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Short Research Paper

Understanding User Contributions in Smoking cessation Online Health Communities

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Abstract: Users make contributions to online communities in different ways. Prior literature has rarely investigated how different user groups make contributions to smoking cessation OHCs. To illuminate the contribution of different user groups in smoking cessation OHCs, this study aims to evaluate user contribution from two dimensions (Content-contribution and popularity) associated with users' questioning and answering behaviors. Based on the user log data collected from a smoking cessation OHC in Finland (Stumppi.fi), we plan to assess user contribution level for four different user groups (lurker, conversation-starter, conversation-replier, and Conversation-starter & replier) based on user activity data via applying entropy method. The research might make theoretical contributions to the literature on user contribution and offer practical implications to smoking cessation OHC service providers.

Keywords: user contribution, smoking cessation, online health community

1. INTRODUCTION

Smoking is still an important health concern around the world, with the World Health Organization estimating that over 8 million deaths are the result of direct tobacco use [1]. Recently, smoking cessation online health communities (OHCs) have become a popular platform to assist smokers who want to quit their smoking habits to achieve abstinence [2, 3]. In such OHCs, users can start a conversation to seek help, to share smoking cessation experience and tips, and to respond to others' postings. This encourages the creation and exchange of user-generated content (UGC). However, in OHCs, most UGCs are contributed by a small number of key users [4]. The majority of users never or only occasionally contribute UGC to the OHCs [5]. Understandably, most of prior studies on user contributions focus on the content contribution of users in OHCs as UGC is important for the sustainable development of OHCs. The other user engagement activities in OHCs have been largely ignored in user contribution research, such as reading, following, sharing, and voting [6]. From an ecosystem perspective, in OHCs like smoking cessation online communities, different users play different roles and make contributions in different ways, thereby complementing each other, and maintaining the ecosystem. Such as lurkers in smoking cessation online communities make contributions to the online communities mainly via reading, following, voting, or sharing UGC with other users though they make no content (UGC) contribution to the online communities at all. Therefore, ignoring the other forms of user contributions other than content contribution might hinder our comprehensive understanding of user contribution in smoking cessation OHCs.

Although recent research has investigated distinct types of users with their own patterns of engagement in OHCs, such as posters and lurkers [5, 7], the understanding of contributions from different user groups is still unclear. The multiple functions of OHCs allow users to contribute to OHCs not only by lurking and posting, but also by following a topic or voting for a topic like thumbs-up. We still lack a comprehensive understanding of how users' different activities in smoking cessation OHCs contribute to the communities. For instance, how do

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users who do not generate UGC contribute to the OHCs? Thus, an in-depth investigation on user contributions to OHCs via analyzing users' different behavior patterns in OHCs is needed to get a full picture of the contribution of all the users in smoking cessation OHCs, not only the UGC contributors as posters, but also lurkers who never make or reply a request in smoking cessation OHCs.

To address the above research gap, this study will investigate user contributions based on users' different activity behaviors in smoking cessation OHCs. Based on the features of the smoking cessation OHCs and associated user activity behaviors, we aim to investigate user contributions among four different user groups (lurker, conversation-starter, conversation-replier, and Conversation-starter & replier) from two dimensions, namely content-contribution and popularity. The research model will be empirically tested through log data collected from a smoking cessation OHC in Finland (Stumppi.fi).

Specifically, based on the four types of user behaviors in Stumppi.fi, we suggest two dimensions of user contributions in smoking cessation OHCs: content-contribution and popularity. And we categorize the Stumppi.fi users into four groups in accordance with their behaviors of initiating a conversation or responding to others: lurker, conversation-starter, conversation-replier, and Conversation-starter & replier. Log data from Stumppi.fi are used in this study to empirically test our proposed model in explaining how different users contribute to the OHC with different activity behaviors.

The rest of this paper is organized as follows. Section 2 provides a literature review on smoking cessation OHCs and user contribution. Then, Section 3 presents the research method that will be employed in this research, including a description of the variables included in the user contribution assessment model, the methods for data analysis, and the data collection plan. Finally, we discuss the potential theoretical and practical implications and highlight the limitations of the current study and future research directions.

