

## **Differing the Impacts of Individual and Group Knowledge Seeking/Contribution Behaviors on Knowledge Sales in Online Q&A Platform: The Moderating Role of Knowledge Contributor Category**

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### **ABSTRACT**

An increasing number of knowledge contributors are generating revenue through knowledge paid Q&A. Previous research on knowledge sales explores the impact of knowledge contributors' characteristics and knowledge contribution behavior on knowledge sales but neglects the role of knowledge seeking behavior. We further examine two types of knowledge seeking behaviors which involve individual and group behavior. We then propose that different categories of knowledge contributors can moderate the impact of two kinds of knowledge contribution behavior and knowledge seeking behavior on knowledge sales. Drawing on signaling theory and relevant literature in knowledge management, we build a research model and validate the model by collecting data from 101,836 data points from 7274 contributors in the Zhihu.com platform. The findings demonstrate that knowledge seeking and knowledge contribution behavior have a significant impact on knowledge sales. Further, group behavior has a different impact compared to individual behavior on knowledge sales. Additionally, the impact of knowledge sharing behavior on knowledge sales differs across various categories of knowledge contributors. Both theoretical and practical implications are discussed.

**Keywords:** Knowledge sales, knowledge contribution, knowledge seeking, individual and group behavior, knowledge contributor category, signaling theory.

### **INTRODUCTION**

Online Q&A platforms have become increasingly important as avenues for both seeking and contributing knowledge among a growing number of individuals passionate about learning. Online Q&A platforms have gained widespread popularity and have evolved into crucial channels for sharing, transferring, and co-creating knowledge among users (Luo et al., 2020). In the past, free Q&A due to its low-threshold nature led to uneven quality, and the user's questions were difficult to solve. Paid Q&A came into being (Zhao et al., 2018). The online paid Q&A services provided by online Q&A platforms which allow users to pay for the answers to their questions have become much more popular. Zhihu.com, a well-known Q&A platform, views knowledge guidance as a breakthrough to increase the effectiveness of questioners in receiving responses. As of 2023, Zhihu.com boasts over 102 million monthly active users, solidifying its position as one of China's largest online Q&A platforms for knowledge sharing (Qiu et al., 2024).

For online Q&A platforms, knowledge sharing behavior is vital as the majority of information created and shared is determined by users' knowledge sharing behavior. Specifically, knowledge sharing behavior takes two forms which involve either answering others' questions which can be regarded as knowledge contribution behavior, or asking questions which is knowledge seeking behavior (Wang et al., 2022). More interestingly, we also find that knowledge sharing behavior can be performed either individually or in a group. For example, users can either contribute their knowledge by directly answering questions or they can engage in public edits, and users on the platforms can seek the answers by directly posting a question or attending the Lives. These two types of knowledge sharing might generate impacts on knowledge sales as knowledge contribution behavior shows a competence signal (Zhao et al., 2018) while knowledge seeking behavior might indicate that the people lack related knowledge in certain areas (Lai et al., 2014). Further, people would be evaluated differently in a group compared with the situation of individuals. The impact of the knowledge contributor categories on knowledge sales is further studied. Knowledge contributors can be classified into famous contributors and grassroots contributors in the Q&A platform based on their distinct styles of presentation and levels of expertise (Zeng et al., 2022). Knowledge contributors who appear in the "Paid Consultation Square" are defined as famous contributors, otherwise they are grassroots contributors. The former will rely on platform support to get more page views, while the latter is relatively unknown. Thus, it is interesting to investigate the impact of different knowledge sharing behaviors on knowledge sales and compare them across different knowledge categories.

However, previous research on knowledge sales explores the impact of knowledge contributors' characteristics and knowledge contribution behavior on knowledge sales but neglects the role of their knowledge seeking behavior (Zhu & Zhang, 2019; Zhou et al., 2022 & Sun et al., 2022). Studying knowledge seeking as a form of knowledge sharing behavior among contributors in Q&A communities is crucial for understanding its impacts on knowledge sales (Wang et al., 2022). Therefore, this study examines the influence of individual and group knowledge sharing behaviors on knowledge sales, while exploring how contributor categories moderate this relationship.

