Diffusion of Mobile Health Apps Among Smartphone Users : Role of Neighborhood Effects, Informational Network Effects, and Social Ties in Health 3.0

** Ankit Kesharwani*
*** Souvik Roy*

Abstract

The convergence of mobile technology with an evolving healthcare delivery system has ushered a wave of disruptive innovations that has bought a paradigm shift in healthcare delivery services; known as Health 3.0. If Health 1.0 was about content (portals, sites like WebMD), and Health 2.0 was focused around communities that capitalize on the knowledge gained by specific patients and their physicians (a diabetes message board), then Health 3.0 is about coherence of health information and active participation from users itself. Digital natives (DNs) are users born after 1980, grown up with digital devices and who are developing N-fluence networks (Topscott, 2008) via the Internet, especially through social media. This study proposed a conceptual model that deals with the diffusion of mobile health apps (mHealth apps) among digital natives (consumer reviews) and the role played by neighborhood effects, social network effects, and opinion leadership in such diffusion.

Keywords : **mobile health apps, digital natives, N-fluence networks, neighborhood effects, network influence**

Paper Submission Date : March 3, 2016 ; Paper sent back for Revision : October 15, 2016 ; Paper Acceptance Date : February 9, 2017

The convergence of mobile technology with an evolving healthcare delivery system has ushered a wave of disruptive innovations that bring a paradigm shift in healthcare delivery services known as Health 3.0. If Health 1.0 was about content (portals, sites like WebMD), and Health 2.0 was focused around communities that capitalize on the knowledge gained by specific patients and their physicians (a diabetes message board), then Health 3.0 is about coherence of health information and active participation from users itself. This study deals with the factors affecting the diffusion of mobile health apps (mHealth apps) among digital natives [1] which is the need of the hour for the marketers of health apps. Recently, there has been an increase in the usage of smart

* *Associate Professor,* IBS Hyderabad, IFHE University, Donthanapally, Shankarapalli Road, Hyderabad - 501203, Telangana. E-mail : kesharwani.ankit@gmail.com
** *Assistant Professor,* IBS Hyderabad, IFHE University, Donthanapally, Shankarapalli Road, Hyderabad - 501203, Telangana. E-mail : souvikroy@ibsindia.org

[1] According to latest Pew research (2011), the current young generation study, work, write, and interact with each other in very different ways than the ways their ancestors had been following. Major aspects of their activities like social interactions, friendships, civic activities are mediated through digital devices. Tapscot (2008), who ranked 9 among top 50 management thinkers for his book, *Grown Up Digital*, referred to digital users as either 'digital natives' or 'digital immigrants'. Digital immigrants are individuals not born into the existence of digital technology; typically, they are users of digital devices or ICT, who started using these at some stage in their adult lives. Digital natives, however, are users who have grown up in between 1977 and 1996. Digital natives are referred to as a subset of the millennial generation who has grown up immersed in a networked world, with access to digital technologies to learn and use them in fluent and sophisticated ways.

phones/tablets in India and worldwide, which will surely benefit the mHealth apps' market as the users of these would download and use many easily accessible and affordable health apps. These apps cover a wide array of common health and fitness-related areas such as anxiety, depression, smoking, alcohol use, psychosis, diet, exercise, weight loss, nutrition, parenting, cognitive performance, relationships, relaxation, sleep, spirituality, general well being etc. (Hsu, Liu, Yu, Zhao, Chen, Li, & Chen, 2016 ; Joshi, 2013 ; Murthy & Kumar, 2015).

In the Indian context, as a result of better online health information for consumers through services like mDhil and Dr. SMS, patients are taking more control of their own health care. mDhil provides basic healthcare information to consumers on three mobile platforms namely: text messaging, web browsers, and interactive digital content. In partnership with Airtel, a mobile network operator, currently mDhil has more than 250,000 active users in India. Hence, we hope that our study will surely enrich the marketers in India and worldwide with the information incorporated regarding the diffusion of mHealth apps. Also, in countries like India, where quality healthcare facilities are still not accessible and available at many places, especially in remote areas, the availability of technologies which facilitate "early diagnosis, early intervention, and early counseling" becomes a paramount (Free, Phillips, Galli, Watson, Felix, Edwards, & Haines, 2013; Hsu et al., 2016). With no running tracks, no cycling tracks, pollution, poor air quality, weather and others, outdoors offer a very restrictive option.

With the growing acceptance of smartphones among the population, mobile health (mHealth) apps would help the people to realize their need to step out, get moving, and to make a conscious effort at getting fit. The objective of this study is to lay down a conceptual framework to understand the diffusion mechanism of mobile health apps. Having knowledge of the key variables would help the policy makers as well as the marketers to reach more population in a shorter period of time, and eventually provide a platform to establish a dialogue between health service providers and its users (Hsu et al., 2016).

Motivation for the Study

In developing countries, the wide prevalence of mobile connections stands out in sharp contrast to the lack of access to basic services that provide wellness and health such as improved sanitation facilities. e.g. in South Asia, mobile penetration was 46% in 2009 ; whereas, only 36% of the people had access to improved sanitation facilities. Here, some mHealth applications like patient tracking using mHealth apps can also support the coordination and quality of care, especially in rural and underserved communities, including the urban poor, women, the elderly, and the disabled. mHealth apps can also be used for supply chain management, reducing delays in medicine shipments, and providing point-of-use technologies for consumers to verify the authenticity of products they buy. According to research by PricewaterhouseCooper (PwC), the convergence of mobile technology with an evolving healthcare delivery system will continue to drive the mobile health (mHealth) market, which will see revenues opportunity worth US $ 30 billion by 2017. Hence, this is a significant economy, and it is important to understand the adoption/diffusion of mobile health apps from a marketer's point of view, looking at the attractive future ahead the healthcare apps have got.

