owners are using their devices. Researchers might monitor the use of social networking applications across a series of months to examine the rate at which social networking usage is growing for a specific segment of the smartphone owner population. Researchers may track the amount of time spent using news and information applications during a specific period of time where a real world event such as natural disaster or economic crisis occurs.

Given the relatively new nature of mobile measurement, even in isolation mobile data is valuable. However, when mobile data is combined with more traditional consumer brand and attitudinal data from the same individuals the value of this combined data set increases exponentially. The ability to be able to profile or "color" these smartphone owners in terms of the types and brands of products they purchase, the other kinds of media they consume and their personal lifestyle and attitudinal descriptors provides researchers and marketers with the ability to understand much more succinctly the mobile behaviors of their customers. Additionally, in situations where the consumer database being matched on a respondent basis has self-report information concerning mobile behavior, researchers can evaluate differences between self-reported and passively collected transactional data to see how well self-reported mobile data corresponds to metered behaviors.

Finally, mobile metrics may also be enhanced by linked consumer databases that contain already existing and more complex analytics such as segmentation systems. Thus the smartphone owner universe could be divided into many useful consumer segments such as shopper type, health and image, investment and other consumer-based segmentation systems. Thus specific segments of consumers with smartphones can be specifically targeted and appropriate messages developed for each segment. In addition, consumer-based data could be utilized in conjunction with mobile behavior data as concurrent drivers to develop new unique segmentation systems that could not be constructed without having the mobile data available to help shape the segmentation system.

Finally, at the top of the heuristic pyramid are new and novel application strategies for mobile metrics, especially those that are enhanced with traditional consumer variables. One scenario involves the application of these metrics in real-time for location-based advertising. As consumers transit near retail store locations, adservers could detect their proximity to the retail store, identify the consumer by characteristics or segment and deploy an advertising message or alert to the consumer that might contain information about a sale or a coupon code that could be redeemed for a discount or free item at the store for example. Once a good understanding of mobile metrics and how they may be usefully enhanced is gained, there appear to be a large number of new opportunities for marketers to utilize this information.

Several Examples of Mobile Measurement Issues

There is sometimes the temptation to assume that the replacement of self-reported data with passively collected data eliminates most of the measurement problems one will encounter when collecting behavioral data, but often passive data collection strategies bring with them a whole new set of measurement issues, as was the case with set top box metering systems for television viewing. Some of the issues that arose from the set top box measurement revolution remain to plague passive measurement in the mobile device environment.

A good example of that is the problem we label the "pocketful of measurement" problem. Most mobile measurement monitoring applications are applications themselves and as such usually can only record basic activities such as the opening of a user application, the duration for which that user application is open and the time that the application is closed. One scenario where this poses a problem is when a smartphone owner opens an application, uses that application and then puts their smartphone back in their pocket or purse without closing the user application. As far as the monitoring application is concerned, the user application was opened and is still open and being used because it has not yet been closed. Eventually the user will reach into their pocket or purse, pull out their smartphone and close the application, perhaps to open another application or they notice that the original application is still open and continue to use it. This results in unusually long duration times for user applications. The issue then becomes what was the duration of time when the application was truly being used by the smartphone owner. In most cases, only the time that the user actively interacted with the user application should probably be counted as time using the application. However, because the monitoring application often cannot readily determine when the app was not actively being used[2] there is the dilemma of determining what to do with these longer duration events.

Another measurement issue is intertwined with the technical characteristics of multi-tasking on smartphones. Many monitoring applications only record data for applications that are considered foreground applications. That is, smartphones can have several user applications open at once, one of which usually sits in foreground and is actively being used by the smartphone user and where all of the application's features and communications are available. Other user applications may also be open but they are in the background and so while technically still open they generally have no or limited functions running. Tombstoning is one of the the technical terms often used for user applications running in the background of a smartphone. The background application is usually swapped out of memory and is frozen until it is brought back to the foreground by the user. Even still, for some mobile platforms, background applications have some services such as geolocation, music play or active phone connection running even while in background. This means that these background applications generate IP traffic that the monitoring application will pick up and record. However, because the owner is generally not using or interacting with the background application, the researcher is likely not to want to count that data in their analyses of human smartphone behaviors. The trick is discriminating between traffic that is generated by human actions from traffic generated either by background applications or by foreground applications without human assistance or direct control.

