Postprint of a Study on the Contribution of User Interaction Features to Knowledge Payment Behavior Prediction

Authors: Deng Shengli, Jiang Yuting

Date: 2023-04-01T00:00:00+00:00

Abstract

[Purpose/Significance] To enrich theoretical research on social interaction behavior and knowledge payment behavior, effectively identify potential knowledge-paying users, and thereby enhance the monetization capabilities of online knowledge communities, this study investigates the contribution and evolving trends of different types and degrees of interaction behavior in predicting knowledge-paying users, building upon previous research findings. [Method/Process] Drawing upon 4 million user social interaction behavior data crawled from the Zhihu community (www.zhihu.com), this study classifies user social interaction behaviors in this community based on different interaction subjects and directions. Subsequently, the random forest algorithm is employed to examine the contribution degree of different types and degrees of interaction behavior to knowledge-paying user prediction, with results analyzed and compared. [Results/Conclusion] The findings reveal that user-to-user interactions exert a greater influence than user-to-platform interactions. Specifically, users' proactive interaction behaviors toward other users have a more significant impact than interaction behaviors received from other users. Moreover, within a certain threshold, the greater the degree of social interaction, the larger its contribution to knowledge payment behavior prediction. Different interaction types exhibit different thresholds; however, beyond this threshold, the relationship ceases to be a simple monotonically increasing one and may plateau or even decline significantly.

Full Text

Research on the Contribution of User Interaction Characteristics to the Prediction of Knowledge Payment Behavior

Deng Shengli, Jiang Yuting Research Center for Information Resources, Wuhan University, Wuhan 429000

Abstract

[**Purpose/Significance**] To enrich theoretical research on social interaction behavior and knowledge payment behavior, effectively identify potential knowledge-paying users, and improve the monetization capabilities of online knowledge communities, this study examines the contribution of different types and degrees of interactive behavior to the prediction of knowledge-paying users and their changing trends, building upon previous research findings.

[**Method/Process**] Based on 4 million user social interaction behavior records crawled from the Zhihu community (www.zhihu.com), user social interaction behaviors were classified according to interaction subjects and directions. The random forest algorithm was then employed to investigate the contribution of different types and degrees of interactive behavior to predicting knowledge-paying users, with results analyzed and compared.

[**Result/Conclusion**] The findings reveal that interactions between users have a greater impact than interactions between users and the platform. Specifically, active interactions initiated by users toward other users exert stronger influence than passive interactions received from other users. Moreover, within a certain threshold, greater degrees of social interaction correspond to larger contributions to knowledge payment behavior prediction. Different interaction types have different thresholds; however, beyond these thresholds, the relationship is no longer a simple monotonic increase and may plateau or even decline significantly.

Keywords: social interaction behavior; knowledge payment; user identification; random forest; contribution degree

---

1. Introduction

As user demand for high-quality content continues to grow, knowledge payment products have gained widespread attention for their ability to reduce information screening costs and provide real-time premium content. Knowledge payment refers to the economic phenomenon where the public uses internet platforms to share their cognitive surplus (including wisdom, knowledge, abilities, and experiences) with others to generate income [?]. Currently, numerous knowledge payment products have emerged, such as Zhihu's "Live," Luogic's "Dedao," and "Fenda." These real-time voice-based Q&A interactions are built on a “sharing” model, and this free-value philosophy has influenced users’ willingness to pay for knowledge. Meanwhile, the knowledge payment model faces challenges including low knowledge quality and inadequate copyright protection [?], with user adoption rates remaining at relatively low levels [?].

Therefore, investigating the behavioral characteristics of potential knowledge-paying users plays a crucial role in identifying prospective paying customers. Existing research on knowledge payment behavior primarily focuses on influencing factors [?], with predictive studies on potential paying users still lacking. The few existing prediction studies only consider live-streaming-related features—such as price and knowledge sharer reputation—as predictors of knowledge payment behavior, without examining the contribution of specific interaction behavior types and degrees to predicting potential knowledge-paying users. Yet user-to-user interaction behavior is critically important for online social websites [?].

This study aims to explore how different types and degrees of user interaction behavior in online knowledge communities contribute to knowledge payment behavior prediction, thereby providing a solid foundation for identifying potential paying users. We seek to address two questions: (1) Which types of user interaction behaviors are most effective for predicting knowledge-paying users? (2) How does the degree of user interaction affect its contribution to predicting knowledge-paying users? The findings will enrich theoretical research on user interaction behavior and provide robust evidence for the relationship between user interaction behavior and knowledge payment behavior.