Though academicians and practitioners both have unanimously accepted that digital natives marked the spot, and their n-fluence started to redefine the marketing rules. There is a lack of significant work to unearth the mechanisms which form this n-fluence among digital natives. The proposed conceptual framework has given directions to explore and understand digital healing behavior is getting widespread acceptance among digital natives through mHealth apps.

Mobile Health (mHealth) App Market

During the last two years, the growth and development prospects of mHealth app market has called for a paradigm shift in the way business entities have a perception of mHealth. Now, it has become increasingly business oriented.

And it would not be early to say that mHealth app market is already into its commercialization stage. According to an industry report, the number of mHealth apps those are available across the two leading platforms, iOS and Android, has more than doubled in only two and half years and crossed the number of 100,000 apps in the first quarter of 2014. Also, the mHealth market revenue touched USD 2.4 billion in 2013 and is estimated to increase by tenfold, aiming to surpass USD 25 billion by the year 2017. The majority, about two-third, of the revenue for mHealth app publishers (individual or company) comes from the app-related services. Typically, these services include health-related information management services (access to experts' blogs, keeping track of health-related information records) or by enabling the users to get directly in touch with medical professionals or consultants virtually. These services are always backed up through secure and complicated structures of servers and/or teams of health-care professionals. The following Table 1 lists down the most commonly practised business (revenue) models being followed by mHealth app publishers :

Table 1. Business (Revenue) Models Practiced by mHealth Publishers

Business Model	Description
Paid-app downloads	Users need to pay to get access to the app.
In-app purchase	Free access and use, but availability of related products on sale.
In-app subscription	Free access and use, but to unlock some specific services, users have to subscribe to the content.
Advertising	Free to access and use, availability of advertiser's sponsored content.
Transactions	Selling pharmaceutical / health content / medical services, usually follow pay-per-use model.
Freemium	Free to access and use, but either for limited time or with limited features.
Subscription	Monthly / annual fee is required to access app content.
Downloadable content	Free to access and use, some downloadable content are available on a paid basis.
Ad-supported	Free to access and use. App also features ad-sponsored contents, usually built and promoted by marketers.

The problem encountered by the mHealth app developers/marketers today is that a vast majority of them nearly (82%) received less than 50,000 downloads for their mHealth app portfolio last year. According to industry insights, only the top 5% reached more than 500,000 downloads. In terms of revenue generation also, about two-thirds of health and fitness app developers/marketers either make no money or make less than USD 10,000. Merely one-fourth mHealth app developers/marketers group make revenue between USD 50,000 and USD 1 million and only this handful of mHealth app developers/marketers have seen success both in terms of growth and revenue. These flourishing mHealth app developers/marketers stand out from the rest in a significant way, thanks to their relatively larger app portfolio, market experience, use of tools for the app development and monitoring process, connection to medical databases, apps, and sensors.

However, no app developer/marketer including the successful ones can be complacent as the available technologies and popular preferences for using these ubiquitous technologies are constantly changing, and simultaneously, they have to keep looking for the factors that will influence the diffusion and adoption of their health apps. Currently, it is important for those developers/ marketers who are planning to implement smartphone technology in behavioral health care to consider the usability and acceptance by end-users in particular. From the marketers'/developers' point of view, feedback from users, when available, can be used to assess usability and preferences of particular apps. Review of published findings from usability and feasibility testing can be another useful way for determining what products may be acceptable. It is also important to consider that some patients will embrace the use of mHealth apps while others might not prefer them or be able to afford them. It is ,therefore, important to have alternative options available in the clinical tool set.

Digital Natives and Their N-Fluence

Literature suggests that consumers' characteristics/traits also have a significant influence on consumers' adoption decision (Agarwal & Prasad, 2000 ; Dabholkar & Bagozzi, 2002 ; Datta & Datta, 2009). According to a recent Pew research report (2011), young people belonging to this current generation like to study, work, write, and interact with each other in numerous ways entirely different from the ways their ancestors used to follow (Hampton, Goulet, Rainie, & Purcell, 2011). Major social aspects of the lives of this current generation like social interactions, friendships, and civic activities are mediated through digital devices (Singh, Panackal, Bommireddipalli, & Sharma, 2016). Prensky (2001), in his article '*On the horizon*,' coined the terms 'digital natives' and 'digital immigrants'. In this context, digital immigrants (DI) are referred to individuals not born into the existence of digital technology; they are users of digital devices or ICT, who started using these at some stage in their adult lives. Digital natives, however, are users who have grown up in between 1977 and 1996. Digital natives (DI) are referred to as a subset of the millennial generation who has grown up immersed in a networked world, with access to ubiquitous digital technologies and the ability to learn and use them in fluent and sophisticated ways.

Even though many digital immigrants have become proficient users of technology, they use technology differently from their counterpart digital natives. So, the way digital natives perceive a new technology could be different for digital immigrants. Moreover, unlike their ancestors, DIs, natives are developing what Tapscott (2008) named "*N-Fluence Network*" via the Internet, especially the social media. These N-Fluences networks are expanding the circle of friends you can have, and are undercutting the conventional wisdom that says we are only separated from people we don't know by six degrees of separation. Specifically, in healthcare-related studies, Christakis and his colleague found that this relationship could extend up to three degrees of influence (Christakis & Flower, 2007). N-Fluence networks have their own social structure like : you have your best friends, your larger circle of acquaintances in your social network, plus the world. Several researchers have also pointed out that rules of engagement are different for each level, which makes life tougher for marketers who are used to the old style of broadcast advertising. Lately, firms are beginning to promote the concept of becoming "friends" in order to influence DNs.

Taking the above facts into consideration, this study aims to conduct a conceptual research on mHealth apps usage behavior by developing a model on mobile health app diffusion and identifying what are the factors that lead to the diffusion of these apps. Considering the current marketing situation, this is the most crucial need of the hour, both from the point of view of developers/ marketers as well as the literature.