Signal theory can effectively respond to the reason why the paid decision happens where there is information asymmetry between two parties (Chen et al., 2020). We thus adopted signal theory to help explain our research question. This study investigates the effects of two behaviors, knowledge contribution and knowledge seeking, on knowledge sales. Additionally, it discusses how the category of knowledge contributors influences these outcomes. This study contributes to advancing our understanding of the knowledge paid behaviors in online Q&A communities. First, previous studies mainly focus on the impact of knowledge contribution on knowledge sales (Zhao et al., 2018 & Sun et al., 2022), this paper proposed knowledge seeking behavior as a signal for knowledge paid behavior. Second, this study further discusses the role of group knowledge sharing behavior on knowledge sales and the relative impacts of individual behavior and group behavior on knowledge sales. Third, our study further investigates the boundary under which different knowledge sharing behaviors impact knowledge sharing behaviors. Furthermore, it offers recommendations and practical guidelines for different categories of knowledge contributors to boost their knowledge sales.

## THEORETICAL BACKGROUND

### Knowledge Sales

Knowledge sales in paid Q&A communities are defined as knowledge contributors exchanging their expertise through the platform (Chen et al., 2020). Previous studies on knowledge sales or payment decisions in Q&A communities have primarily concentrated on the characteristics of knowledge contributors and their behavior in contributing knowledge. For example, Zhao et al. (2018) concluded that factors such as knowledge contributors' competence, trustworthiness, integrity, and reputation positively influence consumers' decisions to make payments for knowledge. Zeng et al. (2022) found that factors such as the volume of content posted by knowledge contributors, their level of recognition, and the size of their follower base positively impact the sale of knowledge. Chen et al. (2021) similarly concluded that the number of previous consultations plays a crucial role, while the number of likes, ratings, and comments each play distinct roles in influencing outcomes. Sun et al. (2022) showed that contributors' experience with knowledge Q&A, the popularity of free Q&A, and cues gained from question characteristics all positively impacted audience size. Li et al. (2023) concluded that knowledge differentiation can increase sales of paid knowledge products, but can negatively affect their eWOM.

In summary, few studies have examined knowledge payment decisions or knowledge sales from the perspective of knowledge sharing behaviors especially knowledge seeking behavior. Previous studies on knowledge payment decisions or knowledge sales often lack segmentation based on the knowledge sharing behaviors of contributors, such as knowledge seeking and knowledge contributing. However, knowledge Q&A communities serve as channels for sharing, transferring, and co-creating knowledge among online users. Knowledge-sharing behaviors are exchange behaviors between contributors and seekers involving knowledge provision and seeking. In a knowledge Q&A community, knowledge sharing behaviors predominantly involve knowledge contribution and knowledge seeking (Wang et al., 2022). Further, few studies have further divided knowledge sharing behaviors based on individual and group behaviors, as well as whether there is a difference between the types of contributors, i.e., grassroots contributors and famous contributors.

This study examines how the knowledge sharing behavior of contributors in paid Q&A communities impacts their knowledge sales. It categorizes contributors into famous contributors and grassroots contributors based on their presence in the consulting plaza, aiming to elucidate how these factors influence users' payment decisions from two distinct perspectives. With this study, we explore, for the first time, how the category of knowledge contributors influences knowledge sales, thereby enriching research on signaling theory within the context of online Q&A communities.

### Knowledge Contribution

Knowledge contribution behavior can be divided into two categories: individual contribution and group contribution. Individual knowledge contribution in knowledge Q&A communities primarily manifests through the free answers provided by knowledge contributors. In knowledge Q&A communities, users with specialized knowledge or life experience are willing to respond to questions from others. Individual knowledge contribution is considered an important component of knowledge contribution, and it also determines the effectiveness of information systems (Liu & Li, 2017).