This issue can be even further complicated by the fact that a few applications that run in the background are actually in use – so-called "phone nannies" that track the geolocation of children for their parents. So this type of application not only runs in background but is also being used not by the smartphone user but by another individual or individuals (e.g. the parents). As smartphones come to have more true multi-tasking capabilities, this kind of measurement dilemma is only going to get more difficult.

Privacy Issues and Mobile Measurement

[2] Most monitoring applications cannot measure many user input moves such as touching an option inside an application or determine whether or not IP traffic generated by the application was generated by the user or automatically by the application.

The issue of privacy is a key element in the measurement of mobile behavior. Recent congressional hearings (Empson, 2011) involving major technology players such as Apple and Google reveal that mobile privacy has become an important issue to the American public. A recent Nielsen survey (2011) revealed that 59% of women and 52% of men felt that location-based information collected by smartphones was a privacy concern. In June of 2011 GroupM was the first major advertising agency to adopt privacy policies for mobile phone data (Bachman, 2011).

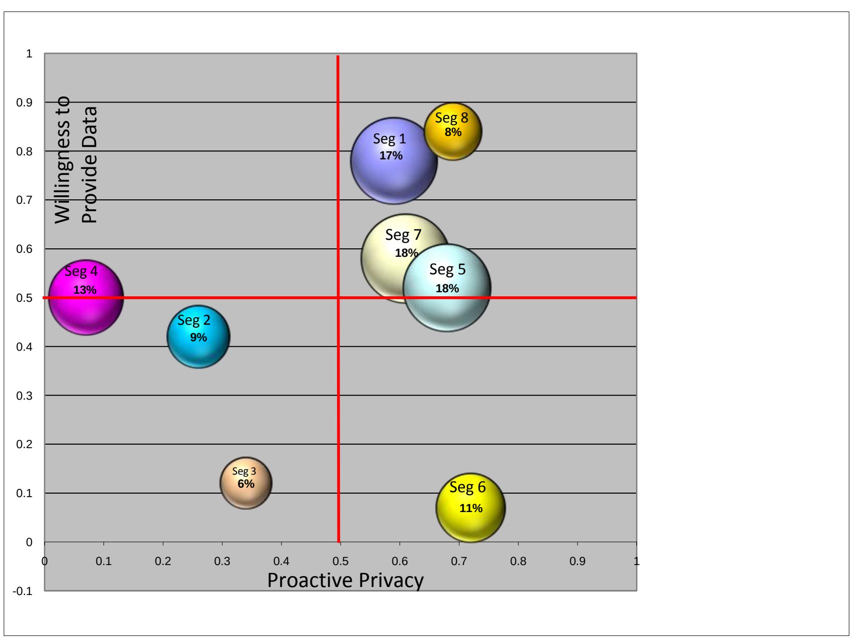
The issue of consumer privacy is a complex one that contains a number of competing dimensions. Often there is a gap between what individuals say they will do in protecting their privacy and what they actually do. This gap tends to narrow when the individual has a negative experience concerning the privacy of some of their personal information. According to the most recent estimates from the National Consumer Study (Simmons, 2010), approximately 13.5% of individuals have experienced some negative experience because of online information about them.

Do negative privacy experiences seem to affect an individual's propensity to exchange personal information for something of value? The answer turns out to be rather surprising. Over 57% of respondents who agreed that they had experienced a situation where online information about them had negative consequences for them also agreed that they would be willing to provide some personal information to a company in order to get something that they want. Conversely, about 46.4% of the respondents who disagreed with the statement that they had experienced a situation where online information had negative consequences for them agreed they would be willing to provide some personal information to a company in order to get something they wanted (Simmons, 2010).

Why would people who have had a negative experience be more willing to trade information in exchange for something they wanted? Perhaps as the research literature suggests, these individuals are taking a more proactive stance towards the privacy and personal information and so feel that they are more in control of the situation, thus being in a better position to understand the risks and intelligently exchange information for something that they want. Some preliminary analyses on respondent level unweighted data seems to bear this out. A principle components factor analysis of some of the early privacy data from Simmons National Consumer Study extracted five factors including 1) proactive control of privacy and 2) willingness to trust companies and trade information in exchange for something of value. A k-means bracketed clustering analysis was performed using the two aforementioned factors and the result was an 8-cluster solution pictured in Figure 2 below.

