Analysis of Influencing Factors on Questioners' Switching Behavior in Paid Knowledge Q&A Platforms: Postprint

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Abstract

[Purpose/Significance] Free knowledge Q&A platforms and paid knowledge Q&A platforms constitute two major channels for problem-solving. This study explores the influencing factors underlying askers' transition from free to paid knowledge Q&A platforms, aiming to enhance user experience and promote the healthy development of paid knowledge Q&A platforms. [Method/Process] First, this paper reviews relevant research on influencing factors of knowledge payment; subsequently, based on the Critical Incident Technique and combined with the Push-Pull-Mooring model, it systematically identifies the influencing factors of askers' transition from free to paid knowledge Q&A platforms; then, the author employs the entropy weight method to compare the weights of each influencing factor in two scenarios: before and after the transition. [Results/Conclusion] The influencing factors of askers' transition behavior encompass five major categories: factors related to free knowledge Q&A platforms, factors related to paid knowledge Q&A platforms, social factors, personal factors, and objective factors, with certain differences observed among these factors before and after the transition. Finally, the author proposes countermeasures and suggestions regarding the publicity mechanism, pricing mechanism, review mechanism, and evaluation mechanism of paid Q&A platforms.

Full Text

Preamble

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Analysis of Influencing Factors on Askers' Switching Behavior in Payment-Based Knowledge Q&A Platforms

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Abstract: [Purpose/Significance] Free-based and payment-based knowledge Q&A platforms represent two major channels for problem-solving. This study explores the factors influencing askers' transition from free to payment-based knowledge Q&A platforms, aiming to enhance user experience on payment-based platforms and promote their healthy development. [Method/Process] First, we review existing research on factors influencing knowledge payment. Then, based on the Critical Incident Technique and combined with the Push-Pull-Mooring model, we systematically examine the factors influencing askers' switching behavior from free to payment-based platforms. Subsequently, we employ the entropy weight method to compare the relative importance of each factor before and after the switching behavior. [Result/Conclusion] The influencing factors of askers' switching behavior include five major categories: factors related to free knowledge Q&A platforms, factors related to payment-based platforms, social factors, personal factors, and objective factors. Moreover, the importance of these factors differs to some extent before and after switching. Finally, we propose recommendations for payment-based Q&A platforms regarding their publicity mechanisms, pricing mechanisms, review mechanisms, and evaluation mechanisms.

Keywords: knowledge payment; payment-based knowledge Q&A platform; switching behavior; Critical Incident Technique; Push-Pull-Mooring model
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With the advent of the sharing economy era, the scope of shared products and services has expanded from transportation and accommodation to the knowledge service industry, fostering innovation in knowledge sharing platform business models—from free knowledge sharing to paid knowledge transactions. Tencent Research Institute divides the evolution of knowledge sharing platforms from free to paid models into three stages: Stage 1 (before 2010) featured exclusively free models, such as Douban, Sina iAsk, Baidu Knows, and Zhihu; Stage 2 (2011-2015) saw the emergence of paid models, such as Docin.com launching paid reading products, Douban Reading opening paid columns, and Weibo and WeChat Official Accounts introducing tipping functions; Stage 3 (after 2016) witnessed existing platforms launching paid models successively, with platforms like Xingzai Yidian (formerly "Fenda"), Zhihu Live, Weibo Q&A, and Ximalaya FM becoming typical representatives of knowledge payment products.

By analyzing the operational mechanisms of knowledge payment products and services, we categorize knowledge payment models into four types. The first is the Q&A model, represented by Xingzai Yidian, Zhihu Value, and Weibo Q&A, where askers and answerers engage in one-on-one paid Q&A, enabling users to obtain personalized information services conveniently and efficiently. The second is the subscription model, represented by Dedao, Ximalaya FM, Zhihu Live, and Douban Time, which primarily provides knowledge services through online courses or themed columns that users can subscribe to based on their needs, allowing them to gain preliminary understanding of specific content. The third is the course model, represented by Coursera, Tencent Classroom, and NetEase Cloud Classroom, featuring rigorous teaching and research systems oriented toward skill-based online learning and education, helping users systematically master knowledge systems or skills. The fourth is the community model, represented by Zhishixingqiu and Duanshu, which builds high-quality content-sharing communities centered around professionals and institutions, providing ample social space for interaction among community members, enabling group owners to timely understand member feedback and adjust content and teaching strategies accordingly.