---

2. Literature Review

2.1 Social Network User Interaction Behavior People use social media to share their views, feelings, and ideas on various topics and promote their activities on platforms like Facebook and Twitter. Consequently, social media platforms provide vast amounts of data related to human behavior, including social interactions [?]. Online social interaction, also known as network interaction, refers to user behaviors conducted through information exchange on network platforms [?]. Online socializing has become an integral part of personal life, playing a key role in supporting communication between media, people, and society in the internet era [?]. Social networking sites offer diverse social interaction functions such as posting articles, commenting, reposting, favoriting, liking, following, and sharing [?].

On Zhihu, for example, people establish connections with friends, relatives, colleagues, and even strangers, generating multiple types of social interaction behaviors. Users can “follow” others’ statuses, “favorite” preferred content and columns, and comment on, like, or share others’ content. Interactions between friends, participation in online activities, product recommendations, and reviews are all freely and voluntarily written, sent, and read among community members. The interaction subjects and directions of these social interactions are not always consistent. Based on the definition of social interaction as "information exchange between participating subjects through a set of information channels (interfaces)" [?], we illustrate the relationships among social interaction types in online communities in Figure 1 [Figure 1: see original paper].

2.2 Factors Influencing User Knowledge Payment Behavior Current research primarily focuses on influencing factors of user knowledge payment behavior, including user-driven factors and online community-driven factors. User-driven factors include the importance and urgency of information needs, trust in paid knowledge, identification with knowledge providers, and familiarity with and trust in the platform. Community-driven factors include knowledge quality, price, visitor volume, and platform usability. Table 1 summarizes these influencing factors.

Most studies examine payment behavior based on live-streaming-related features such as price, content quality, and knowledge sharer characteristics, while neglecting the impact of user interaction behaviors on the platform on payment intention. Additionally, these studies rely on limited data samples. In contrast, this study investigates which social interaction behaviors serve as strong signals for potential knowledge-paying users on the Zhihu live-streaming platform using a larger, more persuasive dataset.

2.3 Knowledge Payment Behavior Prediction Based on User Interaction Data Research on predicting knowledge-paying users demonstrates that user interaction behaviors and data on social media are important bases for identifying potential knowledge-paying customers. Studies have explored the mechanisms underlying this relationship, finding that online social interaction facilitates interpersonal relationship development through trust-building, friendship formation, and promoting interaction [?]. Stronger user intimacy with online communities implies greater community influence on purchase intention [?]. Research on continuous usage intention of web-based services shows that intimacy and familiarity affect users' continuance intention [?]. In social network contexts, cognitive and emotional engagement—namely social interaction—has been proven to increase purchase intention for transactions recommended by friends [?]. Purchase intention is directly driven by social interaction between users and social network communities; the more users interact with others in these communities, the stronger their intimacy and familiarity, making their purchase intention more likely to be influenced by the community [?].

Other scholars have provided strong evidence for knowledge payment behavior prediction based on user interaction data. H.L. Wu and J.W. Wang [?] found that social interactions supported by social networking sites allow users to cultivate, enhance, and maintain online relationships, serving as important predictors of behavioral intention. Y. Zhang et al. [?] demonstrated through a joint big dataset of Facebook and eBay users that purchase behavior can be successfully predicted using only social media information, where user-expressed interests (e.g., Facebook "likes") are important factors for predicting purchase behavior. These studies show that using user social interaction behavior to identify potential paying users is scientifically feasible. However, the contribution of different types and degrees of social interaction to payment behavior prediction has not been deeply investigated. Therefore, this study examines which interaction features and degrees serve as the strongest signals for identifying potential knowledge-paying users.

---

3. Research Methods

3.1 Data Collection Previous research measured variables through small-sample self-reported data collected via questionnaires. This study uses large-scale cumulative interaction data collected from websites as the basis for quantifying user social interaction behavior, obtained through Python web scraping. We recursively crawled nearly all user information existing in Zhihu's social relationship network using users' social relationship attributes. Starting from an opinion leader, we crawled their following and follower lists, then recursively extracted all behavioral information of users from these lists. Users outside this relationship network, having no intersection with any network in the Zhihu social platform, with low participation and minimal information, were excluded from the research scope.

