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Perception of Peer Advice in Online Health Communities: Access to Lay Expertise

Abstract

When seeking advice online about health concerns, forums dedicated to medical themes are increasingly becoming an appreciated source of information for many individuals. In online health communities, patients can ask questions or otherwise seek advice that is particularly relevant to them. While they may find some of the advice useful, other advice may be perceived as less valuable. By studying the advice-seeking, advice-giving, and advice-evaluation behaviours in one of the largest online health communities in Europe, this paper looks at what determines which advice is perceived as helpful, and why. Drawing on network theory, we analysed the interaction data of 108,569 users over twelve consecutive years based on all publicly available information of an established Q&A online health community. Utilising zero-inflated negative binominal modelling, our results show that advice received from others, who have similar predominant interests, is valued more when reaching out for lay expertise. If this advice is given by peers, who can also draw on expertise from other health areas, allowing for a combination of diverse "lay" expertise, the advice is valued even more. Advice provided by those who are quick to obtain the latest knowledge available in the larger community further reinforces these effects. Our findings offer an original view to understand the influence of lay expertise exchanged via online health communities and hold implications for both policy-makers and medical practitioners regarding their approach to patient-initiated use of social media for health-related reasons.

Keywords: advice, peer advice, lay expertise, social network, online health communities

1 Introduction

Over the past decade, there has been a substantial increase in the use of social media in healthcare. A variety of studies have established that patients appreciate social media mainly for informational and emotional support (Smailhodzic, Hooijsma, Boonstra and Langley, 2016). By allowing anyone to access health-related advice quickly and conveniently, internet-based applications contribute to the empowerment of the patient (Hawn, 2009). As patients acquire knowledge about their condition and treatment options, they may feel more prepared for consultations with a medical professional (Bartlett and Coulson, 2011).

However, while online information may reduce the information gap between the clinician and the patient (Lee and Wu, 2014), it could be perceived as challenging the doctor's expertise (Broom, 2005). The advice received from an online forum may or may not be correct, however, and healthcare professionals may be faced with patients who either better informed than before and may have incorrect information. As it takes time to address and filter the information a patient has found online, and the responsibility for the patient's decisions ultimately rests with the clinician, many healthcare professionals react negatively to patients wanting to discuss online advice (Broom, 2005). Although these adverse reactions cause patients to feel less empowered, they continue to search for health information online regardless (Rupert, Moultrie, Read, Amoozegar, Bornkessel, O'Donoghue and Sullivan, 2014). Hence, instead of only dismissing their patients' attempts to become involved in the decision-making, healthcare professionals could reflect on both the beneficial and potentially harmful effects of the growing use of social media for health-related reasons (Antheunis et al., 2013). This article allows for better reflection on what kind of advice people appreciate, which will be beneficial for healthcare professionals, for policy makers, as well as for patients. Healthcare professional can better engage with patients knowing what information patients bring and how they are influenced by others in their uptake of such advice. Policy makers may consider making changes to the healthcare system to accommodate prepared patients. Patients might reflect on what information they perceive as valuable relative to whom they receive such inputs from.

Despite some concerns about the dangers of incorrect self-diagnosis and misinformation spreading online (West, 2013; Rupert et al., 2014), social media provides an opportunity to connect with others in a similar situation regardless of physical distance. By speaking with others, who can sympathise with their circumstances, patients feel more informed and less lonely (van Uden-Kraan et al., 2008; Colineau and Paris, 2010). Even when only reading other users' stories and not actively contributing to any conversation, patients become less anxious (Setoyama, Yamazaki and Nakayama, 2011). Although network support generally improves the psychological well-being of patients across a wide range of illnesses (Chiu and Hsieh, 2012), some social interactions and advice may lead to increased feelings of anxiety and confusion instead (Malik and Coulson, 2010; Coulson, 2013). For instance, hearing about bad experiences from others may encourage and prepare the patient mentally to address difficult times ahead (Chiu and Hsieh, 2012). However, it could also lead to fear and decreased optimism (Malik and Coulson, 2010). Further, a lack of feedback or positive response to information a patient chooses to share with others online may decrease the participant's self-esteem and sense of belonging (Tobin, Vanman, Verreynne and Saeri, 2014). Therefore, recognising under which circumstances an online community appreciates or dismisses contributions helps to identify when and how participating in an online health community is likely to be beneficial. Appreciation in social media settings takes the form of online peer endorsement by means of 'likes' – an indicator that signals relevance and trustworthiness of the information exchanged (Sundar, 2008; Sundar, Xu and Oeldorf-Hirsch, 2009). Indeed, recent work on online health communities has particularly called for future research to consider the nature and the effects of this form of social validation in relation to a broader set of online (health) platforms and with other groups (Hamshaw et al., 2019).

Although some studies have analysed the role of informational and emotional support in online health communities (Sillence, 2016), little is known about why peers appreciate some contributions more than others. While the community's response to remarks somewhat affects the extent to which a user benefits from using social media (Tobin et al., 2014; Hamshaw et al., 2019), the exact reasons leading to either promotion or dismissal of peer advice are not yet fully understood. In line with recent calls in the field, our study explores under which conditions online health communities, and the advice shared, are perceived as helpful (Eysenbach, Powell, Englesakis, Rizo and Stern, 2004; Griffiths, Cave, Boardman, Ren, Pawlikowska, Ball, Clarke and Cohen, 2012; Centola and van de Rijt, 2015; Coulson, 2017; Fan and Lederman, 2017). By analysing all interactions of 108,569 participants of a Question and Answer (Q&A) online health community, we find that some users seem able to give more appreciated advice than others. Drawing on sociology generally, and social network analysis (SNA) specifically, we show that the adviser's lay expertise and ability to access information available within the social network somewhat determines the extent to which the community values peer advice.

2 Background

The Internet allows patients to find information concerning a wide range of health issues, and online health communities have thus become a valuable source of information and reassurance for many different types of patients (Sillence, 2016). As such, they offer emotional support and foster patient autonomy by complementing the information provided by clinicians (Rupert et al., 2014; Ho, O'Connor and Mulvaney, 2014). Especially when confronted with a new diagnosis, patients often search for explanations of their illness and successful treatment options (Johnson and Ambrose, 2006). Much of the advice concerning everyday struggles can be provided by patients who have personally dealt with the condition for some time (Mattson and Hall, 2011). Feeling more informed and learning about coping strategies improves the patient's perceived control and ability to manage the day-to-day implications of their condition (Setoyama et al., 2011).

