Identifying Bands in the Knowledge Exchange Spectrum in an Online Health Infomediary

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ABSTRACT

Online health infomediaries have the objective of knowledge exchange between participants. Visitor contribution is an important factor for the success of the infomediaries. Providers engaged with infomediaries need visitor identification for reputational incentives. However, identification or classification of visitors in online health infomediaries is sparse in literature. This study proposes two dimensions of participation, the intention and intensity levels of visitors, to conceptualize four user categories: community supporters, experiencer providers, knowledge questors, and expertise contributors. The authors validate these categories using a unique large data set collected from a health infomediary for cosmetic surgery, and consisting of 162,598 observed activities of 44,350 visitors, at different participation levels in the year 2012-13. They use cluster analysis to describe similarities and differences among the four user categories. Practice implications are discussed.

Keywords: *Cluster Analysis, Expertise Contributors, Health Infomediaries, Knowledge Exchange, Knowledge Questors, Machine Learning, Participation Experience Providers*

1. INTRODUCTION

Online health information is emerging as a source to effectively manage own health. It is estimated that 30% of Americans have used Internet resources to better understand a medical condition (Fox & Duggan, 2013), and 35% of adults in the United States have used the Internet for self-diagnosis. Prior research suggests that people turn to the Internet to access disease specific information (Dickerson et al., 2004; Koch-Weser, Bradshaw, Gualtieri, & Gallagher, 2010; Schwartz et al., 2006), information about symptoms (Ybarra & Suman, 2006), and for help in determining whether to seek medical attention (McMullan, 2006). The information seeking US adults are mostly younger, more educated, and more affluent than other health information seekers (Tian & Robinson, 2008). In addition, use of online social health networks, websites, and platforms is increasing with the understanding that online communication and support is highly

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effective to manage personal health (Giustini, 2006; Heidelberger, 2011; Thackeray, Neiger, Hanson, & McKenzie, 2008).

The term online health infomediaries is used for online social networks, platforms, websites, and discussion groups in a broad way. Health information is created, updated, and exchanged by people, and electronic communication networks distribute information in bits to provide easy access to visitors. In commercial contexts, infomediaries are defined as independent, third-party firms directing consumer traffic to downstream retailers in a distribution network in electronic markets (Kuruzovich, Viswanathan, Agarwal, Gosain, & Weitzman, 2008). The online health infomediaries provide conduits for health-related information and knowledge exchange, and thus, assist healthcare providers to increase clinical competence through continuous monitoring and support mechanisms (Green & Hope, 2010; McNab, 2009).

Irrespective of the value potential of the online health infomediaries, not many such efforts have been sustainable. Although many providers and other third parties are starting such infomediaries using internet platforms, but the success of an infomediary depends on the participation of a critical mass who can retain the activities and fulfil the objectives of the infomediary. Retention of the critical mass is important that needs a set of incentive mechanisms based on participant contributions. Thus, identification of the contributors, to the extent that what is their degree and extent of contribution in the infomediaray, and providing incentives might work as a sustainable business model for the infomediaries. However, identification and categorization of the contributors is lacking both in research and practice alike; the gap in literature that this study tries to fulfill.

In this study, drawing from online communities and knowledge sharing networks, we propose a typology of visitor behaviors based on participation intention and participation intensity. We propose a four category classification of the health infomediary visitors: *community supporters, experience providers, knowledge questors, and expertise contributors*. To test the validity of this typology, we collected a unique data set from a health infomediary that facilitates discussions about cosmetic treatments and procedures. We use data mining approach to identify and classify the visitors into different groups. Further, we use the result of clustering analysis of patient's activity data to characterize each patient type. The results confirm the four categories of visitor behaviors in health infomediaries, and validate our conceptualization of health infomediary user typology. We discuss the managerial implications of the findings.

2. PRIOR WORK AND THEORETICAL BACKGROUND

2.1. Online Infomediaries

Online infomediaries decouple information components of products and services from physical components, and deliver the information components to consumers using online medium such as internet (Kambil & Van Heck, 1998). In online retail contexts, infomediaries are independent, third-party firms directing consumer traffic to downstream retailers in a distribution network (Kuruzovich et al., 2008). Infomediaries help consumers easily obtain price and other product attributes across products and services, such as financial services, travel, and auto retailing, to name a few (Sawhney, Verona, & Prandelli, 2005). Several studies have empirically demonstrated he positive business value of infomediaries (Chevalier & Mayzlin, 2006; Ghose & Han, 2011; Ghose, Ipeirotis, & Li, 2012).

Some online infomediaries in other context have social objectives. These infomediaries need to rely on social communities and relevant dynamics to create an online community whereby consumers voluntarily provide reviews, comments, post questions, and answer others' questions.

Social infomediaries provide product related information as well as foster a sense of community by employing social technologies. Social infomediaries emerge in two ways. First, pure infomediaries have become more community like by incorporating social technologies to collect user generated content, such as product reviews, which in turn complements price and quality information (Ghose et al., 2012). Second, pure online communities gradually move towards a revenue-generating business model by offering referral services, subscription, and advertisements. This hybrid form gains popularity presumably because online shoppers increasingly rely on alternative sources of information, such as online word-of-mouth or user-generated reviews, in situations where a quality signal, such as a third-party certificate (e.g., Carfax or Kelley's Blue Book), is not present, or where consumers lack sufficient knowledge to assess product value (Godes & Mayzlin, 2004).

Several social infomediaries, each with its own purpose, structure, and user types, have grown exponentially, garnering user-generated content (Rheingold, 1993; Sproull, Kiesler, & Kiesler, 1992); as much as that 84% of the Internet users have participated in an online community (Horrigan, 2001). Online community members are voluntarily engaged in conversations, posting messages, replying or commenting to others' posts, and facilitating discussions (Butler, Sproull, Kiesler, & Kraut, 2002; Joyce & Kraut, 2006). These conversations often generate valuable information unavailable elsewhere, and thus serve as important sources of information for the public. Most of the extant research on online communities center on factors that motivate users' voluntary contributions (Faraj, Jarvenpaa, & Majchrzak, 2011), such as seeking expert advices (Lampel & Bhalla, 2007), reputation enhancement motives (Lakhani & Von Hippel, 2003), self-image (Constant, Sproull, & Kiesler, 1996), interpersonal relationships (Ren, Kraut, & Kiesler, 2007), attitude to help others (Blanchard & Markus, 2004; Constant, Kiesler, & Sproull, 1994) and finally to reciprocate others' helps (Wasko & Faraj, 2005). However, there is a gap in literature on exploring knowledge centric motivation for online participation.

2.2. Health Infomediaries

Healthcare sector provides an ideal context for the growth of social infomediaries. Diagnosing causes of medical problems are complex and multifaceted, often arising from physical as well as cognitive conditions (Johnson & Ambrose, 2006). The rising costs for, and difficulties in, navigating through a complex system of healthcare providers, insurance, and claim processes make online health infomediaries, such as WebMD, more attractive for patients as a viable alternative to self-diagnose and to make more informed decision of hospital visits or even undertake surgeries. In addition to providing access to medical knowledge, some health infomediaries, such as PatientsLikeMe and CureTogether, allow patients to discover other patients, who share similar medical conditions, thus empowering them to take active roles in managing their health. These information exchanges can be valuable to not only patients but also to physicians and healthcare service providers to improve quality care by identifying symptoms, treatments received, and resulting conditions. Healthcare domain exhibits a shift towards social infomediaries; as studies note that 80% of internet users have looked up information about health related topics on the Internet, and 34% of Internet users have read someone else's commentary or experience about health or medical issues on an online news group, website, or blog (Fox, 2011).

