Characterizing Web Use on Smartphones

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ABSTRACT
The current paper establishes empirical patterns associated with mobile internet use on smartphones and explores user differences in these behaviors. We apply a naturalistic and longitudinal logs-based approach to collect real usage data from 24 iPhone users in the wild. These data are used to describe smartphone usage and analyze revisitation patterns of web browsers, native applications, and physical locations where phones are used. Among our findings are that web page revisitation through browsers occurred very infrequently (approximately 25% of URLs are revisited by each user), bookmarks were used sparingly, physical traversing patterns mirrored virtual (internet) traversing patterns and users systematically differed in their web use. We characterize these differences and suggest ways to support users with enhanced design of smartphone technologies and content.

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H.5.4 [Information Interfaces and Presentation]: Hypertext/Hypermedia - User issues;

General Terms
Design, Human Factors, Measurement

INTRODUCTION

The web is a resource for information, communication, and entertainment used by over two billion people worldwide [13]. This ubiquity has led to a large amount of research examining how it is used. Most of the work has focused on understanding behaviors associated with the PC. Now, smartphones are becoming pervasive and making the web accessible in most personal and professional environments [19]. There is even evidence that users spend more time on these devices compared to PCs [20].

Although a substantial amount of research has characterized web use on PCs, there are several reasons why these studies may not apply to web use associated with smartphones. First, internet resources can be accessed through native applications as well as a browser. Second, smartphones are smaller and have different input and display functionalities. Finally, smartphones provide continuous access to the internet in almost any setting. These factors could lead to the development of new patterns of behaviors and routines associated with use of the web on smartphones.

The goal of the present study is to understand the dynamics of these behaviors. We describe users' visiting and revisiting patterns to internet resources through both their smartphone browsers and native applications along with physical locations where their smartphones are used. We update previous work applied to the PC and establish empirical patterns for internet use on smartphones by analyzing naturalistic and longitudinal data logged from user interactions in the wild. User differences are explored along with the influence of experience, physical location traversing, the type of content accessed and user revisiting strategies to provide targeted design recommendations for mobile internet use with smartphones.

BACKGROUND

The web has been a primary focus of human-computer interaction (HCI) research since the 1990s. PC-based studies have developed an understanding of user goals [17], browsing strategies [4], tasks [3], search behaviors [36], revisitation of websites [32], and differences between groups (e.g., novice-expert [12]) among a number of other efforts. Some of the earliest HCI studies of the web used a logs-based approach [4,32]. Internet browsers were instrumented with logging technologies to collect naturalistic usage data instead of observing users completing tasks constructed by researchers. In particular, user recurrence to web content has been a central focus. The first study that examined these behaviors found that PC users visited a small total number of unique websites (i.e., vocabulary); however, the revisitation frequency to this set was high [4] resulting in a revisitation rate of 61% [32]. Shortly after, a similar study (N = 23) resulted in a 58% revisitation rate to web content [32]. From these data, characterizations were developed to understand patterns of web navigation.

Because of the changing dynamics of the web, these revisitation studies on the PC have been revisited [24]. Cockburn and McKenzie [5] collected data for 119 days and found that internet behaviors were even more repetitive. Users visited an even smaller number of sites than older PC studies and reaccessed these sites very frequently. They reported a revisitation rate of 81% from 17 computer science (CS) students. More recently, Obendorf and his colleagues [24] captured web data from a slightly larger and more diverse set of users (N = 25, 64% CS students) to obtain a much lower revisitation rate of 46%. One reason for this large gap between revisitation rates in these studies, they stated, was due to the changing nature of the web. For instance, instead of users reaccessing the same web pages repeatedly, users visit new pages within frequently accessed domains. These studies of recurrent behaviors on the web have been important in understanding different user types and designing better user interfaces for web navigation including history systems [4,24].

Using the Web on Smartphones

As mentioned above, several factors likely drive differences between internet use on PCs and smartphones. Smartphones offer users two primary ways to access resources on the internet. Similar to the PC, users can get to the internet through a web browser. Many web sites that are opened on smartphone browsers automatically display a version of the site that is optimized for smaller screens, though there are usually options to view the full site. Additionally, native applications provide access to mobile content designed specifically for the device. These applications are factory installed or installed by users via an application store (e.g., the Apple AppStore). The combination of more powerful mobile devices and optimized applications and web content has made using internet resources more efficient [22,35].

Still, there are noted usability challenges with the mobile web that apply to current-generation devices. Long download times for page loading appear to be a primary problem [28]. These delays can result in sharp usage decline and considered the largest HCI concern in web usability [21]. Other challenges with using the web on smartphones result from the size of the device. Text optimized to fit on small screen interfaces can be difficult to read [7] and awkward text entry is even more problematic for efficient web use [22,35].

Despite these problems, users access the web frequently through their smartphones. One in four smartphone owners prefer accessing the internet through their smartphones over the PC [27]. Many in this group (33%) have discontinued web connectivity at their residences because of smartphone accessibility. Even with connectivity, users still frequently choose to access the internet at home through their smartphones over their PCs [23].

Smartphones are also widely accessed on-the-go in diverse contexts [33]. Without smartphones, PC users access the internet when they have opportunities to stay at a stationary location for a defined period of time; conversely, smartphone users go online whenever they get the urge [8]. Context drives the nature of these interactions. For instance, smartphone users often access the web in between planned activities [11]. Though smartphone users reported accessing their phones in a small cluster of locations, the nature of the location can inform user needs [18]. Interruption is often expected during these interactions [1]. Nevertheless, technological and usability advances has made computing on these devices more similar to larger computers. For instance, data from Google search logs revealed that users' iPhone searching behaviors are more similar to PCs compared to previous-generation mobile phones [15].

Additonally, individuals use their smartphones to extend and complement their computing on other devices. 75% of the domains visited on users' smartphones were also visited on their PCs [16]. Many times they optimize what they do on their PCs or laptops as opposed to their smartphones. For instance, users choose to compose longer emails on a PC, but use their smartphones for shorter messages [19]. Mobile internet use is generally directed and shorter (e.g., fact finding) rather than the less-directed (e.g., browsing) whereas the reverse has been found for the stationary web [6]. More recent research has shown that this could be a function of user goals in a particular location and not necessarily the technology being used [18].