By July 10, 2017, we had crawled 4,376,500 users' behavioral data from Zhihu's Q&A platform. Due to high time costs of data crawling, we assumed minimal data volume changes during the process. After data cleaning procedures including encoding, sorting, replacing missing values, and removing duplicates, we obtained 4,290,000 clean data records. We removed useless fields such as user ID and avatar links. Additionally, since all users had variable values of 0 for business questions (lacking statistical significance), we deleted the business question variable. Finally, we obtained 17 usable behavioral fields, including 16 types of online social interaction data and the number of paid live-streams users participated in.

3.2 User Interaction Features and Classification Based on different interaction subjects and consistent interaction directions (see Figure 1), we described interaction categories. Interaction behavior classification depends on the initiator and direct recipient of the behavior. When the initiator is a single user (the target user), the interaction type belongs to user → other users or user → platform. If the direct recipient is another single user (other than the target user), the interaction type is user → other users; if the recipient is all platform users or the platform itself, it belongs to user → platform. Similarly, if the initiator is the platform and the recipient is a single user, the type is user → platform; if the initiator is another user and the recipient is the target user, the type is other users → user, which is closely related to platform functional mechanisms. Variable names and meanings are shown in Table 2 .

Among the 17 feature variables, 9 belong to active interactions from users to other users, 5 belong to active interactions from users to the platform, 2 are interactions from other users, and 1 is from the platform. We also classified the target variable (number of paid live-streams participated in) as shown in Table 3 .

3.3 Calculation of Feature Importance (Contribution) High-dimensional datasets with numerous features can reduce algorithm performance and accuracy, making it necessary to select the most important feature subsets based on specific criteria. We chose random forest to calculate feature importance. Random forest is an ensemble learning algorithm that combines multiple weak classifiers to form a high-performance strong classifier, capable of obtaining feature contribution values [**?**].

3.3.1 Principle of Random Forest for Feature Importance Calculation

Random forest uses bootstrap sampling with replacement to select n samples from the dataset to form training sets for generating decision trees. For each node generated, m non-repeating features are randomly selected to partition the new sample set, with the optimal partition determined through Gini coefficient or gain ratio. Assuming the random forest has k decision trees, this process repeats k times. Finally, the random forest predicts the test set through voting. This study uses the Gini index to calculate each feature's (cumulative social interaction behavior) contribution to the target variable (participation in paid live-streams).

3.3.2 Steps for Random Forest Feature Importance Calculation

We evaluated importance through the Gini index. The Gini index for node m is calculated as:

$$GI_m = 1 - \sum_{k=1}^{|K|} p_{mk}^2$$

where k represents the number of categories and p_{mk} represents the proportion of category k in node m. The importance of feature X_j at node m is represented by the change in Gini index before and after branching:

$$VIM_{gini}^{jm} = GI_m - GI_l - GI_r$$

where GI_l and GI_r represent the Gini indices of the two new nodes after branching. If feature X_j appears at nodes in set M in decision tree i, its importance in tree i is:

$$VIM_{gini}^{ij} = \sum_{m \in M} VIM_{gini}^{jm}$$

Assuming the random forest has k trees:

$$VIM_{gini}^{j} = \sum_{i=1}^{k} VIM_{gini}^{ij}$$

Finally, all VIM values are normalized to obtain the final importance scores:

$$VIM_j = \frac{VIM_{gini}^{j}}{\sum_{j=1}^{m} VIM_{gini}^{j}}$$

The importance score is denoted as VIM (variable importance scores), with Gini values represented by GI. Assuming there are m features $X_1, X_2, \ldots, X_m$, the Gini index calculation formula is shown above [**?**].

---

4. Contribution of Interaction Features to Knowledge Payment Behavior Prediction

In our dataset, paying users accounted for 9.4% (404,900/4,290,000). We conducted statistical descriptions of this data, as shown in Table 4 .

4.1 Contribution of User Interaction Types to Knowledge Payment Behavior Prediction The entire experimental process was implemented through Python programming, including data cleaning, chunked data reading and integration, random forest training, prediction, and visualization of contribution values and trends. For random forest training, we used Python's built-in RandomForestRegressor interface to simplify programming.

4.1.1 Contribution Under Overall Prediction Values

First, we calculated the contribution of user interaction types to knowledge payment behavior prediction across all users. We trained a random forest with 10,000 decision trees to evaluate the importance of 17 dimensional features. By observing how each predictor affected model performance, we directly measured feature importance, ranked the features, and visualized them using a horizontal bar chart, as shown in Figure 2 [Figure 2: see original paper].

