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Promoting sales of knowledge products on knowledge payment platforms: A large-scale study with a machine learning approach

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ABSTRACT

With the digital transformation of the global economy, a new mode of knowledge service has emerged on open innovation platforms such as those for the sharing economy. This mode is the paid knowledge-sharing service, where knowledge providers share knowledge with only those who have paid for it. Since an individual customer's purchases are influenced by others around them, we adopted social influence theory to explain sales of such services on paid knowledge-sharing platforms. A machine learning approach was applied to analyze 27,223 text reviews from the Zhihu Live platform (a well-known and large-scale open knowledge community in China). Hierarchical regression models were built to verify twelve proposed hypotheses about the knowledge providers, knowledge quality, interaction quality, and ratings. The results confirm the positive effect on sales of responsiveness (a dimension of interaction quality), and the negative effect on sales of free provider-driven knowledge contributions.

In summary, this study provides a comprehensive framework for antecedent factors of sales of knowledge-sharing services. By introducing to knowledge management notions from the field of e-commerce (e.g., price, quality), this study broadens the understanding of the free-to-paid phenomenon on knowledge-sharing platforms.

Introduction

Driven both by in-depth implementation of both the 5th-Generation (5 G) strategy and by AI technologies in China, knowledge innovation activities have begun to give rise to unprecedented new phenomena on open innovation platforms such as knowledge-sharing platforms (Chen et al., 2019, 2022; Lytras et al., 2021; Peng & Tao, 2022; Davies et al., 2007; Naeve et al., 2008). Paid knowledge-sharing services, as a new mode of knowledge service, developed from online knowledge-sharing after the initial boom of sharing economy (Dabbous & Tarhini, 2021; Liu et al., 2021). For example, in 2016 *Zhihu* launched a new product, *Zhihu Live,* an online real-time broadcast and Q&A platform featuring pay-for-listening (Zhang et al., 2019).

As in the sharing economy, the core idea of paid knowledge-sharing is shared private knowledge ownership, helping knowledge providers to achieve economic rewards (Belk, 2007; Acquier et al., 2017; Frenken & Schor, 2017). It is also a way to help knowledge seekers to acquire knowledge of higher quality from knowledge-sharing platforms (Wang et al., 2020).

Due to the characteristics of knowledge services and their complex sales arrangements, it is necessary to describe the process. Paid knowledge-sharing services have some features that differ from those of traditional knowledge services (Audretsch et al., 2020; Meng et al., 2021). First, the threshold for being a knowledge provider is low on a paid knowledge-sharing platform (Cai et al., 2020). Even general users, more used to being knowledge seekers, have the opportunity to obtain monetary returns by sharing their knowledge.

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Second, knowledge seekers are purchasing services to solve a specific problem within a broad topic (e.g., fashion and interpersonal communication), not systematically learning about a subject (Cai et al., 2020). Third, the process of interaction is vital to paid knowledge-sharing services, as the product attracts more attention than in a traditional knowledge service. Specifically, it is the interaction between the knowledge provider and seeker that sets paid knowledge-sharing services apart from other digital knowledge services (Cai et al., 2018).

Paid knowledge-sharing services take many forms, such as subscriptions, one-to-one consultatations, Q&As, and live sessions (Fu et al., 2020). A live session, as a real-time broadcast and interaction (Fu et al., 2020), is a combination of two payment modes whereby knowledge providers initially broadcast a keynote talk, sharing their prepared knowledge, then answer questions posted by those who listened to the broadcast (Cai et al., 2018). Besides the keynote talk, the interaction between listener and speaker is important to online learning as it not only increases listeners' 'stickiness' and experience of the learning process but can improve their knowledge internalization, yielding better results (Chen et al., 2019). Because of these characteristics, selling this kind of knowledge-sharing service is highly complex.