Public editing is also an important group knowledge contribution behavior in knowledge Q&A communities. In online communities, group knowledge contribution behavior includes group editing of one or more articles (Park & Park, 2016). Public editing allows users to freely and collectively improve and optimize the public content of Zhihu. As a group knowledge contribution behavior, public editing demonstrates the platform's openness and inclusiveness in knowledge sharing and also promotes the continuous updating and optimization of various contents in the community.

## Knowledge Seeking

A knowledge Q&A community is a platform that provides communication and knowledge sharing where users can access the experiences, insights, and knowledge of others, a process known as individual knowledge seeking. Knowledge seeking behavior can be classified into individual knowledge seeking behavior and group knowledge seeking behavior. Knowledge seeking behaviors entail deliberate efforts by individuals to acquire information and insights from external sources, thereby enhancing their cognitive abilities to tackle specific challenges or accomplish particular goals (Qiu et al., 2024). In this research context, we define individual knowledge seeking as a behavior performed by himself or herself by selecting a specific source of knowledge after a direct search (Mickeler et al., 2023). Additionally, when different groups collaborate and seek knowledge, they will creatively solve problems and make better decisions (Chan et al., 2023). Group knowledge seeking is mainly manifested in knowledge Q&A communities in terms of group learning. For example, they can attend in Zhihu.com Lives. We defined this group learning behavior as group knowledge seeking in our study.

## Signaling Theory

Signaling theory was originally proposed in 1973 by Michael Spence, who won the 2001 Nobel Prize in Economics. It was developed based on the concept of information asymmetry (Chen et al., 2020). Signals are utilized for communication, transferring information from individuals who possess more information to those with less (Siering et al., 2018). Signaling theory is widely applied in studies related to consumer purchase decisions, organizational management, and the effectiveness of online reviews (Liang et al., 2024). In this study, addressing information asymmetry is expected to positively impact the sale of knowledge, as consumers cannot assess the quality of the answer until after the transaction is completed. Consequently, in the absence of clear evaluation criteria for the competence of knowledge contributors, relevant information serves as valuable cues or signals during the user evaluation process. For instance, the knowledge sharing behavior of contributors in the community can serve as a signal that helps mitigate information asymmetry between the transaction parties.

## RESEARCH MODEL AND HYPOTHESES

Based on signal theory and related literature on knowledge sharing, we build a research model to explore how knowledge sharing behavior affects knowledge sales in the context of online knowledge Q&A platforms, and how these impacts could differ with different knowledge contributors. Further, we classify knowledge sharing behavior into knowledge seeking and knowledge contribution behavior (Wang et al., 2022), and divided these two types of behavior into individual behavior and group behavior based on the number of people engaging in the behavior. The knowledge contributor category involves both famous knowledge contributors and grassroots knowledge contributors. The research model is depicted in Figure 1.

