Who Contributes What? Scrutinizing the Activity Data of 4.2 Million Zhihu Users via Immersion Scores

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Abstract

Studies of knowledge communities have focused predominantly on contributors who ask questions and/or post replies, while little research has examined the contributions of those who neither pose questions nor suggest answers in knowledge communities. To illuminate member contributions of various sorts, this study evaluated user contribution to knowledge community from three dimensions (influence, content-contribution, and activeness) of immersion. Based on the user activity data of more than 4 million users from Zhihu, the largest online knowledge community in China, we calculated the immersion level for the four user groups (Lurkers, Questioners, Answerers, and Questioner-Answerers) in line with their question-asking and question-answering behaviors in Zhihu. The research findings revealed that Lurkers (members who posted nothing) showed higher community-immersion score than Questioners who asked questions only. The latter, Questioners, had the lowest community-immersion score, while Questioner-Answerers, who posted both questions and answers, exhibited the greatest contribution in the case knowledge community. We further made horizontal comparison of immersion score among the four different user groups and found that when immersion scores of the four different user groups are above a certain threshold, the immersion scores of the four different user groups display a consistent distinguishing pattern. This result highlights the similarity of tendencies in behavioral orientation among different users in knowledge communities. Theoretical contributions and practical implications to be gleaned from this research are discussed.

Keywords: Immersion score, knowledge community, contribution, user engagement, SQA community

1. Introduction

The knowledge community has become a popular forum for individuals sharing knowledge and obtaining solutions based on user-generated content (UGC). Members post questions, provide answers, comment on content, and – in the online domain – often evaluate content (e.g., via a thumbs-up or thumbs-down button) (Fu & Oh, 2019). Some studies have investigated the value of UGC in knowledge communities directly (Ye et al., 2011). Overall, such work has focused overwhelmingly on knowledge contributors – e.g., users who ask questions, post responses, or generate content of both these types for a knowledge community. In so doing, it underestimates the contributions of users who, while not quick to offer questions or replies, read the UGC and add to the knowledge community in other ways. From an ecosystem perspective, users of different stripes may play different roles, thereby supporting each other and maintaining the ecosystem. Hence, ignoring contributions particular to certain user groups might hinder attempts at a comprehensive understanding of knowledge communities.

Though recent years have witnessed some, albeit brief, discussion of distinct types of users with their own patterns of behavior in a knowledge community – such as question-askers – that discussion has been sporadic at best, and the unique contributions to the community from different user groups have been largely ignored or underestimated. Also, there is a paucity of understanding of the activities of particular user groups, and we lack comprehensive consideration reflecting the complementary nature of their contributions to a knowledge community. For instance, do those who never post anything make unique contributions to the community or perhaps even exhibit greater engagement in it than some others do? In other words, an in-depth research on user contribution to knowledge communities via analyzing users' different behavior patterns in knowledge communities is needed in order to get a better and full understanding of the contribution of all the users in knowledge communities, not only the content-contributors as Questioners and/or Answerers, but also Lurkers who never ask or answer a question in knowledge communities.

To bridge the aforementioned research gap, we drew on the concept of immersion scores, familiar from studies of games (Brown, & Cairns, 2004), to investigate user contribution to knowledge communities based on users' different behaviors in knowledge communities. This research focuses on a specific type of user-centered online knowledge community, a social question and answer (SQA) community. Based on the unique features of the SQA context and the associated user activities, we made adaptation of the immersion-evaluation framework in the game filed to the knowledge communities and developed an immersion score model suitable for assessing SQA immersion. The theoretical model was empirically tested through activity data collected from the China-based Zhihu (zhihu.com), an SQA community similar to Quora, which provides knowledge-intensive content to users in China.

Specifically, based on the 18 distinct user behaviors in Zhihu, we proposed three facets of user contributions for immersion in SQA communities, namely influence, activeness, and content-contribution. The three dimensions constitute a holistic metric for user contribution to a knowledge community by engaging with that community (Jennett et al., 2008). And we divided the Zhihu users into four groups in accordance with their question-asking and question-answering behavior in the knowledge communities: Lurkers, Questioners, Answerers, and Questioner-Answerers (i.e., for presence of questioning and of answering behavior). User activity data from Zhihu were applied in this study to examine whether the immersion score can help explain how different users contribute to knowledge communities with different behaviors via information-entropy method. In doing so, this paper aims to provide answers to the following question: How do content generators and content Lurkers make contributions to knowledge communities? Specifically, this study aims to examine user contribution to knowledge communities among content generators (Questioners, Answerers, and Questioner-Answerers) and content Lurkers based on their different behaviors and to provide full understanding of their different roles in support knowledge communities.

The discussion begins with a literature review for contextualization, presented in the next section. After that, we present the research method employed in our work, describing the immersion-assessment model for our SQA community study and also the data collection and coding. Then, the paper outlines the results obtained, with the discussion turning next to elaboration on the key findings. Finally, we consider the implications of this research and clarify its limitations and the future research directions.

2. Literature Review

2.1 Research on SQA Community

Prior research has studied the role of users in online SQA communities, mainly focusing on knowledge-contributors and knowledge-consumers (Liu & Jansen, 2017). For instance, some SQA community studies have investigated the characteristics of the most prolific contributors and how to identify knowledge-sharers (Liu & Jansen, 2017).

In an SQA community, users are able to not only ask and/or answer questions but also make comments on answers or other responses by means of feedback functions. For instance, a knowledge community might have a "Like" button or an "Add to Favorites" button. Some SQA users neither ask or answer questions nor even comment on replies (e.g., by clicking a "Like" or "Favorites" button). In fact, these people account for a large percentage of the users of knowledge communities, and has been defined as Lurkers in knowledge communities (Edelmann, 2013). According to Edelmann (2013), Lurkers also play important roles in knowledge communities and it is necessary to investigate how they contribute to knowledge communities via examining their activities in using knowledge communities.

Users play a variety of roles in the online community ecosystem. Several categories of users have been proposed in typologies based on the forms of user activity in SQA. Table 1, below, summarizes how the literature has categorized users from their activities in a knowledge community.

Table 1. Categories of SQA community users described in the literature

User category	Definition	Relevant studies
Lurkers	Lurkers do not contribute any knowledge content. They mainly browse content posted by other users or look at the activities of other users while present in a knowledge community.	Gleave et al. (2009)
Fans	Fans express acceptance or affection for content or users by such means as clicking a liking or upvote button in a knowledge community.	Haythornthwaite & Hagar (2005)
Questioners	Questioners are those of the users who ask questions in a knowledge community.	Liu & Jansen (2017)

Answerers	Answerers are the members of a knowledge community who respond to questions posted by other users.	Liu & Jansen (2017)
Discussants	The term “discussants” is used for those who exchange opinions with other users in a reciprocal manner within a knowledge community.	Gleave et al. (2009)
Technical editors	Technical editors are the people who correct errors related to the style or formatting of content posted in a knowledge community.	Geiger & Ribes (2010);

It is noteworthy that a user may belong to different groups simultaneously and play different roles in knowledge communities (e.g., both Questioners and Fans). In the literature there are conflicting opinions on the contribution of Lurkers in knowledge communities. Some researchers believed that Lurkers are silent users who only benefit from observing others' interaction in online knowledge communities and have little contribution to online knowledge communities (Van Mierlo, 2014). And some scholars even argued that too many Lurkers in online knowledge communities might damage the vitality of the communities (Sun, Rau, & Ma, 2014).