We build on this research by contributing characterizations of internet use on smartphones, focusing on recursive behaviors similar to PC-based studies. Since there are two ways to access the internet on these devices—via native applications and a browser—our first interest is to describe how both are used. The roles of experience and the task on visit and revisit patterns are explored to this end. We also examine user variability to distinguish mobile users for enhanced design of smartphone systems and content.

METHODS

The logging methodology applied in this study has been previously discussed in detail [31]. However, we briefly describe our data collection and analysis procedures below.

Data Collection

The 24 students (M = 19.2 years old) that participated in our study were not previous smartphone owners and only 8% were CS students. Fourteen of the students were male. They were given iPhones to use for an entire year if they agreed to use it as their only mobile phone. We also provided free unlimited data plans along with unlimited text messaging and 450 phone minutes/month. The instrumented iPhones ran iOS 3.1.3 and were logged continuously for a period of one year. All interactions were recorded unobtrusively and strict privacy constraints were maintained throughout. For instance, all data were attached to participant numbers for anonymity, no content of communications data were collected, and encryption was applied to avoid unwanted eavesdropping. During the study period, we intentionally withheld from introducing novel interfaces, artificial tasks, and researcher-participant meetings in order to decrease participant reactivity. We gave no instructions about how to use the iPhone and two meetings were scheduled to record items such as their bookmarks and answer questions to help interpret the log data.

For this study, we examined web logs along with native application interaction logs. The custom logger recorded every URL visited on the users' browsers, as well as application usage. Both of these logs included the date, time, Cell ID (location), and duration of the interactions.

Data Analysis

Since our interest is internet usage, we analyzed only those native applications that require the internet for their primary functionalities. The native applications with functions that largely do not depend on the internet were manually removed (see Table 1). For instance, the camera application on the iPhone does not require the internet to take pictures or view photos, however it can be used to send pictures over email. Since it is reasonable to assume that cameras are largely used offline, we did not consider this application or similar ones in our analysis. We call the internet-connected native applications that are examined "native internet applications" (**NIAs**) hereafter. Browser use is removed from NIA analysis and presented separately for comparative purposes.

Removed		Kept	
SMS	Voice Phone	Email	Maps
Non-Web Games	Camera	Facebook	Weather
Settings	iPod	Web Games	News

Table 1. Some NIAs and categories of NIAs analyzed along with several we removed.

We organized our web browser logs by sessions. Sessions are defined as when the browser was launched and then closed instead of an arbitrary time delta. Within these sessions, visits to sites (i.e., domains) and pages (i.e., full URLs) were recorded.

Revisitation rates were computed to understand recursive behaviors associated with visiting NIAs and content via web browsers. For enhanced precision [see 24], we present rates separately for NIAs, sites (i.e., domains), and full URLs (i.e., pages) using the below equation.

Revisitation rate = (total visits – unique locations) / total visits

where unique locations is the total number of distinct NIAs, sites or pages accessed by each user. In addition to virtual revisitation on the internet, we also examine physical (location) revistation with the same equation. The value of unique locations here is the number of unique Cell IDs recorded by our logger from each participant's phone use. Total visits account for all visits across these Cell IDs for each participant. Other behavior rates of interest are described below.

RESULTS

Over the entire year, NIAs were accessed much more than browsers. A total of 2,080 unique NIAs were launched across 225,151 visits. In contrast, 7,672 URLs were accessed through browsers accumulating 112,083 total visits. In general, browsers provided access to a wider variety of resources more sporadically while a steady set of NIAs were used more frequently. We first describe visits and revisits to the former and compare with previous PC-based studies. Following this, we characterize NIA and physical location traversing before we explore user differences.

Browser Visits

We were surprised that not all users relied on their browser, even with free service. Users averaged 3.86 browsing sessions per day (*Median* = 3, *SD* = 10.84). Half of our users launched their browsers less than three times per day. The lowest volume user averaged eight browsing sessions per *month*. He, along with four others, stated a preference for browsing on the computer, low information needs requiring the web, and a heaver reliance on voice phone and SMS. The user that relied on Safari the most launched Safari an average of 11 times per *day*. Clearly, there was large variance in browsing use among our participants.

Search was consistently relied upon within browsers. Users issued over 17,500 searches across the entire study period resulting in a 56% query rate (i.e., number of browsing sessions that consisted of at least one search). Users did not vary much in their volume of searches (*M* =53.3%, *SD* = 7.2%) and use of Google. Less than .1% of all queries were conducted outside of Google.com. Most browsing sessions with search (85%) contained less than four queries. According to our users, two reasons for the relatively low number of queries per search session compared to PCs was due to low time for navigating and long page loading times. This was also apparent in the typical length of smartphone web browsing sessions. Browsing sessions were generally under two minutes (*M* = 105.86 sec., *Median* = 96 sec., *SD* = 40.84 sec.) and consisted of a small number of unique sites (*M* = 2.18, *Median* = 1.5 *SD* = 2.88) and total pages (*M* = 6.07, *Median* = 3, *SD* = 3.58) visited per session.

Table 2 shows the differences between browser use on smartphones and PCs. Pages (i.e., full URLs) were not revisited very often (25.3%). Just over 60% of all pages were visited once and 15% were visited twice. Interestingly, these numbers are extremely similar to results obtained from the PC 15 years ago (60% and 19% respectively [33]). Revisitation rate variances were much smaller compared to previous work on the PC [23]. Page revisitation rates were all under 50% (13% to 41%). The site revisitation rate of 90.3% also yielded relatively low variance (86% to 97%).