According to the "China Sharing Economy Development Report 2020" released by the State Information Center, the transaction volume in the knowledge and skills domain reached 306.3 billion yuan in 2019, with both supply and demand sides driving the development of knowledge payment. In the knowledge Q&A field, knowledge seekers are gradually shifting from free to payment-based platforms. Due to accelerating life rhythms and increasing work/study pressures, knowledge seekers experience a certain degree of "knowledge anxiety." Answers on free Q&A platforms often have issues in terms of professionalism, originality, and information volume, causing knowledge seekers to waste considerable time and energy screening content. Knowledge providers include the general public, professionals, and institutions from various fields, who can leverage their knowledge, skills, and experience to answer questions and effectively monetize cognitive surplus and knowledge accumulation. Currently, knowledge seekers' primary pain point lies in the difficulty of balancing quantity and quality—there is an irreconcilable contradiction between overloaded free information and scarce high-quality content. Payment-based Q&A platforms provide direct channels for knowledge seekers to ask specific providers, addressing single-point needs effectively. Moreover, paid Q&A can reduce low-quality questions and answers, fostering positive interactions between seekers and providers.

Existing research on knowledge payment focuses primarily on factors influencing users' payment intention and behavior, with limited literature examining user switching from free to paid products/services. Since traditional Q&A platforms were mainly free-based, with payment-based platforms emerging only in recent years, we argue that factors influencing askers' switching behavior warrant in-depth investigation. This study employs the Critical Incident Technique and the Push-Pull-Mooring (PPM) model to comprehensively examine factors influencing askers' switching behavior from free to payment-based platforms at multiple levels: free platforms, payment-based platforms, individuals, and society. Given that askers' attention to influencing factors may differ before and after switching, we further explore these differences using the entropy weight method. Notably, askers' switching behavior does not mean completely abandoning free platforms but rather becoming more willing to accept and try payment-based platforms, particularly for certain domains or topics where paid models are more popular. This research aims to provide empirical support for related studies and practical guidance for platform design and operational mechanisms.

2. Research Status on Factors Influencing Knowledge Payment

Current literature on knowledge payment intention and behavior primarily draws on Planned Behavior Theory, Social Capital Theory, Perceived Value Theory, and Social Exchange Theory to explore influencing factors. Through literature review, we identify five main influencing aspects: knowledge providers, knowledge seekers themselves, platform service aspects, social factors, and objective factors.

Regarding knowledge providers, their personal profiles and behavioral information—such as follower count, number of answers, published articles, likes received, professional field verification, and real-name authentication—significantly and positively influence users' payment behavior on Q&A platforms. Additionally, providers' reputation, professionalism, interactivity, and homogeneity affect seekers' trust and thus their payment intention.

Regarding knowledge seekers themselves, personal needs, psychological states, and demographic characteristics are primary factors influencing payment intention. Personal needs such as knowledge acquisition, self-improvement, and entertainment significantly and directly/indirectly affect payment intention. Notably, psychological states also substantially impact payment intention, including free mentality (the belief that knowledge/content services should be free), positive reciprocity belief, ethical self-efficacy for online piracy, and trust. Free mentality significantly negatively affects payment intention. Positive reciprocity belief, referring to seekers' support for value exchange with providers, significantly moderates the relationship between economic cost and perceived value. Ethical self-efficacy for online piracy positively affects purchase intention and moderates the relationship between perceived value and purchase intention. Seekers' curiosity positively moderates the relationship between perceived value and continuous payment intention. Individual innovation consciousness significantly affects consumption intention for information content. Trust is also a crucial factor enhancing payment intention. Additionally, demographic characteristics such as gender, age, education level, and income affect payment behavior. G. Punj found that payment amount correlates with income and education level, while payment intention correlates with age and gender. M. Goyanes' research shows that higher income leads to stronger payment intention.

Regarding platform service aspects, seekers consider not only user experience but also perceived value differences compared to similar platforms. In terms of user experience, seekers' attitudes toward payment platforms are influenced by perceived usefulness, ease of use, timeliness, convenience, and security. S. Dutta's research based on Planned Behavior Theory and Innovation Diffusion

Theory shows that complexity of online content acquisition and compatibility of paid content significantly negatively affect payment attitude. Additionally, comparisons with other product/service qualities affect payment intention and behavior. High-quality services significantly affect perceived value differences and promote users' psychological inertia toward new products.

Social factors include social interaction ties, subjective norms, and social influence. Zhou Tao et al., based on Social Capital Theory, found that social interaction ties, shared vision, and shared language significantly affect community identification, with the first two significantly positively affecting payment intention. Social interaction ties include relationship strength, interaction duration, and frequency. J. Choi et al. showed that higher perceived social influence leads to stronger payment intention. G. Oestreicher-Singer et al. found that payment intention is closely related to community participation and social influence. Subjective norms are also frequently mentioned factors affecting payment intention.