Another research stream on knowledge communities have a different opinion on the contribution of Lurkers in knowledge communities. Edelmann (2013) argued that Lurkers participate in a knowledge community through “reading” and “listening,” deeming this a normal form of community involvement and holding that Lurkers should be considered when evaluating user contribution to knowledge communities. Prior literature has applied a variety of theories to explain user contribution to SQA communities based on user behaviors in SQA communities. Wang and Zhang (2016) identified Zhihu users as falling into four distinct groups (“Starter”, “Answerer”, “Technical editor”, and “Follower”), finding that discussion-starters and technical editors usually ask more questions but reply to only a few and have few followers, while Answerers contribute more content and have the largest number of followers and receive the most votes (via use of the “Like” and “Favorites” functions). Though Followers contribute very little content to Zhihu and have the least followers, they still contribute to Zhihu, following most of the topics discussed and the users in Zhihu. Chen et al. (2019) proposed a research framework to explain variation in users' knowledge contribution to SQA communities by considering the interaction of voting and commenting (Chen, Baird, & Straub, 2019). In their research they found that vote is significantly associated with users' knowledge contribution. Positive votes motivate users' knowledge contributions, and vice versa. They also found that commenting plays an important role in motivating online knowledge contribution(Chen, Baird, & Straub, 2019). As Ridings et al. (2006) argued that though Lurkers only consume user-generated content in SQA communities without any visible contributions, they influence SQA communities in their own ways. Lurkers' voting on content, following questions, topics or other users reflect their contribution to SQA communities.

But the current research on the contributions of users in different roles is sporadic. The extent to which they contribute to the community ecosystem is also unclear. Assessing users' level of community engagement in a manner that takes this work further by accounting for the diversity of user behavior displayed in the community should be able to yield more comprehensive evaluation results, covering a broad spectrum of users and their patterns.

2.2 Immersion

The concept of immersion applied in the game field pertains to the specific psychological experience of engaging with a computer game, in which context an immersion score articulates a player's involvement in a game, often measured via three dimensions with regard to an online game (Jennett et al., 2008). These are flow (Sweetser & Wyeth, 2005), cognitive absorption (Agarwal & Karahanna, 2000), and presence (Zahorik & Jenison, 1998). Flow can be defined as "the state in which individuals are so involved in an activity that nothing else seems to matter" (Csikszentmihalyi, 1990). Cognitive absorption, in turn, refers to a state of deep participation with the software (Agarwal & Karahanna, 2000), and presence is described as a psychological sense of being truly present in the virtual environment (Ausburn et al., 2019).

Suggesting, with regard to a game community in particular, that immersion is an experience characterized by its depth, Brown and Cairns (2004) proposed three distinct levels of immersion based on grounded theory: engagement, engrossment, and total immersion. A player proceeds from the shallowest immersion, simple engagement in the experience. With the player's deeper participation, this may advance to engrossment level and, further, to the third level, that of "total immersion."

The concept of immersion has been extended to different contexts beyond games. Brown and Cairns (2004) found that immersion can be a useful concept for characterizing the degree of involvement in both game and non-game contexts. Some scholars have introduced immersion into online social media. Such as Hamilton et al. (2016) defined immersion as a psychological state in which consumers are completely immersed in the social media environment and experience high-level participation and enjoyment at the same time (Hamilton et al., 2016). In addition, Zha et al. (2018) have also introduced immersion into social media to describe the degree to which individuals participate in tasks or objects (Zha et al., 2018). However, these research only borrows the concept of immersion without considering the specific characteristics of social media.

While Brown and Cairns (2004) found that immersion can be a useful concept for characterizing the degree of involvement in both game and non-game contexts, they have pointed out that it remains unclear whether and when immersion in some non-game types of systems, such as traditional work systems, is advantageous. Accordingly, they have called for immersion research to explain the level of user involvement in some related contexts (Brown & Cairns, 2004). Inspired by the arguments of Brown and Cairns (2004), we investigate immersion in the context of SQA community, using user involvement/engagement as a lens for gaining better understanding of user contributions to an SQA community.

It is clear that user involvement is the most important part of the process of generating and sharing content/knowledge in SQA communities. Users may experience an immersive state in which users are fully engrossed within the SQA environment while experiencing involvement in SQA communities via different interaction activities in the communities (Hamilton et al., 2016; Huang, 2006; Novak et al., 2000) Thus, the immersion level of users might help explain to what degree users with different social interaction activities will contribute to SQA communities.

The immersion-score approach originally developed in the game-community context offers potential to contribute to an assessment model aimed at understanding user contributions to a knowledge community rooted in user involvement The level of involvement can vary greatly, with users of a community being active in a given community in different ways and to varying degrees (Brown & Cairns, 2004). Since user involvement in SQA communities varies – some users might be deeply involved whereas others exhibit relatively shallow participation – we argue that instruments measuring immersion can, by illuminating the degree of user involvement in SQA communities, help us explore and, in turn, explain user contribution to SQA communities from the lens of user behaviors in SQA communities.

Some clarifications are in order. While those examining immersion in the gaming context emphasize users' psychological experience of the game primarily, application for the involvement in an SQA community demands a somewhat different focus. Gaming entails a temporary state of immersion, while the SQA experience is connected more with long-term engagement in a knowledge community. Hence, this paper examines user participation over time to explain user immersion in an SQA community. Secondly, game players are immersed in the game world and the play, while SQA users are immersed in the community. We employed corresponding definitions, following the argument of Brown and Cairns (2004): where the former idea of immersion refers to the degree to which players participate in the game and the game playing experience with other players is the core of immersion, we defined immersion for purposes of our study as the degree to which a user participates in an SQA community in which content is a focus.

Recognizing the unique features of the SQA environment as a socialized question-answering community and the importance of user involvement for SQA communities, we applied three dimensions of immersion based on the unique features of SQA as a socialized question-answering community in order to fit to the SQA context, namely content-contribution, activeness, and influence, which are all closely related to user involvement. In other words, due to the different context of SQA communities and games, in this study, we only borrow the concept of immersion from the game domain to evaluate user involvement/engagement in SQA communities rather than the three dimensions (flow, cognitive absorption, and presence) of immersion in game domain due to the different context and focus of the SQA communities.

2.3 Three dimensions for immersion

This article introduces the concept of immersion to quantify the community contribution of SQA users. The contribution and value of users to SQA sites are determined by their online social interactions. Online social interaction, also known as network interaction, refers to the online interaction behavior conducted by users on the network platform through information exchange (Chen & Lin, 2018). Social networking sites provide a variety of social interaction functions, such as posting articles, comments, forwarding, favorites, thumb up, following, sharing, etc. (Allen et al., 2014; Lu, Yu, Guo, & Zhou, 2014). Taking Zhihu as an example, people establish connection with friends, relatives, colleagues, and even strangers, resulting in a variety of social interactions. Users can "follow other people's status, "collect" favorite content, columns. Comment, thumb up, or share others' content. Interactions between friends, participation in online events, generating recommendations and reviews are freely and voluntarily written, sent, and read by Zhihu users.