Figure 2

Preliminary Privacy Segmentation



Note in the upper right quadrant that segments 8, 1 and 7 contain individuals who are above average in terms of being proactive about privacy but at the same time are also more willing than average to provide data in exchange for something of value that they want. The stereotypical expectation here would be that the majority of the segments would appear in the lower right hand quadrant where individuals who are concerned about privacy would also be reluctant to give out personal information. However, only segment 6 seems to fit this stereotype. It turns out that the majority of the segments (43% of unweighted respondents) live somewhere in the upper right-hand quadrant and a good portion of segment 5 also resides in that quadrant as well.

What does this mean for researchers in general and mobile researchers specifically? It suggests that people are in fact willing to part with personal information about themselves as long as there is some sort of exchange for something of value that they want. This is pretty good news indeed, especially considering the level of detailed data that mobile researchers are likely to collect. Will this trend be sustainable? The answer is not readily apparent. While the unobtrusive nature of passive mobile measurement adds to the probability that current attitudes may prevail for some time, there are other factors that may make the public more aware of mobile information privacy.

One of these factors is the emergence of mobile malware. Similar to the malware problems currently plaguing personal computers, cybercriminals have realized the value of mobile data particularly in the mobile banking arena and they are turning to writing malware for mobile platforms (McAffee, 2011). As the threat to mobile devices continues to gain momentum, people are going to become more and more wary of installing applications on their mobile devices – especially ones that collect personal data. As this reluctance grows, the difficulties of researchers who want to collect passive mobile behaviors are going to multiply.

Mobile Pilot Study Design

The mobile measurement pilot study was a small scale study conducted during the period March 16, 2011 to July 10, 2011. The sampling universe was any respondent recruited from the Summer 2010 12 month and Fall 2010 3 month National Consumer Studies (NCS). In order to qualify for the study after contact, the respondent had to indicate that they had a mobile phone that contained at least one of features that the research team had a priori determined would qualify a mobile phone as a smartphone and some sort of mobile data plan. Due to the limitations of the passive mobile monitoring application, only the following mobile platforms were eligible for the study:

- iPhone 3GS and Iphone 4
    - iOS 4.2 and later
- Android phone
    - OS version 1.6 and later
- Blackberry RIM
    - OS versions 5 and 6
- Symbian
    - S60 Version 3.0 and later

Both NCS RDD and address sampling frames were used to ensure that cell phone only households had a positive probability of being selected into the sample. The sample itself was divided by Hispanic ethnicity as well as low yield/high yield criteria into nine separate stratum. The Hispanic ethnicity variable was used to divide respondents into English versus Spanish language recruitment treatments. The yield variable was divided into low yield strata that did not take into account the likelihood of owning a smartphone while the high probability strata utilized a statistical algorithm to identify individuals who were likely to have a smartphone using features self-reported by the respondent in the NCS.

Recruitment for the panel paralleled what a normal panel might experience with panelists recruited through most of the study period before being cutoff about 4 weeks before the end of the study. Traditional panel mortality was also observed for this small panel. Once panel recruitment reached full engagement approximately 4 weeks after the start of the study, the average number of respondents in the pilot study on any given day was 46. Note that there were somewhat more respondents registered for the study but not all respondents had their mobile phones powered on continuously during any given time period. The distribution of active registered respondents across the various mobile platforms was 25.4% iPhone, 44.2% Android, 28.9% Blackberry RIM and 1.5% Symbian.

The small number of respondents meant that any comparisons that focused at the basic unit of the respondent would be tentative at best due to the small sample size. However, when the unit of analysis focuses on finer resolution behaviors such as individual occurrences of application use, voice calls, sms messages and web browsing and other mobile behaviors, there are a significantly larger number of observations that can be utilized for analysis purposes. For example, across the study time period and across all respondents there were approximately 146,000 instances where a mobile application was opened. While this is not an ideal tradeoff because within respondent variation may outweigh between respondent variation, it is still a reasonable compromise for exploratory purposes. Additionally, it should also be noted that the data presented here is unweighted due to the small size of the pilot and the results should be interpreted as exploratory in nature and with some caution.