2. LITERATURE REVIEW

2.1. Research on smoking cessation OHCs

Extant studies have been conducted to investigate smoking cessation OHCs. These studies have revealed two main research streams. The primary research stream focuses on the effectiveness of such OHCs for smoking cessation. This research stream often conducts experiments to test whether the usage of smoking cessation OHCs leads to positive smoking cessation outcomes. For instance, Graham et al. [2] found that people who use smoking cessation OHCs are more likely to stop use tobacco products in three months than non-users. In a Facebook OHC for young adult smokers, 12-month usage was found to be associated with increased attempts to quit and decreased cigarette consumption [8].

The other research stream focuses on social support in smoking cessation OHCs. This research stream typically analyzes UGC in smoking cessation OHCs to identify social support provided to users via content analysis. Informational support, emotional support, and companionship activities have been found to be common in smoking cessation OHCs [9, 10]. This is consistent with research findings in OHCs regarding various health concerns, such as breast cancer [11], Autism Spectrum Disorders [12], and HIV/AIDS [13]. In addition, some studies have applied UGC to detect users' smoking status. For instance, Wang et al. [3] designed an approach to identify smoking status by applying machine learning techniques to classify UGC in smoking cessation OHCs.

Summarizing these research streams, we find that few studies have investigated how different users contribute to smoking cessation OHCs. Previous studies on online communities mostly examined posters' behavior, with less attention paid to other types of users, such as lurkers. In order to ascertain whether all users contribute to smoking cessation OHCs in different ways, it is necessary to assess how different users make contributions to smoking cessation OHCs based on their activities in smoking cessation OHCs.

2.2. User contribution

Many studies have been conducted to investigate different roles of users in OHCs, mainly focusing on posters and lurkers [4, 5, 7]. For instance, the research by van Mierlo [4] has confirmed that the 1% rule can explain the participatory patterns in OHCs. In other words, 90% of users lurk and do not contribute, 9% of users contribute sparingly, and 1% of users contribute the vast majority of UGC in OHCs. In the work of Yang et al. [5], perceived social support from OHCs have been found to exert different influences on commitment between posters and lurkers. Specifically, both perceived recognition for contribution and perceived freedom of expression have a stronger positive influence on the commitment of lurkers than that of posters.

However, this dichotomy unable to capture the complementary nature of different user contributions. In a smoking cessation OHC, postings only reveal the content contribution of users. The more important in online communities is that the posts will be read, shared, followed or voted by other users. In other words, how the posts will influence other users is more important than generating posts. In addition, users can not only post messages, but also offer feedback to posters' postings via different functions provided by the OHC. For instance, a smoking cessation OHC might have an "Add to Favorites" button. Some users who never post messages might use this function to mark and collect their favorite topics purposively. This kind of behavior has often been viewed as lurking in prior studies [6, 14]. Lurking has been found to be a significant form of user engagement [15]. Lurkers could also make contributions to the OHCs as they are "consumers" of the UGC generated by active users [5, 15]. They can contribute to the OHCs in their own ways, such as voting on content, following topics, or adding a poster to favorites [6].

In order to understand how people participate in and contribute to online communities, some researchers have moved further beyond the dichotomy of posting and lurking. For instance, Deng et al. [6] have applied the concept of immersion from gaming field to study user contributions in SQA, and defined immersion as the degree to which a user involves in an SQA in which content is a focus. They categorized users of an SQA into four different user groups: questioners who raise questions, answers who offer answers, lurkers who only read postings, and questioner-answers who offer both questions and answers [6]. They proposed three dimensions to measure user contributions [6]: (1) content-contribution, refers to a state of deep involvement in an SQA via generating contents, such as asking or answering a question. (2) Activeness, refers to a state of influencing users' opinions by interacting with other users, such as following a topic or a user, and adding a favorite to a topic. (3) Influence, refers to a state of influencing other users in an indirect way, such as voting and thanking. Through analyzing user activity data of an SQA, they found that lurkers have higher community-immersion scores than questioners who only ask questions, indicating that lurkers contribute more than questioners [6]. In the context of OHCs, Carron-Arthur, Ali, Cunningham and Griffiths [16] conducted a systematic review and identified 41 participation patterns, from topic-focused responders who respond to others' requests rather than initiate posts to influential users who are leaders in OHCs. They summarized three dimensions to identify user participation patterns in OHCs, including content-based dimension, activity-based dimension, and network-based dimension. In the content-based dimension, prior research mainly applied content generation patterns as metrics to evaluate users' content-contribution, such as information seekers and providers, emotional support seekers and providers [11]. In the dimension of activity, users' various online activities (e.g., time logged in, read, post, and thread initiation) are considered as metrics to identify engagement types, such as caretaker and discussant [17]. In terms of network-based dimension, the social network analysis (SNA) metrics (e.g., out-degree, in-degree) have been used to categorize user types, such as key players, moderate users, and takers [18, 19].