Online health infomediaries differ from traditional online social network services in at least two ways: (1) the existence of these sites has to do something with an individual's health (and, hence may be consequential), (2) the sustainability of the sites depend on whether the platforms can meet the expectation of the visitors in solving some of the health related issues. Visitors who visit the infomediaries seek an access to health related information. Thus, the success of these websites depend on the availability and accessibility of health related information or knowledge that can be exchanged through these sites. The latter is a striking feature of online health infomediaries, as others in electronic commerce context may be focused on the information related to tangible products and services. Second, while traditional health information sites or networks provide primarily technical or facts-driven information such as symptoms or conditions associated with disease, online health infomediaries provide access to cognitive, emotional, and personal information related to health management, thus giving a greater bandwidth of knowledge to service individuals with widely different needs. In other words, the online health infomediaries host a repository of *expert and experience* based knowledge, stocked by a crowd of participants from various background and enabled by Web 2.0 technologies. Thus, visitors are able to find a more relevant and personal knowledge, not readily available in other venues of information platforms.

The knowledge centric focus and demand of health infomediaries pose certain challenges towards sustaining the websites. First, a critical mass of visitors who are ready to seek, access, and digest the information must be present to insure a continuous operation of these websites. Second, the sites need to provide value for each visitor who comes to the infomediary platforms, either guided, or accidentally. For instance, health infomediaries are particularly useful for consumers needing to choose a medical service provider, or finding ways to manage a disease, or simply seeking emotional support with a chronic disease management. While infomediaries that deal with physical goods can organize their knowledge assets in terms of pre-defined attributes, managing knowledge in medical services is difficult, due to the complexity associated with the symptoms, procedures, and treatments (Payne, Bettman, & Johnson, 1993). Given the information asymmetry between medical service providers and consumers, consumers heavily rely on referrals, and will find other patients' reviews particularly valuable (Godes & Mayzlin, 2004). That is, a choice of a sub-optimal medical expert leads to irrevocable consequences that affect well-being (Luce, Bettman, & Payne, 1997).

Third, because the sites often are not traditional firms with resources to produce goods, attracting and retaining volunteers or contributors of knowledge are critical. Fourth, the user generated knowledge should be useful and meaningful, free from personal rants or uninformative content. Thus, the managers of these sites must pay attention to the identification of knowledge sources, contributors, users, as well as maintaining the repository of useful knowledge as a critical requisite to success and sustainability of the website.

In sum, infomediaries in healthcare offer value to patients by increasing the quality of information necessary to choose medical services. Due to their nature as a hybrid of infomediary and online community, health infomediaries attract individuals who have a wide variety of motivations and resultant behaviors which may be only remotely related to buying. Visitor's behaviors on health infomediaries are not yet categorized based on participation intention and intensity. The extant classifications are limited to shopping behaviors in online retailers and hence do not encompass new behaviors found in social infomediaries (Moe, 2003). However, like any infomediary, health infomediaries' primary sources of revenue are referral fees, subscription fees, and advertisements from medical service providers. Therefore, health infomediaries must attract more subscribers by targeting visitors more effectively to increase conversion rate. To this end, the purpose of this research is two-fold: first, we propose a new typology of visitor behaviors in social infomediaries, and second, measure the values of each type in terms of their contribution to health informediaries.

2.3. Sustainability of Health Infomediaries and Knowledge Centric Activities

While identifying website visitors' behaviors has been a primary focus of attention for both researchers and practitioners alike in electronic commerce contexts, health specific knowledge centricity and dependency of experience based knowledge in online health infomediaries make generalizing findings from prior studies difficult. For example, online store visitors demonstrate a wider spectrum of shopping behaviors than physical store visitors, as they search for goods for distant purchase only with a general category in mind (deliberators), browse the store for pleasure (hedonic browsers), or simply gather knowledge with no intention of buying (knowledge-builders) (Moe, 2003). Consequently, identifying visitor types and predicting purchase intent for better targeting are crucial for online retailers' success (Moe & Fader, 2004). However, in health context, such behavioral differentiation based on an end goal of purchasing transaction has no application.

On the other hand, some recent infomediaries gather consumer reviews through social network to accompany price and quality information provided by retailers (Ghose & Han, 2011). Examples are Yelp (for restaurants), TripAdvisor (for travels), and Avvo (for lawyers). As consumer reviews are considered unbiased and trustworthy as compared with retailer-sponsored or expert reviews, these reviews guide other consumers' purchase decisions (Chen, Wang, & Xie, 2011). For instance, a property buyer checks other buyers' reviews of the real-estate attorney on Avvo and soon hires him for the upcoming transaction. Although health infomediaries spawn the new patterns of visitor behaviors—making decisions based upon others' reviews—no extant classification encompasses such behaviors. Again, in online healthcare context the price, quality and trust levels of information have quite consequential implications than other contexts.

This study's focus is health infomediaries that serve as platforms to provide not only medical knowledge and emotional support for patients, but serve patients' needs for information and support through crowd-based reviews and ratings of service providers (i.e. doctors, procedures, etc.). As much as such health infomediaries reduce information asymmetry between patients and doctors, especially outside the hospital walls, they also help in reducing market inefficiencies in the current healthcare system, and providing social value for those who need better information about non-emergency medical procedures. With this background, the primary purpose of this study, therefore, is to identify the visitor behaviors in health infomediaries by drawing from online communities and knowledge networks literature. Since sustainable business model for health information providers is critical, our understanding of business value of different users would enhance our understanding of incentive structure needed. More specifically, we adopt a "90-9-1 rule", a term coined by a Nielsen study (Nielsen, 2006), which denotes unbalanced distribution of visitor behaviors in terms of their contribution level. For instance, almost all users are primarily consumers of user-generated content (UGC), whereas only about one percent of users are producers of such content. On the other hand, a different set of typologies have been proposed, emphasizing the role of users in sustaining online communities of users. For instance, in prior research the reader-to-leader framework identified community leaders who broker relationships among members by empowering and connecting dispersed users, as well as knowledge brokers who facilitate information exchange in health information networks (Preece & Shneiderman, 2009).

2.4. Visitor Behaviors in Health Infomediaries

We propose four types of visitor behaviors on health infomediaries by comparing and integrating behaviors in other contexts such as retail, or from member behaviors in online knowledge-sharing communities (Table 1). We adopt typologies proposed by (Brandtzaeg & Heim, 2011) in online communities literature to develop two dimensions used for classification. Our user behavior typology adopt participation intent and participation intensity as two key element. We first define *social support* as the intent of participation as community-seeking, playing the role of a social broker, facilitating interpersonal relationships. Second participation intention is *knowledge production*, either by contributing knowledge by seeking expert knowledge from medical experts or provide personal experience. Next, we categorize two dimensions for the intensity of participation, in terms of low or high activity levels. To further elaborate, we argue that as a social infomediary, health infomediary combines characteristics of both infomediary with an online community, where it attracts individuals: (i) who seek medical information from both medical experts and the community of other patients, and (ii) who seek a sense of community not necessarily related to knowledge acquisition for use in the elective medical procedures.

