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Mobile wellness application-seeking behavior by college students—An exploratory study

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ABSTRACT

This research explored the mobile wellness application-seeking behavior of college students. In particular, it examined what sources students used to obtain wellness information, what wellness applications students used and for what purposes, how they learned about those applications, and what factors influenced their decision to choose a particular wellness application from multiple alternatives. The results indicated that students most often used websites as sources of wellness information, followed by mobile applications, family and friends, and then physicians. Students most often learned about wellness applications from search engines and application stores. Physicians were the least mentioned source of learning about mobile wellness applications. The most popular application type was calorie and activity trackers. In addition, when asked to rate the importance of various mobile application characteristics in their decision to select a particular wellness application, students rated the usability-related characteristics the highest, followed by the application cost and content quality. This study contributes to current

research and practice in mobile wellness application design and the provision of mobile wellness services. In particular, it can inform application designers and intermediaries about which mobile wellness applications students use, and how students search for and select those applications.

1. Introduction

Wellness is generally defined as a lifestyle or as a preventive approach to maintaining good mental and physical health (Myers, Sweeney, & Witmer, 2000; Wellness, 2012). Promoting wellness is essential for improving people's health and reducing health care costs. One wellness issue in particular—obesity—has been identified as one of the most challenging health crises today; it is a leading risk factor in several life-threatening diseases, such as diabetes, stroke, and cancer (Robert Wood Johnson Foundation, 2011; U.S. Department of Agriculture, 2010). Inadequate nutrition, a lack of exercise, and obesity have become problems among young people, including college students (Grace, 1997). A recent survey showed that more than 28% of U.S. adults aged 20 and over were obese, including almost 25% of adults aged 20 to 39 (Centers for Disease Control and Prevention, 2011). The rates of obesity have been particularly high in the southern states, including Florida (Robert Wood Johnson Foundation, 2011). Surveys have also shown that consumers' use of the Internet and mobile devices for health management has been increasing. Fifteen percent of Internet users have tracked their weight, diet, or exercise routine on the Web. Nine percent of adults who own a cell phone have used applications on their phones to manage their health, and adults aged 18 to 29 were the most frequent users of health applications (Fox, 2011).

Health communication research has shown that the use of Web health information systems and mobile applications leads to increased knowledge, positive health outcomes, and more proactive health behavior (Mamykina, Mynatt, & Kaufman, 2006; Stvilia et al., 2009; Wantland, Portillo, Holzemer, Slaughter, & McGhee, 2004), and it may conserve resources (e.g., by reducing the number of emergency

room visits; Krishna et al., 2003). More research is needed, however, to understand what makes health or wellness applications and information systems useful and usable, and how to promote and increase their use (Ahtinen et al., 2009; Cyr, Head, & Ivanov, 2006; Mattila et al., 2010).

Smartphone ownership has been growing steadily among all age groups. According to a 2013 Pew survey of smartphone ownership, 79% of the U.S. population in the 18- to 24-year-old age group own a smartphone, representing a 10% increase from a similar poll in 2012 (Smith, 2013). With increased ownership, smartphones have rapidly gained ground as channels for tailored health and wellness information distribution and as tools that individuals can use to monitor their health and wellness activities and to log, quantify, manage, and interact with this information. Mobile application stores (e.g., Google Play) list hundreds of thousands of mobile applications with tens of millions of downloads. It is not always clear, however, whether those applications are grounded in high-quality medical and kinesiology research or whether they perform according to the specifications listed in the descriptions (Furlow, 2013). In addition, concern has increased regarding the privacy protection of mobile application users, and governments have had to enact laws and guidelines to regulate the consumer data collection practices of mobile application developers (Guynn, 2013). At the same time, very little research exists on how consumers seek mobile applications on the Web and select from among them. More research is needed to determine how consumers perceive the usefulness and quality of mobile health and wellness applications; whether the consumers' perceived quality corresponds to the actual quality of the application; and whether the models, constructs, and heuristics of quality evaluation identified for Web health and wellness information resources are applicable to mobile applications. With multiple choices available for the same type of product from different providers, the discovery, selection, and recommendation of the "right" product become a challenge for consumers as well as for intermediaries such as search engines, application stores, and health portals.

2. Problem Statement

As the number and variety of mobile wellness applications continue to grow, it is important to understand the wellness activities in which the population engages and their related mobile application-seeking behaviors to design effective application discovery and ranking mechanisms. To achieve that objective, this study explored the following set of research questions: (1) What sources do students use to obtain wellness information and services? (2) What mobile wellness applications do students use, and what are the purposes of using those applications? (3) How do students discover mobile wellness applications?