This study aims to quantify the contribution of all users of smoking cessation OHCs. Such OHCs provide a variety of interaction functions, such as posting messages, response, comments, and favorites, to exchange information and social support [9, 20]. Taking Stumppi.fi as an instance, users can “create a conversation” to disclose current situation and ask for assistance, other users can “reply” by offering informational and emotional support. Some users can purposively select their favorite conversation by clicking the “add to favorite” button. Recognizing the features of the smoking cessation OHC environment as a socialized helping and supporting community and the importance of user involvement for OHCs, we applied two dimensions of user contributions: Content-contribution and popularity, which are all closely related to user involvement. Specifically, we take content-contribution dimension to represent the state of visible and active engagement of OHC users via starting conversations or replying to posts to exchange social support [16, 21]. Besides, popularity reflects a state of being influenced by UGC in a way of browsing, reading, and setting personal favorites, thereby affecting such elements as the number of audiences or UGC consumers [15, 22].

3. RESEARCH METHOD

3.1. Study case

The research case is a smoking cessation OHC in Finland: Stumppi.fi (https://stumppi.fi/). Stumppi.fi is an Internet-based portal for assisting smokers to achieve abstinence. It was initially funded by Finland’s government-supervised not-for-profit Slot Machine Association in 2004, but since January 2017 the funding has come from the Ministry of Social Affairs and Health and the Funding Centre for Social Welfare and Health Organizations. The language of Stumppi.fi is Finnish. It has operated an OHC for ex-smokers and current smokers in Finland since 2007. It had more than 9,000 registered members by the end of 2018.

Unlike general social network sites (SNS), such as Facebook and Instagram, Stumppi.fi does not offer too many functions (e.g., vote, like, and share) for users to interact with others. A simple and effective operation interface is helpful for users to focus on social support they need and avoid social overload [23]. The functions provided by Stumppi.fi include reading posts, creating a new conversation, replying to others’ posts, and adding conversations to personal favorites. Figure 1 shows the front page of the OHC in Stumppi.fi.

Before the data collection, we have obtained an ethical permit from the Ethics Committee of the home university of the authors. With the help of the staff of Stumppi.fi, we have obtained the log data of registered users of Stumppi.fi from 2007 to 2018. Stumppi.fi maintains a complete transactional history of all online events, such as asking questions and responding to others in the threads. This provides literal evidence of user contributions in the OHC, such as reading posts, asking questions, and offering answers to others’ questions. All identifiable information was deleted to protect users’ privacy. In total, we have obtained 5,131 users, 4,514 threads, and 193,089 posting messages.

3.2. The model for assessing user contribution

In Stumppi.fi, users can exchange social support through following ways: (1) create a new conversation to start a discussion, (2) reply to others’ conversations, (3) read others’ conversations and corresponding replies, (4) send private messages to others, and (5) set others’ conversations as favorite topics. Based on these functions provided by Stumppi.fi, we select 6 user-behavior attributes related to user behaviors for the measurements in our proposed contribution-assessment model. Due to privacy issues, we exclude the private message function in our study. Table 1 presents the details of these attributes.

We associate each of these 6 attributes with more appropriate of the two dimensions of user contribution: content-contribution and popularity.