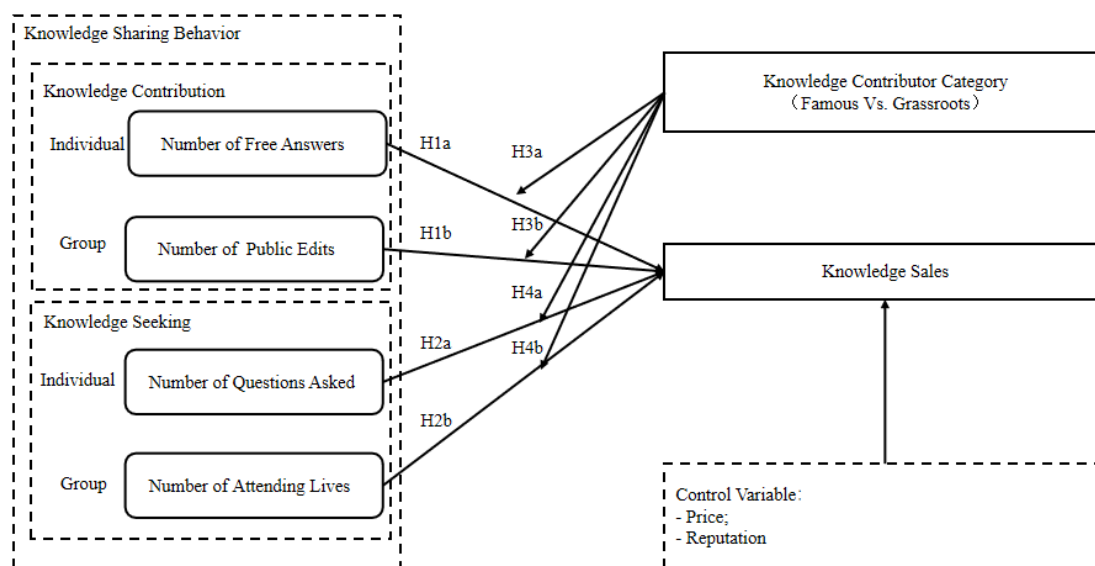


Figure 1: Research Model.

## Individual Knowledge Contribution, Group Knowledge Contribution, and Knowledge Sales

By answering free questions, knowledge contributors can release a signal about their competence (Filiari et al., 2018). The competence of knowledge contributors acts as a benchmark for users to assess the quality of their answers beforehand, thereby positively influencing their decisions to make payments (Chen et al., 2020). Thus, we use the number of answers to constitute an indicator of individual knowledge contribution and propose that the number of free answers will positively impact knowledge sales as hypothesis H1a.

Public editing serves not only as a spontaneous action to maintain and enhance the community's quality but also qualifies as a form of group knowledge contribution behavior. Different from individual contribution behavior, the knowledge contributors together with other knowledge contributors contribute to the knowledge in the knowledge Q&A platform. We argue that public

editing could release both a benevolent signal and a competence signal (Zhao et al., 2018). Thus, we contend that the number of public edits as the group knowledge contribution behavior can increase their knowledge sales as our hypothesis H1b.

*H1a: The number of free answers has a positive impact on knowledge sales.*

*H1b: The number of public edits has a positive impact on knowledge sales.*

### **Individual Knowledge Seeking, Group Knowledge Seeking and Knowledge Sales**

Although knowledge seeking reflects the efforts made by knowledge contributors to enhance their abilities (Veeravalli et al., 2020), knowledge seeking can also reflect their abilities to a certain extent (Lai et al., 2014). Individual knowledge-seeking is mainly manifested in the number of questions asked. Just as Zhihu.com can answer other people's questions for free, it is also possible to ask questions of interest. Group seeking is mainly manifested in the joint participation in Lives.

In our study, consistent with previous studies, we contend that knowledge seeking can reflect their ability by asking questions both individually or through attending Live with others. In particular, knowledge seeking may be perceived as a deficiency in personal knowledge. Similarly, if a user realizes that a contributor is asking the same or similar question or adding the same Live, the user may assume that the respondent is not professional enough to solve his or her problem. Thus, we put forward H2a and H2b that both types of knowledge seeking will decrease knowledge sales for contributors.

*H2a: The number of questions asked negatively impacts knowledge sales.*

*H2b: The number of times attending Lives negatively impacts knowledge sales.*

### **The Moderating Role of the Category of Knowledge Contributor**

Knowledge contributors can be classified into famous knowledge contributors and grassroots knowledge contributors. As grassroots knowledge contributors have a relatively lower perceived competence, more free questions the answer can convey the signal of competence. However, famous knowledge contributors don't have a high demand to prove their competence compared to grassroots knowledge contributors (Zhao et al., 2018). Therefore, we propose hypotheses H3a and H3b: that knowledge contribution behavior, encompassing both individual and group contribution, will have a greater impact on knowledge sales for grassroots knowledge contributors compared to famous knowledge contributors.