Product design and selection is a multidimensional optimization problem involving matching product and user characteristics (Green & Krieger, 1985; Konstan & Riedl, 2012). Quality, which is a product characteristic along with cost, is itself a multidimensional and contextual concept. It is usually defined as "fitness for use" (Juran, 1992). Some of the virtues or dimensions of software quality are accuracy, completeness, reliability, operability, portability, interactivity, security, and privacy. When direct, comprehensive evaluation of the quality of a product is not feasible (e.g., because of the high cost or users' lack of skills or knowledge), heuristics and credibility cues are used to asses quality indirectly (Stvilia et al., 2007; Sundar et al., 2007). Furthermore, different product characteristics and heuristics may convey values of differing importance in users' product selection decisions (Stvilia et al., 2009). Hence, this article investigates the following research questions: (4) What are some of the characteristics that influence students' decision to select a specific mobile wellness application from alternatives? (5) What is students' value or importance structure for those application characteristics?

3. Literature Review

A need exists to evaluate and rank the alternative mobile wellness applications by their quality and value to the consumer. *Quality*, defined as fitness for use (Juran 1992; Wang & Strong, 1996), is contextual and dynamic. Consumers' perception of quality as well as the priorities and value structure for quality may vary with consumers' age, level of education, and cultural background (Stvilia et al., 2009; Yi, Stvilia, & Mon, 2012). Furthermore, as new wellness services and products evolve, consumers' expectations for what constitute mobile wellness applications of higher or lower quality and their perceptions of what constitutes higher or lower quality of a particular type may change. Finally, as the number and variety of mobile wellness applications grow, consumers simply may not have the time or expertise to evaluate mobile applications through use and may have to rely instead on heuristic and indirect evaluations by using application descriptions and quality cues.

For search engines, online stores, review portals, and application developers to maintain their ranking algorithms and better align them with the consumers' perceptions of usefulness and quality, it is essential to identify the structure of consumers' decision making when selecting a wellness application. A significant body of literature exists on the conceptualization of individual information quality criteria, general frameworks for quality criteria, and context-specific models of information product and service quality (e.g., Eysenbach, Powell, Kuss, & Sa, 2002; Fallis & Fricke, 2002; Frické, Fallis, Jones, & Luszko, 2005; Marschak, 1971; Saracevic, 2007; Stvilia, Gasser, Twidale, & Smith, 2007; Tenopir, 1995; Wand & Wang, 1996; Wang & Strong, 1996). In addition, studies have been conducted on consumers' use of different heuristics to make quality and credibility judgments (e.g., Fogg, 2003; Rieh, 2002; Sundar, Knobloch-Westerwick, & Hastall, 2007; Yi et al., 2012), and researchers have investigated the effects of using specific system components on the efficacy of different types of websites. More recently, Sim and colleagues investigated the use of technical metadata and social cues when searching and selecting source code on the Web (Gallardo-Valencia & Sim, 2011; Sim, Umarji, Ratanotayanon, & Lopes, 2011).

Another relevant source of literature for this study is the literature on recommender systems (e.g., Konstan & Riedl, 2012), which includes the literature on recommender systems for mobile applications (e.g., Böhmer, Ganev, & Krüger, 2013). In addition to various features and metrics used to produce the recommendations, one important issue discussed in that literature is whether users are willing to contribute multicriteria ratings for products. Although Konstan, Riedl, Borchers, and Herlocker (1998) found that users were disinclined to provide multicriteria ratings, a different study by Adomavicius and Kwon (2007) showed that use of multicriteria ratings in a recommender system for movies could lead to better recommendations.

The dimensions of quality can be both intrinsic and relational, and quality can be assessed both directly and indirectly (Stvilia et al., 2007; e.g., assessing the reputation or credibility of the creator or author of the application). This process of indirect quality assessment by using various cues or "information scents" can also be conceptualized as sensemaking around the quality and value of the application (Pirolli & Card, 1999; Russell, Stefik, Pirolli, & Card, 1993). When multiple alternatives exist for the same type of product or service, the quality-based selection of an application becomes a search optimization task in a multidimensional search space where the dimensions are quality criteria and cost (Lesser et al., 1998). Visualization is often used to make sense of data and support decision making (Chi & Card, 1999).

Users use social cues and annotations – "information scents" - in predicting the quality or usefulness of information (Pirolli & Card, 1999). First, they should be able to notice and interpret these cues as relevant to their product selection decision (Fernquist, & Chi, 2013; Fogg, 2003). In addition, different types of social cues may convey different levels of importance or persuasion value to the user and may thus influence their decision making differently (Stvilia et al., 2009). Kulkarni and Chi (2013) found that annotations from friends were more persuasive to users in their selection of news articles than were annotations made by people they did not know.