Objective factors such as question type and economic cost also affect payment behavior. G. Hsieh et al. categorized questions into factual, opinion, advice, and non-question types, analyzing them by importance, urgency, and difficulty. They found that users typically choose to pay when facing difficult factual questions. On payment-based platforms, seekers must pay economic costs to access content. Although some studies show that higher costs yield higher quality and longer content, economic cost still significantly reduces payment intention.

In summary, since the emergence of payment-based knowledge services, numerous scholars have studied influencing factors from the five aspects mentioned above. However, few studies have explored factors influencing seekers' switching from free to payment-based platforms. Given the substantial operational differences between free and payment-based Q&A platforms and the complexity of askers' switching motivations, we focus on Q&A platforms to explore these factors. The switching behavior is influenced not only by payment platforms, personal needs, social factors, and objective factors but also by factors related to previously used free platforms. Based on the PPM model and using the Critical Incident Technique, we examine influencing factors and calculate their weights using the entropy method to reveal key factors and provide insights for platform operation.

3. Research Design

3.1 Research Method

The Critical Incident Technique, proposed by J.C. Flanagan in 1954, originated from the U.S. Aviation Psychology Program during World War II. It is a qualitative research method flexibly applicable to various research purposes, such as studying effective/ineffective ways of doing things, facilitating/hindering factors, collecting functional/behavioral descriptions of events, and identifying key event characteristics. Currently, it is widely used in management, marketing, communication, education, and psychology. In library and information science, it has been used to construct information encountering process models, analyze influencing factors in information seeking, and evaluate library service quality.

The Critical Incident Technique consists of five steps: (1) Determine the overall research objective; (2) Develop a plan specifying data collection methods, subjects, and targets; (3) Collect data through interviews, questionnaires, etc., ensuring events are authentic, relationships between subjects and behaviors are clear, and subjects state key influencing factors with reasons; (4) Analyze data by summarizing and describing them effectively, classifying events according to general frameworks/patterns, and conducting reliability and validity tests; (5) Translate data and report results with actionable recommendations. This technique captures critical events from individuals' perspectives, studying their emotional, cognitive, and behavioral impacts, with potential for in-depth interviews to explore underlying reasons.

3.2 Data Collection

This study defines critical events as those influencing askers' switching from free to payment-based Q&A platforms. We collaborated with a well-known domestic payment-based Q&A platform. First, the platform operator selected users who had asked at least 10 questions between January 2017 and May 2018. Then, we sent notifications explaining the interview purpose and significance to recruit willing participants. We collected demographic information from 225 potential interviewees and analyzed their usage records on both free and payment-based platforms, selecting those who used payment-based platforms more frequently after adoption. Finally, we sampled 60 askers through systematic sampling.

Interviews consisted of two parts: (1) Guiding respondents to recall their switching process and related experiences with detailed descriptions; (2) Inquiring about influencing factors before and after switching and how they affected usage. Following the theoretical saturation principle, we stopped interviewing when new respondents no longer provided novel concepts or content. Between June and September 2018, we effectively interviewed 51 askers (coded as T), with each interview lasting 30-60 minutes. Respondent demographics are shown in Table 1 . The gender distribution was relatively balanced. Most askers were aged 25-34 (50.98%), held college/bachelor's or master's degrees (82.35%), and had asked 16-20 paid questions (45.10%).

3.3 Reliability and Validity Analysis

3.3.1 Inter-judge Reliability Test Classification categories can be based on established theoretical models or direct data analysis. This study used the Push-Pull-Mooring model for classification. Five information management graduate students familiar with the PPM model (coded A, B, C, D, E) identified critical events and classified them to construct the influencing factor system.

From interview content, classifiers identified 265 critical events, following S.M.

Keaveney's classification approach (Figure 1 [Figure 1: see original paper]). Two-thirds (177 events) served as the classification sample, with the remaining one-third (88 events) as a validation sample for theoretical saturation testing. Inter-judge reliability was calculated using Holsti's formula (Formula 1):

$R = 2M / (N1 + N2)$ (Formula 1)

Where R is the reliability index, M is the number of categories agreed upon by classifiers, n is the number of classifiers, and N1, N2 are the numbers of categories assigned by each classifier. Reliability > 0.8 indicates good consistency.