Literature Review and Proposition Development

(1) Neighborhood Effect and Social Ties : A few hypothetical and observational studies have risen in economics and humanism to manage a sensation that may be extensively characterized as neighborhood effects or social contagion. Case, Rosen, and Hines (1993) conducted a series of experimental studies and found that spending level of individuals in any specific region is influenced by the levels of spending in other neighboring locales, that is, spending behavior does have a contagious effect on other neighborhood buyers. Previous research in diffusion of innovation research has also demonstrated that users' intention to adopt a new technology depends on their neighbors who have already adopted the technology. Based on this rationale, we propose the following proposition:

- **P1 : The neighborhood effect will have a positive effect on social influence to use a mHealth app.**

These neighborhood effects typically exert their influence through primary groups and secondary groups.

Primary group individuals are "significant others" (Sullivan, 1953), persons to whom people are sincerely tied and whom they see as imperative or powerful in their lives. They are small in size, casual, cozy, and persisting; namely: family members, relatives, and companions. On the other hand, secondary groups are bigger in size and collaborations are more formal, guided by the group norms in comparison to the primary groups. In secondary group, individuals' information around each other is less personal, and individuals may enter and exit at any level they want.

Granovetter (1973) contended that not all social relationships or neighborhood effects have equal effect on individuals' behavior, e.g., not all family members have equal influence over the individual. He suggested that the effect of these primary groups and secondary groups are being moderated by the tie strength an individual shares with that specific group member. Here, tie strength is the measure of time spent together, the enthusiastic force of the connection, the closeness of shared divulgence, and the correspondence in services given to each other. Studies which link social ties and individual wellbeing behavior have found a direct relationship of social ties on the individual's wellbeing practice behavior (Cohen, 1988; Uchino, 2004 ; Umberson, 1987; Umberson & Montez, 2010). Strength of social ties (strong/weak) influences the endeavors of individuals to screen, support, induce, remind, or pressure a man to embrace or stick to positive well - being practices. These endeavors can debilitate hazardous well-being practices, yet can likewise blowback on the off chance that they are seen as excessively nosy or ruling, making disdain and being imperviousness to conduct change (Hughes & Gove, 1981 ; Lewis & Rook 1999). Hence, like the social influence/comparison mechanism, social ties effects can be effective or not, depending on the strength shared between parties. So, we propose that :

➪ **P2 : The impact of neighborhood effect on social influence to use a mHealth app will be moderated by social ties such that the effect will be higher for strong ties as compared to those of weak ties.**

(2) Information Cascade Theory and Total Downloads : Informational cascade refers to the situation "when it is optimal for an individual, having observed the actions of those ahead of him, to follow the behavior of the preceding individual without regard to his own information" (Bikhchandani, Hirshleifer, & Welch, 1992, p. 994). Information cascade theory (ICT) is especially conspicuous in the information technology industry (Duan, Gu, & Whinston, 2008). Alongside informational cascade, a quite similar notion that deserves mention is the concept of network effect which has been defined as the thought that an item turns out to be more and more important as its user base increases (Katz & Shapiro, 1994 ; Iyengar, Van den Bulte, & Choi, 2012). Though, numerous specialists have contended that the critical network effects expected by scholarly scientists in the IT business neglected to materialize (Liebowitz, 2002). The worries about the quality and presence of network effects in the information technology business oblige to visualize the impact of enlightening system impact on social impact. In this paper, we recommend that the impact of others' download behavior could be substantial to the point that it rules the impact of influence of decision makers' own information.

Therefore, information cascades offer a data based clarification for the network effects, recommending that informational cascades could be especially unmistakable on the Internet for two reasons: To start with, the boundless information on the web has made data over-burden among online users (Brynjolfsson & Smith, 2000; Shapiro & Varian, 2013). So, the evaluation of information quality requires broad learning about the items. Also, the quantity of contending items in every item class has developed exponentially as an aftereffect of the Internet's scope and for all intents and purposes, boundless rack space of online retailers. These two reasons made online shoppers often find that they lack the knowledge and time to make the optimal purchase decision out of dozens and sometimes hundreds of sophisticated competing products. In such cases, download statistics which (indirectly) reflect the others' choices and hence could be the most critical factor to influence such decisions in uncertainty, as suggested by the informational cascades theory and network effect. Based on this discussion, we propose the following:

➢ **P3 : Total downloads figure of an app will have a positive impact on social influence to use a mHealth app.**

(3) Informational Network Effect and User Generated Content : Other than considering the total download statistics, tech - savvy users also refer to several user generated contents like customer ratings and customer reviews (Duan, Gu, & Winston, 2008; Venkataraman & Raman, 2016). User-generated content (UGC) is the actual content being created by the users itself, e.g. comments on blogs / wiki / customer review sites / websites / social network sites, audio or video contents, customer ratings, etc. Since these contents are created by its users, they attract more eyeballs and have more credibility than any marketer promoted contents. These UGC give a look of others' assessments of the items and cause later adopters to shape their own choices. The part of past clients' assessment in impacting potential client choice making has turned into an inexorably critical theme for online organizations (Dellarocas, Zhang, & Awad, 2007), and we have seen a great developing enthusiasm for seeing how these appraisals impact clients' selection choices.

Literature has given blended confirmation on the influence of online word-of-mouth on shoppers' decisions and buying choices. Feldman and Spencer (1965) determined that about two-thirds of new residents in a community relied on word-of-mouth to select a physician; and Arndt (1967) showed that respondents who received positive word-of-mouth about a new food product were much more likely to purchase it compared to those who received negative word-of-mouth. These studies have contributed significantly to the cumulative understanding of word-of-mouth behavior. However, it appears that a considerable potential exists for enriched conceptualizations and new research directions on word-of-mouth. These are essential in addressing several significant gaps in understanding word-of-mouth phenomena that exist at the macro level of inquiry (e.g., flows of communication across groups) as well as the micro level (e.g., flows within dyads or small groups). The Appendix A provides a glance through the set of literatures citing that user generated content does share a relationship with users' adoption decision (refer to Appendix A for the literature review summary).