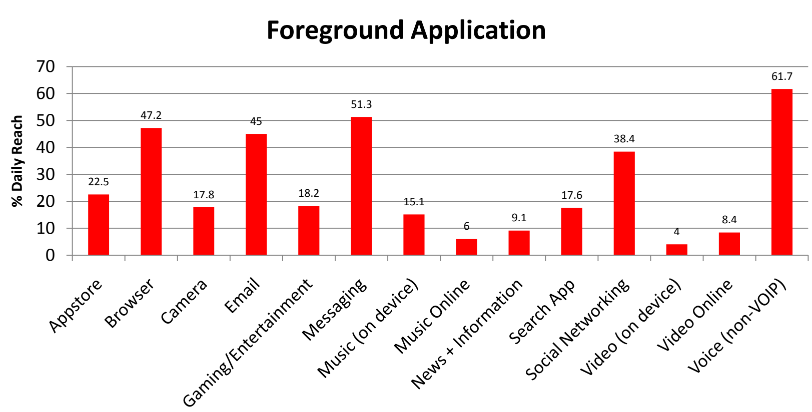
Mobile Typical Day Descriptive Analysis

Typical Day Reach Analysis by Type of Activity

As discussed in the previous section, reach is one of the fundamental metrics for advertising in general and for mobile media in particular. One of the main mechanisms by which advertisers can reach mobile consumers is advertising within a mobile application. Consequently, the magnitude of reach achieved by different types of applications is one of the important factors in deciding where to place mobile advertising. Figure 3 below displays the average percentage daily reach across the pilot study field period for each of a number of key types of applications.

Figure 3

Average Daily Reach By Application



Opening a voice calling application (generally a native app on the mobile phone) has the highest daily reach as one might expect given that a mobile phone's primary function (at least for the moment) is voice communications. This is followed by messaging second and launching a web browser application third. The base for calculating reach is determined by the number of phones in the study during that particular day. Mobile phones are often temporarily turned off for all sorts of reasons – the battery runs down, the respondent does not want to be contacted, the respondent is anxious about having their location recorded by mobile systems, etc. Thus the actual number of individuals reached is going to vary according to these and other factors.

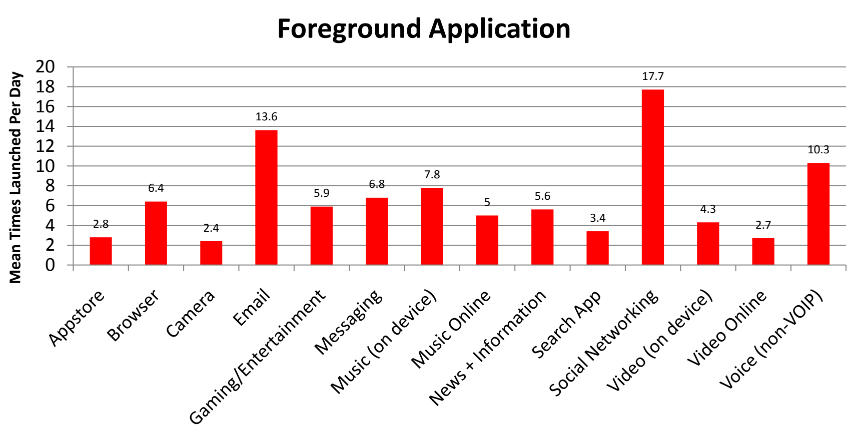
Notice the high levels of social networking occurring on mobile devices as indicated by the fact that on average 38.4% of respondents opened some sort of social networking application at least once during a 24 hour period. Social networking has shown some promise as an advertising channel and it is clear from the data that reaching an audience on a mobile platform can reach a considerable number of people. Interestingly, over one out of five respondents opened the application store on any given day – suggesting that people have a strong interest in searching out and potentially acquiring new applications. Relevant to print publishers pushing content from their titles onto the web, 9.1% of individuals on average launched a news and information application in a given day. This is a non-trivial reach number and perhaps suggests that print publishers may want to further investigate mobile media channels as part of their strategy.

Typical Day Frequency Analysis by Type of Activity

The second foundational mobile and traditional metric is frequency. The question becomes, if someone launched a specific type of mobile application at least once, how many additional times on average during a typical day did they launch that kind of application? Figure 4 below reveals the average daily frequency for opening an application by type across the study time period.