In an SQA community, generating original content is an analogous manifestation of a high degree of user engagement (Leung, 2009). Therefore, we take **content-contribution** to be a dimension of immersion that represents the state of deep engagement of SQA users (Tang, Gu, & Whinston, 2012). Besides, **activeness** refers to a state of influencing people's opinions by interacting with them, thereby affecting such elements as the number of "fans" or retweets (Liu & Liu, 2011). According to Chen et al. (2019) the feedback from users, such as Upvotes and Likes, allows users to assess the contributions of other users in SQA communities, thus rewarding the contributors (Chen, Baird, & Straub, 2019). In other words, a user may feel part of the SQA community when, for instance, obtaining psychological satisfaction upon content he or she has generated receiving attention such as upvotes or Likes from other users in the community. This feedback indicates that the user has had an influence on others in the SQA community. We use the dimension of **influence** to reflect the power or ability for a user to influence the other members of the SQA community in an indirect or invisible way (Li, Bai, Zhang, Tang, & Luo, 2019).

3. Method

3.1 The model for assessing immersion of Zhihu users

In the knowledge community Zhihu, China's largest SQA community, users can ask and answer questions, publish short or long texts, demonstrate attention to other users in various ways, and perform various other actions. On the basis of the functions provided by Zhihu, we selected 18 user-behavior attributes related to user behaviors for the basic measurements in our immersion-assessment model. Table 2 provides the details of these attributes.

Table 2. Items of behavior data and explanation of the variables

Item of behavior data	**Explanation**
Upvote count	The number of positive votes the user has received.
Times "favorited"	The number of this user's replies, threads, and articles collected by other users.
Follower count	The number of people following this user's contributions.
Marked answers count	The number of times this user's answers have been recorded as marked answers in the Zhihu.
Times thanked	The number of times this user's answers have been marked as appreciated by other users.
Answers posted	The number of answers that this user has posted.
Questions asked	The number of questions that this user has posted.
Articles posted	The number of articles that this user has posted.
Commercial-question count	The number of commercial-related issues on which a user has started discussion.
Webcasts hosted	The number of live Webcasts this user has hosted. Zhihu has a function called "Paid live" in which the speaker shares knowledge and opinions with paying users by voice.
Webcasts paid for	The number of times this user has paid to participate in a live Webcast.
"Favorites" collected	The number of replies, threads, and articles collected by this user for easy reference. The list reflects the user's interests and represents the store of knowledge generated by other users that he or she has gathered in Zhihu. The user learns more by focusing on the items "bookmarked" here.
Users followed	The number of users that this user is following.
Topics followed	The number of topics that this user is following.
Columns followed	The number of columns (A collection of UGC generated by other members) that this user is following.

“Favorites” lists followed	The number of “Favorites” lists that this user is following. Users can monitor other users' “Favorites” lists, which are visible to other members of the community.
Questions followed	The number of questions this user is following.
Items shared (“pins”)	The number of times this user has shared items via “pins.”

We associated each of these 18 attributes with the most appropriate of the three dimensions of immersion – again, influence, content-contribution, and activeness. We will now address each of these in turn.

Since the first dimension (influence) refers to the ability of a user to influence others, we took upvote count, number of times thanked, the number of “Favorites” items collected, and the number of marked answers as a proxy for the ability of a user to influence others in Zhihu, together with his or her follower count. Therefore, the proposed immersion-assessment model uses these five user attributes as the indicators for influence.

On the content-contribution dimension, referring to the production of knowledge content in Zhihu, six of the 18 attributes were selected as the indicators for the model we present here. The question count, answer count, article count, and commercial-question count attributes each pertain to a particular content-production method. In addition, the mechanism known as a “Paid live” is available, a form of real-time question-and-answer interaction via Webcasts in Zhihu.

Finally, as discussed above, activeness refers to activities in SQA communities that influence other members' opinions. In this context, we wish to measure the degree to which a user actively follows and responds to others' activities. For our model, seven indicators are assigned to this dimension.

Having performed this initial categorization, we needed to prove the rational basis for this organization and its universality. To this end, we employed the experimental method of card sorting for an understanding of how Zhihu user themselves conceive of the 18 attributes. Card sorting is popular in user testing for its ability to provide researchers with a solid basis for classification from the user perspective (Li et al., 2019).

We invited 50 Zhihu users to take part, carrying out the testing for each in a separate location. After informing the participants about the purpose of the experiment and explaining the 18 Zhihu attributes as well as how to group the 18 features, we asked them to divide the 18 cards (indicating these 18 user features) into three or four categories in accordance with their personal understanding, then name each category after having thus separated them into groups.

The classification performed by these 50 Zhihu users was consistent with the classification proposed in this paper (with the influence, content-contribution, and activeness dimensions) except that some used different naming for their assigned categories. The results from user testing hence show that the classification dimensions and our grouping of the 18 user attributes presented in this paper are generally consistent with the views of Zhihu users.

The immersion-assessment model applied in our study with Zhihu users is depicted in Figure 1.

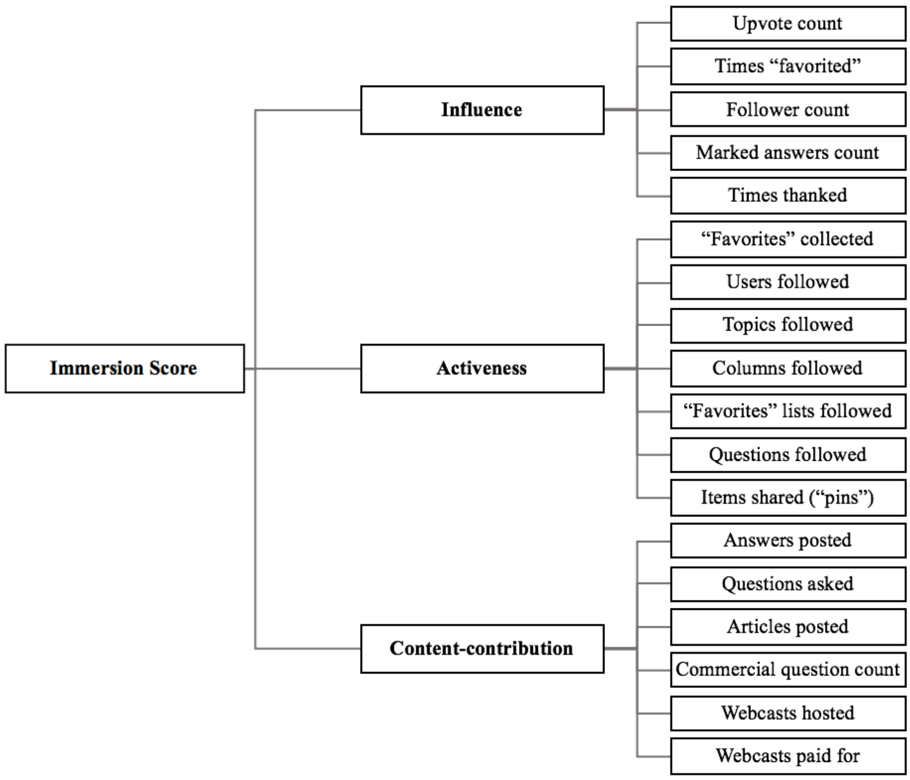

Figure 1. The model for assessing immersion scores of Zhihu users

3.2 Classification of users

We classified SQA users into four categories on the basis of SQA' s unique function of generating and sharing knowledge via questions and answers – that is, in terms of the question-answering and question-posting activities of users. These are i) Questioners, ii) Answerers, iii) Lurkers, and iv) Questioner–Answerers. One could justifiably proceed on the assumption that asking questions and responding to them are the key methods by which a user contributes content to an SQA community. To a certain extent, the number of replies posted by a user reflects his or her desire to make a knowledge contribution and the number of his or her questions reflects that user's demands for knowledge acquisition. The difference between the number of questions and that of answers reflects the user' s preference with regard to gaining and providing knowledge.