Informational cascades theory offers a potential explanation of the mixed results discovered in earlier studies. The theory suggests that the relationship between user generated contents (customer reviews and user ratings) and product adoption is more complicated than previously considered. Instead of assuming that online user reviews / user ratings have a uniform impact across products, informational cascades theory suggests that the impact is moderated by the level of informational cascades when users make his/her adoption decisions. If a product is mainly adopted by users because of informational cascades (i.e. herd behavior), online user reviews have a little impact on its sales. However, if a product is mainly adopted by users who apply their own information to make decisions, online user reviews can significantly influence product sales. So, based on the above discussion, we propose the following :

➢ **P4 : Average consumers' rating of an app will have a positive impact on download behavior of a mHealth app.**

➢ **P5 : Customer review of an app will have a positive impact on download behavior of a mHealth app.**

(4) Opinion Leadership - Sociometric Vs. Self-Reported : Rogers and Cartano (1962) discussed three ways to identify sociometric and self-reported people namely: (a) self-designation, i.e., asking survey respondents to report to what extent they perceived themselves to be influential, (b) sociometric techniques, i.e., computing network centrality scores after asking survey respondents whom they turned to for information or advice, or after observing interactions through other means (e.g., citations among scientists), and (c) the key informant technique where selected people are asked to report their opinion about who the influential's are. It has been found that self-designation is the most popular technique among marketing academics, the sociometric technique has been more popular among social network analysts. The latter technique is also gaining popularity among marketing practitioners to identify influential scientists, physicians, and engineers (e.g., Dorfman & Maynor, 2006). However, still, no doubts exist about the value of both self-reports and sociometric measures.

It is likely that self-reported opinion leadership is one-sided upwards, and it, likewise, reflects self-confidence instead of real influence. Alternately, questions on advertisers' capacity to adequately recognize client's persuasiveness, utilizing sociometric techniques have emerged as of late after a reformation consideration by Watts and Dodds (2007) demonstrating that the clients discriminating in creating a sudden rupture in the rate of dissemination need not be the best associated ones among themselves. However, this implication by Watts and Dodds (2007) came under severe criticism by marketing professionals (Becker, 1970). A lot of that disagreement appears to ignore the fact that the study by Watts and Dodds (2007) was just a simulation, exhibiting a probability, not an exact study giving genuine proof in backing of that plausibility. Still, the simulation results imply the potential challenges that advertisers may confront in recognizing key persuasiveness utilizing sociometric techniques.

While numerous studies have reported proof that one of these two measures of conclusion authority is connected with ahead of schedule selection, others have discovered no impact (e.g., Goldenberg, Han, Lehmann, & Hong, 2009 ; Van den Bulte & Lilien, 2001) or even negative impacts (Leonard - Barton, 1985). All the more significantly, there is no confirmation to date of the impact of one in the wake of controlling for the other. That is, there is no confirmation to date that both have a free impact on the velocity of appropriation. Such confirmation is basic to the case that both measures catch distinctive develops. As in social ties system in interpersonal organization, individuals would be more slanted to proposal of those whom they allude themselves (Sociometric sentiment pioneers) instead of the individuals who spread data without referral. Therefore, we propose that :

- **P6 : Opinion leadership behavior among users will have a positive impact on individual's behavioral intention to download a mHealth app.**

- **P7 : The impact of opinion leadership on individual's behavioral intention to download a mHealth app will be moderated by leadership type such that the effect will be stronger for socio-metric opinion leaders.**

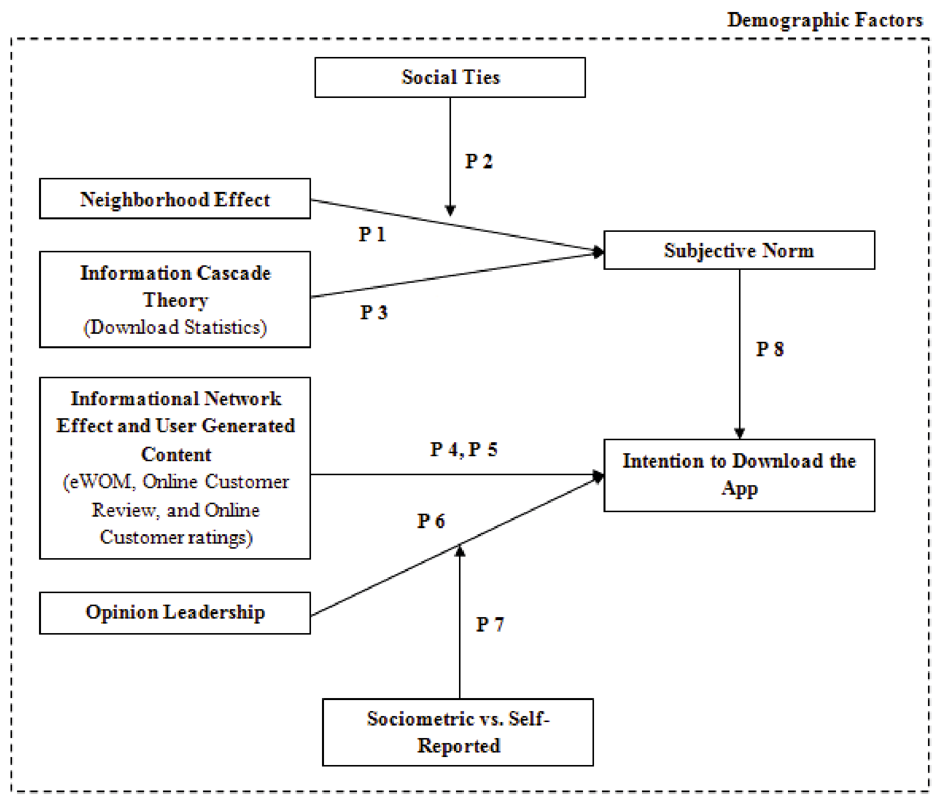
(5) Demographic Factors : The mechanism through which social influences persuade health may be moderated by adopter's gender and his/her age. For example, we know that women's health behaviors and health beliefs differ from that of men. Kaplan and Hartwell (1987) argued that, at least among adolescents, peer norms relevant to health behavior may differ by gender. The degree to which these differences are attributable to different social influence patterns, however, is not clear, and we are unaware of direct tests of this proposition. Unfortunately, studies on social influence and health behavior do not test for gender differences in the potential path between social support, risk behaviors, and health (Yuan, Ma, Kanthawala, & Peng, 2015). In looking at gender and age effects, it is interesting to note that Levy (1988) suggested that studies of gender differences can be misleading without reference to age. Thus, we contend that the influence of social influence on individual intention to adopt mobile apps will be moderated by both gender and age.