Compared to PCs, browsers on smartphones are accessed less frequently, for shorter durations, and to visit fewer pages. One reason for the distinction in overall use is the increased reliance on NIAs as mentioned above resulting in lower browser use. Additionally, users did not access static pages repeatedly leading to a substantially lower page

	PC Studies	iPhone
Mean URL visits per day/user	7.6 - 258.5 [24]	0.4 - 20
Site vocabulary	84 – 2,127 [24]	27 – 543
Mean session duration	476.4 sec. [36]	105.9 sec.
Page visits/session	17.7 [36]	6.1
Query rate	12.5% [36]	56.3%
Queries/session	4.3 [36]	2.1
Site revisitation rate	70% [24]	90.3%
Page revisitation rate	45.6% [24]	25.3%

Table 2. Browser comparisons between platforms.

revisitation rate than previously reported. Instead users relied on search at a much higher rate compared to the PC.

Nature of the Task

We also found a greater distinction between page and site revisitation rates compared to the PC. The full URL (page) revisitation rate was much lower than the site revisitation rate indicating that users access a small number of sites to view different pages [see 24]. For instance, Google was the most visited site followed by a number of blogs and the Rice.edu institutional site. The site revisitation rate for Google was high because all search results pages were within the same domain. However, most search results pages were unique because of different query terms (and thus unique URLs). Similarly, blogs were revisited often across users and yielded a long tail (Figure 1). In contrast, there were more sub-top level pages visited within institutional sites such as the Rice.edu domain (e.g., registrar.rice.edu, dining.rice.edu) and News sites.

The highest ranking pages in Figure 1 were mostly top-level (e.g., home) pages that provided users access to sub-level content within the same site. Since only 9% of all pages were revisited more than 5 times, we manually categorized these pages as (1) log-in pages, (2) subsequent home pages after a log-in, (3) a top-level page (e.g., http://google.com, http://www.espn.go.com), or (4) other. Many were indeed in the first three categories (62%) thus demonstrating how these top-level sites were used as a gateway to other content, often within the same site (substantiated by the high site revisitation rates). The top five sites for each user accounted for a minimum of 22.3% of page visits to a maximum of 91.8% of all page visits with a mean of 73.4%. These top sites, such as Google.com, Rice.edu, and Wikipedia.org, were reaccessed frequently to provide users portals to new or changing information.

Temporal Patterns and Revisitation Strategies

Fragmented browsing across interruptions also resulted in page revisiting. Many short-term page revisits (accessing the same URL within a period of three days) occurred via a page being reaccessed across adjacent web browsing sessions. We found that 21% of all page revisits were due to the loading of a page prevously closed with the browser. Our logger did not record the page visit if it did not load completely. Thus, many users retrieved this information intentionally to continue a previous navigation sequence. Roughly a quarter of these revisits were continued after an interruption such as a text message or voice phone call. The other three quarters of these type of revisits were after the phone display was turned off for some period of time. A few users reported using small periods of free time to access a page for viewing later, perhaps a strategy developed to deal with long page loading times.

Longer-term revisits generally occurred through navigating from top-level pages accessed through search. 37% of sites revisited after three days and 25% of all page revisits after three days occurred through search. All users but one accessed sites in their top three (e.g., neoseeker.com, craigslist.org) via Google consistently throughout the entire

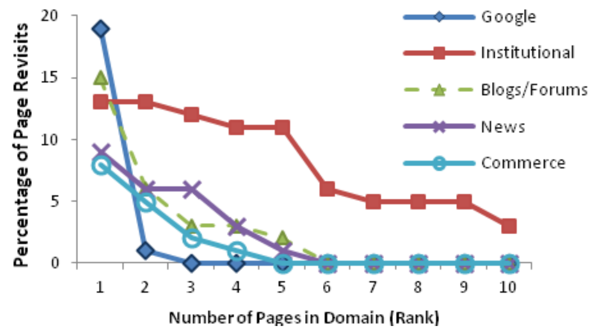

Figure 1. Page revisits by type of site [after 24].

study. Additionally, we asked users, via an open-ended question, to report some of their common strategies for revisiting web pages that they have not been to in two weeks. Every user mentioned the use of search. 50% of our users stated that they use other windows to access sites on a recurring basis. These users assign particular sites or pages to other windows and switch to targeted windows when the content is needed, though most mentioned difficulty in maintaining this strategy. Typing in an address within the URL address bar was mentioned by only one user.

Bookmarks were not used frequently. We recorded the number of bookmarks that were added. 83% of users did not add any bookmarks in Safari. Three users only added one or two bookmarks throughout the entire year. One user added more than two (i.e., 9). Additionally, only two users added bookmarks to their springboards (one linked a single page while the other linked two pages). Based on these data, it did not appear bookmarks or adding icons to springboards constituted primary methods for revisiting. However, 54% of the sites visited also were installed as an NIA (e.g., Google Mobile, Rice, etc.) which appeared to supplant other types of bookmarking to some degree.

Use of Native Internet Applications

Table 3 shows aggregate statistics similar to those reported for the browser above. User vocabularies and visit patterns were diverse. For instance, one user added only 10 native applications to his smartphone over the course of the 12-month study. Conversely, another user installed over 451 native applications. Users also uninstalled a surprisingly large number of applications (M = 82.25, *Median* = 43.34, SD = 29.85). Users were more similar to each other, however, in their revisitation of NIAs. The high revisitation rate of 97.1% was driven by a high number of visits to a set

	Mean	SD	Min	Max
Visits/Active Day	17.40	8.30	1.00	36.00
Vocabulary	124.63	106.17	31.00	475.00
Revisitation Rate	0.97	0.02	0.91	0.99
Hours/Active Day	2.02	1.21	0.26	4.69
NIAs Visited Once	33.00	41.43	0.00	185.00
% Search App Use	0.002	0.004	0.00	0.02
% Visits in Top 10	60.39	13.15	32.39	89.84

Table 3. Summary and variance statistics for NIA use.

of NIAs such as the five most frequently accessed across our users: Mail, Facebook, Maps, Words with Friends and Weather. These five NIAs made up more than 50% of all visits. NIAs that could be used to issue internet searches were installed by 91% of our users. Google Mobile was most common,though one user installed Bing as well. These applications were not used very often; across the entire length of the study, they were accessed an average of 6.2 times over the entire year (*Median* = 5.5, *SD* = 4.97). Similar to sites, NIAs were accessed for dynamic content; dissimilarly, information searches were not issued frequently off-the-browser.

