Influencing Mechanism of User Answer Acceptance in Online Learning Communities (Postprint)

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Abstract

[Purpose/Significance] Research on the influencing mechanism of user answer acceptance helps identify central and peripheral paths, retain high-influence users, ensure high-quality Q&A, and enhance community engagement. [Method/Process] This study constructs a theoretical model of factors influencing answer acceptance, collects data from 1,964 posts on the Renmin University Economic Forum, and analyzes the data using SmartPLS software. [Results/Conclusion] User activity can influence personal influence and answer quality respectively, thereby affecting answer acceptance; answer quality also influences personal influence. The influence of personal influence on answer acceptance far exceeds that of answer quality on answer acceptance, i.e., the peripheral path has a greater impact than the central path.

Full Text

Preamble

Research on the Influencing Mechanism of Users' Answer Recognition in E-Learning Communities

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Abstract

[**Purpose/Significance**] Investigating the influencing mechanism of answer recognition helps identify central and edge paths, retain high-influence users, ensure high-quality Q&A, and increase community activity. [**Method/Process**]

This study constructs a theoretical model of factors influencing answer recognition, collects 1,964 posts from the Renmin University Economic Forum, and analyzes the data using SmartPLS software. [**Result/Conclusion**] User activity can influence both personal influence and answer quality, thereby affecting answer recognition. Answer quality also impacts personal influence. The effect of personal influence on answer recognition far exceeds that of answer quality, indicating that the edge path has a greater impact than the central path.

Keywords: e-learning community; user influence; answer recognition; influencing mechanism
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E-learning communities represent a type of online community where users engage in learning, research, and discussion via internet platforms and network tools [1]. The Renmin University Economic Forum is a prominent e-learning community in China, affiliated with Renmin University and established in 2003. As of March 2018, it had approximately 9.63 million registered users, primarily from universities, government agencies, and enterprises. The forum contains over 300,000 educational and teaching resources covering economics, management, finance, and statistics, enabling knowledge sharing and academic socialization through posting.

In social media environments, e-learning communities have undergone significant changes in learning and communication patterns, evolving from niche communities to open virtual spaces. However, inconsistent answer quality and "flooding" behaviors have substantially diminished the credibility and influence of these communities. Key questions remain unanswered: How many influencing paths exist? What constitutes the central versus edge paths? Does the Matthew effect from traditional learning communities manifest clearly in online environments? Therefore, studying the influencing mechanism of answer recognition in e-learning communities holds important theoretical and practical significance.

1 Literature Review

1.1 E-Learning Communities

Current research on e-learning communities has extensively examined their significance [3], knowledge growth and sharing behaviors [4-5], and social interaction and participation [6-7]. However, few studies specifically focus on answer recognition and its influencing mechanisms in e-learning communities. For instance, Xie Ying studied social interaction strategies among learning communities to improve community cohesion and user participation [6]. R. Yilmaz found that academic self-efficacy and community consciousness affect knowledge sharing behaviors [5]. H. Haron et al. examined how components of participatory engagement theory influence participation processes in e-learning communities [7].

1.2 Answer Recognition

Answer recognition refers to the degree of match between an answer and the questioner's expectations, measured through answer adoption and other users' attitudes toward the answer [8]. Scholars suggest that other users' attitudes can be measured through upvotes [4] and bookmarks [9], while the degree of attention an answer receives can be measured through views, comments, and shares [10-11].

In research on answer recognition in social Q&A services, Shi Guoliang found that answer timeliness and respondent influence positively affect answer recognition, with respondent characteristics having greater impact than answer characteristics [12]. X. Chen et al. discovered that answer usefulness most significantly impacts answer recognition on Zhihu, while interactivity and entertainment also positively influence user acceptance [13]. S. Liao et al. compared differences between posters and lurkers in virtual communities regarding answer adoption intentions, finding lurkers more susceptible to network relationships, reciprocity norms, shared vision, and perceived usefulness, while posters are more influenced by social trust and common language [14].

The Elaboration Likelihood Model (ELM) and Information Adoption Model (IAM) provide theoretical foundations for studying answer recognition mechanisms. ELM posits that attitude formation and change occur through central and edge paths, with the central path emphasizing information quality's impact on receivers' attitudes and the edge path emphasizing other factors' influence [19]. IAM suggests both information content and information sources affect information usefulness and adoption, with content-driven paths as central and source-driven paths as edge paths [20]. Building on ELM and IAM, this study constructs a comprehensive model incorporating e-learning community characteristics.

1.3 User Influence

Personal influence refers to a user's capacity to change other users' behaviors within their social network after taking action [15]. Greater information dissemination capability indicates greater influence [16]. In Twitter research, B.A. Huberman et al. argued that more followers indicate greater influence [17]. F. Riquelme et al. added activity and popularity metrics to PageRank algorithms [18]. Domestic researchers suggest personal attributes (profile, age, gender, occupation) and status information (interest tags, descriptions, activity levels) can measure influence on platforms like Weibo and Zhihu [19-20].