With regards to convenience and accessibility, online health communities expand on traditional support groups. Especially those living with a chronic or disabling condition can fit their online information-seeking more flexibly around the constraints posed by their illness (Seymour and Lupton, 2004). Further, online social networking allows interaction with a more diverse, geographically dispersed group of patients than would otherwise be possible offline. Particularly in the case of rare illnesses, online communities can be the only viable means for geographically dispersed patients to connect and share their experiences with peers (Drentea and Moren-Cross, 2005; Coulson, Buchanan and Aubeeluck, 2007). Further, if nobody in their offline network has similar experiences, patients may feel more supported and less lonely if they can connect with distant others that face similar situations (Colineau and Paris, 2010).

Online health communities as a source of support

Social support intends to "improve coping, esteem, belonging, and competence through actual or perceived exchanges of psychosocial resources" (Cohen et al., 2000). More specifically, four types of social support motivate patients to use social media for health-related purposes: Informational, emotional, esteem and network support (Smailhodzic et al., 2016). By asking questions and sharing experiences, patients learn about conditions and treatments (Setoyama et al., 2011; Coulson, 2013). Rather than informing a patient, sharing emotional difficulties and expressing care intends to primarily improve an individual's mood (Bartlett and Coulson, 2011). Similarly, esteem support encourages individuals to believe in their ability to handle their situation (Chiu and Hsieh, 2012). Further, network support conveys a sense of belonging to combat loneliness and a lack of social interaction with others who have shared attributes (Frost and Massagli, 2008; Mattson and Hall, 2011).

Shared attributes, such as having endured a similar life event or illness, allow individuals to be more understanding of a peer's situation (Thoits, Hohmann, Harvey and Fletcher, 2000; Gage-Bouchard, LaValley, Mollica and Beaupin, 2016). For instance, patients experiencing mental illness are more likely to discuss their health concerns with peers who have also encountered similar circumstances (Perry and Pescosolido, 2015). By requesting advice from their peers, individuals can draw on knowledge and experiences other than just their own (Wills, 1991). A common way to convey health information in online health communities is through personal stories (Sillence, 2016). Such narratives usually describe the course of a patient's illness, the outcome of a treatment, their decision-making process and coping mechanisms (Shaffer and Zikmund-Fisher, 2012). Due to their narrative nature, personal stories usually provide sufficient detail for the reader to assess whether the advice applies to them and adapt it to fit their situation (Sillence, 2016).

Through their participation in online health communities, patients find comfort and advice that complements the support they receive offline (Rupert et al., 2014). In turn, exchanging peer advice online may foster the empowerment of patients (Hawn, 2009). The social support empowers patients by giving them the knowledge, skills and self-awareness needed to identify and accomplish their health-related intentions (Wentzer and Bygholm, 2013). By writing and reading about symptoms, diagnoses and treatments, participants develop non-professional expertise (Nettleton, Burrows and O'Malley, 2005; Griffiths et al., 2012).

Expertise is understood as "special skills or knowledge in a particular subject, that you learn by experience or training" (Pearson Longman, 2014). In the following, we will refer to this combination of theoretical and practical understanding acquired by patients as lay expertise. Unlike a professional expert, such as a doctor or medical researcher, lay experts are ordinary patients with experiential knowledge of their health condition (Monaghan, 1999; Busby et al., 2008). Experiential knowledge is highly personal, or subjective, and cannot replace scientifically validated knowledge (Barker and Galardi, 2011). However, despite potential contradictions with scientific expertise, a growing body of literature acknowledges the importance of patients' claims based on self-study and first-hand knowledge (Barker and Galardi, 2011).

In addition to the experiential advice lay experts can provide, their remarks are often more affectionate and emotionally supportive than those of healthcare professionals (Van Oerle, Mahr and Lievens, 2016). Although healthcare providers have a theoretical understanding of the patient's suffering and often make efforts to empathise with the patient, they usually lack first-hand experience (Colineau and Paris, 2010). Besides their search for information, patients often turn to online health communities for sympathy and shared concern from others in a similar situation (Nambisan, 2011).

Social appreciation of advice

However, since virtually anybody can post advice, the presence and rapid diffusion of misinformation is a growing concern for many healthcare professionals (Domínguez and Sapiña, 2015). Patients may use social media to promote opinions that are not supported by science or find treatment options that do not apply to the patient's particular care (Poland and Jacobson, 2011; West, 2013). Although prior studies of peer interactions in online communities have found low levels of inaccuracy, the information may not fit the needs of the patients (Eysenbach et al., 2004; Esquivel et al., 2006; Gage-Bouchard et al., 2018). Nevertheless, communities may develop practices that improve the quality of the information peers exchange (Hartzler and Huh, 2016). For instance, members may monitor and 'correct' inaccuracies (Esquivel et al., 2006). Many online health communities are designed to support this process by letting users endorse, report or comment on contributions (Borah and Xiao, 2018). As a 'collaborative filter', peer endorsements, such as 'likes' on social media, demonstrate social appreciation and signal relevant and trustworthy information (Sundar, 2008; Sundar, Xu and Oeldorf-Hirsch, 2009). Thus, peers may use their lay expertise to identify and highlight helpful advice.

However, likes may be the outcome of group dynamics, with the degree of being 'liked' as a product of conformity. As such, there is a possibility for likes to influence the way in which users judge and possibly envy others, both potentially leading to conflicts within the community and deceptive actions by some of the users (e.g., Dumas, Maxwell-Smith, Davis and Giulietti, 2017). Dishonest actions and statements used by some users to improve their social status may disturb the community and the value it offers its members.

3 Hypothesis Development

Due to various factors, the community may not exchange and appreciate peer advice equally. For instance, core groups of tens of users or less may provide most of the advice to tens of thousands of more peripheral participants (Introne and Goggins, 2019). However, the effect of social structures on advice exchange is underresearched (Introne and Goggins, 2019). Even when both factually correct, peer advice offered by some users may be appreciated more than that of others. This raises a critical question: How do the adviser's lay expertise and access to information in the social network affect the community's perception of his or her advice?