This study builds on prior research in which we developed a model of online consumer health information quality consisting of the constructs of quality criteria, related cues, and heuristics (Stvilia et al., 2009). The current research extends our prior research to mobile wellness applications. In addition to our previous work, a significant body of literature exists on the conceptualization of individual information quality criteria, general frameworks, and context-specific models of information product and service quality (e.g., Parasuraman, Zeithaml, & Berry, 1988) on the use of different heuristics to make indirect quality (i.e., credibility) judgments of websites (e.g., Fogg, 2003) and on software quality (e.g., Fenton, 1991).

Similar to the quality of other products, most of the time, the users of mobile applications may not have access to or the ability to evaluate the source code of the application, and can only assess its quality either directly through the use of the application or indirectly by using cues in the summary description of the application and social cues, including other users' evaluations and quality incident reports (Gallardo-Valencia & Sim, 2011). The summary description of an application may also explicate the intrinsic quality characteristics of the application (e.g., the use of sensitive resources) obtained through direct evaluation of the code (Lin et al., 2012). The preceding studies provide valuable insights into the different aspects of selecting a particular product or service and the relationships that can affect a consumer's selection decision. However, more research is needed on how consumers seek and evaluate mobile applications in general, and wellness applications in particular.

4. Study Design

The design of this study was inspired by information foraging theory (Pirolli & Card, 1999). Information foraging theory provides models of search optimization by borrowing concepts and terminology from evolutionary biology. One of the central concepts of information foraging theory is the

concept of information scent which refers to imperfect intermediary information that can be used by the user to lower the cost of finding useful information. Finding useful wellness application too can be conceptualized as a search optimization problem. The user may use various information scents to reduce the cost of identifying the "right" application to her/his wellness need(s). Quality is usually defined as "fitness for use" (Juran, 1992). Quality is a multidimensional and contextual and it can be assessed directly, or indirectly using imperfect information - "quality" scents or cues. In addition, information scents need to be "strong" enough users to recognize them as such and use in their seeking of mobile wellness applications. They may assign different values of importance or persuasion to different quality dimensions (e.g., accuracy, completeness, usefulness, usability) and related scents (e.g., author credentials; Stvilia et al, 2009; Choi & Stvilia, 2012). Due to the exploratory and descriptive objective of this study, the scope of this paper was limited to identifying user priorities for different information scents in selecting mobile wellness applications among multiple alternatives. The scope of this paper did not include examining the relationships between application quality dimensions and information scents used in application selection decisionmaking. That part remains the subject of the follow up future research.

The study used a mixed methods approach. Activities consisted of survey administration and postsurvey interviews. After a participant completed the online survey, she/he was scheduled for a face-to-face postsurvey interview which usually took place on the following day. The postsurvey interview was used to debrief the participants about the survey and obtain additional knowledge on what specific wellness application(s) they used, how they found and selected the application, and how they used the application. The designs of the survey and interview instruments were informed by the literature, including use of the quality cue constructs developed in an earlier study of consumer perceptions of the quality of health information websites (Stvilia et al., 2009) and typologies of the software quality problem types and quality cues found in the literature (Fenton, 1991; Gallardo-Valencia & Sim, 2011; Nielsen, 2012). The study also used some of the criteria and structures from the technology acceptance model (Venkatesh & Davis, 2000) and the unified theory of acceptance and use of technology (Venkatesh,

Morris, Davis, & Davis, 2003). In particular, the study used the constructs of technology usefulness and ease of use from the unified theory of acceptance and use of technology and technology acceptance model.

The survey and interview instruments were pretested for validity and readability on five doctoral students in the School of Information at Florida State University. The finalized survey instrument was then administered to 50 students recruited on the Tallahassee campus of Florida State University. To be eligible for participation, students had to own a smartphone and use at least one mobile health or wellness application. To recruit participants, the researchers used announcements to a fitness-related Facebook group and distributed fliers in classrooms at Florida State University. Before participating in a Qualtrics-based online survey and a postsurvey interview, participants were given a consent form approved by the Human Subjects Committee of Florida State University. The form contained information about the project, including information about potential risks associated with participation in the data collection. Participants who completed a survey and an interview were e-mailed a $30 Amazon gift card.

All 50 recruited participants completed both a survey and interview. Fifty-two percent of the survey participants (26 out 50) were female and 48% were male. For ethnicity, the majority of the participants were White (37 out of 50; 74%), five were Hispanic or Latino (10%), three were African Americans, two were Asians, and three defined themselves as multiracial. In terms of education level (status), 92% (46 out 50) were undergraduates, 4% (2 out of 50) were graduate students, and two were pursuing a nondegree certificate.