Also similar to sites, NIAs were used for brief periods of time (*M* = 137.29 sec., *Median* = 62 sec., *SD* = 207.29 sec.). As can be seen by the large difference between the mean and median, this distribution is positively skewed with most NIAs being used for roughly one minute. Of course, the large standard deviation also reflects the fact that durations of NIA use are heavily task dependent and largely a function of what NIAs were installed by each user. For instance, NIAs such as Pandora were used for longer periods of time compared to others (e.g., Weather). Across all NIAs, many were operated independently; 59% of iPhone activations (i.e., the display was turned on) were for the use of one NIA alone before the display was turned off.

From an aggregate perspective, NIAs were visited more than twice the amount of sites. Longitudinally, however, the distinctions between NIA and site visits appeared to be driven by experience. Figure 2 shows sites and NIAs were accessed at similar levels for the first three months of the study. Geometric means are used in these figures to reduce

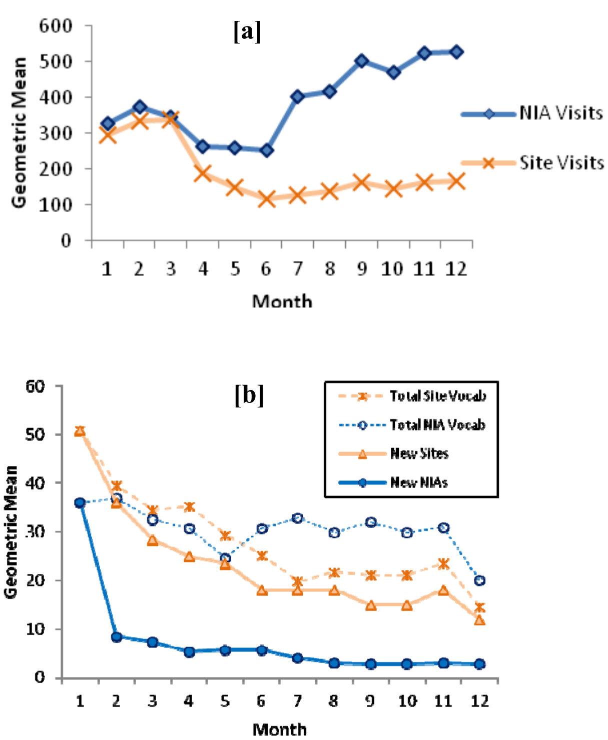

Figure 2. Number of (a) visits, (b) total vocab and new content accessed through NIAs and the browser by month.

the influence of extreme use within each month on our summary statistics. Months 4-6 were during the summer break. Within this period, all internet use decreased; browsing decreased more dramatically compared to NIAs. After the summer, browser use increased modestly compared to the use of NIAs which sharply increased. Users generally reported the low summer use was due to decreased school-related activity along with being closer to friends and family they usually corresponded with online.

New NIAs were not installed and accessed as frequently as sites. New content was visited more than twice as much on sites (*M* = 27.33, *Median* = 25, *SD* = 10.94) compared to NIAs (*M* = 10.04, *Median* = 9.5, *SD* = 9.69). Instead, a more steady set of NIAs were accessed regularly by our users. The installation of new NIAs dropped more sharply after the first month. By the third month, users averaged under eight visits to new NIAs per month. Figure 2b shows how the distinctions between total vocabulary and new content for each modality changed as a function of experience. The small number of new NIAs accessed accumulated with time and by six months NIA vocabularies exceeded site vocabularies. Browsers were continually used to access new content and these new sites generally made up most of users' overall vocabularies within a given month. The sites that were revisited were revisited very frequently resulting in 3-5 sites that were generally revisited heavily for each user and a long tail of unique sites not revisited after one or two visits.

We asked our users about their methods for visitng new sites and new NIAs on their smartphones. In an open-ended question collected after data logging concluded, users described why they used their browser more to access new domains compared to NIAs. 79% stated they did not want to take the time to install an NIA that they perceived would not be used again. Most of these users reported that they used their browser to get quick information and were unable to predict their information needs to install an appropriate NIA ahead of time. One user stated this clearly, "sometimes Google knows what I need better than I do." Five users mentioned that installing NIAs was more like shopping whereas accessing new content on the web browser was more obligatory for information needs.

Visiting and Revisiting Physical Locations

Though smartphones are used in more diverse contexts compared to PCs, we found that users frequently revisit the same places to interact with their phones (*Location Revisitation Rate* = 90.6%). The 24 participants in our study revisited a small set of physical locations at about the same rate as virtual locations (e.g., sites, reported above at 90.3%) though the variance between users was higher for physical locality revisiting (*SD* = 8.63%, *Min* = 61.3%, *Max* = 96.2%). Of course, the level of granularity of our location measurement is coarse; users could be accessing their phones in a number of settings within a given radius and still record under the same Cell ID. Still, the localities we captured reveal physical traversing following patterns similar to web localities. Indeed, the distribution of visits and revisits to places is similar to those for sites and NIAs (Figure 3). Most locations are visited once; however, a majority of smartphone interactions occur within a small subset of places. The high revisitation rate reflects a large number of visits to users' top three to five locations similar to NIA and site revisit rates. Location rates were higher during the academic year compared to summer months, most likely because 91% of our users lived on campus during the former time period.

