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Cross Platform Media Measurement: Mobile and Desktop Online Measurement Comparisons

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Introduction

Understanding cross-platform media behavior is essential to marketers as consumers increasingly use multiple media devices – PC, Mobile, TV – sometimes simultaneously. In response, measurement science – the juxtaposition of high quality survey based research with massive scale, highly granular, passively measured media behavior - has attempted to advance research methodologies to keep pace with digital consumers. While passive measurement has helped capture the full scope of consumers' online behavior, the insights gleaned are only as good as the data captured. Incomplete or inaccurate data may significantly contaminate research studies with implications that may prevent marketers from delivering their product at the right time, in the right way, or to the right people. In this paper, we describe, compare, and analyze active and passive measurement of online behavior that researchers use to understand the ever-evolving digital media landscape. Online measurement may be used directly, or increasingly, within data integration or fusion projects, but in both cases, data quality is important. We provide unique insight into the efficacy and differences between passively and actively collected online behavior because we can directly compare stated versus observed behavior from the same respondents, albeit at different times. The paper begins with background on passive and active measurement in measurement science, a description of the methodological approach, followed by a discussion of the results and implications for future research.

Measurement Science, Active and Passive Measurement

The collection of media and consumer behavior data has a long history, but can be described succinctly as having two key components: active (or stated, self-reported) and passive (or revealed) measurement of behavior, product consumption, brand preferences and attitudes, and more. Generally, media consumption can be measured by asking respondents which media they use over some reasonable time frame for recall, for example, in the past week. Such general media usage data can be used to estimate duplication levels. However, when media measurement requires more granular detail, and in the case of online media, more fragmented and difficult for respondents to accurately recall behavior over even short time periods, active data collection reaches its limits (see Pellegrini, 2005). Measuring attitudes and preferences, including past behaviors and future intentions, requires a more nuanced measurement approach with carefully selected and fielded survey questions to statistically reliable samples. Single source survey measurement of media exposure and purchase and consumption variables is attractive because of the obvious link to a single person, but sample size and respondent fatigue limits the efficacy of such surveys.

For measurement scientists, however, understanding how to bring together active and passive media measurement is paramount in linking deep attitudinal and brand preference survey data with either actively or passively collected media consumption data. In the absence of reliable single source measurement, methodological developments in the integration of disparate media and consumer databases make such strategies more attractive to marketers. Beyond standard data integration variables like demographic characteristics and other factual variables, actual media behavior linkage variables add significant quality to statistical fusions, data integrations and data imputation exercises (Chan, Pellegrini and Whithers, 2011). Stanglein and Protheroe (2012) examined the impact of contaminated exposure group due to reporting differences across passive and active measurement sources looking at TV opportunity to see data collection. In their study, the measure of 'true' TV advertising exposure was a metered panel, with data fusion, survey recall with imputation, TV viewing habits data and finally advertising recall studies offering scalable proxies, potentially, if the level of error related to misclassifying TV exposure was deemed reasonable. Interestingly, all four methodologies that blended active and passive recall of TV exposure contained levels of recall error that would significantly impact the interpretation of advertising effectiveness studies.

Active measurement

Active measurement, whereby a respondent is asked to answer a series of questions by recalling their media activity, has long been considered the definitive methodological approach to collecting consumers' media consumption and behavior. With the increasing popularity of personal digital devices, active measurement remains popular: fully forty percent of journal articles found through the 2013 Social Science Citation Index include at least one self-report (*i.e.,* active) measure regarding frequency of mobile use (Boase and Ling 2013). So long as respondents are willing to participate in self-reported studies, active measurement methodologies will endure but their limitations must be understood clearly to ensure high quality data.

The challenges and strategies to mitigate the limitations of recall are well known (see Kilger and Boals, 2012). In response to a respondent's failed memory, for example, memory-jogging tools can be designed to reduce recall error. Of course, in this scenario the risk of "recall bias," or a false positive, remains. What about respondents who under- or over-report certain behavior in view of what they perceive to be socially desirable? This problem is more difficult because other than admonishing respondents to be truthful and giving them the promise of anonymity and/or confidentiality, there are virtually no tools that the researcher can employ to facilitate—much less guarantee—accurate information. For example, one recent study revealed that 81% of 18- to 24-years-old college students over-reported the number of text messages they sent in a day (Gold and Rauscher 2015). One explanatory theory is that college students see the frequent usage of a smartphone as a marker of popularity or, in other words, that college students perceive text-based communications to be "cool." This type of misdirection, conscious or otherwise, is a consequence of active measurement, and can directly impact data quality.

Passive measurement

Passive measurement has evolved and improved over the recent past. Examples of various passive measurement approaches include 'natural' data streams from TV home set top box (STB) data collecting return path data passively, through to set top TV meters using audio encoding or matching technology to passively collect TV exposure in longitudinal measurement panels, and radio frequency technology (RFID) for the purpose of passively collecting magazine readership within a cross sectional survey. In comparison to active measurement, passive measurement has become the preferred methodological approach to collecting cross-platform online behaviors due to the reliability and accuracy of the data as well as its ability to offset respondents' increasing reluctance to participate in studies that require active participation.