Figure 2 shows that for predicting whether users purchase knowledge payment products, the three most important features are: number of followed columns, number of favorites, and number of followed users. Based on interaction subjects and information transmission direction, these three features all belong to active user $\rightarrow$ other user interaction types.

4.1.2 Contribution Under Specific Prediction Values

However, the above contribution calculations do not reflect how features affect specific predictions. Therefore, we plotted contribution values for specific prediction values. Figure 3 [Figure 3: see original paper] shows contributions of various social interaction behaviors when the prediction value is 1 (paying user), while Figure 4 [Figure 4: see original paper] shows contributions when the prediction value is 0 (non-paying user).

For predicting paying users, the three most important features are number of followed columns, number of favorites, and number of followers, all contributing positively. In contrast, number of followed users and number of times being favorited contribute negatively.

For predicting non-paying users, number of followed columns and favorites remain the two most important features, but number of followed users becomes the third most important feature—different from predicting paying users. Additionally, the two most important features (number of followed users and times being favorited) contribute negatively, while number of followed users contributes positively.

4.2 Contribution of User Interaction Degree to Knowledge Payment Behavior Prediction The above descriptions do not provide a comprehensive explanation of how specific interaction behaviors affect user knowledge payment behavior. Therefore, we plotted the top three most important features and their contribution values for both paying users (followed columns, favorites, followers) and non-paying users (followed columns, favorites, followed users) to explore the relationship between social interaction degree and knowledge payment behavior.

Since random forest is inherently stochastic, contributions for a given number of followed columns exhibit variability. However, the smoothed black trend line still shows an increasing trend. As shown in Figure 5 [Figure 5: see original paper], increased numbers of followed columns correspond to higher contributions, which plateau around a contribution value of 0.4.

We plotted contribution values for number of favorites (Figure 6 [Figure 6: see original paper]). This variable's contribution is nonlinear and non-monotonic: low numbers of favorites have negative contributions, while high numbers have positive contributions. In fact, most users' favorite counts correspond to positive contribution values, peaking at approximately 0.28 when the number of favorites reaches 15-50.

The interaction variable of number of followed users exhibits complex, non-monotonic characteristics. Its contribution peaks at approximately 0.15 when the number of followed users reaches about 200, then declines. Additionally, the number of followed users appears to have a generally negative correlation with the target variable.

The follower count interaction feature reaches mean values for both positive and negative contributions. Maximum contributions occur when follower count is within 10,000, with approximately 0.28 positive contribution and -0.18 negative contribution.

This study explored how interaction behavior types and degrees contribute to predicting potential knowledge-paying users and their changing trends. First, regarding interaction types, we found that the cumulative values of four behaviors—followed columns, favorites, followed users, and followers—are the strongest signals for identifying potential knowledge-paying users. On Zhihu, following columns, favoriting, and following other users are proactive, interest-driven behaviors based on users' hobbies, self-improvement needs, and professional knowledge acquisition, as well as emotional factors and social needs for following active users in specific fields [?]. These spontaneously generated, demand-driven behaviors are powerful indicators of individual needs, which represent one of the most important drivers for users to pay for products [?]. Previous qualitative research based on interview data identified individual needs as the most important characteristic of knowledge payment behavior [?]. Our study, from a quantitative perspective, reaches the same conclusion through big data mining and machine learning algorithms.

Furthermore, from an intimacy perspective, we explain the impact of follower count on knowledge payment behavior. Follower count is an important indicator of user reputation, and higher follower counts significantly enhance users' sense of community belonging and intimacy, which substantially influences payment behavior—consistent with previous research [?] showing that intimacy and familiarity affect users' continuous purchase intention. Additionally, prior studies indicate that stronger user intimacy and familiarity with others make purchase intention more likely to be influenced by the community [?].

Second, our findings on social interaction degree reveal that the relationship between interaction degree and knowledge payment behavior is not always a simple monotonic increase. Previous research suggested that deeper interaction leads to stronger payment intention [?], but we found this is not universally true on Zhihu. Within a certain range, increased interaction degree significantly improves the likelihood of knowledge payment. However, for users with very deep interaction levels, this enhancement effect is weak, as such users are often opinion leaders who primarily play knowledge-sharing roles rather than purchasing knowledge from live-streams. Therefore, they are not the optimal target group for commercial monetization. For the follower count feature, starting from zero, importance increases negatively to reach maximum negative contribution, after which contribution approaches zero. As a personal reputation indicator, follower count has limited promotional effect on knowledge payment behavior, and within a certain range, higher follower counts actually decrease payment likelihood.