Existing research has extensively examined answer recognition and personal influence, primarily in social Q&A and virtual communities. Answer recognition studies focus on influencing factors and adoption intentions, while personal influence measurement predominantly uses social network platforms like Weibo and Zhihu. Research specifically on user influence in e-learning communities remains limited. This study addresses this gap by using the Renmin University Economic Forum as a case study to explore how personal influence affects answer recognition, providing management insights.

2 Research Model and Hypotheses

2.1 Research Model

Answer recognition in e-learning communities essentially concerns information receivers' (questioners or other users) attitudes toward information (answers). Therefore, ELM and IAM models of attitude change and information adoption provide appropriate theoretical foundations. Drawing on these models and e-learning community characteristics, this study constructs a comprehensive model.

2.2 Research Hypotheses

User influence in e-learning communities emphasizes users' capacity to affect others. Shi Guoliang et al. confirmed that personal influence positively affects answer recognition in social Q&A sites [12]. This study measures user influence through academic level, prestige, and user title. Academic level is scored by members viewing posts; prestige is awarded by forum administrators based on contributions; and titles are determined by community points. Higher academic level, prestige, and title increase the likelihood that a user's views will influence others and enhance answer credibility, thereby increasing recognition. Therefore:

H1: Personal influence significantly affects answer recognition in e-learning communities.

In the Renmin University Economic Forum, 精华帖 (featured posts) are selected from regular posts based on: (1) original articles; (2) scarce resources; (3) scarce data and industry analysis reports; and (4) original insights, reflections, discussions, and Q&A. Each criterion has detailed requirements, ensuring featured posts represent quality content. Thus, this study uses featured post count to measure answer quality.

Li Jing et al. [21] and Long Zehui [22] empirically confirmed that perceived information quality significantly affects information adoption. Ding Hanqing found that opinion leaders in SNS networks gain influence through expertise, high-quality contributions, and frequent interactions [23]. In e-learning communities, users providing high-quality answers demonstrate stronger professional competence, becoming opinion leaders whose new answers gain greater trust and recognition. Therefore:

H2: Answer quality significantly affects answer recognition.
H3: Answer quality significantly affects personal influence.

Active users exhibit strong participation and presence in website activities [24]. In e-learning communities, activity manifests through login duration, frequency, and participation in various activities [25]. Wang Huixian divided participation into "participation level" (time and frequency) and "contribution level" (effective operations) [26]. This study uses enthusiasm index, total online duration, and total post count to measure activity level.

Liu Chan [15] and Yuan Fuyong et al. [27] found positive correlations between Weibo user activity and personal influence. Positive relationships between answer quantity and quality have also been confirmed [28]. In e-learning communities, higher activity increases participation and information dissemination, enhancing personal influence. Higher activity also increases posting and replying frequency, improving answer quality. Therefore:

H4: Activity level significantly affects personal influence.
H5: Activity level significantly affects answer quality.

The initial model framework is shown in Figure 1 [Figure 1: see original paper].

3 Data Processing and Analysis

3.1 Data Source

In February 2018, we randomly collected 2,020 historical posts from the Renmin University Economic Forum across three sections: "Latest Replies," "Latest Popular," and "Latest Featured." Data included: (1) personal influence indicators (user title, followers, experience points, featured post count, total posts, registration date); and (2) post influence indicators (views, total replies, upvotes, bookmarks). After removing blank and invalid data, 1,964 valid post samples remained, yielding 11 indicators across 4 variables: enthusiasm index, total online duration, total post count, featured post count, academic level, prestige, user title, post views, total replies, follower count, and bookmark count. Variable-indicator relationships are shown in Table 1 .

Due to large numerical differences in raw data (e.g., post views ranged from 0 to 3,739,172), we applied logarithmic transformation for standardization to minimize processing errors.

3.2 Reliability and Validity Testing

We used SmartPLS for data analysis. First, we assessed convergent and discriminant validity. Convergent validity examines whether indicators effectively reflect their factors; discriminant validity examines statistical differences between factors.

Factor loadings, T-values, Average Variance Extracted (AVE), Composite Reliability (CR), and Cronbach's α are shown in Table 2 . All factor loadings exceed 0.8 and are significant at the 0.001 level. All AVEs and CRs exceed 0.7 and 0.8, indicating good convergent validity. All Cronbach's α values exceed 0.72, mostly around 0.9, surpassing the acceptable threshold of 0.7, indicating reliable scales.

For discriminant validity, Table 3 shows AVE square roots and factor correlation matrices. Each factor's AVE square root significantly exceeds its correlation coefficients with other factors. Likelihood ratio tests on highly correlated latent variables (correlation > 0.8) confirmed they measure distinct concepts, demonstrating good discriminant validity.

3.3 Model Testing

We evaluated model explanatory power and hypothesis significance through path coefficients, T-values, and R^2 variance proportions, shown in Figure 2 [Figure 2: see original paper]. All five hypotheses were supported. R^2 values for answer recognition (0.654), personal influence (0.974), and answer quality (0.592) substantially exceed 0.19 [29], indicating strong model explanatory power.