One of the biggest challenges in passive measurement is that the technical environment associated with Smartphones and Tablets is evolving at a rapid pace and that change continues to accelerate. Device makes and models, their corresponding operating systems and capabilities are changing at such a rapid pace it is not unusual that multiple upgrades and updates are available within the same year. One of the consequences of this rapidly changing landscape is that passive technology agents designed to collect behaviors such as data frequency, reach, and duration of mobile device and PC activities quickly become outdated. This can result in trending issues from one season to the next. For example, a dataset that once included text message frequency for mobile may now be limited to text message duration due to security features a device manufacturer has now implemented in its operating system. Even with these obstacles, passive measurement technology has supplemented or replaced active measurement in the field of cross-platform media studies.

Study Objectives

Using data from the Experian Marketing Services' self-reported (i.e., active) Simmons National Consumer Study (NCS) and Experian's Simmons Connect digital research panel (i.e., passive), this paper examines reporting and measurement differences between active and passive data collection methodologies. Specifically, this research looks at the following questions:

1. Does revealed respondent behavior align with their reported behavior from recall surveys?
2. Is stated recall more reliable when the activities conducted are more frequent?
3. Among those respondents that "say what they do, do what they say", do we see any demographic differences across measures?
4. When should researchers use active data as a supplement to passive data?

The present paper is limited to the first two questions with a discussion on future research directions to look at the final two questions.

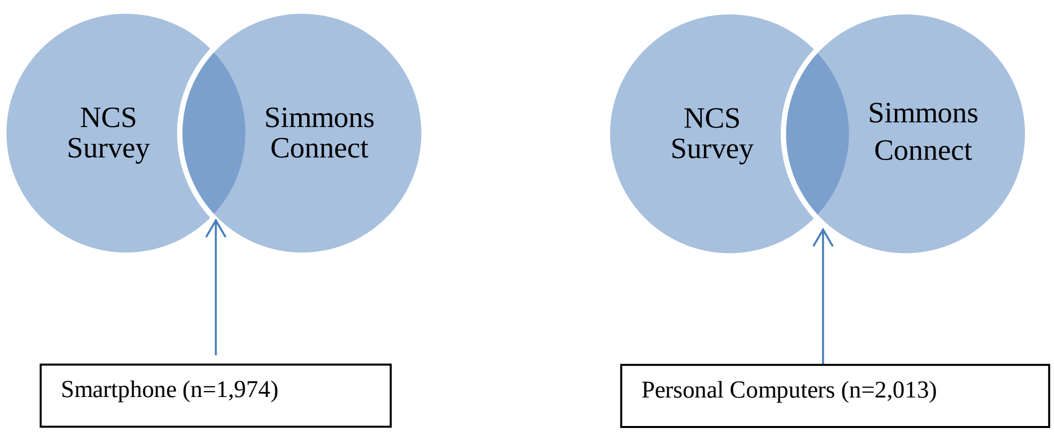
Methodology

Two datasets are used in this analysis. The first is from the nationally representative survey, Simmons National Consumer Study (NCS). Annually, the NCS is a survey of 25,000 adults in the continental United States that measures consumer lifestyles, attitudes, behaviors, and brand preferences, among other things in a given wave. The data is from a cross-sectional probability sample of the US population, continuous data collection and is released on a quarterly basis. In this paper, data for the national sample of adults 18 years and older were derived from a sample of respondents in the continental United States, collected from August of 2013 through March of 2015. The data oversamples telephone exchanges for high income and Hispanic households; however no weighting adjustments will be applied to adjust for the oversample. For the purposes of this paper, data collected from the NCS is the active data.

The second dataset comes from a subsample of the respondents who completed the NCS survey, whose households became in-tab, and who joined the digital research panel, Simmons Connect. Simmons Connect is a media profiling and planning tool that links the NCS active data elements to the digital behaviors of opt-in panelists on different devices. The panelists who join the opt-in digital research panel install a passive measurement application on their mobile (smartphone and/or tablet) devices and/or personal computers that collects website visitation and application usage without any active requirements from the panelist other than installing the application on their devices after joining the panel. Passive measures among smartphone and personal computer at home users were captured from January of 2014 through July of 2015, in order to most closely align a panelist's passive data with the date of entry into the NCS survey. For example, a panelist who returned their survey booklet in January 2014 and subsequently became a member of the Simmons Connect panel in February 2014 would have eligible passive activity for this analysis in our January – March 2014 collection period for Simmons Connect. We chose to align our passive and active data in this manner so that we could most closely reflect the time period a panelist was asked to recall when filling out their survey booklet.

The base for comparison of these two datasets is the digital activities of the panelists. There are 1,974 Simmons Connect cell phone panelists who had actively indicated mobile (smartphone) usage in the last 30 days in the NCS survey. Similarly, there are 2,013 personal computer users who had indicated personal computer usage at home in the last 30 days (see Figure 1). The Simmons Connect panel only recruits respondents who indicated that they used a device that connects to the internet in the last 30 days.