*H3a: The number of free answers will have a higher positive impact on knowledge sales for grassroots knowledge contributors than for famous knowledge contributors.*

*H3b: The number of public edits will have a higher positive impact on knowledge sales for grassroots knowledge contributors than for famous knowledge contributors.*

The impact of knowledge seeking can be different across different knowledge contributors. For famous knowledge contributors, knowledge seeking is generally perceived as a sign of curiosity. However, for grassroots contributors, it may be perceived as a deficiency in knowledge and ability (Lai et al., 2014). Similarly, famous knowledge contributors who attend Lives will show that they keep on learning up-to-date knowledge and be perceived as a good image. However, for grassroots knowledge contributors, attending Lives would display that they lack related knowledge. Thus, we contend that both individual and group knowledge seeking would negatively impact more on knowledge sales for grassroots knowledge contributors compared with famous knowledge contributors as hypotheses H4a and H4b.

*H4a: The number of questions asked will have a higher negative impact on knowledge sales for grassroots knowledge contributors than for famous knowledge contributors.*

*H4b: The number of attending lives will have a higher negative impact on knowledge sales for grassroots knowledge contributors than for famous knowledge contributors.*

## **RESEARCH METHODOLOGY**

### **Data Collection**

To test the research model, we collected data from Zhihu.com as Zhihu.com has a large group of users with more than 200,000 registered knowledge consulting contributors in 2023. Knowledge contributors are also users of Zhihu.com, so all their publicly available basic information is easily accessible. Further, Data from Zhihu.com is used in previous studies on knowledge sales or knowledge paid decisions. Specifically, we randomly selected famous knowledge contributors and grassroots knowledge contributors from March 10 to 15, 2023 by building a crawler program through Python. Finally, 572 famous contributors and 6,702 grassroots contributors were obtained, resulting in a cross-section of 101,836 records. As shown in Table 1, the operational definitions for each variable are listed.

### **Variables and Measurement**

The dependent variable in this study is knowledge sales, which is measured by the number of answers sold by knowledge contributors. The independent variables include individual knowledge contribution, group knowledge contribution, individual knowledge seeking, and group knowledge seeking, which are measured respectively by the number of free answers, the number of public edits, the number of questions asked, and the number of times attending a Live. The knowledge contributor category is the moderator in our model, famous knowledge contributors were assigned a value of 1, and grassroots knowledge

contributors were assigned a value of 0. We controlled the impact of price and reputation in our model as these two variables impact knowledge sales based on previous studies (Zhao et al., 2018). Specifically, the number of followers, likes, favorites, and votes obtained from the knowledge contributors were summed up and used as reputation variables. We did not consider the effect of the score on the results, this is because for almost all knowledge contributors their scores on the platform are close to perfect. Table 1 shows the variables and measurements.

Table 1: Variables and Measurements

Function	Variable	Measurements
Dependent variable	knowledge sales	The sales number of the answers
Independent variable	Individual knowledge contribution	The number of free answers
	Group knowledge contribution	The number of public editing
	Individual knowledge seeking	The number of questions asked
	Group knowledge seeking	The number of times attending a Live
Moderating variables	Knowledge contributor category	Famous contributor=1, grassroots contributors=0
Control variables	Reputation	The sum of the number of followers, likes, favorites, and votes
	Price	The price of the answer

## DATA ANALYSIS

### Descriptive Analysis and Correlations

Knowledge sales, individual knowledge contribution, group knowledge contribution, individual knowledge seeking, group knowledge seeking, and reputation are incremented by 1, followed by the application of the logarithm transformation. Finally, standardization is performed before model validation analysis to reduce kurtosis and skewness. Then, a multicollinearity test was conducted to avoid high correlation between the independent variables which would lead to inaccurate estimation of the regression coefficients. The results indicate that the variance inflation factor (VIF) for all variables is less than 3, suggesting that there is no issue with multicollinearity (Hair et al., 1998). Table 2 shows the descriptive statistics of all the variables and Table 3 shows the correlations of the variables.