The classes Questioners and Answerers match categories utilized before. For instance, the latter has been defined as a group of users who give answers to questions (Wang & Zhang, 2016) while Questioners have been identified as the users who initiate discussion of a question by raising it for the first time (Gazan, 2010). In our study, we used the term “Answerers” for answering-only users, and “Questioners” for questioning-only users. Our additional category Questioner-Answerers was used for those who contributed both questions and answers. Finally, we adopted the usage of past studies for the Lurkers class, defined as those who do not contribute content such as questions and answers but do participate in the community by following topics or other users (Gleave, E., Welser, H. T., Lento, T. M., & Smith, 2009). The descriptions for our four user classes are given in Table 3. Under this classification model, there is no overlap between different categories of users, and all users in a SQA community are covered.

Table 3. Our classification of the Zhihu users' role classes

Class of users	**Description of class**
Answerers	Number of user's questions = 0; number of user's answers > 0
Questioners	Number of user's questions > 0; number of user's answers = 0
Lurkers	Number of user's questions = 0; number of user's answers = 0
Questioner-Answerers	Number of user's questions > 0; number of user's answers > 0

3.3 Calculation of immersion scores

The scoring model, based on information entropy method, serves as a quantitative instrument to synthesize the various user activities into an integrated and comparable score that can facilitate comparison of users in terms of their contributions to knowledge communities. Each activity item corresponds to a specific weight value, which represents the level of importance of the activity in the overall level of evaluation.

There are several common methods for calculating indicator weight: the Delphi method, the analytic hierarchy process, the entropy method, and others. We have chosen the entropy method to determine the weight for each indicator, so as to quantify immersion score for Zhihu users appropriately as it is an objective method which offers greater credibility in comparison to those subjective methods (Riquelme & González-Cantergiani, 2016).

The entropy method generates indicator weights in a manner consistent with the information-theory use of the concept as characterized above. For *m* users and *n* evaluation indicators, the original index data matrix $x = (x_{ij})_{m\times n}$ is formed. For an index indicator $\mathrm{x_j}$, the greater the difference between index value $\mathrm{x_{ij}}$ is, the greater the role of the index indicator in the evaluation as a whole and, therefore, the greater its weight. While the entropy method faces a substantial limitation related to its need for a complete dataset, our sample size is sufficiently large to overcome this issue. In fact, our large sample was one factor behind our use of the entropy method to compute the weighting for immersion score.

The steps for calculating indicator weights by this method are the following:

(1) Normalization of the evaluation matrix:

When the initial data are fed in as input, the indicators may differ in their scale and units. For the same measurable unit to be applied for all indices, the matrix must be normalized.

$$x'_{\mathrm{ij}} = \frac{x_{\mathrm{ij}} - \min\limits_{1\le \mathrm{j}\le \mathrm{n}} x_{\mathrm{ij}}}{\max\limits_{1\le \mathrm{j}\le \mathrm{n}} x_{\mathrm{ij}} - \min\limits_{1\le \mathrm{j}\le \mathrm{n}} x_{\mathrm{ij}}}$$

Note: $(x'_{\mathrm{ij}})_{\mathrm{m\times n}}$ is the normalized matrix. $\max\limits_{1\le \mathrm{j}\le \mathrm{n}} x_{\mathrm{ij}}$ and $\min\limits_{1\le \mathrm{j}\le \mathrm{n}} x_{\mathrm{ij}}$ are, respectively, the maximum and minimum value corresponding to the evaluation index j.

(2) Calculate the information entropy of the index indicators by means of standardized matrix $(x'_{\mathrm{ij}})_{\mathrm{m\times n}}$

$$\mathrm{H_j} = -\left(\sum_{\mathrm{i=1,j=1}}^{\mathrm{m,n}} \mathrm{f_{ij}} \ln \mathrm{f_{ij}}\right)$$

Note: $\mathrm{f_{ij}} = \frac{1+x'_{\mathrm{ij}}}{\sum_{\mathrm{i=1}}^{\mathrm{m}}\left(1+x'_{\mathrm{ij}}\right)}$

(3) The deviation in the coefficients of indices j, G_j is calculated.

$$G_j = 1 - H_j$$

(4) Finally, the weight is calculated:

$$w_j = \frac{G_j}{\sum_{j=1}^{n} G_j} = \frac{1 - H_j}{n - \sum_{j=1}^{n} H_j}$$

By the information-entropy method as presented above, users' immersion score can be computed via the following formula:

$$\text{Score} = \sum_{i=1,j=1}^{n,m} X_{ij} \times \omega_j$$

(Note: x_{ij} is the value of the j_{th} indicator for the i_{th} user, where w_j denotes the weight of the j_{th} indicator).

3.4 Data collection

We collected the data from Zhihu via Python programming. Specifically, we employed a recursive crawling method for collection of the data: We started by choosing an opinion leader who was both a follower of and followed by numerous Zhihu users. We crawled this user's attribute data. Next, we crawled all user IDs (each user has a unique ID) for the followers and followees of this user and, in turn, the attribute data of these users. The process continued until all users in the Zhihu community were traversed via recursive crawling, with the data-collection process ending when the crawler program could not reach any additional users. However, users scattered outside the relationship network were not included in this study because they had no intersection with any user in the relationship network on Zhihu.

Totally, the activity data of 4,376,500 Zhihu users were crawled from Zhihu by July 10, 2017. The data include users' demographic features (gender, location, education background, and employment experience) and their 18 different behavioral attributes in Zhihu. Then we cleaned the data, such as encoding, sorting, replacing the missing values, and deleting duplicate values. After data cleaning, finally we got the activity data of 4,290,484 Zhihu users as valid data set in this study.

4. Results

4.1 Statistical description of the evaluation model

From the data, 21.1% of the users (904,261) were classified as Questioner-Answerers, 45.1% (1,935,182) as Lurkers, 7.8% (334,923) as Questioners, and 26% (1,116,118) as Answerers. Without doubt, Lurkers made up the largest group, indicating that most users in Zhihu made no contribution to the knowledge content by posting questions or answers. The finding is consistent with the prior research finding of Ridings et al. (2006) that Lurkers often account for a larger proportion in online communities. Figure 2 depicts the cumulative frequency distribution for the three types of users who contributed content – namely, Questioners, Answerers, and Questioner-Answerers. Nearly 73% of users who posted questions also posted replies, indicating that most Questioners are also willing to answer questions. However, fewer than 45% of users who gave answers also asked questions, which shows that those users prefer to generate knowledge, with little desire to solicit knowledge in knowledge communities.