(6) Research Model : Based on the propositions made above, as shown in the Figure 1, the conceptual (research) model has been proposed.

Discussion

As shown in the Figure 1, not only this study has documented the existence of N-fluence in mobile apps after controlling for many potential confounds, including demographic factors, this study also tries to document the

Figure 1. Conceptual Model of mHealth App Diffusion



important contingencies in the mHealth diffusion process as well as important differences between the two main operationalization of opinion leadership. While earlier studies have assessed the existence of diffusion of innovation after controlling for marketing effort using actual network data or trying to proxy for social ties by geographical propinquity or group membership (e.g., Duflo & Saez, 2003 ; Van den Bulte & Lilien, 2001), none of those studies have documented how these factors would exert their influence in individual usage settings (Sharma & Kalra, 2011). The moderating role of social ties on these neighborhood effects strategies suggest that not all customers' adoptions and opinions have a same influence on others' adoptions. Some users' adoption behaviors / opinions could weigh higher than the remaining others, which should never be taken for granted by the marketers as either. It is likely to happen that some customers may command a central position in their social network than others, so when a potential user looks for advice, these influential people may control the information. To the best of our knowledge, these social network influences have never been studied before, which can be a unique aspect from a marketer's point of view.

The proposed model (Figure 1) aims to highlight the role of an individual's neighborhood effect whose impact usually gets moderated by the social ties that an individual shares with the sender of the information. This behavior can be linked with the three degree of influence suggested by Christakis and Fowler (2007). The present framework also highlights the herd behavior followed by health conscious customers, that is, users are downloading a specific mHealth app just looking at the download figure of the mHealth app. The same framework also explains the download behavior of those conscious users who look at several user generated contents like app rating, customer reviews, etc. before they download a mHealth app. To capture the effect of opinion leadership on download behavior, the model operationalizes it's both types of operationalization: the self-reported and the socio-metric. This operationalization will attract the researchers' attention towards the customer-centrality research, which utilizes social network analysis approach to identify the influential customers present in the market. The identification and measurement of source of word-of-mouth, particularly over social networks, would enable marketers to manage their communication strategies.

Managerial Implications

The two stakeholders who will get benefited the most from the proposed are the mHealth publishers and health care service providers / facilitators, including insurance companies. For mHealth publishers, the proposed framework lays down the factors and criteria users evaluate before they download a mHealth app. For example, to target the individuals who prefer to follow what others are following, a publisher can highlight its download figures or to show the list of his/her friends already using the app, that is, higher the download figure would make the user believe that these many users can't be wrong, so higher the users' intention to download the mHealth app. Also, the publishers might also include the app ratings, experts' recommendations, customers' reviews, etc. to convince those people who may desire to go through the app usage / benefit details before they actually download the mHealth app. Since the framework is proposed for mHealth app downloads, users typically resort to multiple sources of information, including marketer controlled information (download figures, ratings, reviews, etc.) and non-marketer supported information sources like independent blogs, etc. One of the most influential sources towards whom users often turn back are their social / reference groups. Having observed that the suggestions / recommendations of the people with whom an individual spends his / her most of the time commands a big role, marketers can start to target the individuals where they can use the mHealth app to heal the problems of their friends, family members, etc.

As mHealth apps let tasks to be moved down the healthcare hierarchy, apart from the cost-related benefits, it can also broaden the reach of the health industry to underserved areas by increasing the number of health-workers. With mHealth apps, patients can easily undertake health worker's tasks, and enable health workers to carry out clinic worker's or nurse's tasks, which eventually provide more nurses per doctor to whom doctors can train for non-chronic treatments (Hickey, McMillan, & Mitchell, 2015). All these shifts free up time for doctors to focus on more complex tasks. With the availability of do-it-yourself (DIY) mHealth apps, even quite busy professionals, those who are not getting time to see a doctor and / or aging populations who can't visit a doctor for their regular check-ups are able to live a longer and healthy life.

Limitations of the Study and Scope for Future Research

Like all studies, this study does have some boundary conditions and hence, some key limitations. First, literatures reviewed were primarily based on free apps, which may have excluded relevant studies focused on paid apps that may be useful for use generalization (Hsu et al., 2016). However, a growing trend over recent years has been toward making apps free to download, with more than 90% of apps currently being free. Second, the present framework does not account for the detailing information available at the app store page. Lately, the emphasis in the app industry has moved toward quality control of descriptions and app content in order to provide better quality content to users, which could affect the users' decision to download the mobile health apps. Finally, this study has limited itself to the download decision of an app. Though usually, people download a health app for longer duration, future research should endeavor to go beyond this and can study the stickiness of the mobile health apps or usage behavior of mobile health apps as well. Another implicit scope of the present study is to empirically validate the relationships proposed in the conceptual model.