Figure 1: Intersection of NCS respondents and Simmons Connect Smartphone and PC users.



Active Measures – Applications

In the survey, there are a series of screening or gate questions that determine if the respondent will be asked to answer additional questions in that section. The respondents are asked if they have used an application (a defined term) in the last 30 days (Figure 2).

Figure 2: Application usage gate question

APPS FOR CELL PHONES/ SMARTPHONES OR TABLETS

An app is a software application that you use on a cell phone/ smartphone or tablet.

Have you used any apps in the last 30 days?

	Yes	No
	☐	☐

If respondents check "yes" they are then guided to answer a subset of questions related to what "types of applications" they used in the last 30 days on their Smartphone. These are categories of applications, not specific applications. It is unknown if the respondent is going through the "type of applications" in the booklet sequentially, attempting to recall websites visited within each category, or recalling websites they visited within the last 30 days and then categorizing them under the list of "types of applications." While it may be easier for a respondent to recall specific websites they visited in the last 30 days as a first step, the latter approach which involves categorizing them under "types of applications" requires an extra cognitive process. This is an area of further research at Experian Marketing Services. In Figure 3, we see the categories for the applications asked in the booklet. Self-reported variables for application usage were coded to 1 indicating usage or 0 representing a lack of usage.

Figure 3: Application categories by Type asked in the NCS.

IF YES

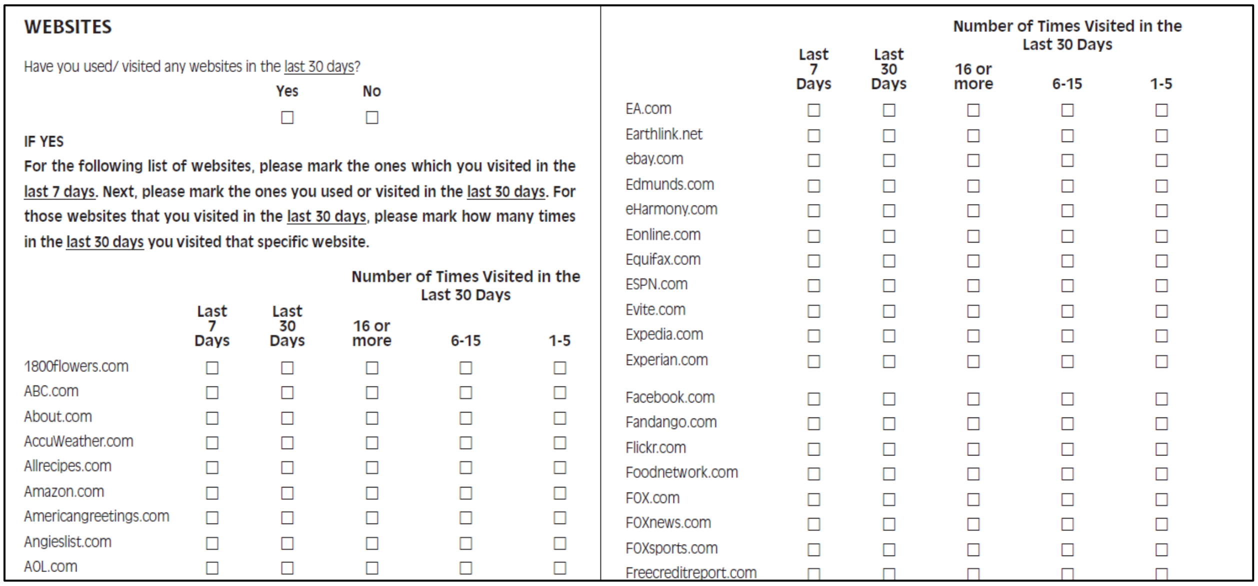
Which type of apps have you used on either a cell phone/ smartphone or tablet in the last 30 days?

	Used on Cell Phone/ Smartphone	Used on Tablet
Banking/ Finance	☐	☐
Books	☐	☐
Magazines	☐	☐
Newspapers	☐	☐
Daily Deals/ Coupons	☐	☐
Food/ Cooking/ Recipes	☐	☐
Games	☐	☐
Health & Fitness	☐	☐
Local Information	☐	☐
Maps/ Navigation	☐	☐
Movies	☐	☐
Music/ Radio	☐	☐
News	☐	☐
Photo/ Video	☐	☐
Search Tools	☐	☐
Shopping	☐	☐
Sports	☐	☐
Social Networking	☐	☐
Travel	☐	☐
TV Shows	☐	☐
Weather	☐	☐
Other types	☐	☐

Active Measures – Websites

Similar to the "application activities" question, a gate question is placed at the beginning of the question series which asks respondents if they visited a website in the last 30 days. If the respondent marks "yes" they are then asked to mark websites they visited in the last 7 and the last 30 days. Following this question, for each website in the booklet a frequency question is asked. A snippet from the survey booklet is shown in figure 4. Data in this analysis was limited to the last 30 day website visitation.

Figure 4: Websites visited.



WEBSITES

Have you used/ visited any websites in the last 30 days?