Similar lay expertise

Advisees are more likely to value and adopt advice when the adviser has shared attributes (Wang, Walther, Pingree and Hawkins, 2008). Somewhat similar experiences and knowledge reduce transfer costs and the effort it takes to explain otherwise unfamiliar concepts (Reagans and McEvily, 2003). Direct interaction between individuals with a similar background, or in our case similar illness and symptoms, is likely to facilitate clear communication based on the common understanding of the source and recipient of the advice (e.g., Hansen, 1999; Ren, Kraut and Kiesler, 2007; Gómez-Solórzano, Tortoriello and Soda, 2019). In healthcare, peers with high experiential similarity, who have personally endured a similar life event, are more likely to offer specialised informational and emotional support (Thoits et al., 2000; Gage-Bouchard et al., 2016). Drawing on the notion of network homophily, and linked to the model of preferential attachment, Criscuolo et al. (2015) argue that grouping individuals with similar expertise enhances the visibility and accessibility of relevant peers. Based on their attributes, similar individuals may be more likely to attach to each other than dissimilar ones (McPherson, Smith-Lovin and Cook, 2001). As a result of their awareness, advisees are more likely to contact individuals whom they know to have expertise similar to their own. We believe the same theory applies to online health communities, which often group the discussion boards based on illnesses and symptoms. By doing so, participants are encouraged to interact with more similar peers whose advice may be more relevant to them. Thus, we hypothesise:

Hypothesis 1. *Perceived usefulness of advice is higher if the adviser's expertise is similar to that of the advisee.*

Diverse lay expertise

With many health conditions, symptoms and side effects being related to one another, the patients' knowledge and experiences often overlap to some extent. Depending on the type and symptoms of the patient's illness, he or she may naturally become acquainted with peers, who, although they share some of the symptoms, may experience a very different set of experiences in addition (Valente, 2010). These differences result in variety between the adviser's and advisee's knowledge.

Consequently, more diverse opinions offer increased learning opportunities (Phelps, Heidl and Wadhwa, 2012). The relevance of dissimilar backgrounds for problem-solving activities is widely recognised in the literature concerning innovation and organisational studies (e.g. Ebadi and Utterback, 1984; von Hippel, 1986; Cummings, Butler and Kraut, 2002; Wong, 2008).

Prior research points to the notion that individuals value advice received from unfamiliar others, who have more resources available, more than advice from peers with fewer resources at their disposal (Constant et al., 1996; Gómez-Solórzano et al., 2019). Indeed, Constant, Sproull and Kiesler (1996) found that advisers without a direct personal connection to the advice-seekers were deemed to provide more useful advice, and were more likely to solve the problems disclosed by the advisee. Thus, there is value to be reaped from interacting with individuals dissimilar from – and unfamiliar to – oneself. Furthermore, new solutions are usually understood as novel recombination of existing knowledge, and therefore rely on the individual's ability to creatively recognise links between different existing concepts (Guilford, 1950). To realise different existing concepts and obtain less redundant information, individuals benefit from more dissimilar contacts (Criscuolo et al., 2015).

Evidently, seeking advice from others, who have knowledge and experience dissimilar to that of the focal individual, also coincides with some degree of uncertainty, as, especially in the context of online advice communities, the advisee cannot assess the adviser's expertise, understanding of the advisee's situation, reliability, or motives for giving either truthful or inaccurate advice (Constant et al. 1996). Particularly, if the advisee has no control over the adviser's incentives, the lack of direct reciprocity may result in less helpful advice (e.g., Thorn and Connolly, 1987). Considering both the benefits and potential disadvantages, we argue that:

Hypothesis 2. *Perceived usefulness of advice from an adviser whose (lay) expertise is similar to that of the advisee is further enhanced if the adviser has access to more **diverse** (lay) expertise.*

Speed of access to peers' lay expertise

Assuming advice, as non-instrumental knowledge, travels along the shortest paths through the network, it seems plausible that individuals, who are close to others are well-positioned to obtain information. By receiving information flows sooner, those who can reach out to others quickly can obtain new knowledge early when it is most valuable (Borgatti, 1995). Although not all information travels via the shortest possible path and may, in the case of gossip, for instance, avoid some individuals altogether (Borgatti, 2005), we believe that lay expertise, which is shared freely across the community, can be obtained quicker if the focal individual can reach out to peers quickly. The ability to gain knowledge quickly may become even more relevant if the adviser is drawing on lay expertise, which is similar to that of the advisee and therefore may find it more challenging to obtain new and relevant input for his or her advice. Assuming that advice seekers are looking for the least obsolete knowledge available in the entire community, we hypothesise:

Hypothesis 3. *Perceived usefulness of advice from an adviser, whose (lay) expertise is similar to that of the advisee, is further enhanced if the adviser has **speedy** access to others' (lay) expertise.*

4 Methods

To test the hypotheses introduced above, we obtained all publicly available information of an established Q&A online health community in July 2017. Interaction data of 108,569 users over twelve consecutive years was collected. In total, we extracted 197,980 discussions with a total of 484,250 replies.

4.1 Setting and Participants

The English-speaking online health community central to our analysis aims to facilitate discussions among patients and informal carers rather than healthcare professionals. As such, the forum is part of an established website offering medical resources for both patients and healthcare providers who are predominantly residing in the United Kingdom and the United States. Unlike some specialised online health communities, the discussion boards of this more general platform are not restricted to a specific medical condition. Instead, when initiating a thread, the user assigns his or her question to one of 344 groups, named after common medical conditions, symptoms or medication. In turn, these groups each belong to one of 32 categories. For instance, *Anxiety Disorders*, *Citalopram, Depression*, *Sleep Problems* and *Substance Misuse* are all part of the category *Mental Health*. These main categories were used to analyse deviations and overlap between different users' predominant interests and therefore assumed lay expertise. Although many medical conditions, and thus the patients' experiences, overlap to some extent, there are some distinct differences in the knowledge and experience of patients who suffer from very different illnesses.

In instances where the chosen category is deemed unsuited, for instance upon request of others in the community, the user or platform-based moderators can move the thread. Besides re-assigning threads to ensure consistency and ease of use for those searching for questions and answers online, the moderators also continuously monitor contributions and remove inappropriate or misleading remarks if necessary. In our sample, just over three per cent of replies were deleted (N=15,206).

While the discussions are visible publicly, readers who want to contribute answers or their own questions are required to create a user profile. Upon registration, users can declare that they are a healthcare professional although this is not validated or shown to the community later. The platform operators report that less than one per cent of all registered users claims to be healthcare professionals. This relatively low percentage is not surprising as the discussion boards are specifically targeted at patients and informal carers such as relatives.