References

Agarwal, R., & Prasad, J. (2000). A field study of the adoption of software process innovations by information systems professionals. *IEEE Transactions on Engineering Management, 47* (3), 295-308.

Arndt, J. (1967). Role of product-related conversations in the diffusion of a new product. *Journal of Marketing Research, 4* (3), 291- 295.

Becker, M. H. (1970). Sociometric location and innovativeness: Reformulation and extension of the diffusion model. *American Sociological Review, 35* (2), 267-282.

Bikhchandani, S., Hirshleifer, D., & Welch, I. (1992). A theory of fads, fashion, custom, and cultural change as informational cascades. *Journal of Political Economy, 100* (5), 992-1026.

Brynjolfsson, E., & Smith, M. D. (2000). Frictionless commerce? A comparison of Internet and conventional retailers. *Management Science, 46* (4), 563-585.

Case, A. C., Rosen, H. S., & Hines, J. R. (1993). Budget spillovers and fiscal policy interdependence: Evidence from the states. *Journal of Public Economics, 52* (3), 285-307.

Chen, P. Y., Wu, S. Y., & Yoon, J. (2004). The impact of online recommendations and consumer feedback on sales. *Proceedings of the Paper Presented at the International Conference on Information Systems (ICIS)* Washington D. C., 58, 710-724. Retrieved from http://aisel.aisnet.org/icis2004/

Cheung, C. M., Lee, M. K., & Rabjohn, N. (2008). The impact of electronic word-of-mouth: The adoption of online opinions in online customer communities. *Internet Research, 18* (3), 229-247.

Chevalier., J. A., & Mayzlin, D. (2006). The effect of word of mouth on sales: Online book reviews. *Journal of Marketing Research, 43* (3), 345-354.

Christakis, N. A., & Fowler, J. H. (2007). The spread of obesity in a large social network over 32 years. *New England Journal of Medicine, 357* (4), 370-379.

Clemons, E. K., Gao, G. G., & Hitt, L. M. (2006). When online reviews meet hyper differentiation : A study of the craft beer industry. *Journal of Management Information Systems, 23* (2), 149-171.

Cohen, S. (1988). Psychosocial models of the role of social support in the etiology of physical disease. *Health Psychology, 7* (3), 269-297.

Dabholkar, P. A., & Bagozzi, R. P. (2002). An attitudinal model of technology-based self-service : Moderating effects of consumer traits and situational factors. *Journal of the Academy of Marketing Science, 30* (3), 184-201.

Datta, D., & Datta, M. (2009). Exploration of connection between culture, corporate communication and consumption with the help of focus groups : An empirical study. *Indian Journal of Marketing, 39* (5), 3-10.

Dellarocas, C., Zhang, X. M., & Awad, N. F. (2007). Exploring the value of online product reviews in forecasting sales : The case of motion pictures. *Journal of Interactive Marketing, 21*(4), 23 - 45.

Dorfman, S., & Maynor, J. (2006). Influence is a tricky thing. Until you learn how to leverage it. *Pharmaceutical Executive, 26* (3), 148-150.

Duan, W., Gu, B., & Whinston, A. B. (2008). Do online reviews matter? An empirical investigation of panel data. *Decision Support Systems, 45* (4), 1007-1016.

Duflo, E., & Saez, E. (2003). The role of information and social interactions in retirement plan decisions: Evidence from a randomized experiment. *The Quarterly Journal of Economics, 118* (3), 815-842.

Feldman, S. P., & Spencer, M. C. (1965). The effect of personal influence in the selection of consumer services. In P. D. Bennett (ed.), *Marketing and economic development* (pp. 440 - 452). Proceedings of the Fall Conference of the American Marketing Association. Chicago: American Marketing Association.

Free, C., Phillips, G., Galli, L., Watson, L., Felix, L., Edwards, P., & Haines, A. (2013). The effectiveness of mobile-health technology-based health behaviour change or disease management interventions for health care consumers : A systematic review. *PLoS Medicine, 10* (1), 1-30. DOI: http://dx.doi.org/10.1371/journal.pmed.1001362

Goldenberg, J., Han, S., Lehmann, D. R., & Hong, J. W. (2009). The role of hubs in the adoption process. *Journal of Marketing, 73* (2), 1-13.

Granovetter, M. S. (1973). The strength of weak ties. *American Journal of Sociology, 78* (6), 1360-1380.

Gretzel, U., & Yoo, K. H. (2008). Use and impact of online travel reviews. *Information and Communication Technologies in Tourism, 10* (4), 35- 46.

Hampton, K., Goulet, L. S., Rainie, L., & Purcell, K. (2011, June 11). Social networking sites and our lives. *Pew Internet & American Life Project.* Retrieved from http://www.pewinternet.org/2011/06/16/social-networking-sites-and-our-lives/

Hennig-Thurau, T., & Walsh, G. (2003). Electronic word-of-mouth: Motives for and consequences of reading customer articulations on the Internet. *International Journal of Electronic Commerce, 8* (2), 51-74.

Hennig-Thurau, T., Gwinner, K. P., Walsh, G., & Gremler, D. D. (2004). Electronic word-of-mouth via consumer-opinion platforms : What motivates consumers to articulate themselves on the Internet? *Journal of Interactive Marketing, 18*(1), 38-52.

Hickey, E., McMillan, B., & Mitchell, C. A. (2015). Practitioners should embrace, not ignore, health apps. *The BMJ, 350*(1), 2336-2337.

Hsu, J., Liu, D., Yu, Y. M., Zhao, H. T., Chen, Z. R., Li, J., & Chen, W. (2016). The top Chinese mobile health apps: A systematic investigation. *Journal of Medical Internet Research, 18* (8), 1-11. DOI : http://doi.org/10.2196/jmir.5955

Hughes, M., & Gove, W. R. (1981). Living alone, social integration, and mental health. *American Journal of Sociology, 87*(1), 48-74.