First, A and B classified the first two-thirds of events based on the PPM model, identifying 18 and 17 categories respectively, with 16 overlapping categories, yielding a reliability index of 0.91. They resolved disagreements and established a 18-category system. Next, C and D validated this system, adding 1 and 3 categories respectively, with 19 overlapping categories, achieving 0.95 reliability. Finally, classifier E reclassified the first portion, achieving 0.95 reliability with the other four classifiers. The five classifiers discussed and finalized a 21-category system. When validating with the remaining one-third of events, no new categories emerged and inter-judge reliability remained > 0.8, confirming the final classification system.

3.3.2 Comprehensive Reliability and Validity Test We used Perrault and Leigh's nominal data reliability formula (Formula 2) to test classification reliability:

$Ir = (F0/N - 1/K) \times K/(K-1)$, where $F0/N \geq 1/K$ (Formula 2)

Where Ir is the reliability index, F0 is the number of events with classifier agreement, N is the total number of events, and K is the number of categories. The calculated reliability index was 0.88, exceeding 0.8 and indicating good consistency.

For validity testing, six experts with Q&A research experience evaluated the classification system. They assessed subcategory relevance on a 4-point scale (1 = irrelevant, 2 = generally relevant, 3 = quite relevant, 4 = very relevant). Using Item Content Validity Index (I-CVI), where scores of 3-4 indicate relevance, all categories exceeded 0.8 validity, with an average of 0.95 (>0.9), indicating good comprehensive validity.

4. Analysis of Factors Influencing Askers' Switching Behavior

4.1 Classification of Influencing Factors

Based on the PPM model and Critical Incident Technique, influencing factors were classified into five categories: free platform-related factors, payment-based platform-related factors, social factors, personal factors, and objective factors (Table 2).

4.1.1 Push Factors Push factors examine negative aspects of free platforms that drive switching, including dissatisfaction with information quality and system quality. Regarding information quality, 22 critical events indicated dissatisfaction: some answers lacked timeliness (T4, T23, T43); some were copy-pasted without addressing specific situations, showing low relevance (T32, T46); some contained contradictions, raising questions about authenticity and reliability (T16, T34, T45). Regarding system quality, 9 critical events showed concerns: content display was sometimes poorly formatted (T28, T32) without highlighting key points (T36, T42); answerer matching needed improvement (T17, T37, T42).

4.1.2 Pull Factors Pull factors examine positive aspects of payment-based platforms that attract switching, including satisfaction with information quality, system quality, and economic benefits. Regarding information quality, 19 critical events reflected satisfaction: askers could pose timely, trending questions to specific answerers (T11, T31); most active answerers were professionals and institutions with high expertise and authority, providing accurate, reliable, and targeted answers (T21, T36, T43). Regarding system quality, 15 critical events showed: platforms were simple and convenient (T12, T32); answer formats enhanced social presence and participation (T15, T39, T45). Additionally, platform mechanisms offered potential economic benefits, increasing willingness to try (T5, T8, T35).

4.1.3 Mooring Factors Mooring factors examine individual, social, and objective aspects that hinder or facilitate switching.

Social factors include social ties, subjective norms, and network externality. Social ties refer to relationship strength, density, duration, and frequency with other users on free platforms; 15 critical events showed that weaker ties increased switching likelihood (T2, T10, T41). Subjective norms involve others' usage and recommendations; 18 critical events showed that recommendation from others increased payment intention (T6, T14, T25). Network externality refers to perceived platform user scale; media promotion and research reports affected switching behavior (T3, T26, T12).

Personal factors include individual needs, capabilities, experiences, characteristics/inclinations, and demographics, reflected in 79 critical events. Askers used payment-based platforms out of knowledge anxiety, self-improvement needs (T1, T13), entertainment, and self-expression (T22, T47). Positive experiences promoted continued use (T33, T49). Individual capabilities, particularly information retrieval and evaluation skills, affected switching (T22, T34). Free mentality and payment mentality were frequently mentioned: the deep-rooted belief that Q&A services should be free strongly negatively affected switching (T7), while support for payment positively affected it (T24, T42). Trust in platforms/answerers also facilitated/hindered switching (T19, T44), as did usage habits on free platforms (T15, T38).

Objective factors include time constraints, question type, and switching costs, involving 51 critical events. Time constraints referred to question urgency; payment-based platforms were preferred for timely professional answers (T18, T51). Question type affected payment decisions (T29, T50). Switching costs included economic costs for answers (T27, T40) and time costs for formulating questions and selecting answerers, especially for universal or trending topics (T16, T30, T47).