Two researchers used content analysis to code postsurvey interview transcripts for the type of sources participants used to learn about mobile wellness applications and the types of uses. Each researcher open coded the complete sample independently. After coding was completed, the resultant schemas were aggregated and differences were resolved, and the researchers used the final aggregated schema to recode the entire sample.

5. Findings

When asked what source(s) they used to obtain health or wellness information and services, 96% of participants indicated that they used websites. The next most frequently selected choice was mobile applications (90%) followed by family and friends (88%), physicians (72%) and social media (34%). The least frequently selected choice was television (14%; see Table 1).

Table 1
Sources students used to find health and wellness information (N = 50).

Source	Num. of Participants	%
Websites	48	96
Mobile applications	45	90
Family and friends	44	88
Physicians	36	72
Social media (Facebook, Twitter, Google+, etc.)	17	34
Printed periodicals and books	12	24
Television	7	14

As Table 2 shows, the mobile applications most frequently used by the participants were MyFitnessPal (15 out of 50), followed by Nike+ Running (9 out of 50), Map My Run (7 out of 50), and Lose It! (6 out of 50). Other applications mentioned by more than one person included S Health, C25K, RunKeeper, Runtastic PRO, Fitbit, WebMD, Sleep Cycle, and Fitness Buddy.

In terms of types of applications, the calorie and daily activity counters (e.g., MyFitnessPal, Lose It!, S Health, Fitbit, etc.) were the most popular among participants in the present study (27 out 50), followed by the running trackers (e.g., Nike+ Running, Map My Run, C25K, RunKeeper, etc.; 21 out of 50), the exercise/workout trackers (e.g., Fitness Buddy, Ab Workouts, Alpha Trainer, etc.; 8 out of 50), the health information databases (e.g., WebMD and Nutrition Facts; 4 out of 50), and the sleep pattern trackers (e.g., Sleep Cycle, SleepBot, and Sleep Maker; 4 out of 50). The applications were categorized according to the main uses reported by participants, not by the sets of available functionalities.

Table 2
Mobile applications used by students (N = 50).

Calorie & daily activity counters	%	Running trackers	%	Exercise and workout trackers	%	Databases	%	Sleep pattern trackers	%	Miscellaneous	%
MyFitnessPal	30	Nike+ Running	18	Fitness Buddy	4	WebMD	6	Sleep Cycle	4	Menstruation and Ovulation Calendar	2
Lose It!	12	Map My Run	14	7 Minute Workout	2	Nutrition Facts	2	SleepBot	2	Period Tracker	2
S Health	6	Couch (C5K, C25K)	6	Ab Workouts	2	Total	8	Sleep Maker	2	QuitSTART	2
Fitbit	4	RunKeeper	6	Alpha Trainer	2			Total	8	Heart Rate	2
Calorie Counter	2	Runtastic PRO	4	Record My Swim	2					Total	8
Fooducate	2	Charity Miles	2	Virtual Gym	2						
MyPlate Calorie Tracker	2	Total	42	Workout Trainer	2						
Weight Watchers	2			Total	16						
Total	54										

Students learned about mobile wellness applications from different sources: by searching Google or application stores by general wellness topic; by browsing application stores for new, trendy applications; by talking with family members and friends; by reading websites and blogs; by finding applications preinstalled on products they purchased (e.g., smartphones); or by receiving recommendations or promotional campaigns on social media. Searching general search engines and application stores was the most frequent way of learning about wellness applications, followed by talking to family members and friends, and reading websites (see Table 3). Regardless of how participants learned about the application, most of the time, they still had to go to the operating system-specific application store to download and install the application.

Table 3
Sources of learning about wellness mobile applications.

Source	Num. of Applications	%

Search engines and application stores	29	44
Family and friends	13	20
Websites	7	11
Came with product	7	11
Social media	6	9
Magazines	2	3
Physicians	1	2

In this study, survey participants were asked to rate the importance of various characteristics of the mobile applications in their selection of a particular wellness application. The list of characteristics and their mean importance ratings are shown in Table 4. The list was compiled based on a review of the literature (see the Related Research section). Because of the exploratory nature of the study, the list included software and information quality-related properties that users could assess only through use (e.g., the application is easy to use, is easy to navigate, provides high-quality content) as well as properties that could be used as scents or cues in indirect quality assessment before the actual use of the application (e.g., recommended on social media). The list also included information scents that were not linked to quality, such as the cost of the application.

On average, participants rated the usability-related characteristics the highest—those easy to navigate and easy to use—followed by the property-related characteristics and the application cost—free or not. The content quality received the next highest average importance rating (see Table 4).

Table 4
Mean importance ratings of the application characteristics.