One of the keys to sustaining a paid knowledge-sharing platform is improving the sales of its services. However, it is still not clear why knowledge seekers may pay to gain access rather than acquire the knowledge free of charge, especially those who share a common user base with a free knowledge-sharing community, such as *Zhihu Live* and *Zhihu* (Zhang et al., 2019).

Our research intends to explore the antecedents of sales of paid knowledge services from the perspective of social influence. Since paid knowledge-sharing platforms can be seen as e-commerce, service quality is one of the determinants of its sales (Cai et al., 2020). In addition, because the standard of knowledge services can be evaluated only after personal use (Nelson, 1974), the quality perceived before purchase is shaped by social interaction with a knowledge provider (Weathers et al., 2007) and previous buyers, such as customer reviews (Pnina et al., 2018).

In this study we focus on investigating sales of a live session. We divide the session into two parts: knowledge and interaction. We aim to explore four research questions: 1) What is the distinct influence of knowledge quality and interaction quality on the sales of paid knowledge-sharing services? 2) How do providers' free knowledge contributions influence the sales of their paid knowledge-sharing services? 3) How does the rating influence the sales of their paid knowledge-sharing services? 4) How does price moderate the influence of providers' free knowledge contributions and the sales of their paid knowledge-sharing services?

Although studies have explored sales of paid knowledge-sharing services, several research gaps need to be solved. First, although informational and normative social influences have been used to explain the acceptance of public information, such as word-of-mouth in e-commerce (Hu et al., 2019), and customers' reviews (Ismagilova et al., 2019), few studies have explored private knowledge services from the perspective of social influence. Investigations of sales have found a herd effect among customers; that is, an individual's purchase is influenced by others' decisions on paid knowledge-sharing platforms (Cai et al., 2020). Despite its prevalence, from a social influence perspective there is little study of the acceptance of private, paid knowledge services.

Second, although Cai et al. (2020) proved that interaction between speaker and listener is critical to sales of paid knowledge-sharing services, for informational influence determinants of quality few studies have investigated the impact of the interaction's quality (e.g., Q&A between speaker and listeners). This aspect is likely to affect the efficiency of the interaction.

Third, for the informational influence determinants of knowledge providers we should consider knowledge-sharing behaviors in the free community. This is because platforms usually share their user base between the free and paying customers: people have the option to obtain, from a common base of potential knowledge providers, the same knowledge either free of charge or for payment. It is not clear how knowledge providers' free knowledge contributions influence the sales of their paid knowledge-sharing services.

Fourth, normative influence should also be addressed when exploring sales of knowledge-sharing services. It happens because individuals have a propensity to seek approval from other group members, so they follow others' opinions (Henningsen & Henningsen-Miller, 2003). However, on paid knowledge-sharing platforms that feature e-commerce and social community, it is unclear whether customers may purchase a niche knowledge service that is less popular (Brynjolfsson et al., 2011), or instead comply with the majority decision and buy the more highly rated product (Duan et al., 2009).

This study is based on a social influence framework to understand further the sales of paid knowledge-sharing services (Cai et al., 2020), and it distinguishes between informational and normative social influences (Deutsch & Gerard, 1955; Wang et al., 2018; Zhao et al., 2018). Paid knowledge-sharing platforms can be regarded as e-commerce platforms, and a higher price make consumers more cautious (Kim, 2005) and likely to choose a similar yet free alternative (Zhu & Zhang, 2019).

In addition to investigating the influence of information and normative social influencing factors on sales of paid knowledge-sharing services, we consider the moderating role of e-commerce attribution (i.e., price). We propose a research model of knowledge quality, interaction quality, knowledge providers, and ratings from a social influence perspective, and take into account the price.

This study used comprehensive data on providers both from a free knowledge-sharing platform (*Zhihu*) and a paid knowledge-sharing platform (*Zhihu Live*). We adopted a text-mining method to quantify from customers' comments the variables of accuracy, completeness, currency, and empathy in specific knowledge-sharing services. We proposed twelve hypotheses on knowledge providers, knowledge quality, interaction quality, ratings, and price. The model was empirically tested by hierarchical regression.