At the point of our data collection, the community counts 108,569 registered users. According to a survey conducted by the community operators, 82 per cent of the members are at least 35 years old, and 68 per cent are female. Further, most users suffer from a chronic health condition, with hypertension, diabetes and mental health issues (e.g., anxiety and depression) being most common. Each of the users has a profile which can also be viewed by both members and unregistered visitors. Besides a short biography the user can choose to write, the user profiles outline the date on which the user has joined the community and his or her prior activity, namely questions and replies posted by the users. However, users can choose to hide information about their prior activity. This did not affect our data collection as we collected all user activity via the threads.

4.2 Data Collection

All data were collected between the 16th and 20th of July 2017 by mirroring the entire website offline. To reduce the delay, the files that changed during one iteration of collecting all files were replaced during the following iteration. As the intervals became shorter, every change between the two points was copied until there were no changes between the iterations. As a result, the entire content of the platform was extracted, despite users interacting during the data collection process.

First, the internal structure of the website including all 32 categories was replicated. Consequently, each category's threads, including all replies, were extracted. When a participant seeks advice actively, he or she usually initiates a new discussion. To add to the discussion, users can either post a reply or comment on other users' replies. Our study mainly focuses on the replies and, to some extent, the user profiles. For instance, how long the participant has been a member of the community for, or the number of questions or replies contributed during this period, may be relevant.

All information was extracted from the website using the R package *rvest* (version 0.3.2). *Rvest* was explicitly developed for data mining (Wickham, 2016). Subsequently, all data were cleaned, prepared, and analysed in R (version 3.3.2) and the respective packages: *dplyr*, *ggplot2*, *stringr*, *readr*, *igraph*.

4.3 Measures

Dependent variable: Peer endorsement

As an indicator of perceived relevance, users can 'like' valuable questions and answers. Multiple studies have indicated the importance of message credibility, with social endorsements in the form of 'likes' occurring across a variety of health-related platforms (Borah and Xiao, 2018). Likes as such represent an explicit form of online social validation (Hamshaw et al., 2019). Especially with regards to replies, positive endorsement by others indicates that a contribution is worth reading or discussing (Sundar, 2008; Sundar et al., 2009). Although a 'like' does not imply whether the advisee has adopted the advice, peer endorsements can indicate whether the advisee and the community as a whole perceive the advice as useful. Likes signal relevance and trustworthiness of the information exchanged. As work on liking in online settings outlines, likes truly indicate enjoyment and appreciation of content (Lowe-Calverley, & Grieve, 2018). Thus 'likes' represent - repetitive - social appreciation as expressed by serial likes forms an explicit, simple yet effective manner to capture the value of advice as provided by an individual source (Hamshaw et al., 2019).

Independent variable: Similar lay expertise

To determine whether the adviser is likely to be knowledgeable about the topic he or she advises on, we compared the medical categories the adviser contributes to. Based on the percentage of contributions in each category, we assigned a score indicating the user's familiarity with the topic. For instance, if the thread belongs to *Cancer*, and most of the adviser's previous replies were posted in the same category, we submit that the adviser has a predominant interest in the category and therefore the assumed similarity between adviser and advisee is high (i.e., closer to 1). If there is little or no previous involvement, e.g., if the adviser usually advises peers in *Allergies*, the experiential similarity between the adviser and advisee is considered to be low (closer or equal to 0).

While we cannot definitely ascertain that a certain individual has significant lay expertise or personal experience with a medical condition, we use the predominant interests in a certain health condition to measure the adviser's familiarity with a certain topic based on prior activity. Further, we tested the similarity not only on adviser-category-level but also the difference of these scores between adviser and advisee, namely the initiator of the thread, for the category of the thread. Unsurprisingly, the results of the robustness test are similar to the original category-adviser comparison, yet the coefficients are somewhat less pronounced (Table 4 in Appendix). Thus, we decided to maintain the original results as the adviser-category measure is richer than the dichotomous comparison between the predominant orientation of adviser and advisee.

Diverse lay expertise

Centrality is the degree to which an individual holds a prestigious or critical position in a network, and thus may be influential in the process of spreading information and ideas (Borgatti and Everett, 2006). Betweenness centrality, a specific type of centrality that is subject to this study, is defined as the number, or proportion, of shortest paths between all pairs of actors the specific actor is positioned on (Borgatti, 1995). Thus, actors with an increased betweenness centrality, who connect different knowledge domains, are able to obtain valuable and varied information more easily (Staber, 2004). Unlike degree centrality, betweenness centrality is not based on the number of ties but the extent to which an actor influences the flow of information by being positioned on many important paths (Freeman, 1979; Borgatti, 1995). Per definition, as established by Freeman (1979), betweenness centrality is calculated as:

$$\sum_i \sum_j \frac{g_{ijk}}{g_{ij}}, \; i \neq j \neq k \qquad (1)$$

In the equation, g_{ij} represents the number of geodesic paths from i to j, so $g_{ijk}k$ is the number of paths that pass through the individual, or node, k. Thus, betweenness centrality describes the routes information can take from one individual to another, each having different lengths as it passes through more or fewer individuals to reach its target. Individuals that are part of many short routes have considerably more access to information than those located on less relevant routes. As a result, betweenness centrality is the sum of the proportions of all shortest routes between any two nodes in the network that pass through individual i. Using R, a directed adjacency matrix was generated based on the edge list extracted from the online community. With the edge list containing a record of each interaction in the network, the adjacency matrix counts the interactions between all individuals in a weighted manner. Subsequently, the R package *igraph* was used to calculate the betweenness centrality scores and visualise the network.

Speedy access to others' expertise

Unlike betweenness centrality, closeness centrality measures how long it will take to spread information from one individual to all others (Valente, 2010). An individual with high closeness centrality can reach out to anyone else in the network quickly. By measuring the average distance of an individual to all others in the network, summing and inverting these distances, the closeness centrality can be established (Freeman, 1979). Normalised closeness, divided by the sum of distances, is calculated as (Freeman, 1979):

$$C_c(i) = \left[\sum_{j=1}^{N} d(i,j)\right]^{-1} \quad (2)$$

Unlike betweenness centrality, closeness centrality focuses on the availability instead of the diversity of the information. By purposefully seeking less original knowledge, the transition cost decreases considerably. Due to the complexity of medical information, much of the advice found in online health communities contains established knowledge, rather than novel ideas.

Control Variables

Following Valente (2010), the size of the adviser's social network was controlled for. Out-degree centrality, or the number of connections from the focal individual to others, measures the person's socialness. We consider the size of the adviser's personal network to affect the adviser's ability to access any expertise, both similar and diverse, more speedily. The visibility of the advice is increased if the category it belongs to has more members, who predominantly read and contribute to the category's threads. Thus, the health category's size was controlled for.