Property	Mean	*SD*
Is easy to navigate	6.38	0.67
Is easy to use	6.14	0.95
Is free	6.06	1.20
Provides high-quality content	6.00	1.12
Allows personalization (e.g., services, content, or both can be tailored to my current context)	5.86	1.13
Has high ratings from users	5.84	1.06
Provides more functionalities than does the alternative	5.56	1.30
Is ranked high by a search engine or a mobile application store	5.48	1.23
Includes little advertising	5.46	1.81
Looks professionally designed	5.44	1.37
Provides additional health or wellness information and tips	4.90	1.36
Is linked to from a site you think is believable	4.86	1.32
Was recommended by a friend(s) or family member	4.70	1.53
Had a good experience with the related website	4.64	1.45
Includes a clear privacy policy	4.44	1.61
Represents or is produced by an organization you respect	4.38	1.34
Was recommended by a doctor(s)	4.30	1.53
Was recommended on social media	4.16	1.50
Includes sources, author credentials, and affiliations for content	4.10	1.56
Has a third-party quality approval or review seal	3.68	1.43
Was recommended by a newspaper or magazine	3.50	1.53
Displays an award it has won	3.44	1.31
Is recommended on the radio or TV	3.22	1.62
Represents or is produced by a nonprofit organization	2.96	1.41

To identify the value or importance structure of the application characteristics in students' decisions regarding which wellness application to select, the study applied factor analysis with principal components analysis to survey participants' ratings of the application characteristics. Both the Bartlett and Measure of Sampling Adequacy (MSA) tests for the sample pointed to a significant level of correlation (Bartlett test: $\chi^2 = 579.2$, $p < 0.001$; MSA = 0.59) among the characteristics. The analysis selected the first eight factors with eigenvalues greater than one. The eight factors represented 74% of the total variance in the sample. In addition, because the sample size was small (50 participants), the cutoff size for the criteria loadings on the factors was set at 0.75 (Hair, Black, Babin, Anderson, & Tatham, 2005; see Table 5).

Table 5

Factor loadings of the application characteristics

	Component							
Property	1	2	3	4	5	6	7	8
Easy to use	0.14	–0.03	0.03	***0.90***	0.08	–0.03	0.05	–0.10
Free	–0.04	0.19	0.10	0.00	0.13	0.09	–0.05	***0.84***
Recommended by a friend(s)	0.41	0.52	0.05	0.03	0.10	0.17	–0.21	–0.33
Recommended by a doctor(s)	0.37	0.30	0.52	–0.01	0.13	0.09	–0.13	–0.40
Looks professionally designed	–0.16	–0.10	***0.82***	0.18	0.22	–0.05	0.08	0.16
Had a good experience with the related website	0.49	0.07	0.35	0.05	–0.08	0.35	0.02	–0.19
Provides additional health or wellness information and tips	–0.07	0.51	–0.11	0.54	–0.20	0.37	–0.01	–0.02
Includes sources, author credentials, and affiliations for content	0.09	0.30	0.49	0.06	–0.13	0.57	–0.23	0.18
Has a third-party quality approval or review seal	0.13	0.71	0.19	–0.06	0.20	0.09	0.16	0.21
Includes a clear privacy policy	0.07	0.05	–0.06	0.06	0.08	***0.84***	0.18	0.04
Provides high-quality content	0.03	0.06	0.09	0.08	0.31	0.33	***0.75***	–0.21
Includes little advertising	0.19	0.17	–0.05	0.21	–0.15	–0.06	0.72	0.12
Provides more functionalities than does the alternative	–0.10	***0.78***	–0.09	0.34	0.03	–0.07	0.26	0.08
Easy to navigate	–0.06	0.28	0.16	***0.76***	0.09	0.14	0.35	0.13
Allows personalization (e.g., services, content, or both can be tailored to my current context)	0.45	0.07	–0.44	0.25	0.25	–0.05	–0.07	0.11
Represents or is produced by an nonprofit organization	0.29	***0.83***	0.00	0.03	0.16	0.05	0.05	0.07
Has high ratings from users	0.09	0.29	0.11	–0.06	***0.80***	0.07	0.14	0.03
Is ranked high by a search engine or a mobile apps store	0.18	0.04	0.10	0.13	***0.80***	–0.04	–0.07	0.07
Is linked to from a site you think is believable	0.28	0.48	0.28	0.19	0.19	0.27	–0.25	–0.29
Displays an award it has won	0.58	0.16	0.36	0.18	0.27	–0.32	–0.10	0.12
Represents or is produced by an organization you respect	0.48	0.18	0.58	–0.09	0.24	0.00	0.00	0.03
Recommended on the radio or TV	***0.81***	0.31	0.07	–0.07	0.00	–0.09	0.12	–0.02
Recommended by a newspaper or magazine	***0.78***	0.13	–0.15	–0.04	0.22	0.02	0.05	–0.21
Recommended on social media	***0.81***	–0.10	–0.01	0.12	0.04	0.28	0.12	0.06

Note. Extraction method: PCA; rotation method: Varimax with Kaiser normalization.