User Differences in Accessing the Internet

Until now, we have described empirical patterns of behavior associated with internet use via smartphones and the physical locations where users interacted with their smartphones. In this section, we examine the large user variance reported above to characterize smartphone users in their visiting patterns. To this end, we developed NIA-to-site indices. These measures were computed for each user with the following equation:

NIA-to-site index = (NIA visits – site visits) / (NIA visits + site visits)

Positive values reflect greater use of NIAs compared to sites on the browser. Negative values show greater use of the browser relative to NIAs. A score of zero reflects that users accessed both NIAs and sites via their browser at the same proportion. As Figure 4 shows, our users varied greatly in their reliance on each modality. An inverse correlation was also found between overall internet use and NIA-to-site indices (r = -.61, p = .001). Thus, most participants visited NIAs; however those that used the internet more via their smartphone also more frequently accessed sites via their browsers. For clarity and reasons we explain more in detail below, we call users lower in NIA-to-site indices **Pioneers** because, while they visited NIAs (i.e., "native territory"), they also frequently accessed new information on the web. Those with higher indices we call **Natives** because they largely avoided exploring the web on their browsers, but accessed resources native to the device. We keep the index as continuous to avoid strict compartmentalization of users into two user types. We instead imply that users at each end of the spectrum can manifest behaviors at the other extreme, though perhaps not as frequent.

Pioneers' larger reliance on their web browsers resulted in higher site (r = -.54, p < .01) and page (r = -.44, p = .02) revisitation rates. There was not a significant correlation between NIA-to-site index values and NIA revisitation rates (r = .09, p = .69). Interestingly, however, we found that Pioneers revisited physical locations at a higher rate though not quite reliable at a .05 alpha level (r = -.26, p = .10) and used their phone in more unique localities across the entire study period (r = -.29, p = .08). We expect that with a larger sample size these p-values would reach statistical significance. Still, these results provide some evidence that Pioneers' and Natives' unique traversing patterns in virtual space (i.e., the web) manifest similarly in the real world.

When the browser was accessed, Natives tended to use it in conjunction with NIAs and for quick searches. As NIA-to-site indices increased, the proportion of browsing sessions that consisted of only one URL that loaded before the session ended increased as well (r = .51, p = .01). 63% of these followed access to another NIA. For instance, many of these browser visits occurred directly following the Mail NIA suggesting that Natives were following a link in an email message. Interestingly, Natives also yielded higher query rates (proportion of browsing sessions that included at least one search) when they did access their browser (r = .41, p = .02). The strength of this correlation increased when we removed browsing sessions that directly followed use of another NIA (r = .55, p < .01). In other words, when Natives launched Safari from their springboards there was a high probability that a search would be issued.

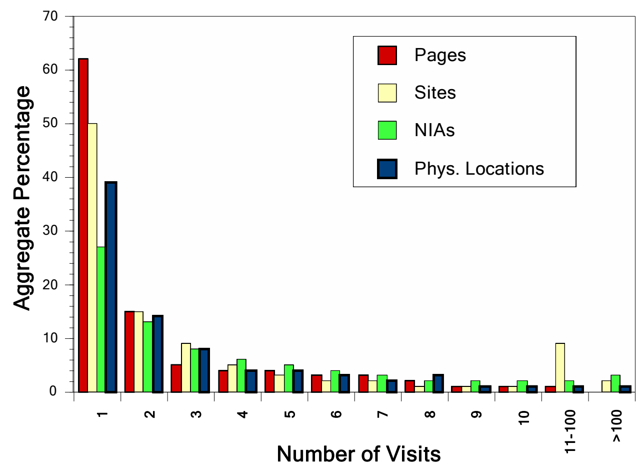

Figure 3. Aggregate percentages of pages, sites, NIAs and physical locations (Cell IDs) by their number of visits.

Pioneers accessed their browser more from their springboard and in isolation of other NIAs. This led to different browsing patterns. As NIA-to-site indices decreased, users tended to access more pages per session (r = -.39, p = .03) leading to each session lasting for longer periods of time (r = -.37, p = .04). Though they yielded fewer sessions with queries (lower query rates), Pioneers averaged more queries per browsing session (r = -.37, p = .04). Thus, when Pioneers used search they tended to search more within the same session. This resulted in more new content consumed reflected by higher unique site vocabularies per session (r = .69, p < .001). Clearly, Pioneers relied on their web browsers for repeated visits to pages and then ventured to explore new information.

Natives used NIAs differently than Pioneers. First, they tended to spend less time on each NIA launch, though not quite significantly different (r = .30, p = .06). They did not differ from Pioneers in the installation of new NIAs. Thus, since Natives and Pioneers yielded similar NIA revisitation rates and vocabularies, it appears differences in use of NIAs is influenced by other factors. Indeed, the coarse location revisitation rates we report above highly correlate with NIA revisitation rates (r = .63, p < .001) suggesting external stimuli likely prompt routine (or habitual [25]) use of NIAs. Still, user differences characterized here show differences in how NIAs are accessed. Natives accessed more NIAs

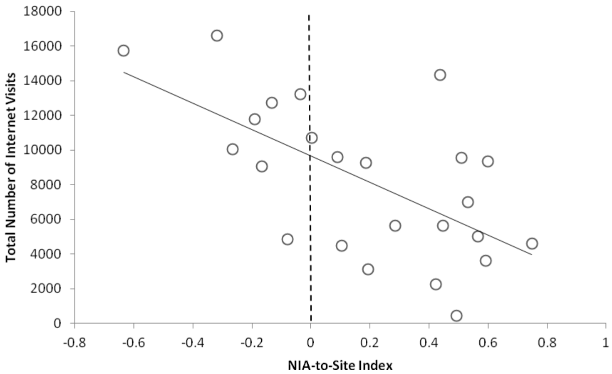

Figure 4. Scatter plot of total visits by NIA-to-site index values.

once without any revisits (r = .41, p = .02). Interestingly, Pioneers uninstalled more NIAs (r = -.34, p = .04). Natives use NIAs briefly and leave unused NIAs deserted on their springboards. Pioneers, on the contrary, spent more time on each NIA when launched and uninstalled more NIAs.