We also control for the perceived medical risk associated with each health category. Contributions to higher health risk categories may be perceived differently from those in lower health risk categories since the knowledge pervaded potentially impacts the participants to the former kind of thread (much) more. For instance, knowledge exchanged about terminal cancer is likely to impact participants differently from knowledge exchanged about skin affections. This is further substantiated by a higher number of average posts in the categories. For instance, *Cancer* has an average of 12 replies per thread, whereas *Skin & Nails* only receives an average of 5 replies. Based on the occurrence of terms, which belong to the word field "death", the health category's perceived risk was determined. The three categories with the highest risk factor are *Mental health, Senior health,* and *Cancer. Kidneys, bladder & genitals; Eyes; Bones, joints and muscles* are associated with the lowest risk. An overview of all medical categories, their risk factors and size can be found in Table 3 (Appendix). While this approach does not allow us to measure the actual risk, as validated by medical professionals, for instance, we believe the occurrence of words, such as dying, fatal, or mortality, quantifies the perceived fear of the patients to some degree. Naturally, these terms occur more frequently in some domains than others and do not necessarily indicate the patient's quality of life or actual survival rates.

In line with previous studies on the quality of questions and answers (e.g., Ravi et al., 2014), the text length of the advice is controlled for. A more detailed, longer response is expected to be more helpful. By matching the individual words used with an open-source, freely available medical dictionary (Aristotelis, 2014), the ratio of medical content, such as medication or symptoms, was established. The dictionary contains 98,119 words, including trade and generic drug names (FDA approved: 01 July 2017), DSM-IV and ICD-10 terms, and other anatomical, dermatological and surgical terms. We believe that a larger proportion of medical terms used may indicate medical severity that differs across communities, and therefore may influence overall activity levels and thus the probability to receive likes. In addition to informational support, emotional support is expected to affect the community's perception of the adviser's remarks. To control for the level of sympathy expressed by the adviser, the wording of the advice was analysed using IBM Watson Natural Language Understanding. IBM Watson uses Machine-learning algorithms to match the words used against a coded database to establish the sentiment of any given text (IBM, 2019). In recent studies, IBM Watson has demonstrated its potential to analyse very large datasets (e.g., Hatz et al., 2019; Pan et al., 2019).

5 Data Analysis

First, the descriptives and correlations between the variables of interest were assessed. To explain, at the level of the reply, how the perceived helpfulness of advice is affected by the adviser's lay expertise and social network position, we performed a zero-inflated negative binomial regression.

As a result of the substantial number of community members that do not post replies or receive likes, our dataset is characterised by a substantial number of zeros in our dependent variable (76,35% = 0). Hence, in order to address potential over-dispersion in our data, and after a Vuong test of our regression models, a zero-inflated negative binomial model is the preferred approach for data analysis, rather than a negative binomial model in our case (Vuong, 1989; Long, 1997). Based on a two-step approach, a zero-inflated negative binomial specification employs two components that correspond to two zero generating processes. The first process is governed by a binary distribution that generates structural zeros. The second process is governed by a Poisson distribution that generates counts, some of which may be zero. A negative binomial count model was run to capture the zeros for those members that may have decided to not post in the period under observation while continuing to be a member. In its essence zero-inflated negative binomial modelling assumes that the data come from a mixture of two populations: one where the count is always zero and another where the count has a Poisson distribution (Burger, van Oort and Linders, 2009; Greene, 2008). In this case, the former group consists of members engaged with the community, but not opting to post in the period under observation, hence not receiving any likes as a result. The latter consists of employees also engaged in the same community who did post – some of which received likes while others received no likes at all. We apply the variable community tenure as a zero-inflation parameter in our inflated model to control for the likelihood of a member reporting zero likes as this may distort interpretation based on the count model. The ZINB model was estimated using R (version 3.3.2).

6 Results

Table 1 provides summary statistics and correlations for all the variables included in the regressions. About one-quarter of the 450,681 contributions in the dataset were endorsed at least once, with a mean of 0.44 likes per post. Replies have a mean age of 660 days and mean length of 94 words each. On average, 32 per cent of these words are terms that match with the medical dictionary. Further, most of the advisers contributed to threads that were associated to the health category, in which they posted the majority of their advice. A proportionately small number of replies, 61,618 of 450,681 contributions, were posted in a health category that did not match the adviser's usual area of expertise, thus explaining the high mean of the independent variable lay expertise: similar ($M = 0.83$, $SD = 0.28$).

– INSERT TABLE 1 HERE –

We find no substantial correlations between the variables, except for the adviser's network size, measured as degree centrality, and lay expertise: speed, measured as closeness centrality ($r = 0.33$). This correlation is substantially lower than established by Valente, Coronges, Lakon and Costenbader (2008), who found an average correlation of 0.81 across 58 networks. Individuals with high degree and closeness centrality have direct or short paths to others and can, therefore, interact with many others directly and quickly transmit information. Especially closeness, namely the speed of access to peers, describes efficiency (Friedkin, 1991).

Table 2 presents the results of the zero-inflated negative binomial regression. Model 1 is a baseline model that includes the control variables to avoid misinterpreting the main effects. It reinforces our expectation that the concentration of medical terms affects the extent to which the community appreciates the peer advice ($\beta = -.098$, $p < .001$). When not controlling for sympathetic wording in addition to the use of medical terminology, the negative effect is considerably larger. While most of the controls do not have a substantial effect, the size of the adviser's network affects the probability of the advice being perceived as helpful in all models considerably (Model 1, $\beta = .784$, $p < .001$).

– INSERT TABLE 2 HERE –

Model 2 includes the effect of advising in a health category, which requires knowledge similar to that of the lay expertise of the adviser. Despite the relatively small coefficient ($\beta = .087, p < .001$), the effect is positive and significant, thus providing support for Hypothesis 1. The direct effect of dissimilar and readily available lay expertise are introduced in Models 3 and 4. Advice, which is provided by an adviser with access to diverse lay expertise in the network is more likely to receive endorsements from the community (Model 3, $\beta = 1.052, p < .001$). Further, the interaction term of having access to dissimilar information, in addition to an overlap of expertise between advice and adviser, is positive and significant (Model 8, $\beta = 1.766$, $p < .001$). When combined, the effect is substantially more meaningful than the direct effect alone, thus supporting Hypothesis 2.