Based on the participation intensity and intention, visitors in a health infomediary can be classified into four categories: community supporters, experiencer providers, knowledge questors, and expertise contributors. First, we define “knowledge type” as producing user generated content that involves the mode of acquisition. More specifically, we use “expertise” and “experience” as two modes of knowledge acquisition, where expertise implies that a user is unlikely to possess such knowledge and must acquire from experts such as doctors. On the other hand, experience implies that knowledge is socially constructed, in which a user is likely to share her experience and build knowledge with the help of others in the community. Based on high-level of activity, we classify two user types, along expertise or experience seeking knowledge producers. Expertise Contributors are goal-oriented searchers, but they are seeking expert knowledge from both doctors and other patients. They ask doctors questions and read other patients’ reviews, often requesting further information from other patients. Table 1 provides this 2 X 2 matrix of classification, and Table 2 provides the definitions and descriptions of each of these four categories.

The first visitor type is the *Community Supporters*, whose intention is to provide social support to the community by facilitating discussions. Although these visitors contribute less or a few comments, but mostly those are related to the social fabric, connectivity or similar intentions. They are not much willing to contribute any personal experiences, comments or expertise in the infomediary. The second set of visitors are *Experience Providers*, who provide social support to the community by leading discussions, and try to motivate it with their own personal experiences. These group of visitors would contribute frequent reviews, vouch on them more and would set up the tone of personalized discussions and experience sharing in the forums.

The third set of visitors that we conceptualize are *Knowledge Questors*, a set of visitors who are primarily there in the infomediary to seek, search and collect information about a disease, procedure, doctor or experiences with a provider. Although they do not contribute direct

Table 1. Classification of Visitor Behaviors in Social Infomediaries

Participation Intensity **Participation Intention**	**Low Activity**	**High Activity**
Social Support	Community Supporters	Experience Providers
Knowledge Production	Knowledge Questors	Expertise Contributors

Table 2. Definition and Description of Visitor Behaviors in Social Informediaries

Typology/ Category	Definition	Description
Community Supporters	A visitor who provides social support to the community by facilitating discussions	- Contributes one-time or few - Contributes in the form of comments - Not willing to share personal experiences
Experience Providers	A visitor who provides social support to the community by leading discussions	- Contributes often and frequently - Contributes in the form of reviews - Willing to share personal experiences
Knowledge Questors	A visitor who provides knowledge by directing questions to community and experts	- Contributes one-time or few - Asks questions, and contributes to reviews - Willing to reveal personal information
Expertise Contributors	A visitor who provides knowledge by directing questions to experts	- Contributes often and frequently - Contributes in the form of question, own comments, expertise and related information - Willing to reveal personal information

knowledge from their own experience, but they are great elements in the infomediary to seek and provides knowledge as a whole, by directing questions to community and experts. Often to seek the information, they would be willing to reveal personal information, disease regime or similar information that is needed in the context of the disease, procedure or provider on which they seek the information. We conceptualize a fourth set of *Expertise Contributors*, who are highly active visitors and participate vividly in the health infomediary. This group provides knowledge by directing questions to experts, sharing own expertise or offering help, and are willing to reveal or relate issues to their own personal information.

Past research has shown that user content contribution follows a 90-9-1 pattern (Nielsen, 2006), which indicates that few users are unlikely to engage in activities that require significant effort. According to the literature, only about 1% of online communities' users are responsible for generating content, while the rest of the community users are consuming content. A group of users are responsible for primarily facilitating interpersonal communication. Furthermore, it is unlikely to find a large group of users who possess knowledge to answer questions. Thus, we expect that in the context of online health infomediaries, the *knowledge production users will be fewer in number than users with the intention of providing or garnering social support.*

Prior literature mentions a lack of knowledge contributing members for motivational issues. For instance, participants may fear criticism from community for contributing information (Ardichvili, Page, & Wentling, 2003), which would explain participation inequality of "90-9-1 rule", reported by the Nielsen study (Nielsen, 2006). In addition, the types of contribution a participant makes may be limited, ranging from transactional – rating, tagging – to collaborative – developing relationships, working together – according to "reader-to-leader" framework (Preece & Shneiderman, 2009). In our context, high activity users are members who have overcome such fear, possess knowledge, or both, whereas low activity users do not possess knowledge. *We expect the high activity users to be fewer than low activity users* because: (1) people who undergo some health procedures would seek or contribute to others, because they want to let others to know about it, and (2) when someone is very sick or on the verge of dying, probably he will not have enough motivation to come and discuss anything on a health infomediaries.

In the context of this study of the cosmetic surgery health infomediary, such knowledge requires expertise from not only medical knowledge, but also understanding of human psychology. Given that complications from medical procedure can results in death, not having sufficient knowledge presents even greater risk in contributing knowledge to community than in other types of online community where implications from incomplete or incorrect knowledge may not incur such risk. On the other hand, knowledge contribution in the form of social support does not require such technical expertise but encouraging words to appease the psychological state of the recipients. A friendly gesture in the form of comforting words, or celebrating successes of surgery may be sufficient to generate psychological benefits. To sum up, we expect that in the context of the cosmetic surgery portal of our study, the participation differentiation will be highly visible, because of consequential or experimental nature of health management associated with cosmetic surgery. Based on these discussions, we specifically expect that the *high-activity users will be fewer in number than low activity users in a cosmetic surgery health infomediary.*

Experience Providers are those who generate most content either by providing reviews of the doctors or procedures they have undertaken previously and by commenting on others' reviews. The types of knowledge generated by these users are socially constructed, where users share their personal experience and build knowledge through social interactions. Dedicated leaders are found in many knowledge-building communities, like Wikipedia. Their motivations are to earn visibility and to improve self-esteem by demonstrating their knowledge (Constant et al., 1994; Lakhani & Von Hippel, 2003; Wang & Fesenmaier, 2004). On the foregoing discussions and because of the nature of knowledge producers, we expect that: *(1) Expertise Contributors will generate higher number of content in terms of questions than Experience Providers, and (2) Experience Providers will generate higher number of content in terms of reviews and comments than Expertise Contributors.*

In contrast to high activity users, low activity users either lack motivation or did not receiver sufficient feedback from the community. Thus, they lack the commitment to engage in multiple types of activities. Rather, their activities will likely be exclusive to one type. Within this category, c*ommunity supporters* are socially motivated and provide comments on others' posts. Applying this characterization to the context of cosmetic surgery, the supports would like to help other would-be-surgery-aspirants. They have faced or experienced the pain or happiness with the surgical process. Further, they will also reciprocate the help they have got earlier through similar sharing process from others. The give-and-take human behavior of community supporters radiates as a substantial way that is intended to help others, in comparison to some visitors who would visit health infomediaries to purchase or seek services. These supporters have little intention to purchase another elective surgery, yet read others' posts and occasionally provide comments presumably because they want to help others, and reciprocate others' help they received when they underwent a procedure earlier. Thus, we expect that: (1) Community supporters will generate higher number of content in terms of reviews and comments than Knowledge-peripherals, and (2) Knowledge-peripherals will generate higher number of content in terms of questions than Community Supporters.