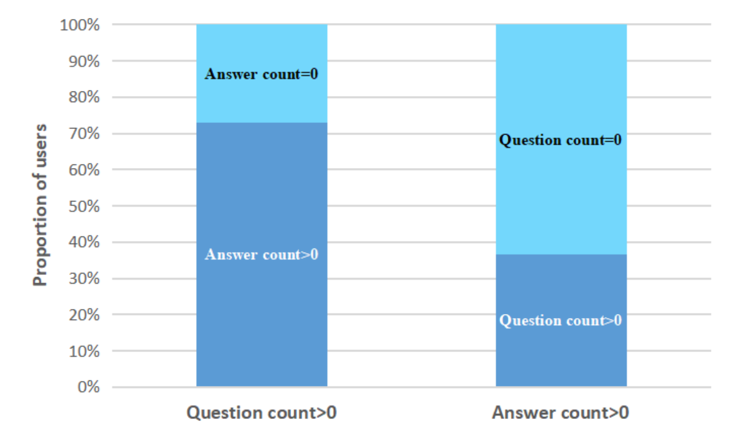

Figure 2. Cumulative frequency diagram representation of the users

The distribution of users presented above might be affected considerably by the assessment mechanisms applied in knowledge communities. For instance, these communities normally reward Answerers by facilitating their efforts to gain reputation in the community and thereby become opinion leaders. Studies have shown that most questions in an online SQA community are posted by low-reputation users, while high-reputation users constitute the main source of answers, especially answers tagged as “high-quality” (Movshovitz-Attias, Movshovitz-Attias, Steenkiste, & Faloutsos, 2013). Two factors decrease the number of pure Questioners: Some highly knowledgeable users tend to answer questions only, seeking to establish strong knowledge-based authority. At the same time, people seeking more or better answers to their questions require greater visibility on the site, which is achieved through a better reputation. This may motivate them to give answers.

For each of the four user classes, we calculated a sum for each attribute (the total count for that indicator across all users in that class), a mean for it (the average contribution of a user of that type to that indicator), and a ratio (the proportion of the relevant user group’s contribution to the community’s total count for said indicator). The results are shown in Table 4.

Table 4. Statistical description of features of each of the four user classes

	Questioners		**Answerers**		**Questioner-Answerers**		**Lurkers**	
	Sum (ratio)	Average	Sum (ratio)	Average	Sum (ratio)	Average	Sum (ratio)	Average
Items shared (“pins”)	19,964 (0.0572)	0.0596	99,630 (0.2855)	0.0893	171,837 (0.4924)	0.1901	57,549 (0.1649)	0.0297
Webcasts paid for	87,282 (0.0534)	0.2606	509,257 (0.3118)	0.4565	635,122 (0.3889)	0.7027	401,476 (0.2458)	0.2075
“Favorites” lists followed	590,768 (0.0487)	1.7641	4,152,986 (0.3426)	3.7224	4,580,879 (0.3779)	5.0681	2,796,315 (0.2307)	1.4451
Marked answers count	0 (0.0000)	0.0000	7,415 (0.3027)	0.0066	17,082 (0.6973)	0.0189	0 (0.0000)	0.0000
Webcasts hosted	23 (0.0077)	0.0001	947 (0.3163)	0.0008	1,748 (0.5838)	0.0019	276 (0.0922)	0.0001
Times thanked	1,648 (0.0000)	0.0049	37,317,836 (0.3246)	33.4489	77,640,188 (0.6753)	85.8972	11,268 (0.0001)	0.0058
“Favorites” collected	884,721 (0.0699)	2.6419	3,822,428 (0.3019)	3.4261	4,128,025 (0.3261)	4.5670	3,824,478 (0.3021)	1.9765
Times “favorited”	852,174 (0.0029)	2.5447	99,213,044 (0.3367)	88.9271	192,319,385 (0.6526)	212.7726	2,295,195 (0.0078)	1.1862
Columns followed	725,593 (0.0528)	2.1667	4,196,261 (0.3052)	3.7612	5,412,814 (0.3936)	5.9885	3,416,181 (0.2484)	1.7655
Users followed	8,101,786 (0.0525)	24.1928	48,170,446 (0.3119)	43.1764	59,861,815 (0.3876)	66.2281	38,321,090 (0.2481)	19.8042
Follower count	2,602,289 (0.0122)	7.7707	59,143,173 (0.2769)	53.0115	145,803,026 (0.6826)	161.3092	6,056,366 (0.0284)	3.1299
Upvote count	209,464 (0.0004)	0.6255	175,072,002 (0.3171)	156.9214	375,445,430 (0.6801)	415.3741	1,334,502 (0.0024)	0.6897
Questions followed	9,501,947 (0.0374)	28.3738	81,274,067 (0.3197)	72.8480	121,799,012 (0.4791)	134.7524	41,672,311 (0.1639)	21.5361
Product questions	2 (0.1111)	0.0000	2 (0.1111)	0.0000	11 (0.6111)	0.0000	3 (0.1667)	0.0000
Articles posted	37,395 (0.0419)	0.1117	278,632 (0.3119)	0.2497	398,663 (0.4463)	0.4411	178,642 (0.2000)	0.0923
Topics followed	6,729,245 (0.0673)	20.0943	28,354,821 (0.2837)	25.4151	30,444,773 (0.3046)	33.6826	34,412,548 (0.3443)	17.7843
Answers posted	0 (0.0000)	0.0000	8,271,570 (0.3091)	7.4140	18,487,722 (0.6909)	20.4539	0 (0.0000)	0.0000
Questions asked	536,011 (0.1528)	1.6006	0 (0.0000)	0.0000	2,970,838 (0.8472)	3.2868	0 (0.0000)	0.0000

Notes: The bold data in the table 5 represents the values we discussed in the following part.

Questioner-Answerers provided 84.72% of all questions, while Questioners posted 15.28% of them. The corresponding figures for answers are 69.09% from Questioner-Answerers and 30.91% from Answerers. This finding suggests that Questioner-Answerers contributed the most questions and answers in general. Furthermore, Questioners asked, on average, 1.6 questions, which is lower than the equivalent figure for Questioner-Answerers (3.29). On average, Answerers gave 7.4 answers, well below the Questioner-Answerers average (20.45).

Though Lurkers did not add to the question or answer pool, these users contributed a substantial proportion of the count for following of topics (34.43%), the total number of “Favorites” in the system (30.21%) and following of users (24.81%) and of questions (16.39%). Finally, contributions from Questioners are weak with regard to the various attributes, apart from number of questions (15.28%). Lurkers contribute more than Questioners in term of many behaviors.

4.2 Findings for immersion scores

We computed the weights for all 18 user-behavior attributes used to characterize the three dimensions of immersion, working from the full corpus of user data with the aim of synthesizing all the indicator values into a single metric: immersion score.