Yes ☐ No ☐

IF YES

For the following list of websites, please mark the ones which you visited in the last 7 days. Next, please mark the ones you used or visited in the last 30 days. For those websites that you visited in the last 30 days, please mark how many times in the last 30 days you visited that specific website.

	Last 7 Days	Last 30 Days	Number of Times Visited in the Last 30 Days: 16 or more	6-15	1-5
1800flowers.com	☐	☐	☐	☐	☐
ABC.com	☐	☐	☐	☐	☐
About.com	☐	☐	☐	☐	☐
AccuWeather.com	☐	☐	☐	☐	☐
Allrecipes.com	☐	☐	☐	☐	☐
Amazon.com	☐	☐	☐	☐	☐
Americangreetings.com	☐	☐	☐	☐	☐
Angieslist.com	☐	☐	☐	☐	☐
AOL.com	☐	☐	☐	☐	☐
EA.com	☐	☐	☐	☐	☐
Earthlink.net	☐	☐	☐	☐	☐
ebay.com	☐	☐	☐	☐	☐
Edmunds.com	☐	☐	☐	☐	☐
eHarmony.com	☐	☐	☐	☐	☐
Eonline.com	☐	☐	☐	☐	☐
Equifax.com	☐	☐	☐	☐	☐
ESPN.com	☐	☐	☐	☐	☐
Evite.com	☐	☐	☐	☐	☐
Expedia.com	☐	☐	☐	☐	☐
Experian.com	☐	☐	☐	☐	☐
Facebook.com	☐	☐	☐	☐	☐
Fandango.com	☐	☐	☐	☐	☐
Flickr.com	☐	☐	☐	☐	☐
Foodnetwork.com	☐	☐	☐	☐	☐
FOX.com	☐	☐	☐	☐	☐
FOXnews.com	☐	☐	☐	☐	☐
FOXsports.com	☐	☐	☐	☐	☐
Freecreditreport.com	☐	☐	☐	☐	☐

Passive Measure

Smartphone panelists were classified into 45 unique application categories and while PC panelists were classified based on websites activities. Simmons collects Android data based on a 10 second polling frequency and iOS and PC data in real time as web traffic is generated by the user.

Table 1 below provides the list of the 15 unique smartphone categories used for this analysis. To qualify, a category must have an incidence level of about 10% or higher for both active and passive data (a natural break in the data). Analyses for personal computers were limited to the websites that were displayed in the NCS booklet that met an incidence of level of about 10% or higher for both the active and passive data. This reduced the website analysis to 27 websites. The content of the websites varied between social media sites, weather, news, sports, and included websites for television and travel websites. Websites were grouped by category and website as shown in table 2. All passive behaviors were based on binary code of 1 indicating the presence of the behavior and 0 indicating that the behavior was not observed.

Table 1: Smartphone Passive Measure Applications

Business & Finance	Music & Audio Online	Shopping	Travel
Games	News & Media	Social Media	Video Online
Location Based Services	Photo	Sports	Weather
Maps	Search	Television Program Streams	

Table 2: Website Categories

Category	Digital Behavior	Category	Digital Behavior
Business & Finance	Paypal.com	Shopping & Classifieds	Amazon.com
Computers, Internet & Electronics	BestBuy.com		Coupons.com
Entertainment - Television & Movies	Netflix.com		Craigslist.org
Lifestyle- Home & Family	Allrecipes.com		Ebay.com
	Foodnetwork.com		Groupon.com
News & Weather	Weather.com	Social Networking, Video/Photo Sharing & Dating	Facebook.com
Reference- Education, Employment & Real Estate	WebMD.com		Linkedin.com
	Wikipedia.org		Pinterest.com
Search Engines & Portals	AOL.com		Twitter.com
	Ask.com		YouTube.com
	Bing.com	Sports	ESPN.com
	Google.com	Telecommunications	Verizon.com
	MSN.com	Travel	MapQuest.com
	Yahoo.com		

Analysis and Results

Demographic Profile of Smartphone Phone and PC Panel Sample

The NCS data in this paper draws across 6 survey "waves" or 18 months of data. Table 3 shows the Winter 2015 data (weighted to census population), 18 months of data for this study (unweighted), smartphone users and personal computer users. For comparative purposes the smartphone panelist and personal computer panelists will be made to the entire 18 month period. The demographic composition for Smartphone users is as follows; 73% Female, 56% are married, 34% have a college education, the mean age is 41.2 years, with 65% employed full-time or part-time. Those that entered into this study using a PC device 66% are Female, 56% are married, 34% have a college education, the mean age is 48.05 years and 55% are employed either full-time or part-time. The two sub populations will both be evaluated independently. While sample characteristics of each sub population do not mirror nationwide parameters; the intent of this paper is not to generalize results to the national population, but to examine the extent respondents self-report and behave in similar manners. Regardless of the device, in general the sub-population data compared to the NCS data over represents females (73% compared to 57% in NCS), the smartphone sub-population tends to be younger with the average age of 41.2 years old compared an average age of 49.6 in the NCS data file, while the personal computer average age is slightly lower with an average of 48.05 compared to 49.6 years. The smartphone Hispanic sub-population is at parity with NCS data, with the personal computer Hispanic sub-population, lower in comparison to the NCS dataset.