Last, Knowledge Questors are the patients who have already narrowed down to a few doctors, and simply want to compare the doctors on a few dimensions (e.g., price, scheduling, and logistics) before making the final choice. We propose that knowledge producing users in a healthcare social infomediaries are likely to be larger in numbers than relation seeking users, with the rationale that anonymity of users makes it difficult to interact and sensitive nature of health information. Further, we expect that for low activity users, knowledge brokers are likely to be larger in numbers than relation brokers, while for high-activity users, knowledge brokers are likely to be smaller in numbers than relation brokers. This argument follows from the understanding that better community integration in terms of interpersonal interaction via review-comment exchanges, and perhaps shared interest (percent of top 20 topics), activity type will shift from knowledge production to relation seeking. Finally, we expect that engaged users are likely to contribute more personal knowledge. Next, we present the data analysis and results that support these proposed differentiation across health infomediary visitors.

3. METHOD

3.1. Research Context

To empirically validate our typology framework and the expected differences that we highlighted in the theoretical background section, we collect and analyze patients' (i.e. visitors') activity data from an online health social infomediary, where patients and doctors discuss cosmetic surgery. We use the name AlterOn for this online health social infomediary as an alias to preserve confidentiality of the infomediary and the users. AlterOn helps patients learn about benefits and risks associated with plastic surgeries and connect them to qualified medical service providers. Specifically, the site provides information about various plastic surgery topics, such as generic description of procedures, risks, recovery time, and, additionally, provides a forum wherein patients can connect to cosmetic surgeons and share their reviews of doctors with other patients. AlterOn's revenues are from subscriptions from doctors and medical associations whose primary interests are to attract potential patients.

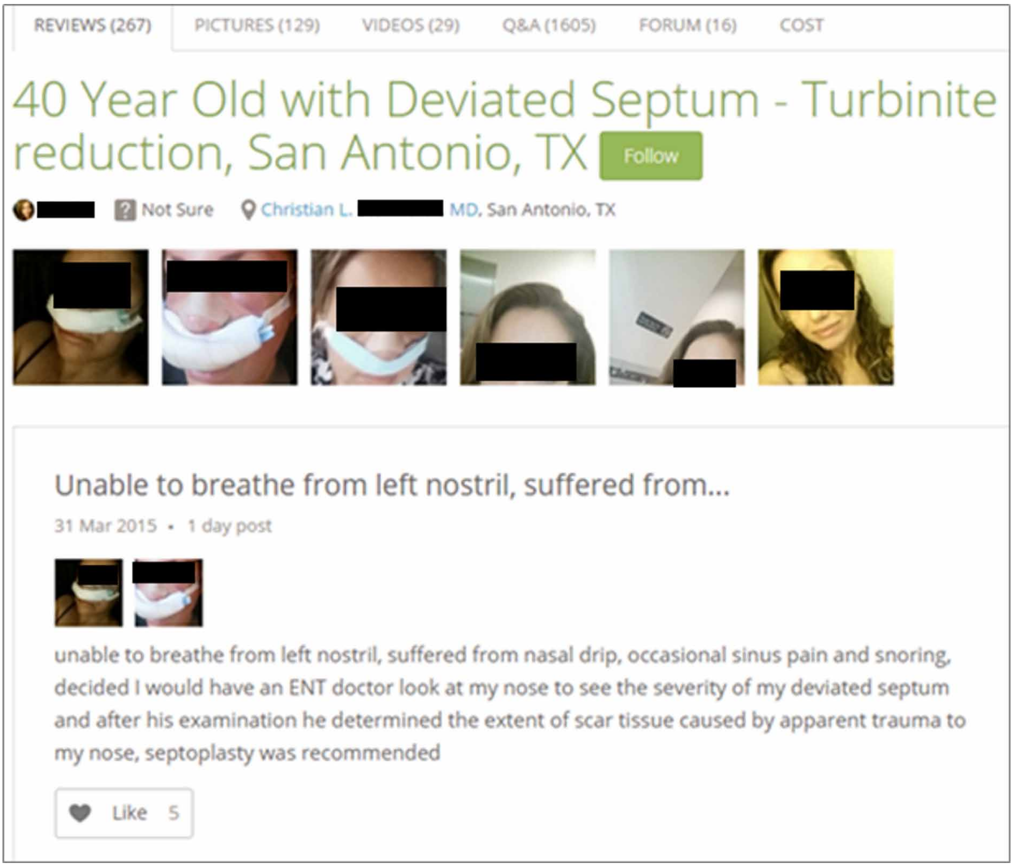
In AlterOn, there are two ways in which patients can engage in knowledge production. First, patients post reviews of surgeries they have undertaken, which sometimes include before and after photos, date, location, and the name of doctors who performed the surgery (REVIEW). By posting a review, a patient is contributing valuable personal knowledge associated with health conditions and treatments. Given that this type of knowledge is not readily available in current healthcare system due to protection of privacy, others gain reduce information asymmetry between patients and medical service providers. Second, a patient who in in need more expert knowledge can post questions to doctors, whose identity and credentials are verified and who pay monthly subscriptions to AlterOn (QUESTION). This activity is in contrast with REVIEW, which can be thought of as knowledge produced by patients from their own experience, whereas QUESTION is a type of knowledge generated by medical service providers. In addition, from information systems perspective, this activity type is stored in the database as a separate object than REVIEW and can be searched on accordingly.

In addition to knowledge production activities, patients can engage socially with other members by reading and interacting with other members' reviews and questions. For instance, a member can leave open comments for public views (COMMENT), or contact the member directly in a private message. Replies to a member's knowledge amplify individual and group interactions and linked to successful online communities (Arguello et al., 2006). Comments associated with REVIEW activities are exclusive to patients; however, any doctor who is a subscriber (i.e. identity verified) can answer QUESTION activities, in order to receive a star rating, ranging from zero to five stars, to mitigate any conflict of interest between patients and medical service providers.

Last, should a patient become interested in undergoing a treatment, she may contact a doctor in a secure communication mode for consultation (CONSULT), where each doctor has a profile page with detailed information about the service offerings, location, and reviews by patients.

To illustrate, we briefly review a patient who is suffering chronic breathing problem, due to nasal septum deviation, which is a common physical disorder of the nose affecting 80% of people (Aaronson & Vining, 2014; Davis, 2014). The causes for the deviates septum may be genetic or post-injury trauma to the nose, and symptoms include nosebleeds, headache, facial pain, and sleep apnea. Figure 1 shows a 40-year patient suffering from nasal septum deviation,

Figure 1. Illustration of Review Activity



describing her conditions discussion with a doctor about her decision to go through a surgery. Based on her review, other members provide her social support by leaving comments (Figure 2). For instance, a member with the handle "mng120" shares her experience:

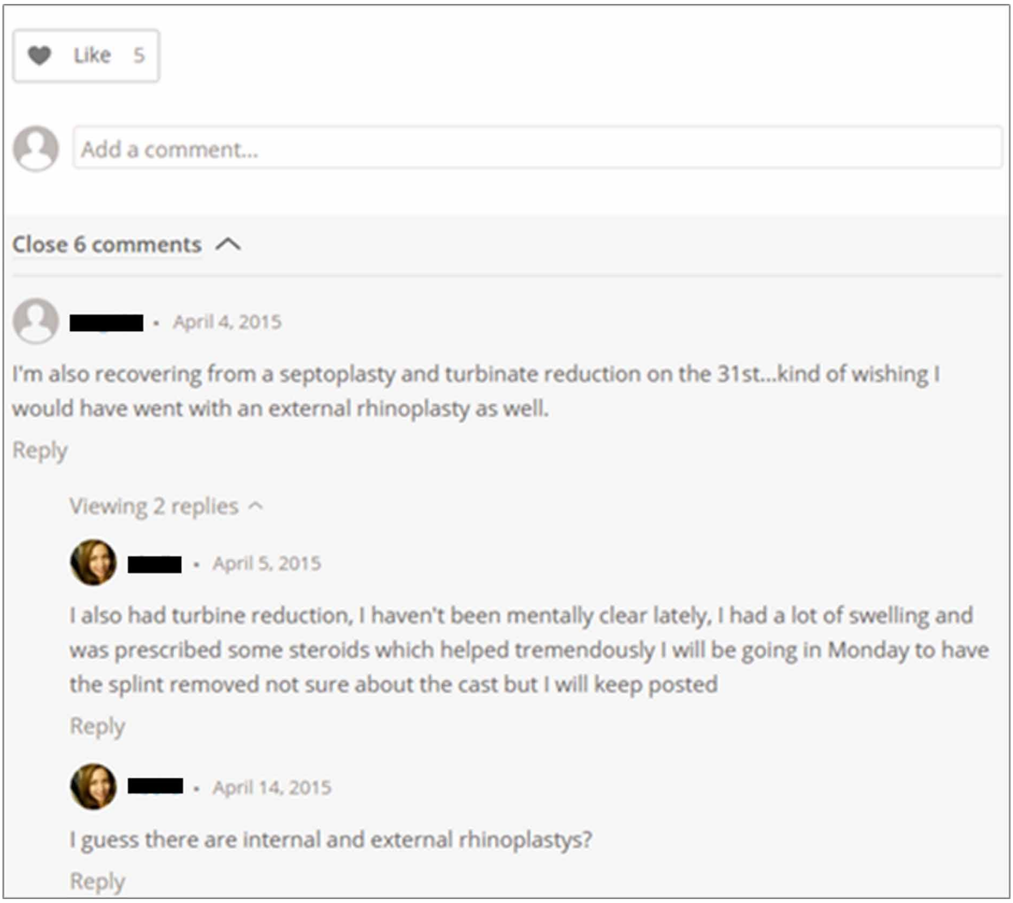
I'm also recovering from a septoplasty [SURGERY] and turbinate reduction on the 31st…kind of wishing I would have went with an external rhinoplasty as well.

This comment is also drawing participation from a third member who had similar treatments but experiencing post-treatment pain. In addition, this discussion is moving from social interaction to an inquiry: "I guess there are internal and external rhinoplastys?"

Thus, sharing personal knowledge and social interaction can not only connect people but also increase shared knowledge.

In situations where a line of inquiry between patients about specific disease reaches an end, patients can visit "Questions and Answers" link to find more information about the disease. Figure 3 illustrates a page where exchanges of common inquiries exchanged between patients and doctors are shown. A common set of questions include recovery time associated with surgery,

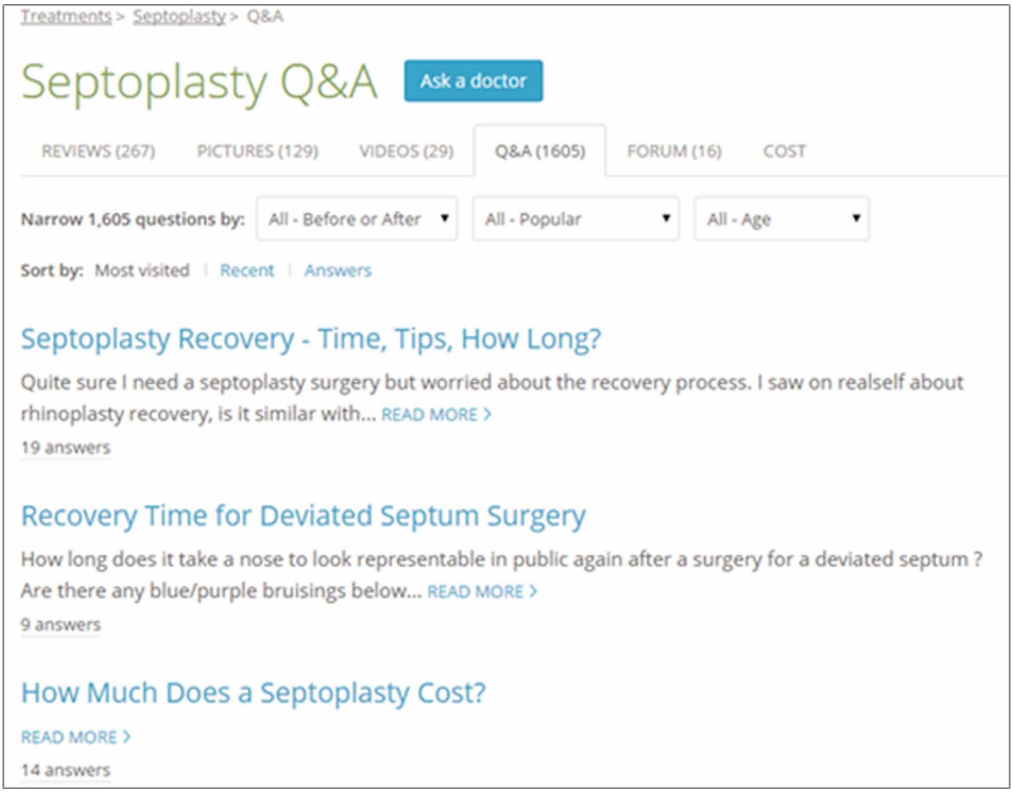
Figure 2. Illustration of Comment Activity



costs, and other tips to recover faster. Finally, should a patient has decided to contact a doctor to opt for a surgery, she can contact the doctor she likes by filling out a private form (Figure 4).

The context of the cosmetic surgery of the AlterOn site provides a level of nuance to this study. While not so much consequential, plastic surgery has a lot of patient-attractive and post-surgery characteristics. Plastic surgery deals with the repair, reconstruction or replacement of physical defects of form or function involving skin, musculoskeletal system, hand, breast and trunk, external genitalia or cosmetic enhancement of these areas around the body. Cosmetic surgeons have a challenge to improve overall appearance, while optimizing the functionalities and outcomes of the reconstructive procedures. Most popular procedures entail the use of injectable substances, such as arm lift surgery, breast augmentation, brow lift or cosmetic ear surgeries. However, cosmetic surgery procedures have a number of challenges or post-surgery issues, such as scars from big procedures like tummy tucks and breast lifts, mismatch of the procedure such as a breast implant procedure leading to gapped and drooping breasts, or procedures reacting to un-reported drugs or supplements often leading to cardiac arrests or fatal issues. Often the cost of fixing a bad plastic surgery job is higher than the original surgery. Many of these points are ignored by patients, and information is not available otherwise than the experience from patients.