Besides studying both free and paid platforms in a single study, we focused on the separate roles of detailed dimensions of knowledge quality and interaction quality. Our findings reveal the threats to sales of knowledge-sharing services, such as knowledge providers' provider-driven knowledge contributions and ratings. We also proved that the responsiveness of interaction influences sales positively.

The structure of this study is as follows. Section 2 introduces the paid knowledge-sharing services and social influence theory used in this study. The third explains the development of the hypothesis. The fourth presents the data, research methods, and analysis results of this article. Sections 5 and 6 are the results and discussion. The seventh gives the implications and limitations, and the last section is the conclusion.

Theoretical background

Live session: A paid knowledge-sharing service

Knowledge-sharing is usually understood as the exchange of knowledge between knowledge providers and knowledge seekers (Lee, 2001). It has two sub-processes: one is that knowledge providers externalize their knowledge into information or another externalized form, and the other is that knowledge seekers acquire information and internalize (such as learning) into their own knowledge (Hendriks, 1999).

Knowledge-sharing itself can be regarded as a service, for knowledge owners not only provide knowledge to meet seekers' needs but help them to understand and absorb knowledge (Ipe, 2003).

Depending on whether the knowledge is shared freely or with payment, online knowledge-sharing platforms can be either free or paid (Wang et al., 2020), where paid knowledge-sharing platforms support the individual activities of seeking, providing, sharing, and paying for th access to knowledge-based services (Hamari et al., 2016; Qi et al., 2019).

There are two types of paid knowledge-sharing service: provider-driven or seeker-driven, depending on the user type. Seeker-driven mode is initiated by the knowledge seeker's need to solve a specific problem by payment, and knowledge providers answer their questions for monetary gain; while in the provider-driven mode, knowledge providers actively design the content themselves for one-to-many promotion, and only those seekers who pay for it can obtain the knowledge that is shared (Zhang et al., 2019).

Paid subscriptions, one-to-one consultations, paid Q&As and live sessions are the commonest knowledge services, in practice. Paid subscriptions use a provider-driven mode, where customers pay a monthly or annual fee for access to knowledge-sharing services from a provider, initially in the form of pictures, documents, audio, and video (Zhang et al., 2018). By contrast, one-to-one consultations and paid Q&As are driven by seekers, who post their knowledge requirements. Knowledge providers reply to the request and receive payment (Zhang et al., 2019).

A live session is a combination of the provider- and seeker-driven modes. It is initiated by the knowledge provider delivering a real-time keynote address (broadcast) on a specific topic. Before a session starts, potential customers pay to listen to the broadcast as it is aired, and they have the opportunity to put questions to the live speaker and receive a reply during the broadcast. Even after a live session ends, customers can pay to listen to the recording and these interactions between the speaker and previous listeners. Interactions with knowledge providers can create not only additional benefit for customers (Chen et al., 2019) but additional value in the knowledge services, which rely on providers (Cai et al., 2020). For a live session, customers and knowledge providers co-create value through the interaction of knowledge sharing, which is the most distinctive feature of all knowledge services on paid knowledge-sharing platforms. Moreover, knowledge seekers not only want high-quality knowledge from the professionals; they also want direct interaction with them in the knowledge-sharing community (Chiu et al., 2006). Interaction may be expected of a knowledge service on a paid platform, transited from a social community such as *Zhihu Live* and *Zhihu*.

In this study we focus on live sessions, which are comprised of knowledge (i.e., live content initially created by speakers) and interaction (i.e., questions and answers between speakers and listeners).