Table 3: Demographic Profile of Cell and PC Subpopulation: NCS Winter 2015

	Total	Smartphone Users	Personal Computer Users	NCS	Panel - Phone	Panel – PC @ Home
	233,984,893	152,015,731	169,251,709	41,174	1,974	2,013
Variables						
GENDER						
Male	48.2	47.5	47.5	43.2	27.4	33.7
Female	51.8	52.5	52.5	56.8	72.6	66.3
AGE						
18-24	12.1	14.8	12.7	9.0	9.3	6.6
25-34	17.3	21.9	17.8	13.0	25.4	15.5
35-44	16.8	20.7	18.3	16.1	27.4	20.0
45-54	18.2	19.2	19.0	19.9	21.1	21.8
55+	35.7	23.3	32.2	41.9	16.9	36.2
ETHNICITY						
Hispanic	15.6	16.0	12.7	30.6	28.9	23.4
Non-Hispanic	84.4	84.0	87.3	69.4	71.1	76.6
MARITAL STATUS						
% Married	53.2	55.0	55.9	58.6	55.6	56.1
PRESENCE OF CHILDREN						
Under Six Years	14.6	18.4	14.4	14.5	24.1	16.3
Six to Eleven Years	14.1	17.4	14.2	16.5	26.6	18.2
Twelve to Seventeen Years	14.1	17.1	14.5	17.3	23.2	18.2
EDUCATION						
High school graduate or less	42.1	34.2	32.7	41.2	30.1	30.1
Less than 1 yr college to 3 full yrs	28.9	31.8	31.4	28.1	35.7	35.6
College graduate or more	29.1	33.9	35.9	30.7	34.2	34.4
HOUSEHOLD INCOME						
Less than $35K	26.8	18.5	20.4	24.1	22.0	26.0
$35K LT $50K	12.5	11.1	11.4	13.2	13.1	14.0
$50K LT $75K	18.2	18.5	19.3	17.9	21.3	21.6
$75K LT $100K	13.6	15.9	15.1	13.4	13.8	14.1
$100K or more	28.8	35.9	33.8	31.4	29.8	24.4

In the following section, results are presented that examine the first two original research questions of self-reported versus passive measures for a Simmons Connect panelist. Recall that the first research question addresses whether respondents behave in the same way as they report they are behaving in traditional mail surveys, while the second looks at recall differences and frequency. This issue of reporting behavior differences is discussed for the smartphone subpopulation first, and then followed by a similar discussion for personal computer users.

Smartphone Results

Table 4 summarizes a number of key measures for Smartphone users' passive behavior relative to the active or self-report usage, including both self-reported and passive reach, the agreement rate between self-reported data and passive data when a panelist self-reports an activity (or 'active true' in column 2) and finally the agreement rate between self -reported and passive data when we see a panelist using a specific application category (or 'passive true' in column 4). Out of the 15 applications studied, the top three passive applications were Social Media applications, Maps and Navigation applications, and Video Online applications with incidence levels of 85.4%, 79.5%, and 76.6% respectively. In contrast, the top self-reported applications differ with six in every ten panelists reporting Weather applications (60.33%), slightly more than half (55.2%) indicating Map application usage followed closely by Games (52.6%). If there was strong agreement between recall and passive panelist behavior, we would expect the agreement columns (two and four, respectively) to contain percentages in the higher ranges, perhaps 70-95%. In fact, we do see strong 'active true' percentages for the top 8 application categories, and these are associated with self-reported reach figures ranging from 18-60%. The low self-reported Video Online reach contrasts sharply with the passive reach figure, suggesting a mis-alignment of online video application data between the category definition as presented, and the way a panelist would categorize this application. This speaks to respondent burden and error rather than active or passive true agreement and the need to continually refine the survey instrument to minimize respondent burden and ambiguity.

In general, *panelists appear to under-report Smartphone application usage*. The passive reach figures in column 3 are generally higher than the active reach figures in column 1, with the greatest difference for Video Online/Movies (absolute difference of 58%), followed by Social Media/Social Networking (absolute difference of 34.6%) and Maps and Navigation applications (absolute difference of 24.3%) and Search Tools (absolute difference of 22.9%). Furthermore, the generally low passive true agreement rate in column 4 is consistent with under-reporting of smartphone application usage by panelists. For example, the highest passive true agreement rate is 66.4% for Weather, which is not even in the top 8 of the active true agreement rate from column 2. Notable exceptions to this pattern are TV program streams and Location Based Services, and here we suspect that panelists may be mis-reporting local information applications within this category and hence the low incidence and over-reporting; we return to these issues in the discussion. Overall, table 4 shows that, for most categories, if a respondent told us they use an application, they are generally correct. However, just because we passively observed a person use a type of application, it does not mean that the panelist recalled doing this activity. For example, for respondents who told us they do use Social Media, we observed passive activity in that category for 93.3% of respondents, whereas of the people we did observe using Social Media, only 55.5% told us they use it.