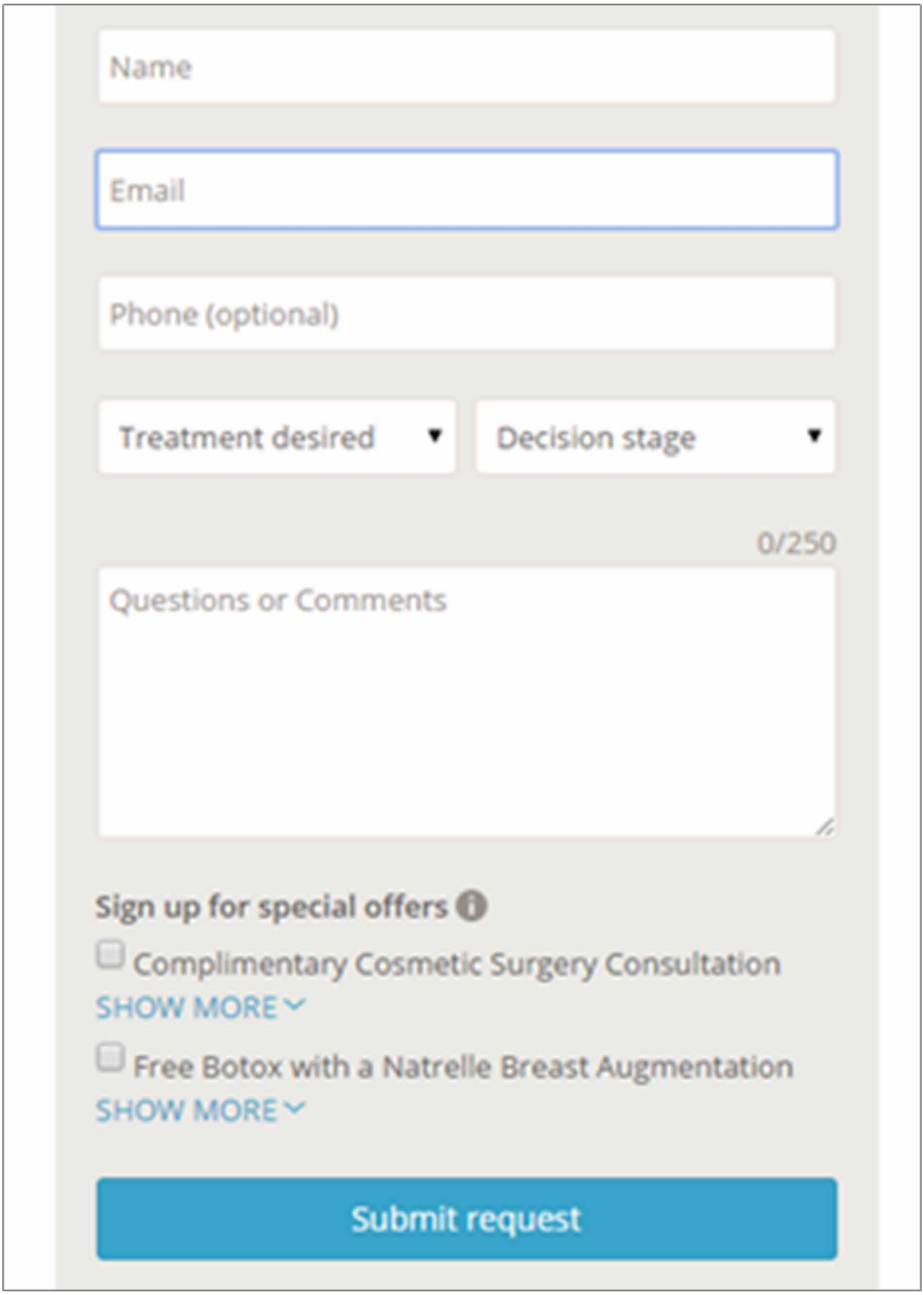
Figure 3. Illustration of Question Activity



Thus, our context is vivid with the knowledge centric and exchange parameters needed for this study. In addition, a cosmetic surgery patient may shy away to share his or her experience due to the taboo concerned with such procedures, than say a cancer or diabetic patient.

To put our typology framework in context, we conceptualize knowledge generation processes in two ways. First, users generate *personal knowledge* by sharing their personal experiences, in terms of pre-surgery and post-surgery conditions. This crowdsourced knowledge generation provides valuable information about a range of subjective knowledge that are not readily available through health information exchange, such as pain levels, complications, and side effects. In addition, more abundance of this knowledge sources is likely to be valuable asset for health infomediaries. Thus, we operationalize personal knowledge with REVIEW. Further, users also generate *expert knowledge* by exchanging questions and answers with doctors. Expert knowledge generation through doctors is likely to produce more objective information about procedure costs and provider reputation to make a more informed decision for others. Thus, we operationalize expert knowledge exchange with QUESTION. Next, building community norm through member interaction is accomplished by adding comments to another member's posting reviews. Without the benefit of exposing real identity observed in online health networks, commenting is the only way to build and sustain online communities through member interaction. Thus, we operationalize *social support* with COMMENT. Last, lurkers, those users whose activity primarily consists of consuming others' generated content, are not typically considered valuable assets in online community context. However, they provide indirect benefit in health infomediary context, because

Figure 4. Illustration of Consult Activity (Interpreted and Coded from the Filled in Data in the Form)



they represent potential service consumers of medical providers' services. For instance, the size of community, where lurkers dominate in numbers, is primary determinant of subscription and advertising price, for medical providers. This set of visitors are theorized as Community Supporters, and in the research context, we operationalize service intention on a subset of Community Supporters, who have contacted doctors for service consultation with CONSULT.

3.2. Data Collection

We obtained visitor activity data from AlterOn and conducted analysis to empirically assess the four visitor types we proposed earlier. The data set includes a total of 44,350 visitors, with 162,598 observed activities in the AlterOn health infomediary in the year 2012-13. For each user, the sample observation includes a count of each activity – Review, Comment, Question, and Consult, along with user-specific information such as date a user joined the website, location, etc. To code low and high activity visitors, we applied the heuristics suggested in prior research, such as that of shopping behavior of visitors in the context of firms, where a user with four or less activities is unlikely to return (Moe 2003). If a patient or visitor has contributed at most four activities before becoming inactive, defined as lack of visit logs for thirty days or longer, he or she was taken as a low activity user. High activity visitors were taken as those who have contributed at minimum ten or more activities. Base on this scheme, out of the 44,350 visitors, 4,129 are high activity visitors who contributed 40,221 activities; and 56,667 were classified as low activity patients doing 122,377 activities or contributions on the platform.

We made sure our data set did not include those users whose total activities fall between four and ten. We limited our sample selection of activity data up to the first ten observations of each user during the first ninety days from joining the community, to control for tenure without drawing conclusions a priori on why certain users become more active. This restrictive sampling potentially also removes many lurkers, which may create a bias in our analysis, and reduce the scope of our study to users with at least partial intent to stay in the community.

Given that the site does not require a user to enter personal information other than location information, we are not able to summarize demographic information for the full sample. However, we were able to obtain basic demographic information for the partial sample through survey and a third-party data services, based on online profile and cookies information. Of the 132,262 users from the website registered at the time of data collection, we were able to match 21,716 users with gender information. The distribution of gender for the matched sample is 26.78% male. For the study sample, the distribution of gender for the 2,347 matched users is 27.14% male. In terms of age, the full sample included all age groups from 18 to over 75, with the age groups spanning 18 to 54 representing 68.5% of the matched sample, whereas the study sample included 68.2% of the matched sample. While our sample skews toward more female in the sample, there is sufficient representation from male, as well as age groups, thus generalizing our results to more general population may be limited.