The speed of access to new information in the network has a statistically significant and positive direct effect on peer endorsements (Model 6, $\beta = .321, p < .001$). However, when introduced as a moderator in Model 9, the interaction term is negative ($\beta = -.175, p < .001$). Nevertheless, when combined with the other moderator, diverse lay expertise, the effect of speedy access is positive and significant (Model 10, $\beta = .148$, $p < .001$). In line with Hypothesis 3, we thus found support for our prediction that the adviser benefits from having speedy access to peer expertise, especially if the adviser's lay expertise is diverse at the same time.

The interaction effects of speedy access and access to diverse lay expertise are also supported by the interaction plots illustrated in Figure 1 and 2, respectively.

– INSERT FIGURES 1 AND 2 HERE –

7 Conclusions

From various fields, researchers and policymakers have made efforts to understand the behavioural and social causes of human behaviour in health communities. With the advent of online communities, online health communities continue to challenge healthcare professionals in their health advice, being called upon to provide for an alternative of validating opinions. Indeed, also historically, individuals have probably always sought advice about their health status from peers, yet can now do so much more readily and pervasively, contacting distant peers as well. As a consequence, policymakers and medical professionals should prepare for patients to possibly have already sought extensive advice when they request medical services.

Responding to these developments, this study examines the social influencing behaviour from one's online social contacts as one partakes in an online health community. Drawing on the social sciences, particularly network theory, this study investigates the appreciation of the advice received by studying the advice-seeking, giving and evaluating behaviours in one of the largest European online health communities at the level of the advice seeker. We argue and show that advice received from others, who share similar health-related interests is valued higher. If this advice is given by individuals who can also draw on expertise from other health areas, allowing for the combination of “lay” expertise with alternative expertise settings, the advice is valued even more (positive moderation). In addition, if the advice is provided by those who are quick to obtain the latest knowledge available in a large community, the advice given is also valued more (positive moderation). As such our findings speak to a literature that explores appreciation in online communities, positioning online peer endorsement by means of ‘likes’ – as a current social validation indicator that indicate appreciation of content (Lowe-Calverley, & Grieve, 2018). We add by reflecting on the relational antecedents to such signals of appreciation, showcasing how the influence of lay expertise exchanged via online health communities depends on a various relational indicators.

For designers and operators of online health communities these insights are of specific relevance. While not affecting the validity of our data, the fact that online health communities often only allow positive feedback, i.e. likes, and not down-votes may make it more difficult for patients to determine what advice is helpful to them. This is a potential drawback in comparison to other more solution-focused online discussion boards, for instance in the context of software development or crowd-sourcing. Similarly to Hartzler and Huh (2016), we believe that allowing users to flag potentially irrelevant or false content may relieve the workload of the community-based moderators and therefore reduce the time users may be exposed to potentially harmful information.

Further insight into the relational conditions that drive or restrict patients from using medical advice may be valuable to health care professionals such as physicians, pharmacists and nurses. In their daily practice, they are increasingly required to interact with patients that second guess, or at the very least cross-check their medical advice via online health communities. For instance, in relation to the worry medical professionals might have about the nature of the advice individuals receive online, our study suggests that the more medical terms are used in a reply, and the more serious or 'risky' the condition the advice seeker's question is about, the less likely it is that the advice is perceived as helpful. People seek to understand what a medical situation they may have means for themselves, explained in lay terms, and do not seem to appreciate advice that stresses the risks of a medical condition.

While we cannot ascertain what the medical quality of the advice obtained for the advisee is, we are able to determine how much they appreciated the advice. We find that when advisers are able to connect readily to advice-seekers because they have a similar knowledge background, this increases the chances of the advice given being valued ('liked'). When the adviser also has knowledge from other medical knowledge domains he or she can leverage as well, the advice is appreciated even more. In addition, being able to access knowledge from similarly-interested peers anywhere in the community quickly also results in increased peer endorsements. Further, our results suggest that medical advice-seekers value advice-givers who have a certain degree of sympathy.

Additional qualitative research will need to confirm this, investigating when exactly patients ask for advice, but our findings seem to suggest that perhaps many individuals, even among those who are actively seeking advice, come to seek initial information and perhaps mostly consolation. They may also search for pointers of where to find additional information which may or may not be different from that given by their primary care provider. This could explain why advisees do not like medical terms in responses. In this latter interpretation, the peer advice individuals receive is not to be contrasted with the advice medical professionals provide. Instead, it satisfies the need for emotional rather than mostly information support. A broader and deeper understanding of why advice-seekers endorse a response to their question and how peer and professional advice may be interpreted and valued using different metrics would add to the quantitative study of the patterns of behaviour in the network that we analysed.

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Table 1: Descriptive Statistics and Pair-wise Correlations on Data for Advice ($N = 450,681$)

Variable name	Mean	S.D.	Min	Max	1	2	3	4
1. Community endorsements	0.44	1.38	0.00	198.00				
Visibility								
2. Adviser's network size	.88	.30	.00	1.00	.05*			
3. Health category size	0.60	0.32	0.00	1.00	0.00	0.12*		
Context								
4. Health category risk	0.29	0.32	0.00	1.00	0.00*	0.06*	0.35*	
5. Text length	93.88	97.10	0.00	2,874	0.07*	−0.03*	0.03*	0.00
6. Medical content	0.32	0.10	0.00	1.00	0.00	0.02*	−0.03*	−0.07*
7. Sympathy	0.41	0.27	0.00	1.00	0.03*	0.10*	0.07*	0.19*
Lay expertise								
8. Lay expertise: similar	0.83	0.28	0.00	1.00	0.01*	−0.14*	0.05*	−0.04*
9. Lay expertise: diverse	0.03	0.11	0.00	1.00	0.05*	0.10*	0.07*	0.16*
10. Lay expertise: speed	0.68	0.46	0.00	1.00	0.05*	0.33*	0.08*	0.02*

Variable name	Mean	S.D.	5	6	7	8	9	10
Context								
6. Medical content	0.32	0.10	0.12*					
7. Sympathy	0.41	0.27	−0.10*	−0.20*				
Lay expertise								
8. Lay expertise: similar	0.83	0.28	0.02*	−0.01*	0.03*			
9. Lay expertise: diverse	0.03	0.11	0.01*	0.04*	−0.04*	−0.16*		
10. Lay expertise: speed	0.68	0.46	−0.04*	0.02*	0.15*	0.01*	0.21*	

*$p < .05$.