Table 2: Descriptive Statistics.

Variable	Mean	SD	Min	Max	VIF
Ln (Individual knowledge contribution+1)	5.375	1.520	0	10.703	1.258
Ln (Group knowledge contribution +1)	3.504	1.803	0	9.986	2.349
Ln (Individual knowledge seeking +1)	1.443	1.306	0	8.074	2.161
Ln (Group knowledge seeking +1)	1.076	1.318	0	5.337	1.076
Ln (Reputation +1)	11.458	1.627	4.990	16.333	1.274
Ln (Price +1)	3.223	1.413	0.693	9.210	1.009
Knowledge contributor category	0.070	0.263	0	1	
Ln (Knowledge sales +1)	2.156	1.791	0	10.331	

### Model Validation

We build a research model on the impact of different types of knowledge sharing behavior together with the knowledge contribution category on knowledge sales in the knowledge Q&A platform. As this study delves into how a dependent variable

is concurrently influenced by multiple independent variables, multiple linear regression analysis is utilized to analyze the research model. The multiple linear regression equation is given by:

$$y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \theta_1 X_1 X_5 + \theta_2 X_2 X_5 + \theta_3 X_3 X_5 + \theta_4 X_4 X_5 + e \quad (1)$$

Y denotes the number of knowledge sales,  $\beta_0$  represents the regression constant, and the regression model consists of  $\beta_1$ ,  $\beta_2$ ,  $\beta_3$ , and  $\beta_4$ .  $X_1$  represents individual knowledge contribution,  $X_2$  represents group knowledge contribution,  $X_3$  represents individual knowledge seeking,  $X_4$  represents group knowledge seeking, and  $\beta_1$ ,  $\beta_2$ ,  $\beta_3$ , and  $\beta_4$  represent its impact respectively. In this study, four interaction terms  $X_5$ ,  $X_6$ ,  $X_7$ , and  $X_8$  were constructed according to the categories and behaviors of the responder, in which  $\beta_5$ ,  $\beta_6$ ,  $\beta_7$ , and  $\beta_8$  represented the effects of the interaction terms respectively. The control variables, price, and reputation are represented by  $X_9$  and  $X_{10}$ .  $e$  represents the random error term.

Table 3 Correlations.

	KS	KCC	IKC	GKC	IKS	GKS	PR	RP
KS	1.000							
KCC	0.518***	1.000						
IKC	0.299***	0.069***	1.000					
GKC	0.176***	-0.033**	0.427***	1.000				
IKS	0.089***	-0.043***	0.439***	0.767***	1.000			
GKS	0.111***	0.018*	0.082***	0.170***	0.141***	1.000		
PR	0.234***	0.142***	0.135***	0.051***	0.020***	0.094***	1.000	
RP	0.323***	-0.101***	0.372***	0.288***	0.173***	0.103***	0.180***	1.000

Note: KS = Knowledge sales; KCC= Knowledge contributor category; IKC= Individual knowledge contribution; GKC= Group knowledge contribution; IKS= Individual knowledge seeking; GKS= Group knowledge seeking; PR=Price; RP=Reputation; \*\*\*P < 0.001; \*\* P < 0.01; \* P < 0.05.

Table 4 Main Regression Results.

	Model1	Model2	Model3 (FKC)	Model4 (GKC)
Price	0.181*** (0.011)	0.080*** (0.009)	-0.076** (0.031)	0.106*** (0.009)
Reputation	0.290*** (0.011)	0.293*** (0.010)	0.386*** (0.028)	0.335*** (0.011)
Individual knowledge contribution		0.131*** (0.011)	0.274*** (0.032)	0.142*** (0.011)
Group knowledge contribution		0.110*** (0.142)	-0.009 (0.046)	0.140*** (0.015)
Individual knowledge seeking		-0.089*** (0.141)	-0.041 (0.046)	-0.190*** (0.015)
Group knowledge seeking		0.047*** (0.009)	0.064* (0.029)	0.054*** (0.009)
Knowledge contributor category		0.520*** (0.009)		
Individual knowledge contribution× Knowledge contributor category		0.022** (0.009)		
Group knowledge contribution× Knowledge contributor category		-0.036** (0.013)		
Individual knowledge seeking× Knowledge contributor category		0.017 (0.014)		
Group knowledge seeking× Knowledge contributor category		-0.001 (0.009)		
Observations	7274	7274	572	6702
R <sup>2</sup>	0.136	0.443	0.386	0.236