4.2 Weight Analysis of Factors Before and After Switching

We invited original respondents to rate factor importance before and after switching on an 8-point scale (0 = no influence, 1-7 = increasing influence). We then analyzed the two datasets using the entropy weight method, which determines weights based on factor score variation—higher weights indicate greater score dispersion and discrimination.

The analysis involves four steps: 1. Build matrix and normalize: Xij represents normalized score for sample i on factor j 2. Calculate proportion of sample i's value under factor j (Formula 3) 3. Calculate entropy value for each factor (Formula 4) 4. Calculate factor weights (Formula 5)

Factor weights before and after switching are shown in Table 3 . Before switching, lower-weight factors were switching costs, personal characteristics/inclinations, personal experiences, and dissatisfaction with free platform information/system quality. After switching, lower-weight factors were network externality, individual needs, demographics, social ties, and personal experiences, indicating more consistent ratings for these factors.

Scatter plots visualize changes by plotting factor weights against critical event counts (Figures 2 [Figure 2: see original paper] and 3 [Figure 3: see original paper]). For free platform factors, dissatisfaction weights increased after switching, with information quality receiving more attention than system quality. For payment-based platform factors, information and system quality weights decreased while critical events increased, indicating consistent attention and evaluation after switching. Economic benefit weights showed high dispersion with relatively many events, suggesting strong pre-switching influence. Social factors shifted from upper-right to lower-left, indicating decreased attention and more consistent ratings after switching. Among personal factors, needs, experiences, and demographics maintained stable low weights, while capabilities and characteristics/inclinations increased; notably, characteristics/inclinations weight increased by 0.0655, largely due to formation of payment mentality. For objective factors, time constraints and question type maintained high weights with few events, indicating focused attention by a small group. Switching cost weight increased slightly with fewer events, possibly because increased identification with knowledge payment weakened economic cost perception after switching.

5. Discussion

5.1 Recommendations

Based on our findings, we propose recommendations for payment-based Q&A platforms regarding publicity, pricing, review, and evaluation mechanisms.

Before switching, personal characteristics/inclinations showed consistent ratings with many critical events. For publicity mechanisms, platforms should popularize knowledge payment concepts to gradually establish payment mentality and reduce cognitive lock-in on free services, thereby increasing payment intention. Platforms can also offer free trials to attract users and weaken usage habits on free platforms. Since economic cost perception negatively affects perceived value and payment intention, pricing mechanisms should be improved. Currently, answerers set prices without negotiation. Platforms could allow flexible pricing, enabling askers to set prices or negotiate, or implement growth-based pricing that dynamically adjusts prices based on answerers' performance metrics (number of answers, likes, followers, eavesdroppers), allowing answerers to choose whether to increase prices.

After switching, behavior correlates with satisfaction with information quality and personal experiences. Platforms must strengthen review and evaluation mechanisms to ensure quality. Some platforms allow all users to become answerers without verifying profile information, creating mismatches between displayed and actual capabilities that affect answer quality. Platforms should require answerers to provide proof for profile information. Regarding evaluation mechanisms, current platforms lack appropriate standards; askers can only judge quality indirectly through eavesdropper numbers, likes, followers, and answer counts. Platforms should implement rating systems allowing askers to score answers and provide social spaces for paid users to comment. High-rated answerers could receive "excellent answerer" titles, which significantly positively affect answerers' switching behavior, reflecting askers' preference for quality providers. Platforms can also use evaluation content to delete low-quality content and promote high-quality content, ensuring information quality and helping askers select appropriate answerers.

5.2 Summary and Limitations

This study first reviewed literature on knowledge payment influencing factors. Then, based on the PPM model and Critical Incident Technique, we analyzed interview content to classify influencing factors into five categories: free platform factors (information/system quality dissatisfaction), payment-based platform factors (information/system quality satisfaction, economic benefits), social factors (social ties, subjective norms, network externality), personal factors (individual needs, experiences, capabilities, characteristics/inclinations, demographics), and objective factors (time constraints, question type, switching costs). Using the entropy weight method, we compared factor weights and critical event counts before and after switching. Finally, we proposed recommendations for publicity, pricing, review, and evaluation mechanisms. This research enriches PPM model application in knowledge Q&A and provides insights for platform operation and design.

Limitations include: (1) Potential recall bias when askers remember switching processes; (2) Data collection relied solely on interviews without analyzing actual usage behavior. Future research will compare actual usage data between free and payment-based platforms to identify behavioral differences.

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Author Contributions

Liu Zhouying: Research design, data analysis, manuscript writing;
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Note: Figure translations are in progress. See original paper for figures.