Table 2: Zero-inflated Negative Binomial Regressions Predicting Social Appreciation[a]

Variable name	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	
Visibility											
Adviser's network	0.784***	0.796***	0.731***	0.633***	0.754***	0.643***	0.638***	0.770***	0.654***	0.644***	
size	(0.016)	(0.016)	(0.016)	(0.017)	(0.016)	(0.017)	(0.017)	(0.016)	(0.017)	(0.017)	
Health category	−0.019	−0.027**	−0.009	−0.033***	−0.026**	−0.039***	−0.035***	−0.019	−0.040***	−0.027**	
size	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	
Context											
Health category	−0.109***	−0.101***	−0.177***	−0.092***	−0.163***	−0.086***	−0.141***	−0.132***	−0.088***	−0.107***	
risk	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	
Text length	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	
Medical content	−0.098**	−0.097**	−0.165***	−0.081*	−0.169***	−0.080*	−0.144***	−0.173***	−0.078*	−0.151***	
	(0.042)	(0.042)	(0.042)	(0.042)	(0.042)	(0.042)	(0.042)	(0.042)	(0.042)	(0.042)	
Sympathy	0.355***	0.347***	0.412***	0.301***	0.398***	0.295***	0.349***	0.403***	0.300***	0.350***	
	(0.013)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	
Lay expertise											
Lay expertise:		0.087***			0.219***	0.071***	0.186***	0.332***	0.201***	0.199***	**H$_1$**
similar		(0.013)			(0.013)	(0.013)	(0.013)	(0.014)	(0.025)	(0.025)	✔
Lay expertise:			1.052***		1.164***		0.983***	2.192***		2.091***	
diverse			(0.029)		(0.030)		(0.030)	(0.059)		(0.061)	
Lay expertise:				0.322***		0.321***	0.257***		0.463***	0.137***	
speed				(0.009)		(0.009)	(0.009)		(0.025)	(0.027)	
Lay expertise:								1.766***		1.863***	**H$_2$**
similar x diverse								(0.081)		(0.083)	✔
Lay expertise:									−0.175***	0.148***	**H$_3$**
similar x speed									(0.029)	(0.030)	✔
Constant	−1.723***	−1.803***	−1.709***	−1.820***	−1.907***	−1.884***	−1.956***	−2.033***	−2.000***	−1.994***	
	(0.023)	(0.026)	(0.023)	(0.023)	(0.026)	(0.026)	(0.026)	(0.026)	(0.032)	(0.032)	
Log-likelihood	-378312	-378290	-377570	-377612	-377435	-377596	-377006	-377189	-377579	-376739	
LR-test		44.895	1485.3	1401.9	1755.4	1432	2613.5	365.95	1146	533.43	
DF	10	11	11	11	12	12	13	13	13	15	
N	450681	450681	450681	450681	450681	450681	450681	450681	450681	450681	

$^{*}p < .05$;$^{**}p < .01$;$^{***}p < .001$.

[a] The likelihood ratio (LR) test compares Models 2, 3, 4, 5 and 6 to Model 1 and Models 8, 9 and 10 to Model 7.

Appendix

Table 3: Overview of Medical Categories

Medical category	Users	Size	"Death"	Risk
Allergies	886	0.047	17	0.103
Blood	903	0.048	36	0.168
Bones, joints and muscles	15,261	0.841	504	0.1
Brain and nerves	18,137	1	992	0.247
Cancer	978	0.052	99	0.565
Chest and lungs	3,336	0.182	254	0.417
Child health	588	0.03	16	0.166
Contraception and sexual health	189	0.008	2	0.071
Deficiency	302	0.014	3	0
Diabetes and hormone problems	3,686	0.201	117	0.127
Ears, nose, throat and mouth	4,762	0.261	135	0.127
Eyes	1,895	0.102	35	0.06
General	1,402	0.075	62	0.168
Gut, bowel and stomach	10,227	0.563	462	0.191
Health promotion	3,198	0.174	116	0.151
Heart and blood vessels	4,540	0.249	288	0.42
Immunisations	43	0	1	0.067
Infections	10,461	0.576	396	0.159
Injury and accidents	1,154	0.061	21	0.044
Kidneys, bladder and genitals	1,220	0.065	19	0.04
Liver and gallbladder	2,327	0.126	77	0.129
Men's health	2,728	0.148	75	0.111
Mental health	15,425	0.85	5058	1
Operations and surgical procedures	3,917	0.214	133	0.054
Senior health	1,729	0.093	184	0.558
Skin and nails	5,777	0.317	166	0.17
Substance misuse	346	0.017	30	0.398
Symptoms	4,809	0.263	199	0.163
Teenage health	311	0.015	2	0.023
Tests and investigations	1,991	0.108	100	0.241
Women's health	12,916	0.711	510	0.149

Table 4: Zero-inflated Negative Binomial Regressions Predicting Social Appreciation with Similar Lay Expertise Measured between Adviser and Advisee (robustness)[a]

Variable name	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	
Visibility											
Adviser's network	0.746***	0.754***	0.729***	0.628***	0.737***	0.637***	0.633***	0.737***	0.634***	0.628***	
size	(0.017)	(0.017)	(0.017)	(0.018)	(0.017)	(0.018)	(0.018)	(0.017)	(0.018)	(0.018)	
Health category	0.027*	0.020	0.029*	0.014	0.021	0.008	0.009	0.024	0.008	0.013	
size	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	
Context											
Health category	−0.133***	−0.127***	−0.165***	−0.118***	−0.159***	−0.113***	−0.135***	−0.153***	−0.111***	−0.126***	
risk	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	
Text length	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	
Medical content	−0.145**	−0.148**	−0.156**	−0.127**	−0.159***	−0.130**	−0.138**	−0.156**	−0.131**	−0.137**	
	(0.048)	(0.048)	(0.048)	(0.048)	(0.048)	(0.048)	(0.048)	(0.048)	(0.048)	(0.048)	
Sympathy	0.381***	0.374***	0.392***	0.332***	0.385***	0.327***	0.337***	0.384***	0.326***	0.334***	
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	
Lay expertise											
Lay expertise:		0.138***			0.142***	0.125***	0.129***	0.185***	0.065**	0.065**	**H_1**
similar		(0.012)			(0.012)	(0.012)	(0.012)	(0.014)	(0.023)	(0.023)	✔
Lay expertise:			0.485***		0.498***		0.332***	1.442***		1.299***	
diverse			(0.038)		(0.039)		(0.039)	(0.133)		(0.137)	
Lay expertise:				0.258***		0.255***	0.240***		0.181***	0.103***	
speed				(0.009)		(0.009)	(0.010)		(0.025)	(0.027)	
Lay expertise:								1.041***		1.070***	**H_2**
similar x diverse								(0.139)		(0.143)	✔
Lay expertise:									0.084**	0.153***	**H_3**
similar x speed									(0.027)	(0.029)	✔
Constant	−1.741***	−1.865***	−1.730***	−1.815***	−1.859***	−1.928***	−1.920***	−1.902***	−1.874***	−1.865***	
	(0.025)	(0.028)	(0.025)	(0.025)	(0.028)	(0.028)	(0.028)	(0.028)	(0.033)	(0.033)	
Log-likelihood	-305000	-304900	-304900	-304600	-304800	-304500	-304500	-304800	-304500	-304500	
LR-test		123.94	164.32	743.76	296.45	846.57		560.35	60.667	70.440	
DF	10	11	11	11	12	12	13	13	13	15	
N	450681	450681	450681	450681	450681	450681	450681	450681	450681	450681	