First, on the content-contribution dimension, referring to generating and sharing content in Stumppi.fi [16, 21], two attributes, including conversation created and replies, are selected as the indicators for the model we propose here.

Second, on the popularity dimension, referring to being influenced in a way of reading and setting personal favorites [15, 22]. In this context, we intend to measure the degree to which audiences consume and appreciate the UGC provided by posters, we consider reads count, participant count, and replies count and favorites as proxies for the popularity in Stumppi.fi. Figure 2 presents the model for assessing user contribution.

Table 1. Items of behavior data and their explanations

Items	Explanation
Conversation created	The number of conversations that a user has created.
Replies	The number of replies that a user posted.
Reads count	The total number of reads of conversations that a user has created.
Participants count	The total number of participants of the conversations that a user has created.
Replies count	The total number of replies of the conversations that a user has created.
Favorites	The number of conversations that a user marked as “favorite”. The user can directly join in the marked conversation by clicking the favorite topics button.

3.3. Classification of Stumppi.fi users

We classify Stumppi.fi users into four categories on the basis of functions of seeking and sharing social support via conversations and replies – that is, in terms of the conversation-creating and conversation-replying activities of users. These are (1) conversation-starters, refers to those who start a conversation by creating a new discussion. (2) Conversation-repliers, refers to those who only offer replies to others’ conversations. (3) Lurkers, refers to those do not post messages. And (4) Conversation-starters & repliers, refers to those generate content by both starting and responding to conversations. We assume that creating conversations and responding to them are the core methods by which users share social support and help others in the smoking cessation OHC. To a certain extent, the number of conversation created by users reflects their demands for personal disclosure and social support acquisition, and the number of replies posted by users reflects their desire to respond to others’ requests and offer informational and emotional support. The major difference between the creators and respondents is the users’ preference regarding obtaining and offering social support in smoking cessation OHCs. Lurkers refer to users who do not generate content, but contribute the OHCs via other behaviors such as reading and following other’s postings [5, 24]. Table 2 presents the descriptions for our four user classes.

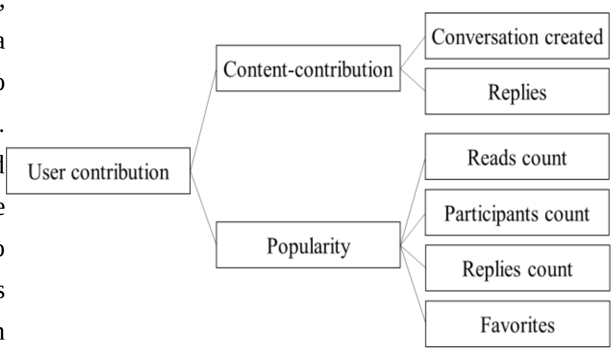

Figure 2. The model for assessing contribution of Stumppi.fi users

Table 2. The classification of users

Class of users	Description
Conversation-starters	Number of conversations a user started > 0; Number of a user’s replies = 0
Conversation-repliers	Number of conversations a user started = 0; Number of a user’s replies > 0
Lurkers	Number of conversations a user started = 0; Number of a user’s replies = 0
Conversation-Starters & repliers	Number of conversations a user started > 0; Number of a user’s replies > 0

3.4. Calculation of user contribution

Entropy method is an objective weighting method, which determines the weight of each index according to the information provided by the observed value of each index. We can use entropy value to judge the dispersion degree of an index. The greater the dispersion degree of an index, the greater the influence of this index on the comprehensive evaluation. Specifically, for an index, the greater the gap between each observation value of the index, the greater the role of the index in the comprehensive evaluation. The smaller the difference between the observed values of the index, the smaller the role of the index in the comprehensive evaluation. If all the observed values of an index are equal, the index has no effect in the comprehensive evaluation. In order to objectively assign index weights and avoid errors caused by human factors, we plan to use entropy method to calculate index weights in this study.

The realization process of entropy method is as follows:

(1) Constructing data matrix:

$$S = \begin{bmatrix} x_{11} & \cdots & x_{1m} \\ \vdots & \ddots & \vdots \\ x_{n1} & \cdots & x_{nm} \end{bmatrix}_{n*m}$$

Note: x_{ij} is the observed value of the j_{th} index in the i_{th} sample.