Experience

We also explored how experience with the iPhone influenced use of the browser relative to NIAs. We considered that one reason NIA-to-site indices were so low was due to high early browser use. Recall that all of our users were not previous smartphone owners. We thought that computer experience could have transferred to users' smartphone use and led to higher web browsing early in the study. Thus, we assessed differences in NIA-to-site indices between the first and second halves of the study. We found that 20 of the 24 users' difference scores were positive showing an increase in NIA use over browser use during the second half of the study. The mean of these difference scores (M = 1.56, SD = 2.43) was significantly greater than zero (t(23) = 3.14, p = .01). Thus, users' reliance on NIAs relative to their browsers increased with experience; however, this was not the case for every user. Query rates on the browser also increased with experience. Using a similar approach using difference scores, we found that the second half of the study consisted of 5% more sessions that contained at least one search. This increase also yielded a mean difference score reliably greater than zero (t(23) = 2.17, p = .04).

Taken together, use of the phone over time led to increased reliance on NIAs and a greater use of search on the browser. The iPhone seemed to afford users to optimize both modalities by accessing NIAs for repeated use of favorite content and browsers for searching for and use of new and fleeting information.

DISCUSSION

The goal of this study was to characterize web interactions with smartphones using a deliberately naturalistic and longitudinal methodology. Indeed, because our logger unobtrusively collected interaction data from ecologically-valid environments over a substantial period of time, we submit the behaviors examined in this study were particularly realistic. At the broadest level we found differences between technologies—the PC and the smartphone—in how the internet was accessed and differences between users in how the latter was used. We discuss both findings in turn before we provide design recommendations.

Using the Web on Smartphones

Clearly, the web browser is not as fundamental to smartphone use as it has appeared to be with PCs. The *highest* frequency user in the current study averaged fewer URL visits per day (20) compared to the *lowest* frequency user in the most recent PC study published in 2008 (24.9). This difference between platforms was both because the browser was accessed less often and, when it was accessed, it was for shorter periods of time. Indeed, smartphone browsing sessions were roughly three times shorter than PC browsing sessions in both duration and pages visited.

Revisitation patterns were also dissimilar. Page revisitation rates were much lower than previous PC-based studies. Many of these revisits were continued after an interruption or to a top-level portal only to get to targeted (new) content. We see the former as a unique characteristic of mobile browsing. The latter reflects the lack of browser use to revisit static content. Though pages were not revisited often, sites were revisited at levels much higher than any previous PC study. Clearly, a small set of domains provide users access to a much larger number of diverse pages suggesting designers should surface these portals when the browser is accessed (as discussed below).

The distinction between computing platforms in volume of use became more pronounced with experience as browser use gave way to higher NIA activity. NIAs consumed most visits to the internet, especially after users became more experienced with their devices. These visits were short and concentrated to a relatively stable vocabulary of NIAs that were frequently revisited. When our users first received their smartphones, they seemed to apply mental models developed from computer use and relied heavily on their smartphone browser for touring a large number of sites and accessing these sites often. However, instead of bookmarking these sites within their browsers, users installed NIAs that "stuck" to their vocabularies for longer periods of time. In a sense, this emphasis on a new type of bookmarking (installing NIAs to springboards) has afforded iPhone users to optimize their devices. NIAs were used more frequently to access a stable set of resources in particular contexts. Web browsers became a tool that afforded searching for and consuming new and dynamic information with low likelihood of repeated visits. Adding the former required users to predict their information and entertainment needs while the latter was used more ad hoc. The clear message to web designers is to point users to installing the NIA to increase the probability of revisits.

Even with these links to install an NIA, our study suggests that it is difficult for new NIAs to become part of users' "active" vocabularies. Not all NIAs that are installed are used frequently. Many are removed after one visit or deserted on a springboard and not accessed more than a few times (recall Figure 3). Interestingly, the mean vocabulary rates for NIAs within each month did not increase much across the entire length of this study, though new NIAs were installed. This suggests total NIA vocabularies are somewhat fixed for users; as new NIAs are added, others are either uninstalled or left on springboards with low likelihood of revisits. Of course, there was large user variance in most aspects of internet use on smartphones confirming that personalization based on each user's unique usage patterns and contextual needs is an important design strategy for mobile space.

Different Types of Smartphone Users

Indeed, previous studies have found differences between smartphone users at several orders of magnitude [9]. Here, we characterize these differences building on a growing line of empirical research in HCI. Catledge and Pitkow [4] described differences between PC web users based on browsing patterns. One type, "Serendipitous Browsers" did not yield repeated sequences of URL visits. "Searchers", in contrast, were repetitive in short navigation sequences. Teevan et al. [34] labeled users at these extremes as "Filers" and "Pilers". Filers designated explicit locations to organize their electronic information. Pilers, on the other hand, were unstructured and used different search strategies to retrieve their electronic information. Extending findings in education, Ford [10] found that "Holists" issued more exploratory searches and valued serendipitous encounters with new information. In contrast, "Serialists" follow a linear pattern to learning and navigate on the web in a more sequential manner. White and Drucker [36] similarly described PC users as "Explorers" and "Navigators". The former prefers undirected browsing and discovery of new information. The latter prefers rapid access to target information and performed more directive searching to desired content.

We now characterize mobile users at two ends of a similar behavioral continuum. At one end, "Pioneers" relied on their browsers more and these interactions yielded visits to more diverse content, longer sequences of URLs per session, more searches within each browsing session and higher rates of revisiting across modalities. This larger consumption seemed to reflect that these users "settle" on a small subset of favorite resources on the browser very frequently. However, they also continue to pioneer in these browsing sessions with search and visiting of new content for more sundry reasons. This behavioral pattern manifested somewhat in NIAs as well; perhaps exploring more within NIAs reflected by longer visits and clearing out room on their springboards for new NIAs. Pioneers also revisited physical locations at a higher rate and used their iPhones in more unique localities. Clearly, these users are most similar to "Serendipitous Browsers", "Holists", "Explorers" and "Pilers" in that they consume more diverse amounts of information, interact for longer sequences when on the web and traverse in more localities in the real world.

On the other end, Natives did not access the internet as much and did not venture outside of "native territory" to visit as much new content. They are most similar to "Searchers", "Filers", "Serialists" and "Navigators" in this regard and because they rely on shorter navigation sequences using search when on their browsers. Web browsers were sparingly used to discover new information; though it was used directly after another NIA. Natives yielded web sessions shorter in terms of both pages visited and duration. Similarly, NIA launches from their vocabularies were for shorter durations as well.