6. Conclusion and Future Work

Based on the random forest algorithm, this study examined how social interaction behavior types and degrees contribute to predicting potential knowledge-paying users. First, regarding interaction types, features have different importance when predicting paying versus non-paying users. For predicting paying users, followed columns, favorites, and followers contribute most, while for non-paying users, followed columns, favorites, and followed users are most influential. Thus, these four interaction features contribute most to knowledge payment behavior prediction. As Table 2 shows, following columns, favoriting, and following other users belong to the user → other user type, while followers belong to the other users → user type. These four behaviors all represent user-other user interactions, indicating that user-to-user interactions contribute far more to prediction than user-platform interactions. Among these four behaviors, only one represents passive interaction from other users, suggesting that active user behaviors contribute more to predicting potential knowledge-paying users than passive behaviors. Among all interactions, individually demand-driven behaviors play the most important role in identifying paying users.

This study provides new theoretical insights. First, it quantitatively confirms previous qualitative findings that individual needs—including interests, self-improvement, emotional needs, and social needs—are the most important drivers for purchasing knowledge payment products. Second, it refines interaction objects and paths based on interaction behavior definitions, offering new research perspectives for studying user interaction behavior on social websites.

The results also provide practical significance for online knowledge platforms to identify potential knowledge-paying users. The findings suggest that on Zhihu, behaviors related to following columns, favoriting, and following users should be primary predictive indicators. These active interaction behaviors, as the most important identification features, can effectively reduce platform time for feature screening. Additionally, using the random forest algorithm to quantitatively analyze the importance of different interaction feature types has proven adaptable to massive user datasets.

Regarding interaction degree, we found that the relationship between interaction degree and behavior is not always monotonic. Increased interaction degree within a certain range significantly impacts payment behavior, with different interaction types having different thresholds. Beyond specific ranges, this impact plateaus or even declines. Theoretically, this provides necessary constraints for previous research conclusions. Practically, monitoring users' cumulative interaction degree offers an effective way for platforms to identify potential knowledge-paying users. According to our results, when an interaction feature's degree falls within a specific interval, payment likelihood is maximized, enabling targeted live-stream product placement.

Compared with existing research, this study's innovations include: (1) Theoretically identifying potential knowledge-paying users from a user interaction behavior perspective and explaining the theoretical basis; (2) Using large-scale real user interaction data (4 million records) for more scientific and credible results; (3) Considering almost all interaction behaviors on Zhihu, removing only statistically meaningless fields for more comprehensive findings; (4) Employing the scientific random forest algorithm for feature importance calculation on large-scale data, with effective Python-based visualization for improved readability.

Limitations include examining only one online community, making feature variables not universally adaptable. Future research should explore online knowledge communities with different cultural backgrounds and operational models [**?**] to obtain comparable behavioral characteristics.

References

[1] China Internet Association Sharing Economy Working Committee, National Information Center Sharing Economy Research Center. China Sharing Economy Development Report 2017 [EB/OL]. [2019-08-26]. http://www.sic.gov.cn/archiver/SIC/UpFile/Files/HtmlEditor/201703/20170302125144221.pdf.

[2] LI G. Exploring users' motivation to contribute in online platforms [EB/OL]. [2019-08-26]. http://laitinej.mbnet.fi/jouni/Artikkelit/DC_paper_4.pdf.

[3] NG C S P. Intention to purchase on social commerce websites across cultures: A cross-regional study [J]. Information & management, 2013, 50(8): 609-620.

[4] ZHOU T, TAN Q. Research on knowledge-paying user behavior mechanism based on social capital theory [J]. Modern Intelligence, 2017(11): 48-52.

[5] LI W. Online knowledge payment platforms: Where to go? [J]. Library and Information Service, 2018, 183(3): 2.

[6] ZHAO Y, LIU Z, SONG S. Why should I pay for the knowledge in social Q&A platforms? [C]//International conference on information. The United Kingdom: Springer, Cham, 2018: 577-582.

[7] DENG S, TONG J, LIN Y, et al. Motivating scholars' responses in academic social networking sites: an empirical study on ResearchGate Q&A behavior [J]. Information processing & management, 2019, 56(6): 102082.

[8] SCHOEN H, GAYO-AVELLO D, TAKIS METAXAS P, et al. The power of prediction with social media [J]. Internet research, 2013, 23(5): 528-543.