Iyengar, R., Van den Bulte, C., & Choi, J. (2012). *Distinguishing among mechanisms of social contagion in new product adoption: Framework and illustration* (Marketing Science Institute Working Paper Series 2011. Report No. 11-119). Retrieved from http://cn.cnstudiodev.com/uploads/document_attachment/attachment/230/download.cfm.pdf

Joshi, D. J. (2013). An analysis of the existing literature on B2C E-commerce. *Indian Journal of Marketing, 43* (12), 34-46. DOI: 10.17010/ijom/2013/v43/i12/80512

Kaplan, R. M., & Hartwell, S. L. (1987). Differential effects of social support and social network on physiological and social outcomes in men and women with Type II diabetes mellitus. *Health Psychology, 6* (5), 387-395.

Katz, M. L., & Shapiro, C. (1994). Systems competition and network effects. *The Journal of Economic Perspectives, 8* (2), 93-115.

Lee, J., Park, D. H., & Han, I. (2008). The effect of negative online consumer reviews on product attitude: An information processing view. *Electronic Commerce Research and Applications, 7* (3), 341-352.

Leonard-Barton, D. (1985). Experts as negative opinion leaders in the diffusion of a technological innovation. *Journal of Consumer Research, 11* (4), 914-926.

Levy, J. A. (1988). Intersections of gender and aging. *The Sociological Quarterly, 29*(4), 479 - 486.

Lewis, M. A., & Rook, K. S. (1999). Social control in personal relationships: Impact on health behaviors and psychological distress. *Health Psychology, 18* (1), 63-71.

Liebowitz, S. (2002). *Rethinking the networked economy: The true forces driving the digital marketplace.* AMACOM Div. American Management Association, Dallas.

Litman, B. R. (1983). Predicting success of theatrical movies: An empirical study. *The Journal of Popular Culture, 16* (4), 159-175.

Moe, W. W., & Trusov, M. (2011). The value of social dynamics in online product ratings forums. *Journal of Marketing Research, 48* (3), 444 - 456.

Murthy, D. N., & Kumar, B. V. (2015). Internet of things (IoT): Is IoT a disruptive technology or a disruptive business model? *Indian Journal of Marketing, 45* (8), 18-27. DOI: 10.17010/ijom/2015/v45/i8/79915

Prensky, M. (2001). Digital natives, digital immigrants part 1. *On the Horizon, 9* (5), 1-6.

Rogers, E. M., & Cartano, D. G. (1962). Methods of measuring opinion leadership. *Public Opinion Quarterly, 26* (3), 435-441.

Shapiro, C., & Varian, H. R. (2013). *Information rules: A strategic guide to the network economy*. Boston : Harvard Business Press.

Sharma, M., & Kalra, D. (2011). An empirical study of online social influence marketing with reference to customer's product purchase decision and product recommendation. *Indian Journal of Marketing, 41* (8), 68-77.

Singh, A., Panackal, N., Bommireddipalli, R. T., & Sharma, A. (2016). Understanding youngsters' buying behavior in e-retail: A conceptual framework. *Indian Journal of Marketing, 46* (10), 53- 62. DOI: 10.17010/ijom/2016/v46/i10/102857

Sullivan, H. S. (1953). *The collected works* (Vol. 1). New York City, USA: Norton.

Tapscott, D. (2008). *Grown up digital: How the net generation is changing your world HC.* New York City, USA: McGraw-Hill.

Uchino, B. N. (2004). *Social support and physical health: Understanding the health consequences of relationships*. New Haven, Connecticut, USA: Yale University Press.

Umberson, D. (1987). Family status and health behaviors: Social control as a dimension of social integration. *Journal of Health and Social Behavior, 28* (3), 306 - 319.

Umberson, D., & Montez, J. K. (2010). Social relationships and health a flashpoint for health policy. *Journal of Health and Social Behavior, 51*(1), 54 - 66.

Van den Bulte, C., & Lilien, G. L. (2001). Medical innovation revisited : Social contagion versus marketing effort1. *American Journal of Sociology, 106* (5), 1409 - 1435.

Venkataraman, N., & Raman, S. (2016). Impact of user-generated content on purchase intention for fashion products: A study on women consumers in Bangalore. *Indian Journal of Marketing, 46* (7), 23-35. DOI: 10.17010/ijom/2016/v46/i7/97125

Vilpponen, A., Winter, S., & Sundqvist, S. (2006). Electronic word-of-mouth in online environments: Exploring referral networks structure and adoption behavior. *Journal of Interactive Advertising, 6* (2), 8 - 77.

Vivekananthamoorthy, N., Naganathan, E. R., & Rajkumar, R. (2016). Determinant factors on student empowerment and role of social media and eWOM communication : Multivariate analysis on LinkedIn usage. *Indian Journal of Science and Technology, 9* (25), 1-12.

Watts, D. J., & Dodds, P. S. (2007). Influentials, networks, and public opinion formation. *Journal of Consumer Research, 34* (4), 441 - 458.

Yuan, S., Ma, W., Kanthawala, S., & Peng, W. (2015). Keep using my health apps: Discover users' perception of health and fitness apps with the UTAUT2 model. *Telemedicine and e-Health, 21* (9), 735-741.