4 Research Results

Figure 2 shows all five hypotheses are supported. Specifically:

(1) Personal influence affects answer recognition more than answer quality. The β coefficient for personal influence on answer recognition is 0.603, while answer quality's β is 0.229. This likely reflects the high specialization of content in the Renmin University Economic Forum. Users with limited professional knowledge rely more on posters' personal attributes (academic level, prestige) when evaluating answers. The Matthew effect explains this phenomenon, describing how advantages and disadvantages accumulate over time, manifesting as core trends and concentration in academic fields [30]. Users with higher academic level, prestige, and titles produce posts perceived as more authoritative, receiving higher recognition. This validates Shi Guoliang et al.'s finding that respondent characteristics affect answer recognition more than answer characteristics [31], suggesting a reversal of ELM and IAM's central and edge paths in e-learning communities.

(2) Activity level most significantly influences personal influence. The β coefficient for activity level on personal influence is 0.763, compared to 0.282 for answer quality. Higher activity indicates greater participation. The enthusiasm index is rated by other users when posts solve problems or prove helpful. Combined with long online duration and high post counts, this reflects high activity. Active users post more frequently, increasing viewership and information dissemination, thereby enhancing personal influence. With rapid post turnover, low-activity users' contributions quickly become buried, limiting their influence.

(3) Activity level significantly affects answer quality. The β coefficient is 0.769. This likely results from the forum's strict regulation of "flooding" behavior. When flooding is controlled, more active users generate more high-quality answers. Active participation is driven by users' confidence in their knowledge and proficiency with the platform [32]. Frequent interaction and information exchange increase users' knowledge and willingness to solve problems, improving answer quality.

5 Conclusions and Recommendations

5.1 Conclusions

This study reveals that, consistent with ELM and IAM, multiple paths influence answer recognition in e-learning communities. User activity affects personal influence and answer quality, which in turn affect answer recognition. Answer quality also influences personal influence. Personal influence's impact on answer recognition far exceeds that of answer quality, indicating a reversal of the central and edge paths identified in ELM and IAM. These findings align with Shi Guoliang et al.'s research on social Q&A communities, confirming that "respondent characteristics affect answer recognition more than answer characteristics." This demonstrates that vertical communities like e-learning communities have distinct operational characteristics and response mechanisms compared to general information dissemination.

This study's contribution lies in identifying key influencing factors (user activity, personal influence, and answer quality), analyzing their interactions, and determining the most impactful path to answer recognition, thereby enriching user behavior theories in e-learning communities and providing insights for promoting healthy user interaction and enhancing community value.

5.2 Recommendations

Based on these findings, we propose:

(1) Encourage user interaction and high-quality answers. Users should actively engage in academic discussions, posting, replying, and voting to increase their influence. E-learning communities feature strong social interaction elements [6], and learning occurs through social processes. To enhance influence, users should improve post quality and interact frequently with others. Different communities may use different activity metrics, but online duration, post count, and user interaction effectively measure activity.

(2) Strengthen regulation and penalties for "flooding" behavior. E-learning communities are knowledge-sharing platforms where answer quality profoundly affects academic atmosphere. Strict content review mechanisms and reporting procedures should be established. Jiang Wen argues that information redundancy and overload burden users seeking high-quality answers [33]. Clear reward systems encouraging users to report flooding can effectively suppress such behavior and improve knowledge-sharing efficiency.

(3) Implement incentives to increase user activity. To improve overall answer quality, administrators should design simple, engaging sections. For example, daily questions displayed on the main interface with experience points or forum currency rewards for participants. High-quality answers selected manually and featured on the main page with generous rewards (levels, medals) can motivate users. Administrator participation and experienced users' involvement in community management can also increase engagement [3].

(4) Mitigate negative Matthew effects while fostering positive community culture. User quantity is crucial for Q&A community development, and higher resource regeneration rates improve user quality [35]. While personal influence's Matthew effect helps users identify experts, its negative effects limit new users' visibility. Administrators should establish rules to promote new users, strengthen reciprocity and knowledge accumulation, and ensure professional visibility for newcomers, creating positive community culture that mobilizes users at all levels.

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Chen Juan: Designed research framework, collected literature, processed data, wrote and finalized the paper.
Deng Shengli: Revised research framework and supplemented important content.

Research on the Influencing Mechanism of Users' Answer Recognition in E-Learning Community

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Abstract: [Purpose/significance] Study of the influencing mechanism of users' answer recognition helps identify central and edge paths, retain high-influence users, guarantee high-quality Q&A, and increase community activity. [Method/process] After building a theoretical model of answer recognition, collecting data from 1,964 posts on the NPC Economic Forum, SmartPLS software is used to analyze the data. [Result/conclusion] User activity can affect personal influence and answer quality separately, thus affecting answer recognition. Answer quality also affects personal influence. The impact of user influence on answer recognition is far greater than that of answer quality, that is, the edge path has a greater impact than the central path.

Keywords: e-learning community; user influence; answer recognition; influencing mechanism

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