Figure 4

Average Frequency of Launch by Application



One application that is launched often as one might expect is a voice call application with 10.3 launches per day. Assuming that one call is made or received when the application is launched[3] this works to about 310 phone calls per month. Even though this is an unweighted estimate, this compares favorably to recent Pew estimates (Pew, 2010) that on average five mobile calls are made and five calls received on a mobile phone during a typical day.

Notice that social networking has the highest average frequency per day of being launched. That is, if an individual chooses to use social networking from their mobile phone, the application is launched an average of 17.7 times during the day. One of the reasons that this frequency is so high is due to the nature of social networking, especially networking applications such as twitter, where there are often multiple short bursts of messages often from large personal social network throughout the day. Similarly, an email application is launched on average 13.6 times per day, suggesting that individuals are checking their email

[3] Making the simplifying assumption that the number of times multiple calls are made per application launch somewhat cancel out the number of times the application is launched without making a call

on a regular basis, perhaps when they are notified by the mobile device of incoming email traffic. The pattern of frequent application launches is one that makes reasonably good sense given that these applications are communications driven and the primary function of the smartphone is mobile communications.

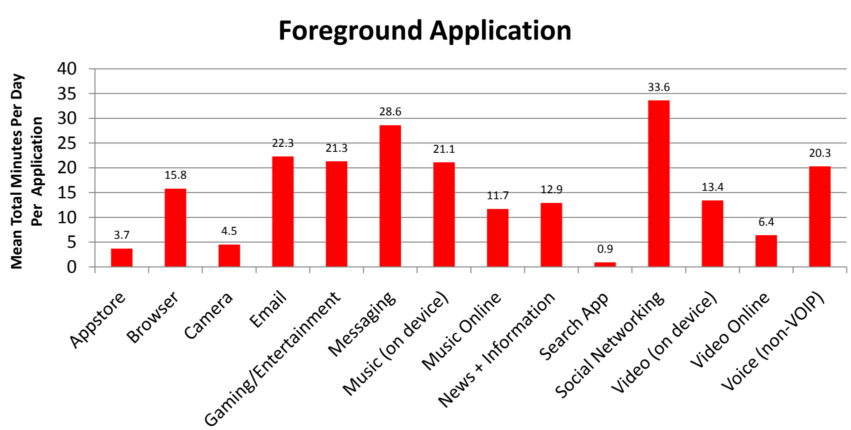
Many mobile phone users are also looking for content and information. A person who uses a web browser during their daily activities is on average likely to launch the web browser over 6 times a day while those seeking news and information content using their mobile phone on average launches a news and information application 5 times day. Looking at the frequencies in Figure 4 and keeping in mind the exploratory nature of the pilot study, one nevertheless is struck by the frequency with which an individual uses their mobile phone applications for a particular purpose, given that they are inclined to launch a specific type of mobile application.

Typical Day Duration[4] Analysis by Type of Activity

Once a mobile application is open, the amount of time that the person spends using that application can vary widely, often depending upon the type of application that is launched. As with other media channels, the longer the individual is exposed to a particular channel, the larger the opportunity to see advertising embedded in the channel content.

Figure 5

Average Daily Duration of Launch by Application



Looking at Figure 5 above, on any given day that a respondent launched a social networking application one or more times, they spent on average a total of 33.6 minutes using those social networking applications during that day. Surprisingly, the total duration for social networking exceeds the total average time that an individual spends with a voice call application open[5]. Combining this relative higher duration level with the higher frequency and probability of interfacing with a social networking application, it can be appreciated how significant the role of social networking plays in mobile behavior and marketers may be well advised to focus their attention in this area.

[4] The "pocket full of measurement" issue here was addressed by making the assumption that typically no mobile application would be open and actively used for more than 1 hour. Approximately 0.5% of the duration data was effectively assigned the mean duration for that application to adjust for this phenomenon.