Based on the entropy-method formulae reproduced above, we employed Matlab to calculate the weight for each indicator for the three dimensions (see Figure 3). These results point to SQA users' degree of immersion being determined most by their content-contribution behavior, with users' influence too being an important contributor to immersion score, whereas a user’s activeness has a relatively small impact on immersion score. The weights for each indicator on each of the three dimensions in the immersion-assessment model are presented in Figure 3.

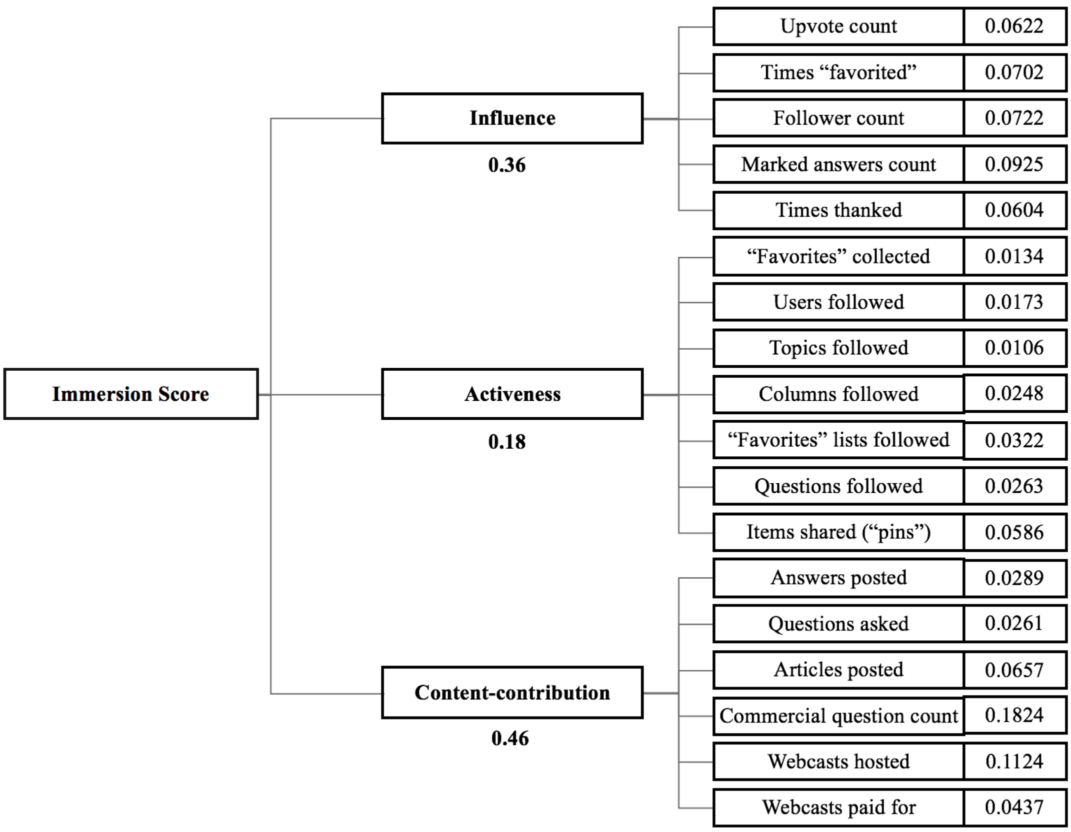

Figure 3. The breakdown of the Zhihu users’ immersion scores

For a deeper understanding of each user group’s unique way of contributing to Zhihu against the backdrop of immersion, we compared the four user groups in terms of the three dimensions.

4.2.1 Influence score

We generated dual-logarithmic-scale graphs (log－lot plots) to depict the four different user groups' contributions to Zhihu in terms of the three dimensions of immersion. The curves in Figure 4, below, show the influence scores by user groups, with the largest influence contribution at the top and the smallest at the bottom. The x-axis represents the user’s ranking from 1 to n, where 1 refers to the user with the highest influence score, and the corresponding y-coordinate represents the user’s influence score (see Figure 4).

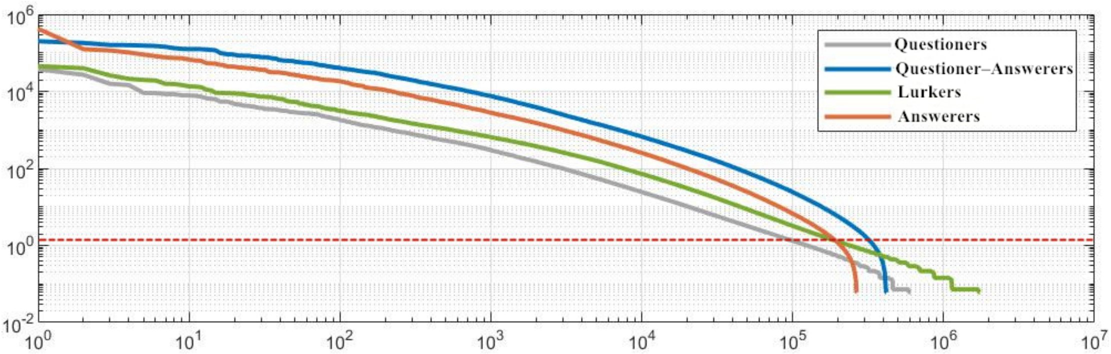

Figure 4. A plot of users’ influence scores

(Note that both the x- and the y-axis use logarithmic scale)

The graph shows that users' influence scores follow a power-law distribution. In other words, most users have a low score on the influence dimension, while there is a small set of users who have a very high influence score. When influence scores are above a certain threshold, represented in the graph by the ordinate value of the straight horizontal line, the four classes of users exhibit a consistent pattern in their scores: the classes cluster with a consistent ranking. In this paper, we will refer to this threshold as the “critical value.” The critical value specifically for user-influence score is 1 (100). Above this level, with the same rank within the respective groups, users in the Questioner–Answerers class always exhibit higher influence scores than Answerers, and then of Lurkers and Questioners. This clustering by user groups is no longer visible below the critical-value line – i.e., for those who made very small or limited contributions.

The most likely reason for the influence scores of Questioner–Answerers being above those of Answerers is that users who post both questions and answers gain more visibility than those other users via their questions. Influence scores for Lurkers are greater than the values for Questioners, with one possible reason being that Questioners users only ask questions; the main purpose behind their immersion in the community is to acquire knowledge, and there is little motivation to interact with other members. On the other hand, even though Lurkers users do not contribute any textual content, their interaction with other users via following others or expressing appreciation for others' knowledge contribution constitutes a greater de facto contribution than what users in the Questioners class provide.

4.2.2 Content-contribution score

Figure 5 presents a log–lot plot for the content-contribution scores of our four distinct user groups. A pattern similar to that described above can be observed, with the critical value found when the content-contribution score reaches a certain point between 0.1 (10^{-1}) and 1 (10^0). This threshold is lower than that for the influence score, reflecting the score levels being lower for users' content-contribution than for influence.