Table 4: Smartphone Active and Passive Reach, Agreement Rates

Digital Behavior Category	Phone Applications Category (Self-Reported)	Self-Reported Reach	Self-Report Yes / Passive Observed	Passive Reach	Passive Observed / Self Report Yes
Social Media	Social networking	50.8%	93.3%	85.4%	55.5%
Maps	Maps/ Navigation	55.2%	85.5%	79.5%	59.4%
Video Online	Movies	18.0%	82.9%	76.6%	19.5%
Games	Games	52.6%	82.2%	69.2%	62.5%
Shopping (Combined)	Shopping (Combined w/Coupons)	38.1%	74.7%	58.5%	48.7%
Business & Finance	Banking/ Finance	46.1%	70.2%	50.2%	64.4%
Weather	Weather	60.3%	69.4%	63.1%	66.4%
Photo	Photo/ Video	46.5%	69.2%	67.9%	47.4%
Music & Audio Online	Music/ Radio	45.7%	62.9%	52.9%	54.4%
Search	Search Tools	34.9%	58.3%	57.8%	35.1%
News & Media (Combined)	Magazines, News, Newspapers (Combined)	31.6%	48.1%	36.8%	41.3%
Sports	Sports	15.4%	47.4%	20.6%	35.5%
Travel	Travel	10.1%	25.6%	12.2%	21.3%

Television Programs Streams	TV Shows	10.5%	13.0%	9.0%	15.2%
Location Based Services	Local Information	22.8%	11.4%	9.5%	27.3%

To evaluate what might be driving the reporting differences observed in Table 4, we looked at the frequency with which a panelist might be conducting an activity, and broke this into quartiles seen in table 5, below. What we see is that across the board, when a panelist is seen using an application frequently, they are more likely to remember that they have conducted this activity. Continuing to use Social Media as our example, we see that less than half of users that were observed using a social media application infrequently (40.1%) reported that they used this type of application, however roughly two thirds (63.9%) of the most frequent users recalled using these applications. It is interesting to note that even among our most active users, we still see a high degree of under-reporting in our self-reported data, with 36% of our most active social media users failing to report they used a social media application. Again, the key exceptions to this strong pattern of increased frequency associated with increased self-report are TV and Location services which again are likely impacted by mis-alignment between the applications a respondent uses and the classification category they need to select in the survey.

Table 5: Active Smartphone Applications by Passive Quartiles

			Passive Frequency Quartiles			
		No Usage	**1**	**2**	**3**	**4**
Digital Behavior Category	**Phone Applications Category (Self Report)**		**Self-Reported %**			
Social Media	Social networking	23.1%	40.1%	56.7%	61.5%	63.9%
Maps	Maps/ Navigation	39.1%	50.0%	54.7%	64.1%	68.3%
Video Online	Movies	13.2%	12.8%	17.8%	22.0%	25.4%
Games	Games	30.4%	48.1%	59.8%	67.3%	74.8%
Shopping (Combined)	Shopping (Combined w/Coupons)	23.2%	34.8%	48.8%	50.3%	60.2%
Business & Finance	Banking/ Finance	27.5%	52.2%	65.2%	71.8%	67.6%
Weather	Weather	49.9%	56.5%	60.0%	72.6%	76.3%
Photo	Photo/ Video	44.5%	42.1%	45.1%	47.8%	54.3%
Music & Audio Online	Music/ Radio	36.0%	44.0%	51.2%	57.2%	65.1%
Search	Search Tools	34.5%	34.2%	32.9%	33.9%	39.6%
News & Media (Combined)	Magazines, News, Newspapers (Combined)	26.0%	31.7%	39.3%	44.0%	48.6%
Sports	Sports	10.2%	26.4%	33.9%	33.3%	47.1%
Travel	Travel	8.5%	17.9%	18.2%	23.8%	24.6%
Television Programs Streams	TV Shows	10.0%	17.9%	9.3%	17.3%	18.2%
Location Based Services	Local Information	22.3%	20.8%	26.5%	28.3%	30.6%

Personal Computers (PC) Results

At this point, we turn our attention to the personal computer panelists. As with the smartphone results, we would expect relatively high agreement rates if self-report and passive observation line up as we would like. In fact, the top 8 categories show active true agreement rates above 70% and all the way to 95%. However, looking at the 'active true' and 'passive true' agreement rates of passive vs self-reported website usage indicates a generally *high degree of under-reporting for website activity*. For example, Google.com shows 92.4% of our sample have passive activity at Google.com, however only 58.4% of our sample report that they used Google.com in the past month (comparing columns 3 and 1). A potential explanation for this difference may be the timing of the passively collected data versus the self-reported data. For the purposes of this analysis, we have allowed a person to count as a passive user if they visited the websites in any month of the most recent quarter following their inclusion into the Simmons Connect panel. Additional timing concerns exist in that the period of observation is after, as opposed to concurrent with, the period for which we have asked a panelist to recall their activity.