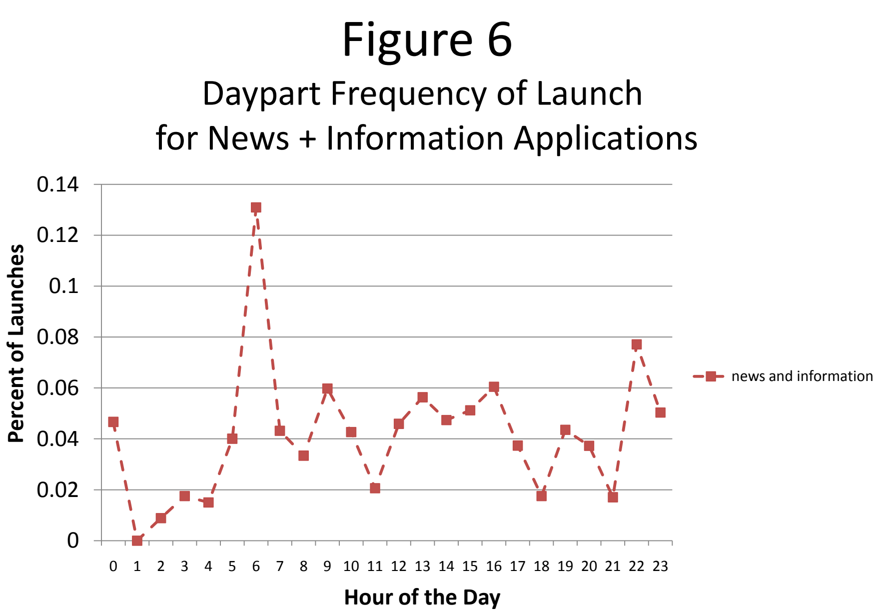
[5] Note that this is not the total number of minutes spent on voice calls, rather it indicates the total amount of time spent with the voice application open.

A close second is the messaging application category where if the respondent opened a messaging application at least once that day, they spent an average of 28.6 minutes during the day where the message application(s) were open. Similarly, if the respondent opened an email application at least once that day, they spent an average of 22.3 minutes during the day with an email application open. This pattern of higher use of communications applications makes sense as it did in the previous frequency analysis given the primary purpose of the mobile phone as a communications device.

In terms of commercial content, it can be seen that there are non-trivial total mean duration times per day for both music and video consumption – people are indeed using their mobile phones as media playing devices. In addition as one might expect given the current pricing model of charging by the gigabyte by mobile carriers for data transmission, more minutes are consumed by respondents for music (21.1) and video (13.4) physically present on the mobile phone than is the case for obtaining these media directly online through streaming (online music 11.7 and online video 6.4 minutes respectively). Finally, if respondents launched a news and information application one or more times during the day, they spent an average of 12.9 minutes with that type of application open across the day.

Daypart Decomposition by Type of Activity and Duration of Activity

Mobile behavior can also be decomposed into behaviors on a hour by hour basis. The time of day likely has an effect on how many and what kind of mobile applications are launched. Communications and news/information gathering likely follows diurnal cycles and because mobile phones are often with us even when we sleep (Pew, 2010), understanding patterns when specific types of applications may be launched could be useful to marketers.



In Figure 6 above, we see a rather logical pattern in terms of mobile launch frequencies by hour of the day. The vertical axis on the chart represents the percentage of the specific application type launched during that hour aggregated across all respondents and across the entire pilot study time period.

When do respondents look for news, information and other types of content that might be relevant to print publishers pushing their content onto the web? First of all, the number of launches indicated in the chart follow a reasonable path that coincides with human sleep and work patterns. Again looking at Figure 6, we can see that a noticeable spike in news and information application launches occur during the early morning hours, which makes reasonable sense because individuals are likely looking for news that happened overnight or information that will be helpful in their upcoming day . A much smaller secondary spike occurs in the late evening hours as people made an effort to catch up on news of the day that occurred while they were busy with the day's activities. This pattern may suggest times of the day where peak mobile audiences for news and information typically sought after by magazine audiences may be found.

Mobile Behaviors and Magazine Attitudes

As the American consumer broadens their media consumption patterns into the mobile arena and print publishers push material onto mobile platforms in the effort to provide a richer medium in which to publish their content, it will be useful for magazine publishers to better understand where magazine receptive audiences are spending their time on mobile platforms. This is especially true because magazine content and advertising pushed via mobile applications will have direct same-platform competition for time spent from other content-rich applications such as web browsing and online video. In addition, there will be competition for application face-time time on the mobile device from its primary functions as a communications device.

In this analysis we will use the average time that a specific type of mobile application is open to represent engagement in that the mobile platform – the longer on average the mobile application is open, the more engaged the respondent is assumed to be in the mobile platform when holding the type of mobile application constant. Respondents will generally be divided into three categories to conserve sample size within the data set. While the sample size in this pilot study precludes a more rigorous examination of this topic area that would include specific magazine titles, there are enough instances of application launches within the data set to provide an initial exploratory directional look into the relationship between magazine readership and mobile behaviors.