How can these user differences be explained more theoretically? First, we submit these distinctions reflect patterns explained by differing cognitive styles identified in previous learning and HCI studies [see 37]. Because stable behavioral differences, similar to differences between *holists* and *serialists*, manifested across virtual and physical traversing in our study, our smartphone users differed because of how they varied along this cognitive spectrum. Second, these differences between users could have manifested because of the types of contexts visited and user goals within those settings [See 18]. Natives seemed to actively use their smartphones more as tools to accomplish short information needs. Pioneers seemed to use their smartphones actively and passively for both utilitarian and hedonic reasons. Pioneers may have developed more habitual routines as they revisit more of the same locations to access their phones [26]. Since they do not visit more physical locations, perhaps they compensate by traversing more on the web to content previously settled on along with additional explorations. This hypothesis should be tested in additional research. Finally, our results could be driven by an interaction between these two factors.

Design Implications

Our study suggests several ways to support smartphone users. Even though we direct these recommendations toward users at each end of the continuum, we purport that each suggestion would be beneficial for all users. Indeed, users along the entire spectrum can display both types of behavioral patterns and gain from enhanced designs.

We think **Pioneers** could benefit from capabilities previously reported for similar types of users [e.g., 36] along with several suggestions for mobile space:

- **Optimize content for mobile browsing and NIAs**: Content designers should not ignore designing a usable mobile site for web browsers. Many new smartphone users rely heavily on their browsers to access the internet and find information to be bookmarked via installing the NIA. Additionally, the mobile browser continuously provides a vehicle for many users at all experience levels to access new content with low likelihood of revisiting. Optimized content for mobile browsing should assume users are new and provide clear "knowledge-in-the-world" to support first-time interactions along with clear links to add bookmark through installing the NIA, adding the site tag to a springboard, or the top browser bar.
- **Better design of mobile browsers:** Most certainly, our study suggests that the real estate used for the URL address bar can be better exploited for personalized

access to favorite content. Since many of the sites and pages revisited were Top-Level Pages (e.g., home pages), designers should surface these portals to avoid unneeded typing, searching, and page loading. For instance, the Google search bar could double as the URL address bar for pasting URLs and for autocomplete functionality to revisit pages. The free space on the top browser bar (no longer occupied by the URL address bar) could be used to access top-level sites based on each user's most visited sites or adaptable for users to add and edit based on their perceived needs. For sites with a short tail (such as the institutional sites in Figure 1), these personalized buttons could display a menu with the most visited sub-level sites when selected.

- **More intelligent springboards:** We submit, based on our findings, that springboards can be designed more effectively to support discovering new NIAs. This could take several forms. For example, user profiles could be developed from NIA and browsing history to provide suggestions based on content visited. Smartphone designers could give users the option to designate one springboard page for recommender capabilities. This springboard may allow users to try NIAs before they permanently install or buy applications. In other words, a recommender system would install suggested NIAs for trying out instead of relying on the user to browse, install, and try out the app for him- or herself. Most users had room on their springboards for such a capability. We recommend, especially for Pioneers, a Springboard page designated for "Try-before-you-buy" NIAs already installed based on previous usage. Part of this springboard space could be used for browser access. For instance, an auto-bookmark mechanism to provide links to a top-level site from a user's unique history could be leveraged similar to the Windows Start Menu. Perhaps even a static top-level page with links to sub-level resources would be beneficial for more efficient interactions.

Natives could also benefit from design features to help them get to desired information more quickly:

- **Predictive systems:** More predictive capabilities are needed to attenuate mobile HCI problems mentioned above such as page loading and awkward text entry. Activity gathered from other devices can be useful to this end [16]. According to our study, each user's history of web use on their smartphones could provide ways to predict likely site destinations. Most overall internet use was dominated by a relatively small set of sites and NIAs. Using contextual information and most frequented sites to preload pages (e.g., top-level pages) would be beneficial to avoid long page loading delays.
- **Web search from the springboard**: When Natives accessed their browsers, it was usually for quick searches. Queries were conducted most often on the web. It may be beneficial to offer a vehicle to search from the springboard. For instance, instead of capabilities to "search your iPhone" from the springboard, it may be more useful to have a "search the web" bar right on the springboard main pages.
- **Identify Springboards**: Across the entire study, NIA vocabs were generally higher than what could fit on one springboard page. Natives did not uninstall NIAs much compared to Pioneers. Also, they used more NIAs just once. Taken together, it seems like springboards could be designed to more effectively support revisits. Perhaps one way to do this is giving users options to identify each springboard. Another way might be to set up reminder for NIAs previously installed that have not been used over a period of time. This reminder could alert NIAs to this resource and perhaps encourage increased usage.

Limitations

Of course, these findings should be generalized with caution because of several limitations in the current study. Foremost, our small sample size does not represent the entire range of the millions of smartphone users around the world. However, the number of users analyzed here is roughly equivalent and perhaps more diverse than many of the previous studies that have informed our research. Second, we only examined the use of iPhones. Future research should assess how our results generalize to other devices. Third, the PC studies are slightly older and we suspect current PC web use has changed (at least for smartphone owners). It is unclear how use of a smartphone with a PC impacts the latter. Future studies should assess intra-user differences across PC and smartphone platforms.

CONCLUSION

Bearing these limitations in mind, this study contributes an empirical characterization of web use on smartphones. We established behavioral patterns associated with browsing, NIA use and physical locations where smartphones were used to build on previous descriptions of user differences. Indeed, we found these differences were stable across virtual and physical location visiting with smartphones.