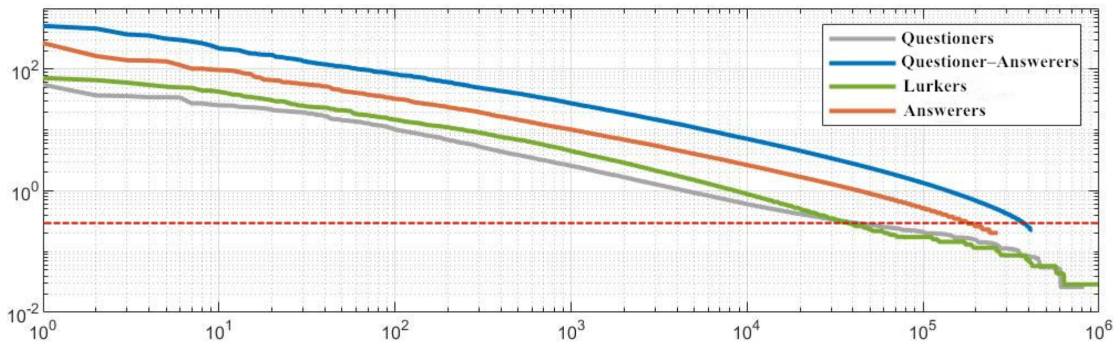

Figure 5. A logarithmic plot of user content-contribution scores
(Note that this is a log–log plot)

The pattern of the four user classes' ranking for content-contribution scores is on the same order as that seen with influence scores. Questioner–Answerers is the class with the highest scores for this dimension, followed by Answerers, Lurkers, and Questioners, in that order. Figure 8 attests to an astonishing result: we found that Lurkers made a greater content contribution than Questioners. The main reason is that Lurkers are very active in participating in paid live.

4.2.3 Activeness scores

Figure 6 depicts the user classes' distributions for the final dimension, activeness. The critical value for user activeness scores lies between 1 (10^0) and 10 (10^1). Above this threshold, a consistent pattern of ranking between classes can be observed. The critical value is higher for this score than for the influence and content-contribution components of the immersion score, because of activeness scores being higher overall than the scores for the other two dimensions.

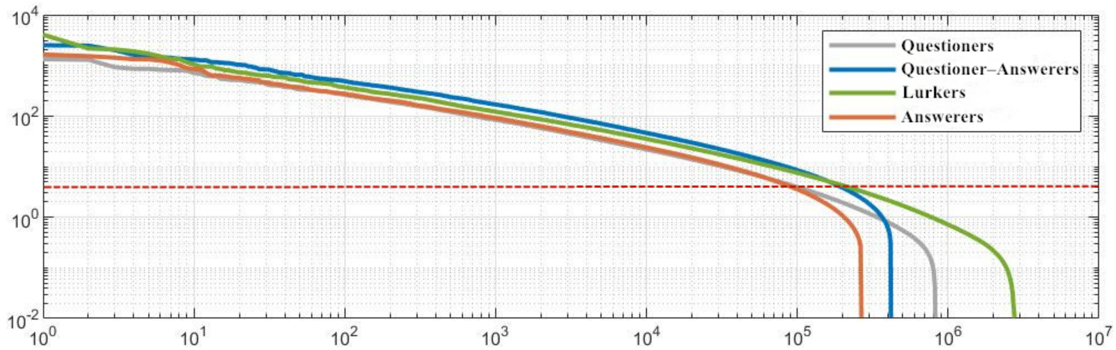

Figure 6. A logarithmic plot of activeness score
(Note that both the x-axis and the y-axis apply logarithmic scale)

When we consider those users with activeness scores exceeding the critical value, we find that the Questioner–Answerers had the highest scores, followed by Lurkers. Although Lurkers do not contribute any content by posting questions or answers, they play an important role in evaluating the content posted by other users via behaviors such as giving “Like” feedback. Accordingly, Lurkers are an important element of a thriving knowledge community. For instance, without their contribution, high-quality answers might not necessarily get spotted and thereby garner a large quantity of “Like”. In addition, often a “Like” by a single Lurker could motivate the user receiving it to contribute more knowledge to the community.

4.2.4 The overall immersion scores of the four user classes

Finally, users' overall immersion scores too follow a power-law distribution, as shown in Figure 7. Above the critical-value cutoff, Questioner–Answerers displayed the highest immersion scores, followed by Answerers, Lurkers, and Questioners, in that order. This pattern is in line with the ones found for influence and for content-contribution scores. The ranking of the user classes is as follows: we found Questioner–Answerers and Answerers to be highly immersed, Lurkers to show medium immersion, and Questioners to display low immersion scores. In other words, Mixed-Behavior Users and Answerers showed high levels of engagement in the SQA community, while Lurkers had a medium level of engagement and Questioners exhibited low engagement.

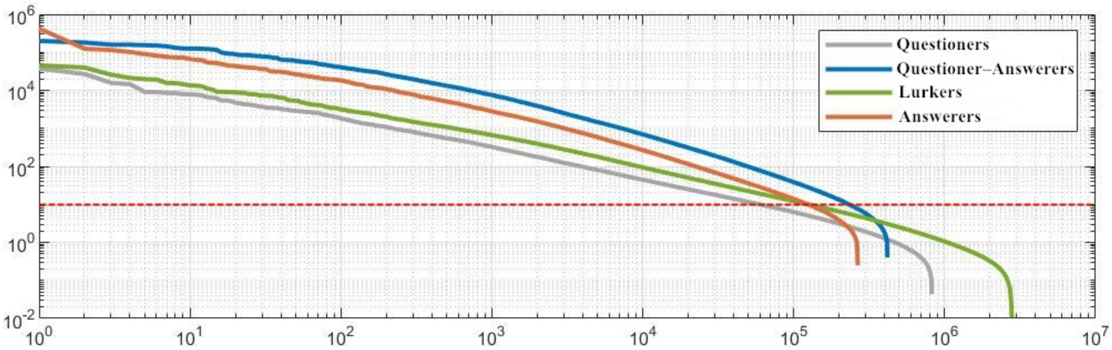

Figure 7. A log–log plot of the immersion scores
(Note that both axes are on logarithmic scale)

5. Discussion

In SQA, those highly active users raise questions, not just answer them. The active engagement of this group (Questioner–Answerers) in SQA contributes the majority of the content to SQA.

Past studies asserted that Lurkers are inactive users in knowledge communities (e.g. Kokkodis, Lappas, & Ransbotham, 2019). Surprisingly, our research results in this study show that the Lurkers were more engaged in SQA than Questioners, even though Lurkers generate no primary content in SQA. Indeed, reference can be found in the literature to such an idea, with Edelmann (2013) indicating that Lurkers contribute to a knowledge community via their typical forms of involvement, such as listening and reading. In the SQA environment, Lurkers not only read and attend to others' contributions, but they also vote, follow, and "Like" the content generated by others in community activities. While not creating primary content, they do interact with other users, mainly in a manner focused on feedback to UGC. Such observation contradicts some of prior studies, indicating that Lurkers participate in online communities only by reading content (e.g. Hurtubise et al., 2019).