Note: FKC = Famous knowledge contributors; GKC = Grassroots knowledge contributors;

\*\*\*p < 0.001; \*\* p < 0.01; \* p < 0.05.

The results in Table 4 show that both individual knowledge contribution ( $\beta = 0.131$ ,  $p < 0.001$ ) and group knowledge contribution ( $\beta = 0.110$ ,  $p < 0.001$ ) have a significant positive effect on knowledge sales, which supports H1a and H1b. Individual knowledge seeking behaviors ( $\beta = -0.089$ ,  $p < 0.001$ ) negatively impact knowledge sales, supporting H2a. However, group knowledge-seeking behavior ( $\beta = 0.047$ ,  $p < 0.001$ ) had a significant positive effect on knowledge sales, which is opposite to H2b. For the moderating role of the knowledge contributor category, as shown in Model 2 in Table 4, the knowledge contributor category positively moderates the effect of individual knowledge contribution ( $\beta = 0.022$ ,  $p < 0.05$ ) on knowledge sales, supporting H3a. This implies that for famous knowledge contributors, engaging in free answers has more power on knowledge sales compared to grassroots knowledge contributors. However, the contributor category negatively moderated the effect of group contribution ( $\beta = -0.036$ ,  $p < 0.01$ ) on knowledge sales, which is contrary to the H3b. Last, the knowledge contributor category neither moderates the effects of individual knowledge seeking ( $\beta = 0.017$ ,  $p > 0.05$ ) nor moderates the impact of group knowledge seeking ( $\beta = -0.001$ ,  $p > 0.05$ ) on knowledge sales, thus H4a and H4b are not supported. The R square in Model 2 is 0.443.

### Robustness Check

To check the robustness of the results, we use the panel Tobit model to run the data. The panel Tobit model is a multiple regression model that corrects the problem of truncation of the dependent variable and controls for possible influences such as individual heterogeneity, thus improving the accuracy and robustness of the model. Table 5 demonstrates the results of the analysis of the panel Tobit model. Based on the results in Table 5, the results are consistent with Table 4, proving that the results are robust.

Table 5 Tobit Regression Results.

	Model1	Model2	Model3 (FKC)	Model4 (GKC)
Price	0.182*** (0.017)	0.260*** (0.073)	-0.067** (0.032)	0.092*** (0.026)
Reputation	0.291*** (0.018)	0.241*** (0.084)	0.269*** (0.028)	0.294*** (0.029)
Individual knowledge contribution		0.322*** (0.087)	0.220*** (0.033)	0.122*** (0.031)
Group knowledge contribution		0.126*** (0.113)	-0.008 (0.047)	0.120*** (0.041)
Individual knowledge seeking		-0.178*** (0.109)	-0.037 (0.047)	-0.092*** (0.041)
Group knowledge seeking		0.093*** (0.071)	0.050* (0.030)	0.153*** (0.026)
Knowledge contributor category		0.820*** (0.066)		
Individual knowledge contribution× Knowledge contributor category		0.388*** (0.063)		
Group knowledge contribution× Knowledge contributor category		-0.154* (0.088)		
Individual knowledge seeking× Knowledge contributor category		0.112 (0.091)		
Group knowledge seeking× Knowledge contributor category		-0.062 (0.058)		
Observations	7274	7274	572	6702
R <sup>2</sup>	0.058	0.206	0.141	0.106

Note: FKC = Famous knowledge contributors; GKC = Grassroots knowledge contributors;

\*\*\*p < 0.001; \*\* p < 0.01; \* p < 0.05.