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REFERENCES

1. Abowd, G.D. & Mynatt, E.D. Charting past, present, and future research in ubiquitous computing. *ACM Trans. on Computer-Human Interaction,* 7, 2000, 29-58.
2. Bales, E. *et al*. Planning, apps, and the high-end smartphone: exploring the landscape of modern cross-device reaccess. In K. Lyons et al. (Eds.): *Pervasive 2011, LNCS 6696, pp. 1-18*. Berlin: Springer.
3. Byrne, M., John, B., Wehrle, N.S. & Crow, D.C. The tangled web we wove: A taskonomy of www use. *In Proc. CHI 99,* ACM Press (1999), 544-551.

4. Catledge, L.D. & Pitkow, J.E. Characterizing browsing strategies in the world wide web. *In Proc. WWW 1995,* ACM Press (1995), 1065-1073.
5. Cockburn, A., McKenzie, B. What do web users do? An empirical analysis of web use. *International Journal of Human-Computer Studies*, 54(6), 2001, 903-922.
6. Cui, Y. & Roto, V. How people use the web on mobile devices. *In Proc WWW'08,* ACM Press (2008), 905-914.
7. Duchnicky, R.L. & Kolers, P.A. Readability of text scrolled on visual display terminals as a function of window size. *Human Factors,* 25, 1983, 683-692.
8. Ericsson Consumer Labs. From apps to everyday situations, 2010. http://www.ericsson.com
9. Falaki, H. et al. Diversity in smartphone usage. *In Proc MobiSys 2010*. ACM Press (2010). 179-194.
10. Ford, N. *et al*. Information seeking and mediated searching. *JASIST,* 53, 2002, 728-735.
11. Gallette, D.F., *et al*. When the wait isn't so bad: The interacting effects of website delay, familiarity, and breadth. *Info. Systems Research,* 17(1), 2003, 20-37.
12. Holscher, C. & Strube, G. Web search behavior of internet experts and newbies. *Computer Networks,* 33, 2000, 337-346.
13. Internet World Statistics, 2011. Retrieved May 2011: http://www.internetworldstats.com/stats2.htm
14. Kaikkonen, A. Full or tailored mobile web-where and how do people browse on their mobiles? *In Proc. of Mobility '08*, 1-10.
15. Kamvar, M., Kellar, M., Pater, R. & Xu, Y. Computers and iPhones and mobile phones, oh my! A logs-based comparison of search users on different devices. *In Proc. WWW 2009*. ACM Press.
16. Kane, S.,*et al*. Exploring cross-device web use on PCs and mobile devices. *Human-Computer Interaction – INTERACT 2009*, Springer (2009), 722-735.
17. Kellar, M., Watters, C. & Shepherd, M. A field study characterizing web-based information-seeking tasks. *American Society for Information Science and Technology,* 58(7), 2007, 999-1018.
18. Lee, I., Kim, J. & Kim, J. Use contexts for the mobile internet: A longitudinal study monitoring actual use of mobile internet services. *International Journal of Human-Computer Interactions,* 18, 2005, 269-292
19. Matthews, T., Pierce, J. &Tang, J. No smartphone is an island: The impact of places, situations, and other devices on smartphone use. *IBM Technical Report #RJ10452,* 2009.
20. Newark-French, C. Mobile apps put the web in their rear-view mirror, 2011. http://blog.flurry.com
21. Nielsen, J. User interface directions for the web. *Communications of the ACM*, 42(1), 1999, 65-72.
22. Nielsen, J. Mobile Usability, 2009. http://www.useit.com/alertbox/mobile-usability.html
23. Nylander, S., Lundquist, T. & Brännström, A. At home and with computer access – why and where people use cell phones to access the internet. *In Proc. CHI 2009,* ACM Press (2009), 1639-1642.
24. Obendorf, H., Weinreich, H., Herder, E. & Mayer, M. Web page revisitation revisited: Implications of a long-term click-stream study of browser usage. *In Proc. CHI 2007*, ACM Press (2007), 597-606.
25. Oulasvirta, A., Rattenbury, T., Ma, L. & Raita, E. Habits make smartphone use more pervasive. *Pers Ubiquitous Computing,* Published online: 16 June 2011.
26. Perry, M., O'hara, K., Sellen, A., Brown, B. & Harper, R. Dealing with mobility: Understanding access anytime, anywhere. *ACM TOCHI,* 8(4), 2005, 323-347.
27. Pew Research Center. *Internet and American Life Project,* 2010. http://www.pewinternet.org
28. Roto, V. & Oulasvirta, A. Need for non-visual feedback with long response times in mobile HCI. *In Proc. WWW 2005*. ACM Press (2005). 775-781.
29. Sellen, A.J., Murphy, R. & Shaw, K.L. How knowledge workers use the web. *In Proc. SIGCHI 2002*. ACM Press (2002). 227-234.
30. Selvidge, P. Examining tolerance for online delays. *Usability News*, 5(1), 2003. http://psychology.wichita.edu/surl/usabilitynews/51/delaytime.htm.
31. Shepard, C., Rahmati, A., Tossell, C.C., Zhong, L. & Kortum, P. Livelab: Measuring wireless networks and smartphone users in the field. *ACM Sigmetrics Performance Evaluation Review, 38(3),* 2011, 15-20.
32. Tauscher, L. & Greenberg, S. How people revisit web pages: Empirical findings and implications for the design of history systems. *International Journal of Human Computer Studies*, 47(1), 1997, 97-138.
33. Taylor, C.A. *et al.* Always on: A framework for understanding personal mobile web motivations, behaviors, and contexts of use. *Int'l Journal of Mobile HCI,* 1(4), 2009, 24-41.
34. Teevan, J. *et al*. The perfect search engine is not enough: A study of orienteering behavior in directed search. *In Proc CHI,* ACM Press (2004): 415-422.
35. Tossell, C.C., Kortum, P., Shepard, C., Rahmati, A. & Zhong, L. Performing common tasks on handheld mobile computers. *In Proc. of HFES* (2010).
36. White, R.W. & Drucker, S.M. Investigating behavioral variability in web search. *In Proc. WWW 2007*, ACM Press (2007), 21-30.
37. Witkin, H.A. *et al*. Field-dependent and field-independent cognitive styles and their educational implications. *Review of Educational Research,* 47, 1977, 1-64.