The authors evaluated the internal consistency of the factor constructs with Cronbach's alpha, except for the factors that consisted of only one criterion, such as Free, Content Quality, Looks Professionally Designed, and Includes a Privacy Policy. The alpha values of the constructs Easy to Use, High Ratings, Produced by a Nonprofit Organization, and Recommended by the Media were above the generally accepted lower limit of 0.70 (0.76, 0.73, 0.76, and 0.83, respectively).

The properties that loaded significantly on each factor were then used to develop summated scales. Eight scales were developed by averaging the scores of the properties assigned to each factor (see Table 6). The Easy to Use scale had the highest average importance score, followed by the Free, Content Quality, and High Ratings scales. The Recommended by the Media scale had the lowest average perceived importance score.

Table 6
Constructs of the application characteristics.

Constructs	Average rating	Characteristics
Easy to use	6.3	Easy to use, easy to navigate
Free	6.1	Free
Content quality	6.0	Provides high-quality content
High ratings	5.7	Has high ratings from users; ranked high by a search engine or a mobile applications store
Looks professionally designed	5.4	Looks professionally designed
Includes a privacy policy	4.4	Includes a clear privacy policy
Produced by a nonprofit organization	4.3	Represents or is produced by a nonprofit organization; provides more functionalities than does the alternative
Recommended by the media	3.6	Recommended on the radio or TV; recommended by a newspaper or magazine; recommended on social media

6. Discussion

The first research question examined the types of sources students used to obtain wellness information and services. The most frequently selected source was websites (96%), followed by mobile applications (90%), family and friends (88%) and physicians (72%) (see Table 1). Having websites and family and friends in the top three of most frequently named sources of health and wellness information matches the findings of a previous study on the perceptions of consumer health information quality, which similarly identified those types of sources as the most frequently used (Stvilia et al., 2009). Likewise, it was not a surprise to find mobile applications as the second most frequently selected source by participants that all of them used at least one mobile wellness application on a regular basis. This finding, however, points to an opportunity to further utilize mobile applications to disseminate health and wellness knowledge

through context tailored prompts and recommendations, not just to provide access to self-quantifying services.

Physicians were selected as the fourth most frequently used source. This result perhaps points to the issue that patients and physicians exchange relatively less wellness information during physician office visits compared with the amount of information consumers receive when they read health or wellness websites. This result could also be caused by students simply had few needs to use physicians' services because of their younger age and likely having fewer health problems.

The second research question investigated what mobile wellness applications were used by students and for what purposes. The most frequently selected application type was calorie and daily activity counters, followed by running and workout trackers (see Table 2). Some participants mentioned that they used several applications for different wellness needs. Others used more than one application for the same type of activity to achieve context-specific objectives (e.g., to share their activity data for charity):

> "I use Charity Miles still with the Runtastic PRO. And that, all you do is click start and it just goes however much you run or bike or whatever, it donates money to charity. And then you just finish and record your data." (i7)

Fewer students used health information databases such as WebMD to find answers to specific health or wellness questions, or to diagnose themselves:

> "I have chronic bronchitis. . . . I get the flu, I get sick a lot, almost every month I have a cold. And sometimes it is bronchitis. I don't have steady health insurance now. I use that [WebMD] more to diagnose what I have and then I can go and, like, based on the symptoms that I'm having, I use WebMD to see if it's reoccurring, like I need an antibiotic or if it's just a common cold or something like that. I use it kind of to gauge what medication I need to take." (i35).

Similarly, fewer students mentioned using applications to track their physiological states (e.g., sleep, menstrual cycles) or vital signs (e.g., heart rate). This may change in the future, however, as the cost of sensors decreases rapidly and the collection of physiological data becomes less expensive and obtrusive.

Information Foraging Theory was used to motivate this study. Although Information Foraging Theory was developed as a cognitive theory of information seeking, use, and organization, its conceptualizations and metaphors can provide an explanatory framework for mobile application seeking activities as well. Students seeking mobile wellness services can be conceptualized as foraging activities. Their mobile wellness service diets then would be shaped by their wellness service needs, access to the sources or "patches" of those services (i.e., mobile applications, application stores), the relative value and the cost of seeking and consuming those patches, and, other environmental constraints.