(2) Non-negative processing of data

If there is a negative number in the data, the data need to be non-negative processing. In addition, in order to avoid the meaninglessness of logarithms in entropy calculation, data translation is required.

For bigger, better indicators:

$$x'_{ij} = \frac{x_{ij} - \min(x_{1j}, x_{2j}, \ldots, x_{nj})}{\max(x_{1j}, x_{2j}, \ldots, x_{nj}) - \min(x_{1j}, x_{2j}, \ldots, x_{nj})} + 1$$

$(i = 1, 2, \ldots, n; j = 1, 2, \ldots, m)$

For smaller, better indicators:

$$x'_{ij} = \frac{\max(x_{1j}, x_{2j}, \ldots, x_{nj}) - x_{ij}}{\max(x_{1j}, x_{2j}, \ldots, x_{nj}) - \min(x_{1j}, x_{2j}, \ldots, x_{nj})} + 1$$

$(i = 1, 2, \ldots, n; j = 1, 2, \ldots, m)$

(3) Calculate the entropy value of the j_{th} index:

$$e_j = -k \sum_{i=1}^{n} P_{ij} \log(P_{ij})$$

Where $P_{ij} = \frac{x_{ij}}{\sum_{i=1}^{n} x_{ij}}$ $(j = 1, 2, \ldots, m)$. So k is equal to 1/In m.

(4) Calculate the coefficient of difference.

$g_j = 1 - e_j$

Note: the larger the g_j, the more important the index.

(5) Calculate index weight.

$w_j = \frac{g_j}{\sum_{j=1}^{m} g_j}$ $(j = 1, 2, \ldots, m)$

(6) Calculate the combined score.

$$S_i = \sum_{j}^{m} w_j * P_{ij} \ (i = 1, 2, \ldots, n)$$

4. POSSIBLE IMPLICATIONS AND LIMITATIONS

Our study may provide theoretical contributions to the literature regarding user contribution in online communities. First, this study attempts to investigate the contribution of all the users of a smoking cessation OHC from two dimensions (content-contribution and popularity) based on their activities in smoking cessation OHCs, including conversation-starters, conversation-repliers, lurkers, and Conversation-starters & repliers. Our findings may add new insights into user contribution in OHCs via providing detailed explanations on how different users contribute to OHCs from their popularity and content-contribution in smoking cessation OHCs. As we know, this study might be the first study to use all user activity data in smoking cessation OHCs to explain user contribution in OHCs, which will provide research findings with high validity and reliability.

Second, this study aims to investigate the contribution of different users from a role complementarity perspective. Different from prior studies focusing on users who generate content while ignoring other contributors such as lurkers, this study considers all different user groups, including lurkers and posters. Our findings might offer a comprehensive picture of how different user groups complement each other in smoking cessation OHCs.

Third, this study purposes to explain the user contributions in smoking cessation OHCs by adopting a user contribution assessment model derived from the characteristic features of smoking cessation OHCs. Our research might offer an approach to evaluate users' engagement in smoking cessation OHCs.

This study may also offer practical implications to smoking cessation OHCs service providers on individual users' engagement and their contributions to the OHCs. First, the findings of different forms of contributions by different user groups might assist service providers to adopt customized strategies to promote the contributions. Second, the user contribution assessment model might offer a tool to monitor users' engagement in different dimensions, and then develop personalized management for users based on their user contribution scores. Third, smoking cessation OHC service providers should view smoking cessation OHCs as an ecosystem as different users play different roles and support each other in the OHCs. Service providers should pay attention to the user contribution of both positive users (content generators) and passive users (lurkers).

This research has following limitations. Firstly, the data are only collected from a smoking cessation OHC in Finland (Stumppi.fi). Future work could replicate this study in countries with different cultures to increase the generalizability of the research findings. Second, this study is only conducted in the context of smoking cessation OHCs. Future research could consider other OHC contexts, such as OHCs focusing on alcohol, cancer, and fit, to test the proposed contribution-assessment approach in different OHCs.

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