## DISCUSSION

### Key Findings

According to the results of the regression analysis, this study has the following important conclusions:

First, knowledge contribution which involves both individual knowledge contribution and group knowledge contribution has a positive impact on knowledge sales. Specifically, the impact of individual knowledge contribution can positively influence knowledge sales for both grassroots and famous knowledge contributors. Further, this impact is bigger for grassroots knowledge contributors. For the impact of group knowledge contributions, the results show that it only impacts the knowledge sales for grassroots knowledge sales which indicates that its impact on sales is bigger for grassroots knowledge contributors compared to famous knowledge contributors.

Second, knowledge seeking which involves individual knowledge seeking and group knowledge seeking has impacts on knowledge sales. Specifically, the impact of individual knowledge seeking has proved to hurt knowledge sales at the grassroots but not for famous knowledge contributors. For the impact of group knowledge seeking, it positively impacts knowledge sales for grassroots and the positive relationship is Borderline significant which indicates that group knowledge seeking is beneficial for all the knowledge contributors. This inconsistent result can be explained by the hidden effect of the group on the individual, that the impact of individual behavior can be hidden in a group (Liu et al., 2024). Thus, the negative influence of knowledge seeking is hidden in the group knowledge seeking.

### Theoretical Implications

First, the results have proved that knowledge sharing behavior which involves knowledge contribution behavior and knowledge seeking behavior has an impact on knowledge sales. While previous studies mainly focus on the impact of knowledge contribution on knowledge sales (Zhao et al., 2018 & Sun et al., 2022), this paper further proved that knowledge seeking behavior can be regarded as another type of important signal when discussing knowledge sales, which has theoretical contributions by validating the role of knowledge seeking behavior on knowledge sales.

Second, the results indicate the relative impact of group knowledge sharing behavior and individual knowledge sharing behavior on knowledge sales. Most previous studies focus on the impact of individual knowledge contribution behavior on knowledge sales (Zhou et al., 2022), less attention has been paid to the role of group knowledge sharing behavior on knowledge sales and the relative impacts of individual behavior and group behavior on knowledge sales.

Third, our study explored the different factors impacting knowledge sales across different knowledge contributors. While previous research mainly focuses on only one type of knowledge contributor (Zhu & Zhang, 2019; Zhao et al., 2018; Zhou et al., 2022 & Sun et al., 2022), our study further explains the boundary considered under which different knowledge sharing behavior in influencing knowledge sharing behaviors.

### Practical Implications

First, based on the results, for grassroots knowledge contributors, both individual knowledge contribution and group knowledge contribution are positively related to knowledge sales. Further, the individual knowledge contribution has a higher impact on knowledge sales compared to the impact of group knowledge contribution. Thus, for grassroots knowledge contributors whose professional competence certification is still lacking, it is important to increase the knowledge contribution especially individual knowledge contribution by answering more questions. For grassroots knowledge contributors, the results show that group knowledge seeking is beneficial while individual knowledge seeking hurts. Thus, the grassroots knowledge contributors should perform more group knowledge seeking behavior like attending lives to enhance their competence.

Second, individual knowledge contribution behavior shows a strong impact on knowledge sales for famous knowledge contributors while group knowledge contribution behavior does not. This indicates that famous knowledge contributors can spend more time mostly on answering free answers than public editing. Further, individual knowledge seeking does not hurt the sales for them, and attending Live is also beneficial which suggests that they can freely ask questions on the platform and attend more Lives to boost knowledge sales.

### Limitations and Future Research

First, we did not collect the data from all the knowledge contributors due to Knowledge's strict control on the amount of data and the limited level of personal crawlers. Thus, further research can find ways to collect more data to test the proposed research model. Second, this study did not consider the impact of types of questions. Further research can classify the questions and test whether the results of the research model will be different across different types of questions.

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