3.3. Analysis

We first describe distribution of patients' activities in our sample. To do so, we collected and analyzed the activities data using unsupervised machine learning approach that tries to find hidden structure in unlabeled data. As shown in Table 3, neither high- nor low-activity members post often, with only about 10% of each group posting reviews. While low-action members engage in commenting other members' posts, asks questions to doctors, and contact doctors for consultation equally, high-action members comment on other members' posts predominantly, followed by directing questions to doctors.

Table 3. Frequency of the Four Activities between Low- and High-Action Members

	Low-Activity Visitors		High-Activity Members	
	Number of observed actions	**Percentage**	**Number of observed actions**	**Percentage**
Review	11,869	9.7%	3,787	9.4%
Comment	42,836	35%	32,179	80%
Question	24,474	20%	3,973	9.9%
Consult	43,198	35.3%	282	0.7%
Total	122,377	100%	40,221	100%

As this contrast in behavior difference between activity levels may indicate presence of multiple member types, we continued the analysis by applying a k-means clustering, using the four activity variables, to identify distinct groups according to activity level and knowledge contribution (Table 4). A clustering analysis is a type of exploratory data mining technique to identify groups of patients based on activity types. The method is considered unsupervised learning that results in generating groups, where patients in the same group exhibit similar behaviors but differs from patients in other groups. The technique does not necessarily a identify "true" number of groups hidden in the data, but the researcher needs to determine the optimal number of groups to sufficiently fit the data but also draw important findings from the resulting clusters such as being able to differentiate and characterize each cluster from others.

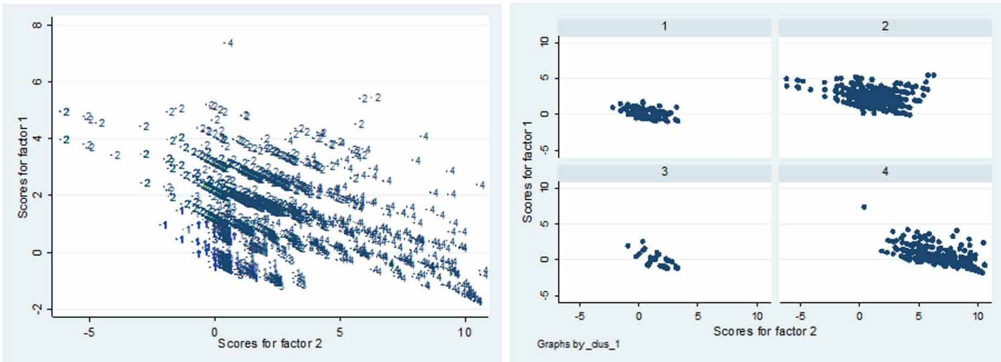
After conducting multiple clustering analyses by varying the number of clusters from three to eight, we settled with four clusters, as these clusters provided meaningful differences in terms of patient activities. In addition, we compare whether discussion topics are more homogeneous or diverse across clusters. These four clusters show similarities within each cluster but show dissimilarities between clusters, which we illustrate with factor analysis using principal component and rotation (Figure 5).

Table 4. Clusters based on Activity Types

	Low Actives		**High Actives**		**t-test**				**Wilcoxon/Mann-Whitney test**			
Activity Type	Soc (L1)	Know (L2)	Soc (H1)	Know (H2)	L1-L2	H1-H2	L1-H1	L2-H2	L1-L2	H1-H2	L1-H1	L2-H2
Review	0.02	0.59	0.76	0.44	-0.57	0.32	-0.74	0.15	**-94.05**	**11.46**	**-107.81**	**6.40**
Comment	1.09	0.00	8.70	2.92	1.09	**5.78**	**-7.61**	**-2.92**	**131.15**	**30.27**	**-129.84**	**-59.11**
Question	0.01	0.24	0.25	4.00	-0.23	**-3.75**	-0.24	**-3.76**	**-57.32**	**-32.31**	**-48.87**	**-30.61**
Consult	0.00	0.15	0.15	2.20	-0.14	**-2.05**	-0.14	**-2.05**	**-47.30**	**-24.79**	**-39.24**	**-21.98**
Cluster Size*	67.4%	15.9%	15.5%	1.2%								

Note:
- *All coefficients in bold are statistically significant at p<0.01 level*
- *Total number of users included in the sample for the cluster analysis is 24,769*

Figure 5. Graphical Illustration of Clusters Analysis Results (Note: Clusters 1 and 3 are "low" action members, whereas clusters 2 and 4 are "high" action members)



4. RESULTS

Based on our clustering analysis, we find behavioral patterns between the clusters quite distinctive according our theoretical framework. First, similar to behaviors observed in typical online communities setting, we find that high action users are few in number; approximately 16% of the users in our data set have completed ten actions in the first 90 days. While this number seems quite high, our data set has already removed many lurkers. To put in perspective, 16% of the users translate into approximately 4,000 users, and this number represent less than 10% of the initial sample with which we started. More important, of the high action users, only 293 or 1% of the sampled users contributed knowledge activities such as posting questions to doctors as well as sharing their personal experience, whereas the rest of the high action users focused their effort in contribution social support activities. We find similar distinction between the two clusters of low action users. Smaller cluster of low action users contributed knowledge, mostly via posting questions to doctors, whereas the other cluster focused their effort in contributing social support.

Next, we further characterize two clusters under low and high activity according to type of knowledge contribution a typical member in the cluster makes. For instance, the difference between knowledge contribution and social support are not only significant in sustaining the online community for drawing and retaining membership but also indicative of generating revenue associated with consulting doctors. Based on the frequency of REVIEW and QUESTION, representing knowledge production, and COMMENT, representing social support activities, the difference in activities between clusters are statistically significant, based on Wald tests.

The two clear clusters in low-action members, and the two clusters in high-action members, support our proposed visitor behaviors (Table 5). Cluster H1 represent expertise contributors because H1's primary activities are brokering knowledge and expertise contribution and seeking through the conversations between patients and doctors. H1's primary activities are asking doctors questions and reviewing/commenting on others' reviews about doctors and procedures. Cluster L1 is expected to represent knowledge questors in the sense that L1 ask questions to doctors on a variety of topics, not limited to the top 20 topics, which suggests that these members are exploring and gathering information about medical procedures with little intention to purchase. Cluster H2 seems to reflect experience providers based upon the frequency of activities observed, their primary activities, and the topics associated with their activities. Specifically, H1 is one of the high-activity groups, indicating that these are active participants. Second, H1's

Table 5. Results of Cluster Analyses

	Definition	Clusters Identified	% of activities associated with top 20 topics
Experience Providers	A user who provides social support to the community by leading discussions	Social (L1)	53.1%
Community Supporters	A user who provides social support to the community by facilitating discussions	Knowledge (L2)	51.5%
Knowledge Questors	A user who provides knowledge by directing questions to community and experts	Social (H1)	88.8%
Expertise Contributors	A user who provides knowledge by directing questions to experts	Knowledge (H2)	52.7%

primary activities are to generate reviews and to comment on others' reviews, suggesting that they are primary content-creators. Also, H2's activities are heavily focused on top 20% topics, which means that they focus their activities on the topics presumably in their attempt to attract other members' attention. Lastly, Cluster L2 reflect supporters in that supporters are defined as those who provide emotional support to others with little intention to purchase. Likewise, L2's primary activity is to comment on others' posts.