The first analysis looks at the relationship between mobile phone behavior (as measured by the time spent with a specific class of application) and the number of unique magazine titles screened into in the last six months. The three categories in the table represent either a low (1-6), medium (7-11) or high (12+) number of unique magazines screened by the respondent in the last 6 months.

Table 2

Unique Magazines Read by Mobile Application Duration

magcount		**Mean Seconds per App Launch**				
		Low (1-6)	**Medium (7-11)**	**High (12+)**	**Overall F**	**Overall prob**
Applications						
	Messaging	69.4^{2,3}	80.5^{1,3}	102.8^{1,2}	28.8	<.0001
	Email	117.6^{2,3}	220.3^{1,3}	148.7^{1,2}	28.0	<.0001
	Voice	103.2^{3}	96.5^{3}	148.3^{1,2}	37.4	<.0001
	Social network	74.7^{3}	77.7^{3}	98.2^{1,2}	6.7	.001
	Gaming	107.8	129.2^{3}	94.1^{2}	6.3	.002
	Browsing	131.1^{3}	146.0^{3}	285.9^{1,2}	54.6	<.0001
	Camera	72.3^{3}	70.1^{3}	130.5^{1,2}	4.5	.012
	Music	214.4^{3}	253.7^{3}	56.3^{1,2}	15.4	<.0001
	Online Music	28.3^{3}	69.5	115.7^{1}	11.7	<.0001

Table 2 presents the means and the results of a one-way anova analysis for each specific application listed. Because the exact nature of the relationship between these two types of variables is unclear, post-hoc Scheffé multiple-group comparison tests were utilized to compare the means across the groups[6].

When looking at the comparison between the low and high screener categories across the mobile application categories it can be seen that with the exception of gaming and music applications, high screening respondents have longer durations of application use than the low screening applications. This provides some initial evidence that there may be a somewhat positive relationship between the number of magazines screened and engagement in a particular type of mobile application. This is likely some positive news for magazine publishers who are wondering about the potential parasitic effects of providing some of their magazine content on another platform that perhaps might prove to be more engaging than traditional print magazines. It appears that these types of mobile applications may not in fact be attenuating traditional magazine readers but instead merely drawing them to another medium where they can consume additional content and information.

The difference in relationship direction for music and online music applications is an interesting exception here. One structural difference between the two types of mobile applications is that many mobile phone plans have data limits where additional transmitted data over those limits incur additional costs while music residing on the platform is downloaded only once and does not have that limitation. This perhaps may have something to do with the contradictory directional indications for these two types of mobile applications.

Another key characteristic of magazines readers is their propensity to read advertisements in magazines. Are individuals who are likely to read magazine advertisements also highly engaged in different types of mobile applications? Table 3 below provides a preliminary look at this question.

Table 3

Read Magazine Ads for Curiosity by Mobile Application Duration

magads		Mean Seconds per App Launch				
		Any Agree	Neither Agree/Disagree	Any Disagree	Overall F	Overall prob
Communications						
	Messaging	112.9^{2,3}	55.7^{1,3}	137.4^{1,2}	141.0	<.0001
	Email	453.2^{2,3}	242.4^{1,3}	69.2^{1,2}	199.1	<.0001
	Voice	88.8^{2,3}	106.7^{1,3}	125.0^{1,2}	14.4	<.0001
Comm/Content Blend						
	Social Network	186.6^{2,3}	80.2^{1}	92.9^{1}	34.3	<.0001
Content						
	Browsing	104.6^{3}	80.9^{3}	261.1^{1,2}	63.3	<.0001

The question from the National Consumer Study reads "I often read ads in magazines out of curiosity". The mobile applications themselves are grouped into three different types: communications, content and applications that blend the two dimensions in a taxonomy similar to Stafford, Stafford and Schkade (2004). For two of the three mobile communications applications, individuals who agreed to this statement had shorter durations for voice call applications and messaging applications being open. This may imply that mobile smartphone users who are using the device primarily for immediate

[6] The subscripts attached to the means indicate for which means the Scheffé tests were statistically significant at the $p < .05$ level. The number indicates the first, second or third column mean was compared against the annotated mean and found to be statistically significant for that particular comparison.

communications may be less visually and content focused than those who are using some of the smartphone's richer contextual and visual features. For mobile email applications, the mean duration for having that type of application open is significantly longer for those who agree with the question than those that disagree, suggesting that those mobile phone users who are more engaged in reading email are also more receptive to magazine advertisements. Perhaps it is the common mode of communications between email and magazine advertisement – that is reading – that provides the positive correlation between reading magazine advertisements and engagement in mobile email applications.