Similar to Smartphone application results, when a panelist has identified that they used a specific website we see that often, their passive data agrees (second column of table 6). Looking at google.com, we see that 95% of the time, if a person has told us they use google.com, we observe activity at google.com as well. However, as with Smartphones, when we observe a panelist using a website, they have not necessarily recalled this activity. For example, only 60% of the panelists we observe visiting Google.com told us they use Google.com. Earlier in the Smartphone section, we saw that when people were asked to recall whether they used Business and Finance applications, we had fairly high agreement rates with their passively collected data. This was also true for Weather applications. Interestingly, when asked to recall specific Weather or Business and Finance websites, panelists did not seem to have as high a degree of recall for websites in these two categories, although our sample size is small, with only one website qualifying in each category. Overall, when a panelist was asked to recall what websites they visited, they were most likely to remember their search engines (with 75 – 95% of panelists who self- reported activity having passive activity as well). They were also likely to under-report their search engine visitation – with the exception of Google.com, only 16-47% of panelists for which we observed passive activity told us they visited the given website. Facebook and YouTube also had high rates of agreement when the panelist reported using the site and both had modest agreement when we observed activity at those sites.

Table 6: PC Active and Passive Reach, Agreement Rates

Category	Website	Self-reported Reach	Self-Report Yes / Passive Observed	Passive Reach	Passive Observed / Self Report Yes
Search Engines & Portals	Google.com	58.4%	95.1%	92.4%	60.1%
Social Networking, Video/Photo Sharing & Dating	Facebook.com	69.6%	90.0%	86.2%	72.7%
Search Engines & Portals	Yahoo.com	40.5%	89.2%	76.8%	47.1%
Social Networking, Video/Photo Sharing & Dating	YouTube.com	50.0%	85.5%	82.2%	52.1%
Search Engines & Portals	Bing.com	12.1%	78.7%	59.6%	16.0%
Search Engines & Portals	AOL.com	11.7%	75.4%	25.0%	35.3%
Search Engines & Portals	MSN.com	13.4%	75.2%	44.9%	22.5%
Shopping & Classifieds	Amazon.com	50.0%	74.3%	66.0%	56.3%
Reference- Education, Employment & Real Estate	Wikipedia.org	21.5%	61.0%	45.2%	29.0%
Shopping & Classifieds	Ebay.com	29.3%	58.9%	39.8%	43.3%
Telecommunications	Verizon.com	13.8%	54.2%	19.6%	38.0%
Business & Finance	Paypal.com	21.8%	54.1%	27.9%	42.2%
Social Networking, Video/Photo Sharing & Dating	Pinterest.com	16.7%	52.7%	27.7%	31.8%
Shopping & Classifieds	Craigslist.org	28.0%	52.0%	27.3%	53.3%
Social Networking, Video/Photo Sharing & Dating	Linkedin.com	13.2%	51.3%	26.8%	25.2%
Social Networking, Video/Photo Sharing & Dating	Twitter.com	10.6%	48.8%	27.2%	19.0%

Search Engines & Portals	Ask.com	13.4%	43.0%	30.4%	19.0%
Sports	ESPN.com	11.5%	39.2%	12.5%	36.1%
Entertainment - Television & Movies	Netflix.com	23.1%	37.4%	17.4%	49.6%
Shopping & Classifieds	Groupon.com	15.9%	36.6%	15.2%	38.2%
Travel	MapQuest.com	28.4%	34.2%	21.7%	44.6%
Lifestyle- Home & Family	Foodnetwork.com	11.0%	33.0%	12.0%	30.3%
Computers, Internet & Electronics	BestBuy.com	16.3%	32.9%	16.3%	32.8%
Reference- Education, Employment & Real Estate	WebMD.com	12.4%	32.8%	18.0%	22.6%
Shopping & Classifieds	Coupons.com	12.0%	32.4%	14.2%	27.3%
News & Weather	Weather.com	25.2%	32.0%	18.5%	43.4%
Lifestyle- Home & Family	Allrecipes.com	21.0%	28.8%	14.4%	42.2%

To further examine our PC results, in Table 7 we show the PC data broken out by quartiles of visitation for the passive data. As with Smartphones, recall is higher when a panelist has been observed using the website frequently, and this is a strong and consistent pattern across virtually all the categories reported in the table. Facebook shows a high level of self-report among those that visit the site infrequently as well as the most frequent users (from over 60% to almost 86%). Looking at some of the shopping sites such as Ebay and Amazon, we see that less than half the least frequent passive visitors self-reported using these sites while the most active users had similarly high (around 67%) self-report rates. This level of under-reporting is surprising given the more engaged interaction with shopping sites versus other types of content. Said another way, almost 33% of the most active visitors to shopping sites fail to report this activity in the survey.