It is also interesting to note that low activity users are interested in non-popular topics, whereas high-activity users are focused in more popular topics. Thus, we suggest that similarity of interest is positively associated with high level of contribution. On the other hand, if less discussed topics can be better coordinated through IT, then low-activity users could be converted into high-activity users.

5. DISCUSSION

There has been a strong need to facilitate knowledge exchange among various stakeholders in healthcare ecosystem to reduce costs, and reduce communication gap between healthcare providers and patients. Mostly this exchange and communication was based until now on hospital based systems or around that. For example, hospitals would create multidisciplinary clinics in which oncology or cancer care experts, for example, set up a weekly discussions and treatment plans for patients at their hospitals. But the effectiveness of such meetings is limited due to the locality and time related constraints. Further, social stigma, search and access costs may be limitations for the existing brick and mortar communication and exchange avenues. By using a health infomediary system such as described in the context of this paper, healthcare entities can reach out to more people or public and help improve their awareness treatments and educate them on the importance care. In addition, providing access to knowledge, experts and social support, the health infomediary platforms are valuable in providing the effectiveness of care. In other words, health infomediary platforms could be used for patients or interested public to be connected to existing health care entities on the health issues in many different ways to serve knowledge platforms.

With the emerging concept and value proposition of health infomediaries as knowledge exchange platforms, it is important to know the characteristics of visitors to these infomediaries in terms of their knowledge and participation quotient. This study has the objective to provide a categorization of visitors to a health infomediaries engaged with knowledge exchange for cosmetic surgery. We theoretically proposed a classification scheme based on infomediaries research in other contexts, and applying the health care contextual nuance to it. The categorization was based on their participation intensity and intention; and we proposed to validate the four categories: community supporters, experiencer providers, knowledge questors, and expertise contributors. Using a unique dataset on 44,350 visitors and *162,598* activities of these visitors from an online health infomediary engaged with consumers to provide a discussion platform about cosmetic treatments and procedures; we found support for the four categories. Further, we use cluster analysis to support, and establish these categories.

The findings of our analysis suggest that there are two types of users who join an online health infomediary: one type who is primarily seeking information about medical knowledge, and another type who is simply seeking social interactions. Between the two, the latter type is greater in numbers, but is unlikely to provide financial benefit to medical service providers. For the infomediary, the latter type is a source of business value in terms of advertising revenue since social users are more engaging.

The second finding is that the size inequality of social and knowledge type is consistent across "low" and "high" intensity, which could have managerial implications in terms of "conversion"; that is, a user who joins the community stays and increases participation. The following two scenarios would describe ways in which this conversion may occur. First, user types may be somewhat unrelated to or less in participation intensity, for example, social type continues to stay engaged and contributes mainly in the form of comments. Whereas, knowledge participant type continues to generate knowledge, but focuses effort into expert knowledge rather than experience knowledge. In addition, the contribution of knowledge participants shifts from reviews and questions to questions exclusively, and they focuses more on general topics (i.e. top 20) rather than peripheral topics. The second scenario is that the user type is related to participation intensity. This may occur in two ways: (1) Social type shifts participation from social to knowledge, with contribution type shifts from comments to questions, and (2) Knowledge type shifts participation from knowledge to social contributions, with a shifting of the contribution type from reviews and questions to comments. However, as a limitation to the current study, we do not explore the conversion process associated with these scenarios, which future studies may seek to explore.

For a health infomediary, the findings imply that both social and knowledge components are vital to sustainability of the online community. First, focusing too much effort in providing expert advice or medical information may not be sufficient to keep the users, as it is clearly illustrated by the bulk of the community users engaged in social activities. Second, nurturing users who generate both expert and experience knowledge is critical to keep the medical service providers who provide a bulk of financial capital to sustain the infomediary. To inform the providers' or designers' of health infomediaries, this study highlights the importance of design parameters that can provide reputations or highlight the contribution of high activity users. High activity users are the ones who share experiences and provide expert comments. Thus, identifying these groups of visitors and possibly acknowledging their contributions is a first step. Second, reputation system can be designed on the infomediaries to level the activities of these experience and expert commenters to provide score based incentives. The scores can be made public to garner trust of visitors on these contributors. Finally, although low activity users do less action, but they are essential to the infomediary. Specifically, the actions of low activity visitors with respect to the community support and knowledge quest cannot be ignored on these sites. Motivating the low activity users will make the health infomediary a place for highly participative and interactive that will be based on support seeking and providing and knowledge seeking and providing activities. Although this study does not highlight these conduits, but the activities and the categorization of visitors provide the underlying rationale for these conduit of interactions. In other words, the categorization of visitors in this study inform that knowledge interaction between a set of low action seekers and supporters, and high action experience and expert contributors are essential elements for the success of the infomediary as a knowledge exchange platform.

The findings of this study is generalizable to many other contexts. The direction and findings from the study related to the analysis of user behavior in communities are highly informative in several ways. For example, such discussions may lead to identification of new patterns to manage certain chronic diseases, or sharing the best practices to manage diseases with patients, as is the objective of the health infomediary Crohnology.com. Similarly, another initiative, the Smart Patients out of Silicon Valley has created an online community and information database for cancer patients and their caregivers with the objective that people can learn from each other about treatment, clinical trials and latest science, and how it all fits into the context of their experience. Some infomediaries can really help in fostering health and wellness amongst population by observing activities, such as that of a Romanian startup Social Rehub that has a mobile app that incentivizes friends to end bad habits by making them accountable for their actions. Some participation data analysis in infomediaries may lead to identification of flu or disease syndromes which can then be prevented to spread to public. Furthermore, as much as information sharing in online infomediaries are emerging as a global phenomenon dissolving bounding, some discussions regarding quality and pricing of procedures may have implications for global competitiveness in health delivery and medical tourism areas.

In conclusion, the focus of this study is to explore the nature of visitors in health infomediaries. Using prior literature, and contextualizing to health context, we identified and classified the visitors based on their knowledge and activity levels. We proposed to explore four categories: community supporters, experiencer providers, knowledge questors, and expertise contributors. We use a unique data set collected from an online health social infomediary engaged with consumers to provide a discussion platform about cosmetic treatments and procedures. The data consists of total of 44,350 visitors, with 162,598 observed activities at different levels in the year 2012-13. We use machine learning approach and cluster analysis to support, and identify the four categories, and conducted empirical analysis to find differences amongst these categories in terms of their significant differences. Findings suggested that both social and knowledge components are vital to sustainability of the online community, with their varying levels of participation intent and intensity. A health infomediary can design different incentives and reputational structure to motivate different groups of visitors, and help in the conversion process of visitors along the way form mere lurkers to more participators. Furthermore, such incentives will help in the knowledge production, gathering and exchange process, which is the primary objective of the health infomediary, along with the social conduit that it tries to establish as secondary objective.

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