The third research question examined how students learned about mobile wellness applications. Similar to other types of products, information about mobile wellness applications can be received passively through serendipitous encounters and various 'push' technologies or actively through purposeful search. As expected, most often participants discovered mobile applications through general topical searches in a search engine or an application store. The second most frequently mentioned way of finding out about a mobile wellness application was suggestions from a friend or family member. This category also included a participant learning about applications indirectly when a family member installed the application by using a shared application store account:

> "I used to work in gym, and so I know a lot of people use the app. My old roommate, she's started working out a lot and so she started using it. So, I was like, 'Oh, maybe I should try it.' So I just learned from my roommates and from being in the gym." (i38)

> "My mom uses it. It's on my iPad. When she downloads apps, they come on my iPad as well. So I saw it pop up one day and I asked her, 'What is this?' She totally got me into using it, and taught me what she uses it for." (i30)

Some participants also mentioned using wellness applications that came preinstalled on their phones. Others were introduced to mobile wellness applications after they purchased sensor-enabled running shoes:

> "I wasn't really specifically searching for apps like that. It just happened to come to me when I bought the shoes. On the box, it said that it has the functionality. So I decided to check it out. I went on the App Store, looked at it, and I ultimately bought the device and put it in the shoe that helps you track the run." (i32)

Reading websites, blogs, and posts on social media was another frequently mentioned way of learning about wellness applications. Some applications that enable users to share reports of their workouts (e.g., routes ran) on social media with little or no effort could serve as an indirect advertisement and attract new users:

> "I saw someone on Facebook using it because you could post the route on Facebook. So when I saw there're using and they're enjoying it, that was one of the things that made me go and look for the same apps." (i18)

It is important to note that participants mentioned physicians least often as sources of learning about mobile wellness applications (see Table 3). This could be due to the younger age of the study participants. One would expect students to have less frequent interactions with physicians about wellness issues compared with other adult age groups. Likewise, it is important to note that none of the participants mentioned learning about mobile wellness applications from university health services. The findings of this study could be used by university health centers to develop recommended lists of mobile applications tailored to the wellness needs of the student population.

The fourth research question examined different characteristics that influenced students' decisions to select specific mobile wellness information and their priorities for those characteristics (i.e., value structure). In addition to the predefined choices for the characteristics, which might have influenced the

application selection decisions given to the participants to rate (see Table 4), the participants identified additional application characteristics that affected their decisions, such as the size of the application, the number of downloads, the interface aesthetics, and the ability to analyze sensor data and provide notifications relevant to the user's context. As one participant noted in a comment,

> "[The application] should have special algorithms to show the relevant information rather than just raw data (e.g., number of steps taken)." (s15)

This can also serve as an example of how "enriching" (Pirolli & Card, 1999) an application with contextual, adaptive data analysis and presentation capabilities can reduce the cost of obtaining useful information and services. The cost of application use can also be reduced by providing an effective, usable interface which requires a fewer number of clicks to access a particular feature, and/or less cognitive effort to make sense of the application's interface components.

Other types of cost could be users receiving advertisements and requiring them to enter information to gain access to the application.

> "I don't really like when they ask my email … I like ones [applications] that take as little information as possible. Name, email, and then you put in the password - I don't like ones that ask you whole bunch of information." (i15)

Students used different information "residues" (Furnas, 1997) or "information scents" (Pirolli & Card, 1999) to identify relevant wellness applications (e.g., descriptions, ratings, reviews, icons). In addition, they perceived the quality and importance of those cues differently. For example, different sources of scents could be perceived as of different credibility and that might affect the user's willingness to act on a particular scent.

> "I don't really look at the reviews because a lot of times … I know developers can go back there and add their own reviews or something like that. What I really considered were the screenshots on there. I looked at it, and it just looked like really well-designed and like really easy to use." (i21)

> "I mean, I am active on social media, … but I don't feel like it's credible information. You see ads on there about health and wellness apps, that's not something that was to me and say "Oh Facebook told that now I need to use it." I don't find that to be credible source." (i31)

Students used specific types of information scents to assess different quality characteristics of applications. For instance, screenshots were found helpful for assessing application's usability. An icon referencing a brand, on the other hand, could instill trust in the application.

> "I can tell by the screen shots provided .... That's a big deal, especially for mobile apps that's used for health, then you're going to be perhaps running or using it or doing other things. It should be clean and features and functions of it have to be very easy to access, not a lot of steps and..." (i25)

> "I don't know. I went through. I chose it based off the icon. If it looks cool, if it has like, the Nike one obviously seems reputable since it's gotten Nike." (i30)

Furthermore, users might have different priorities for different quality criteria in different contexts. For instance, often a user might not look for specific mobile diet. She might not have an "objectified need" (Kaptelinin & Nardi, 2012), a specific motive, and not know what she is looking for. She might browse simply to kill time. In those instances, affective quality properties of applications such coolness or novelty could be the only factors that might influence the user's selection of a particular application.