[9] CHEN C C, LIN Y C. What drives live-stream usage intention? the perspectives of flow, entertainment, social interaction, and endorsement [J]. Telematics and informatics, 2018, 35(1): 293-303.

[10] BLAZEVIC V, WIERTZ C, COTTE J, et al. GOSIP in cyberspace: conceptualization and scale development for general online social interaction propensity

[J]. Journal of interactive marketing, 2014, 28(2): 87-100.

[11] ALLEBS M, CHORLEY M J, COLOMBO G B, et al. Exploiting user interest similarity and social links for micro-blog forwarding in mobile opportunistic networks [J]. Pervasive and mobile computing, 2014, 11: 106-131.

[12] LU X, YU Z, GUO B, et al. Predicting the content dissemination trends by repost behavior modeling in mobile social networks [J]. Journal of network and computer applications, 2014, 42: 197-203.

[13] STORRS G. A conceptualisation of multiparty interaction [J]. Interacting with computers, 1994, 6(2): 173-189.

[14] LIU X, FENG J. Research on the influencing factors of the willingness to pay for knowledge consumers in the knowledge payment platform [EB/OL]. [2019-08-27]. https://aisel.aisnet.org/cgi/viewcontent.cgi?article=1016&context=&seiredir=1.

[15] CAI S, LUO Q F, FU X, et al. Paying for Knowledge: Why people paying for live broadcasts in online knowledge sharing community? [EB/OL]. [2019-08-27]. https://aisel.aisnet.org/pacis2018/286.

[16] CAI S, LUO Q, FU X, et al. Paying for live broadcast: predicting internet knowledge product sharing [EB/OL]. [2019-08-27]. https://pdfs.semanticscholar.org/ab6b/210302138823e79b39

[17] ZHANG S, WANG W, LI J. Research on influencing factors of users' online knowledge payment behavior [J]. Library and Information Service, 2017, 61(10): 94-100.

[18] LI G, LU Y, TENG S. Research on users' online knowledge payment behavior—Based on the theory of planned behavior [J]. Library Science Research, 2018, 429(10): 39-50.

[19] BOCK G W, ZMUD R W, KIM Y G, et al. Behavioral intention formation in knowledge sharing: examining the roles of extrinsic motivators, social-psychological factors, and organizational climate [J]. MIS quarterly, 2005, 29(1): 87-111.

[20] LEE Y, KWON O. Intimacy, familiarity and continuance intention: an extended expectation-confirmation model in web-based services [J]. Electronic commerce research and applications, 2011, 10(3): 342-57.

[21] SHIN J K, PARK M, JU Y. The effect of the online social network structure characteristics on network involvement and consumer purchasing intention: focus on Korean social promotion sites [C]//The 11th International DSI and the 16th APDSI Joint Meeting, Taipei: Asia Pacific Decision Sciences Institute, 2011.

[22] WU H L, WANG J W. An empirical study of flow experiences in social media [C]//Proceedings of the 22nd international conference on World Wide Web. Brazil: ACM, 2013: 1521-1532.

[23] ZHANG Y, Pennacchiotti M. Predicting purchase behaviors from social networks [EB/OL]. [2019-08-27]. https://aisel.aisnet.org/pacis2011/215.

[24] XU S, LI D. Weighted feature selection algorithm based on random forest [J]. Statistics and Decision, 2018(18): 25-8.

[25] YAO D, YANG J, ZHAN X. Feature selection algorithm based on random forest [J]. Journal of Jilin University (Engineering Edition), 2014, 44(1): 137-141.

[26] ZHOU T, TAN Q, BAYAN T, et al. Research on the mechanism of social interaction's effect on users' knowledge payment intention [J]. Library and Information Service, 2019(4): 94-100.

[27] WANG J J. A research on the development trend of knowledge payment based on Zhihu [M]//LI Zhiqing. The new silk road-Leads through the Arab peninsula: mastering global business and innovation. Bingley: Emerald Publishing Limited, 2019: 229-237.

[28] LI W, AI P, XU Y. Research on user payment models and payment intention in online paid Q&A platforms [J]. Library and Information Service, 2018, 62(13): 24-29.

[29] WU N. Viewing knowledge payment from Zhihu Live [J]. Research on Transmission Competence, 2019, 3(4): 11.

Author Contributions

Deng Shengli: Determined the research topic, proposed the overall research framework, and revised the manuscript.

Jiang Yuting: Responsible for research design, data collection and processing, and manuscript writing and revision.

Note: Figure translations are in progress. See original paper for figures.