*$p < .05$; ** $p < .01$; *** $p < .001$.

[a] The likelihood ratio (LR) test compares Models 2, 3, 4, 5 and 6 to Model 1 and Models 8, 9 and 10 to Model 7.

Figure 1: Interaction plot (Similar lay expertise and access to diverse lay expertise)

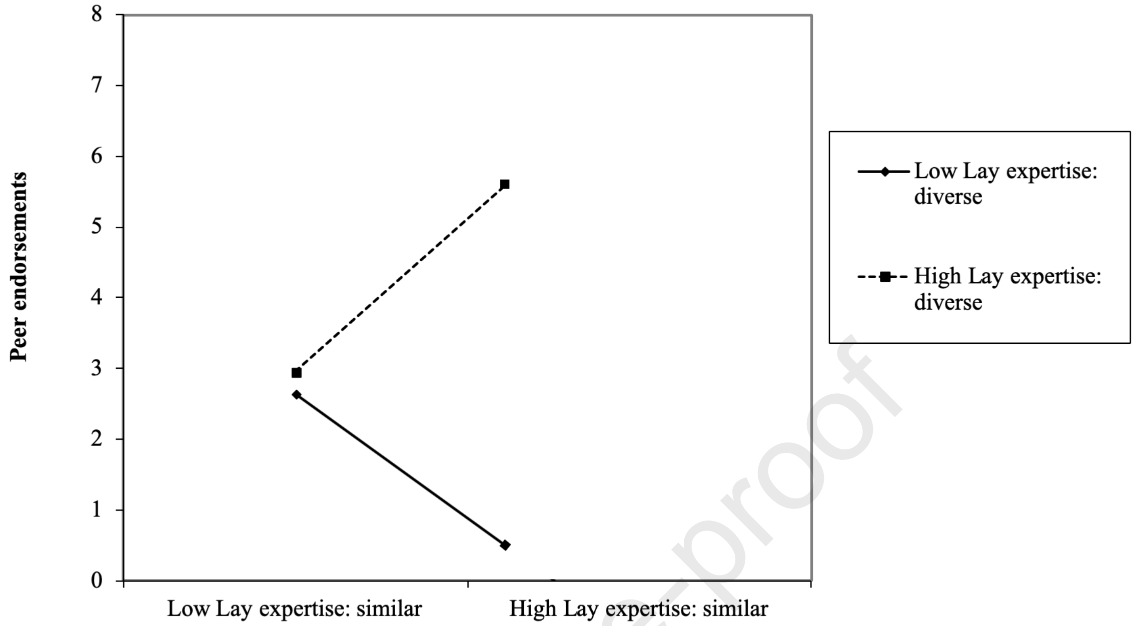
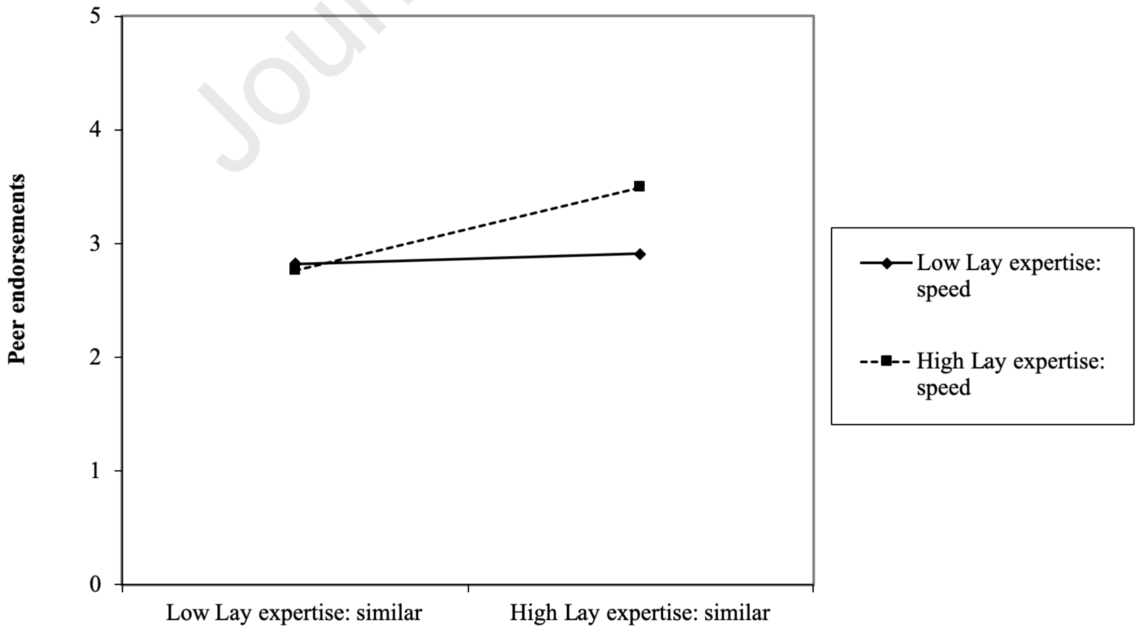


Figure 2: Interaction plot (Similar lay expertise and speedy access)



Highlights

– People readily seek health advice online

– People value advice from others who have similar predominant health interests

– People value advice from knowledgeable others

– People value speed of access to their peers' expertise

All authors contributed equally.