Several studies have explored the determinants of sales of knowledge products on paid knowledge-sharing platforms from various theoretical perspectives. It has been found that, from a cue utilization perspective, respondents' cues (experience and popularity on paid knowledge-sharing platforms) and question-related features (i.e., length) are inversely proportional to the number of buyers (Sun et al., 2022). From a social learning perspective, the key antecedents of sales of paid knowledge products include knowledge seekers' identification, reciprocity norms, trust, and commitment (Cai et al., 2020). Furthermore, Cai et al. (2020) found a herd effect among customers whereby an individual's purchases are influenced by the decisions of others on the paid knowledge-sharing platform (Cai et al., 2020). When both knowledge and interactive process are considered regarding the complex real-time dialogue on paid knowledge services, it is not clear what key factors affect sales.

Social influence theory: informational and normative influence

Social Influence Theory (SIT) is a theoretical lens to view the conformity of buyer behavior, influenced as it is by those around them (Burnkrant & Cousineau, 1975; Ifinedo, 2016). Since knowledge services are 'experience goods', from an SIT perspective (Cai et al., 2020), so potential customers' purchasing decisions on a paid knowledge-sharing platform could be based on the quality perceived before the purchase, which is shaped through social interactions with both knowledge providers (Weathers et al., 2007) and previous buyers (such as customer reviews) (Reinstein & Snyder, 2005).

Influence may be of two types: informational or normative (Deutsch & Gerard, 1955; Wang et al., 2018; Zhao et al., 2018). Informational influence refers to how information recipients judge the received information, which may be derived from its quality (such as approximation to the reality) and the provider's power (such as authority and proficiency in the area of questions) (Deutsch & Gerard, 1955; Zhao et al., 2018). On the other hand, normative influence is defined as the degree of conformity to the perceived norms or expectations of others or the group (Deutsch & Gerard, 1955; Zhao et al., 2018).

Both informational and normative social influence have been used to explain knowledge adoption in free knowledge-sharing communities (Chou et al., 2015). Since knowledge seekers may find or receive answers to their questions from providers with varying degrees of expertise in a specific area, they need to evaluate these answers and adopt one. This evaluation process is primarily affected by factors of informational social influence (Wathen & Burkell, 2014). In addition, in the virtual community where knowledge seekers are easily exposed to others' opinions, their evaluation of knowledge adoption is affected by normative influence (Kim et al., 2011).

Social interaction has also been investigated in e-commerce research, referring to the activities that users participate in to influence others' behaviors (Godes et al., 2005). Electronic word-of-mouth (e-WOM) is one of the most critical types of social interaction on online shopping platform (Wang & Yu, 2017). In this study, we focus on social influence on private knowledge services from providers rather than on public information such as e-WOM.

In this study we use social influence theory as our theoretical framework to explain the mechanism of knowledge payment service sales. In the paid knowledge-sharing community, in a critical step in the knowledge-sharing process that reflects the recipient's acceptance, payment for knowledge is promoted by social interaction, especially interaction with knowledge providers. Knowledge services are 'experience goods' so cannot be touched, watched, or felt prior to purchase, so potential customers must form their expectations of the quality through social learning from previous customers (Cai et al., 2020). For example, by observing others' purchasing experiences, potential customers can imitate their purchase behavior, known as vicarious learning, This can be strengthened by social interaction with the model (Myers, 2018). Moreover, in the online market there is an information asymmetry between sellers and buyers (Berger & Gleisner, 2009); before making their purchasing decisions, knowledge consumers are uncertain and feel an ambiguity to knowledge providers. They need cues to evaluate whether are able to give valuable and useful knowledge services, which refers to symbolic payment for learning for knowledge (Cai et al., 2020).

Similar to free knowledge adoption, knowledge purchase can be explained simultaneously by both informational and normative influence. Besides, research has already been undertaken on informational and normative influence on online buyer behavior (Huang et al., 2011; Johnson et al., 2018; de Luna et al., 2019; Park et al., 2019). For example, Huang et al. (2011) studied the impact on movie sales by other people's comments in social media, and found that the visibility and favorability of the comments boosted sales. In addition, Park et al. (2019) found that social influence, through multiple experiential and social benefits, also promotes the adoption of the online payment behavior.