> "I was initially attracted because of the novelty of the app. … I haven't seen very many that allow you to scan the barcode. I thought that that's much easier than having to type the name of the food and brand of the food..." (i27).

In this study, we applied factor analysis to students' importance ratings of application characteristics to their decisions to select a specific application. The factor analysis identified eight underlying factors (see Table 6). On average, students rated highest the characteristics related to application usability, followed by the properties of application cost and content quality. The cues that enabled students to indirectly evaluate the quality of an application, such as the properties grouped under the High Ratings and Looks

Professionally Designed constructs, were rated lower. In addition, students seemed to be very sensitive to the price of the application:

> "I use it because it's free. I'm interested in the Weight Watchers one, but you have to join the program. There is a lot to it that I don't need." (i45)

Furthermore, having paid applications installed could also increase application transfer cost when the user had to switch to a different phone.

> "I am never going to buy an apps more than $1. I just don't want to... I have to change my phones all the time, and it's too much hassle" (i20)

It is important to note that the High Ratings construct was ranked only fourth, after the usability and content quality-related constructs. Students seemed to prefer evaluating applications through use rather than relying on ratings from prior users, algorithmic rankings from search engines, or indirect quality assessment cues and heuristics, such as the type of provider that produced the application (see Table 6). Most of the applications had a free version or a trial version, which enabled students to evaluate the application directly through use, or as one participant summarized in a comment, "to see if it actually works for me" (s4). However, as the number of applications grows, their selection through use could become a less feasible option, and consumers might have to rely increasingly on algorithmic rankings and ratings from prior users.

Participants rated the Application Providing more Functionalities than Alternative characteristic as seventh on average, and the characteristic did not load on any of the factors of the model (see Tables 4 and 6). Potentially, a service rich application should be able to attract new and retain the existing users who might have moved to a higher level(s) of a particular wellness activity. However, to achieve that, users should be aware of those functionalities, and, more importantly perceive those as useful.

> "When I started, I was starting out like just running a little bit, and now I'm training with a friend for half-marathon, so we're running three days a week. We need something that's going to track it and

makes sure that I'm keeping on track all that kind of stuff. So, I guess the more I got into it, the more I realize, like how much functionality it had, and I guess I haven't really looked into the other apps as much." (i8)

The study has a limitation. The sample size used was smaller than the generally accepted case-variable ratio for factor analysis. A follow-up study with a larger sample size should be conducted to confirm the factor model suggested by this exploratory research. In addition, since the sample was small and non-random, the study's findings cannot be generalized to the University's undergraduate student population.

7. Conclusion

This research explored the mobile wellness application-seeking behavior by college students. In particular, we examined what sources students used to obtain wellness information, what mobile wellness applications they used and for what purposes, how they learned about those applications, and what factors influenced their decision to choose a particular wellness application from among multiple alternatives. The most frequently selected source of wellness information was websites, followed by mobile applications, family and friends, and then physicians. In contrast to the sources of wellness information, physicians were the least mentioned source of learning about mobile wellness applications. None of the participants mentioned learning about mobile wellness applications from university health services. The most popular application type was calorie and activity trackers. When asked to rate the importance of various mobile application characteristics in their selection of a particular wellness application, students rated the usability-related characteristics the highest, followed by application cost and content quality.

The findings of this study could be used to assist student health centers in developing recommended lists of mobile wellness applications that are tailored to the needs of students. The research results could also be used to assist application developers, search engines, and application stores in designing product

summary descriptions that more effectively support students' search for and selection of wellness applications.

Students seemed to prefer evaluating applications through use rather than relying on ratings from prior users and algorithmic rankings from search engines and application stores. When there are multiple alternatives for the same type of product or service, the quality-based selection of an application becomes a search optimization task in a multidimensional search space where the dimensions are quality criteria and cost (Lesser et al., 1998). The single-aggregate quality scores (e.g., an average user ratings score) for applications presently used by most of the application stores may not support the multidimensional nature of application quality problems and feature preferences of users. Likewise, a single-aggregate quality score may not reflect application type-specific criticalities of the quality problems found (Choi & Stvilia, 2013). It is essential to understand how to develop effective product summary templates, quality visualizations, and indicators that reflect the multidimensional nature of quality and that can support more nuanced quality-based application selection. Furthermore, for users to use the application rating annotations, they should first be able to notice and interpret them as relevant to the task. Future research directly related to this study will further examine users' preferences for various application characteristics, including quality preferences, and will develop and evaluate application summary templates with user-perceived multidimensional quality visualizations and indicators.

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