Table 7: PC Users Active Websites by Passive Quartiles

		Passive Frequency Quartiles				
		No Usage	1	2	3	4
Category	**Website**	**Self-Reported %**				
Search Engines & Portals	Google.com	37.9%	50.5%	59.7%	62.3%	67.9%
Social Networking, Video/Photo Sharing & Dating	Facebook.com	50.4%	60.3%	68.0%	76.8%	85.9%
Search Engines & Portals	Yahoo.com	18.8%	24.5%	32.0%	60.1%	71.7%
Social Networking, Video/Photo Sharing & Dating	YouTube.com	40.7%	42.2%	46.3%	55.8%	63.9%
Search Engines & Portals	Bing.com	6.4%	6.4%	10.8%	16.9%	30.0%
Search Engines & Portals	AOL.com	3.8%	8.7%	11.5%	43.4%	78.4%
Search Engines & Portals	MSN.com	6.0%	10.9%	12.8%	17.9%	48.0%
Shopping & Classifieds	Amazon.com	37.9%	43.6%	51.9%	61.9%	67.2%
Reference- Education, Employment & Real Estate	Wikipedia.org	15.3%	20.0%	23.1%	31.7%	41.2%
Shopping & Classifieds	Ebay.com	20.0%	22.5%	37.5%	49.7%	66.7%
Telecommunications	Verizon.com	7.8%	26.4%	31.9%	41.8%	53.0%
Business & Finance	Paypal.com	13.8%	24.8%	34.9%	48.0%	57.0%
Social Networking, Video/Photo Sharing & Dating	Pinterest.com	10.9%	18.0%	25.4%	36.4%	49.0%

Shopping & Classifieds	Craigslist.org	18.5%	36.5%	49.6%	62.3%	64.5%
Social Networking, Video/Photo Sharing & Dating	Linkedin.com	8.8%	15.3%	17.8%	25.6%	41.4%
Social Networking, Video/Photo Sharing & Dating	Twitter.com	7.4%	11.6%	12.5%	12.5%	40.0%
Search Engines & Portals	Ask.com	11.0%	15.4%	18.4%	18.5%	24.6%
Sports	ESPN.com	8.0%	17.5%	24.4%	43.4%	60.9%
Entertainment - Television & Movies	Netflix.com	17.5%	42.2%	55.1%	44.2%	59.8%
Shopping & Classifieds	Groupon.com	11.9%	25.0%	34.5%	40.0%	52.0%
Travel	MapQuest.com	23.9%	37.0%	30.5%	46.3%	62.6%
Lifestyle- Home & Family	Foodnetwork.com	8.4%	26.3%	20.0%	25.0%	50.9%
Computers, Internet & Electronics	BestBuy.com	13.1%	27.8%	23.8%	26.3%	53.1%
Reference- Education, Employment & Real Estate	WebMD.com	10.2%	17.4%	16.5%	20.0%	35.8%
Shopping & Classifieds	Coupons.com	9.4%	11.2%	24.1%	25.9%	51.3%
News & Weather	Weather.com	21.0%	29.3%	33.7%	55.9%	52.1%
Lifestyle- Home & Family	Allrecipes.com	17.5%	38.3%	29.3%	43.9%	60.9%

Summary and Discussion

Passive mobile measurement technology is the preferred methodological approach to collecting behaviors of panelists on mobile devices because it requires no recall efforts and collects information on time spent, reach, and frequency across a wide range of mobile activities, including website visitation and app usage. By integrating this passive, cross platform measurement with high quality survey based, cross platform consumer/media information, a comprehensive view of myriad consumer behaviors is created. The challenges of passive cross platform measurement, like frequent OS updates and new mobile device releases, do not preclude the value that passive data brings cross media research so long as the active and passive databases can be linked reliably without losing the valuable behavioral and attitudinal characteristics of each data set.

With access to both passive and active consumer and media behavior data, this looked at research questions related to data quality and potential data bias related to collecting and eventually linking active and passive data. For example, do respondents actually behave the way they report during a traditional mail survey process? And, how does this behavior vary across light and heavy users or by category of website or application. Using a subset of Experian Marketing Services' Simmons National Consumer Study and Experian's Simmons Connect, we explored the difference between self-reported versus actual behavior by comparing self-reported behavior with passively observed data. We found consistent patterns of under-reporting for Smartphone and PC online behaviors, with the former showing more sever under-reporting. This result points to further research to ensure survey instruments and treatments are optimized to collect the right quantity, quality and detail of online behavior so as to balance respondent burden with research requirement. We also found that the most frequent users were the most likely to self-report for both the Smartphone and PC samples, with the latter showing a stronger relationship to frequency. With both the PC and Smartphone samples, we found that the top categories reported in our study had high 'active true' agreement rates which provides comfort in continuing to collect some online behavioral data, albeit refined for respondent ease and to avoid mis-alignment of measurement categories as we saw with lower reach TV and Location based applications.

Future research will explore demographic differences across measures and an analysis of traditional market segmentation research implications. That is, we can explore the efficacy of segmentation systems that have been created using self-reported attitudes and behaviors, by examining whether passive digital behavior can validate or enhance the important segmentation building process. Finally, we can look at the likelihood that these respondents indicate their intent to purchase, for example, a big-ticket item (major appliance, car, etc.) or medium ticket (small appliances and electronics) and online passive online behavior. Essentially answering the question: does intent to purchase these higher priced items affect online behavior? We believe this paper presents a significant contribution to the cross platform measurement agenda, and empirically tests several important research questions using unique and powerful data sets.

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