Interestingly, comparing the time spent on web browsing reveals that those that are more engaged in mobile web browsing are less likely to read magazine ads out of curiosity. One potential explanation might be that their experiences with more interactive advertisements on the web may be attenuating their propensity to read advertisements in magazines. Simola et al (2011) found that animations in web-based advertisements disrupted reading the content on websites – it may be possible that individuals who experience these distracting online advertising effects may then go on to be less likely to read advertisements in another medium such as magazines.

Finally, the preliminary data from the pilot study suggests that individuals who are more engaged in mobile social networking applications are more likely to read magazine advertisements out of curiosity. A link between curiosity in advertising and social networks as suggested by Garg et al (2009) may be part of the explanation. Social networks may help satisfy an individual's need to find out more about people they know and this general trait of curiosity about the world around them may extend to reading magazine advertisements as well.

Comparison of Actual Versus Self-Reported Mobile Behavior

One of the useful consequences of utilizing respondents from a large syndicated mail study for a mobile panel is the opportunity to compare actual metered behavior versus self-reported data in the mail study. While the sample sizes for the pilot preclude any sort of conclusive comparison, it is still instructive to briefly examine and compare meter versus self-report behaviors.

Table 4 represents an analysis of data from the National Consumer Study question "The extra features of my cell phone are more important than traditional calling features" against actual metered behaviors of these individuals. Individuals who agree that the extra features of their mobile phone are more important than traditional calling features should spend more time using these extra features than those individuals who do not think they are as important.

Table 4

Using Smartphone Extra Features Compared to Traditional Voice

Tradcell		**Mean Seconds per App Launch**				
		Any Agree	**Neither Agree/Disagree**	**Any Disagree**	**Overall F**	**Overall prob**
New Features						
	Messaging	$125.8^{2,3}$	$59.9^{1,3}$	$90.3^{1,2}$	112.6	<.0001
	Email	97.2^{3}	102.9^{3}	$201.6^{1,2}$	41.5	<.0001
	Browsing	172.8^{2}	$353.3^{1,3}$	152.8^{2}	69.7	<.0001
Traditional Voice						
	Voice	107.1^{2}	$70.4^{1,3}$	129.2^{2}	19.9	<.0001

When it comes to forms of messaging (instant messaging, SMS, MMS messaging) the hypothesized relationship is there – individuals who agree with the statement that the extra features of their cell phone are more important than traditional calling features do spend more time on average than those who disagree with the statement. Conversely, respondents who spend more time on their mobile phone on voice calling applications are more likely to disagree with the mail based importance question. These two results support the initial hypothesis that self-report and metered measures are correlated.

The data for web browsing applications, while in the correct direction is inconclusive because the comparison was not statistically significant (p=.63). When more sample is available, rerunning this analysis may provide a more definitive answer. Finally, looking at email application mobile behavior, a result opposite to that expected is observed. Individuals who disagree that the extra features of their cell phone are more important than traditional calling have longer duration times for mobile email applications than those that agree with the statement. It is unclear from the data why this might be the case. Perhaps it is because these individuals are also not regular email users in the personal computer-based environment that we find this to be case. More investigation is warranted here to ascertain whether or not this is the case. However, in summary, the evidence here finds that there is some partial support for the correlation between actual metered mobile behavior and self-reported data concerning the same types of activity.

Summary

The objective of this paper was to present and discuss some of the methodological issues and challenges present in the emerging area of mobile measurement as well as examine several audience issues that magazine publishers may face in pushing their content to mobile phone platforms. As print publishers migrate their content to mobile platforms they face new challenges in terms of same-platform competition from mobile applications that provide content such as mobile web browser applications as well as from other types of applications such as social networking applications that may be taking time spent opportunities away from mobile magazine consumption. As a follow up to this pilot study, a much larger research program is being undertaken. Data from this study will provide significantly more insight into the linkages between traditional media such as magazines and newspapers and mobile phone behaviors.

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