Appendix A. Literature Review Summary on User Generated Contents

Study	Synopsis	Methodology	Results
eWOM (Hennig-Thurau, Gwinner, Walsh, & Gremler, 2004)	The authors in this study tried to understand the motivations behind a consumer's decision to engage in eWOM communication on web-based consumer-opinion platforms.	Sample size consisted of around 2,000 consumers, and factor score regression analysis was used as the statistical tool.	The resulting analysis suggested that consumers' desire for social interaction, desire for economic incentives, their concern for other consumers, and the potential to enhance their own self-worth are the primary factors leading to eWOM behavior. Further, eWOM providers can be grouped based on what motivates their behavior, suggesting that firms may need to develop different strategies for encouraging eWOM behavior among their users.
eWOM (Cheung, Lee, & Rabjohn, 2008)	The authors tried to examine the extent to which opinion seekers are willing to accept and adopt online consumer reviews and which factors encourage adoption.	Using dual-process theories, an information adoption model was developed to examine the factors affecting information adoption of online opinion seekers in online customer communities. The model was tested empirically using a sample of 154 users. PLS was used as the statistical software to test the hypothesis.	The results showed comprehensiveness and relevance to be the most effective components of the argument quality construct of the research model, making them key influencers of information.
eWOM (Vilpponen, Winter, & Sundqvist, 2006)	The authors tried to clarify the existing terminology of electronic word-of-mouth behavior, to examine the kind of network structure that will emerge in the electronic environment, and finally, to explore the impact of the network structure on the acceptance of an innovation in such a communication environment.	The network structure was measured with three network measures commonly used in marketing studies: density, clique, and centrality and a sample size of 360 were used.	Results indicated that the structure of an electronic communication network is different from the traditional interpersonal communication network structure.
eWOM (Hennig-Thurau & Walsh, 2003)	The authors tried to examine why customers retrieve other customers' on-line articulations from Web-based consumer-opinion platforms.	Structural equation modeling was used as the statistical tool to test the hypothesis. The sample size used in the study was around 2903.	The results illustrated that consumers read on-line articulations mainly to save decision-making time and make better buying decisions.
Online Consumer Reviews (Lee, Park, & Han, 2008)	The authors tried to study the effects of negative online consumer reviews on consumer product attitude.	The proposed hypotheses were tested by three-way analysis of covariance. The sample size used in the study was around 248 respondents.	The results showed as the proportion of negative online consumer reviews increases, high-involvement consumers tend to conform to the perspective of of reviewers, depending on the quality of the negative online consumer reviews; in contrast, low-involvement consumers tend to conform to the perspective of reviewers regardless of the quality of the negative online consumer reviews.

Online Consumer Reviews (Duan et al. 2008)	The authors tried to examine the persuasive effect and awareness effect of online user reviews on movies' daily box office performance.	Regression analysis was used as the statistical tool to test the hypothesis. The sample size used in the study was around 497 respondents.	The results suggested that consumers are not influenced by the persuasive effect of online word-of-mouth, although they are affected by awareness effect generated by the underlying process of word-of-mouth.
Online Customer Reviews (Gretzel & Yoo, 2008)	The authors tried to investigate how other travellers' reviews informed the trip planning process.	Chi-square statistics was used and the sample size was around 7000.	The results showed that reviews are used mostly to inform accommodation decisions and are currently not used much for en route travel planning. Gender differences were found for perceived impacts of reviews, with females reaping greater benefits from using reviews, especially in terms of enjoyment and idea generation.
Online Consumer Ratings (Moe & Trusov, 2011)	The author tried to measure the impact of social dynamics in the ratings environment on both subsequent ratings behavior and product sales.	Sample size used was around 500. Win BUGS and Gelman-Rubin statistics was used to test the model.	The results showed that although ratings behavior is significantly influenced by previously posted ratings and can directly improve sales, the effects are relatively short lived once indirect effects are considered.
Online Consumer Ratings (Clemons, Gao, & Hitt, 2006)	The author used online reviews in the craft beer industry to study the relationships between online reviews and the success of new product launches.	281868 product ratings were used as the sample size and regression analysis was used as the statistical tool.	The results showed that the variance of ratings and the strength of the top quartile of reviews played a significant role in determining which new products grow in the market.
Consumer Ratings (Litman, 1983)	The author tried to examine how critic's ratings can influence the box office success of movies.	Multiple regression analysis was used as the statistical tool. Movies between the time-period of 1972-1978 were used as the sample data.	The results showed that critics' ratings are significant factors in explaining box office revenue.
Online Customer Ratings (Chen, Wu, & Yoon, 2004)	The authors in this paper tried to empirically investigate the impacts of recommendations and consumer feedbacks on sales.	610 data points were used as the sample (book reviews) and regression analysis was used to test the hypothesis proposed in the study.	Consumer ratings are not correlated with sales.
Online Customer Ratings (Chevalier & Mayzlin, 2006)	In this study, the authors tried to characterize the patterns of reviewer behavior and examine the effect of consumer reviews on firms' sales patterns.	500 data points were used as the sample (book reviews) and regression analysis was used to test the hypothesis proposed in the study.	Online amateur book ratings affect consumer purchasing behavior.
Online Customer Ratings (Dellarocas, Zhang, & Awad, 2007)	In this study, the authors tried to capture some of the unique aspects of the entertainment industry and test their performance in the context of very early post release motion picture revenue forecasting.	The data set consisted of 80 movies released in 2002 and novel hazard function was used as the statistical tool.	Online amateur movie ratings can be used as a proxy for word of mouth.
Online Customer Ratings (Duan et al., 2008)	In this study, the authors tried to examine the persuasive effect and awareness effect of online user reviews on movies' daily box office performance.	The data set consisted of 71 movies released between 2003 and 2004 and regression analysis was used as statistical analysis.	The rating of online user reviews has no significant impact on movies' box office revenues.

e-WOM (Vivekananth-amoorthy, Naganathan, & Rajkumar, 2016)	The authors in this study tried to identify the key factors that influence LinkedIn usage and the role of eWOM communication in enhancing social connectivity and engagement of students in meaningful activities to improve their social and academic standings.	Structural equation modeling was used as the statistical tool to test the hypothesis. The sample size used in the study consisted of young university students.	The results of the study revealed that expert opinion seeking, networking with professionals, and notification of profile changes had significant positive effect on eWOM communication that engages the students in social networking sites with positive outcomes like enhancing their personal efficacy, add academic and social values. eWOM communication, in turn, had a positive effect on student empowerment.