Our results show that, with regard it their contributions to enhancing the interactions within a SQA community, Lurkers outperforms Questioners and Answerers. Specifically, the Lurkers make significant portion of contributions on the following of topics (34.43%), the total number of "Favorites" in the system (30.21%), and the following of users (24.81%) and of questions (16.39%). These attention behaviors in SQA communities will motivate content contributors, such as Questioners and/or Answerers, to continuously contribute knowledge on SQA platform (Jin, Li, Zhong, & Zhai, 2015). Their continuous content generation will in turn provide more useful materials and interaction opportunities for the Lurkers, thus forming an effective cycle of the information ecosystem in the SQA platform. Thus, our study suggests that Lurkers are more active than others in SQA from a view of community interactions. In other words, they play an important role in the community by engaging in SQA in a manner different from generating content.

In this study, Questioners were found to be the least immersed in Zhihu. Primarily, pure Questioners want to acquire knowledge helping them solve specific problems, without being motivated to provide knowledge to others. The resulting limited engagement with Zhihu led to the Questioners' contribution to Zhihu being less than that of other members, such as Answerers, Lurkers, and Questioner-Answerers. The findings on the less contribution of the Questioners to SQA communities is inconsistent with the findings of Hurtubise et al. (2018) that the Questioners contributes more contribution to knowledge community. Though the Questioners have the least contribution to the SQA communities compared to the other three user groups, their important role in the SQA communities cannot be ignored as quality questions are very important to the sustainability of the SQA community, such as the Answerers' contribution will be limited Questioners' questions from the Questioners (Zhang, Zhang, Luo, Wang, & Niu, 2019). Studies have also shown that the more a user contributes to an SQA community, the higher the cost of switching to another community (Zhang & Jiang, 2018). In other words, Questioners might be even more possible to switch to other communities due to their limited and least contribution to an SQA community.

In addition, our analysis reveals a threshold effect. For the three different dimensions of immersion, the four categories of users scored at different minimum thresholds (dotted red line). For scores above this threshold, users with different question-and-answer features showed absolute consistency, while for scores below this threshold, immersion levels of different categories of users showed an irregular trend. The value within the threshold is the most stable performance of users in this dimension. Therefore, these thresholds can help us compare user performance levels in different dimensions, and the higher the lowest threshold, the higher the overall performance level. In the study of this paper, the ranking of the lowest threshold from large to small dimension is: activeness > influence > content contribution level, and then the ranking of performance level from large to small dimension is: activeness > influence > content contribution level.

6. Implications and limitations

Considering a large data set through the powerful lens of immersion scores, we investigated how distinct user groups contribute to an online knowledge community. This work makes several contributions that are of value for both academic discourse and practitioners.

Our study contributes to a number of new theoretical insights. First, this study contributes to the literature by examining the contribution of all the users of SQA communities via evaluating their immersion score from three dimensions (influence, content-contribution, and activeness) based on their behaviors in SQA communities, including Lurkers, Questioners, Answerers, and Questioner-Answerers. This study extends our current understandings of user contribution in SQA communities via providing detailed explanations on how different users in SQA communities contribute to SQA communities from their influence, content-contribution, and activeness in SQA communities.

Secondly, we have a comprehensive understanding of the contributions of various users in the knowledge community from the perspective of role complementarity. Past studies placed emphasis almost exclusively on people who answer others' questions while largely ignoring the contributions of users with other characteristics, such as Lurkers and people who pose but do not answer questions. Our research enriches the body of work on knowledge contribution based on user interaction behaviors in knowledge communities, rounding it out by considering all different user groups. This full picture of the spectrum of contributions to knowledge communities helps to show how they complement each other – knowledge communities are akin to an ecosystem.

Thirdly, this study introduced the concept of immersion scores, familiar from the game community, in the context of SQA communities and described users' engagement in knowledge communities from the perspective of immersion for the first time. To explain contributions to those communities, this research offered an immersion-assessment model derived from the characteristic features of SQA communities. This work provides evidence that immersion scores indeed can be used to assess users' engagement in knowledge communities if taking considerations of the features of SQA communities in developing immersion dimensions. Thus, immersion score can help explain the difference in contributing to SQA communities among the different user groups based on their particular activities therein (which indicate engagement), such as for posters and Lurkers.

Finally, we quantified immersion scores based on a large number of user behavior data, which provided an effective reference for the theory of immersion quantization. Our immersion-score-based approach to examining user contributions to knowledge communities entailed empirically testing the proposed research model with a large set of data collected on SQA users in China. This approach is groundbreaking since research on immersion has heretofore relied mainly on questionnaires or experiments with relatively small sample sizes. The data-rooted approach taken and the objective metrics created provide evidence that real-world behaviors of knowledge-community users can be utilized as a good data source for immersion-score assessment aimed at understanding the contribution to those communities from a user-engagement perspective.

In light of our findings, we can offer some practical suggestions to assist practitioners and operators of knowledge communities, especially SQA, in understanding individual users' engagement in and contribution to online communities. Firstly, the distinct user groups we identified (Lurkers, Questioners, Answerers, and Questioner-Answerers) were found to contribute each in their own way to the Zhihu community. This finding on different forms of engagement implies that if an SQA or other knowledge community is to thrive, the various user groups should be taken into consideration. Efforts can be made to understand their respective contributions, and customized strategies can be developed to enhance their contributions. These might include means of motivating pure Questioners to answer questions too and of encouraging pure Answerers to raise questions themselves. After all, those who both ask and answer questions contribute the most to knowledge communities and thereby become the most immersed.

Secondly, platform operators can manage users and function modules of the platform by monitoring users' scores in various dimensions. From the perspective of user management, the platform can conduct personalized management of users according to their scores in different dimensions. For example, users with high scores for content contribution can be invited to ask questions or answer questions. For users with high activeness scores, the platform can recommend Knowledge Payment Products for their consumption. From the perspective of functional module management, modules with generally low scores need to be improved in module design to improve the user' s utilization rate. Also, an immersion threshold was developed to evaluate the user' s immersion level. These thresholds were determined through the interface of images, which provided a new and effective method for the comparison between dimensions.

Thirdly, platform operators should consider knowledge communities, especially SQA communities, as an ecosystem as different users (such as Lurkers, Questioners, Answerers, and Questioner-Answerers) play specific, often complementary roles and support each other in knowledge communities. The research findings in this study also show that Lurkers make contribution to activeness in SQA communities, outperforming Questioners. Thus, platform operators should also pay attention to the user contribution of both the Lurkers and the content generators (such as Questioners, Answerers, and Questioner-Answerer).

The foregoing notwithstanding, there are several limitations to applicability that should be acknowledged. Firstly, the user-behavior data were collected from an SQA environment based in China, so caution should be applied in generalizing the findings to other cultural backgrounds. Future research should replicate this study for understanding user contribution to knowledge communities situated in cutting across cultural environments (e.g., by considering Quora) and exploring cross-platform user behavior too, if possible. In addition, the proposed immersion-assessment model was tested in the context of knowledge communities, specifically SQA. Further research can be conducted in contexts with similarities to SQA environments, such as social media services (Facebook, Twitter, etc.), exploiting user-immersion scores to understand user contributions in those environments via a model analogous to that proposed here. Finally, we focused on instantaneous user behavior and were not able to take into account developments in interaction over time when assessing immersion. Knowledge-community users' behavior patterns might change – for instance, evolving as their membership of the community continues. Therefore, future research should consider the evaluation factors when investigating user contributions to knowledge communities from the immersion perspective.

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