Table 1 describes two social influence processes on a paid knowledge-sharing service platform, observed from the perspective of

Table 1
Underlying framework in our research: social influence theory.

Social influence type	Social influence from providers in the paid knowledge-sharing platforms	Observable factors in this research
Informational influence	Knowledge quality	Accuracy, completeness, currency, format
	Interaction quality	Responsiveness, assurance, empathy
	Knowledge provider characteristics	Social capital, reputation
Normative influence	Ratings of knowledge product	Ratings

knowledge providers (Trenz et al., 2018; Zhang et al., 2019, 2023. We outline how each affects sales of knowledge products.

In the next section we describe our research model and hypothesis development in detail.

Hypothesis development

This study intends to investigate, from the perspective of information and normative social influence, the factors influencing sales of services for paid knowledge-sharing platforms. The research model proposed is shown in Fig. 1, and includes knowledge quality (accuracy, completeness, currency, and format), interaction quality (responsiveness, assurance, and empathy), knowledge provider characteristics (social capital and reputation), free knowledge contribution (provider-driven and seeker-driven), ratings, and price. Of these, knowledge quality, interaction quality, and factors relating to the knowledge provider are the determinants of information influence, while ratings are a normative influence. As an attribution factor in knowledge service, price plays a moderating role between free knowledge contribution and sales. In the following we elaborate arguments for each hypothesis' development.

Informational influence determinants of the quality of paid knowledge-sharing services

The determinants of informational influence have three dimensions: source, message, and receiver (Hovland et al., 1954; Chou et al., 2015). The study of knowledge adoption, features of the source, and the message have been the main focus, from the receiver's perspective, while informational influence is determined by knowledge quality and source credibility (Chou et al., 2015). In order to investigate the sales of knowledge products from the customer's view (i.e., receiver perspective), we focus on features of both the products of knowledge-sharing services (i.e., message factors) and the providers (i.e., source factors).

Quality of paid knowledge-sharing services

Service quality, usually a multidimensional concept, can be understood as consumers' overall view of the extent to which a certain service meets their expected needs (Al-Debei et al., 2022). Since a live session has two parts, the content of transferred knowledge (i.e., a keynote talk) and the interaction between the speaker and listeners, the quality of a paid knowledge-sharing service not only includes the quality of knowledge as a service itself but the interactive quality generated by consumers in absorbing their internalized knowledge while acquiring such services. In this study, we investigate the effects on sales of services by knowledge quality and interaction quality.

Knowledge quality. Since individuals seek knowledge in order to learn (McLure-Wasko & Faraj, 2000) or perform certain tasks (Gray & Meister, 2002), we use the concept of knowledge quality by Kyoon Yoo et al. (2011): "the extent to which the awareness and understanding of ideas, logics, relationships, and circumstances are fit for use, relevant and valuable to context, and easy to adapt". Quality of knowledge can be evaluated by knowledge customers' intrinsic, contextual, and representational views of data and information quality (Rao & Osei-Bryson, 2007). Specially, we focus on four dimensions of knowledge quality: its format (indicating representational aspect); its completeness and currency (indicating contextual aspect); and its accuracy (indicating intrinsic aspects) (Wand & Wang, 1996; Wang & Strong, 1996; Nelson & Todd, 2005; Kyoon Yoo et al., 2011).

Accuracy is defined as the extent to which knowledge is correct, unambiguous, objective, meaningful, and reliable (Wang & Strong, 1996; Kyoon Yoo et al., 2011). Accurate knowledge helps receivers to learn the reality. Beyond the intrinsic view, the contextual view takes into consideration the user, task, and application of knowledge. *Completeness* refers to the extent to which knowledge is sufficient and all relevant content is covered within the task (Becerrafernandez & Sabherwal, 2001; Kyoon Yoo et al., 2011), while *currency* refers to the extent to which the knowledge is up to date, effective, and accurately

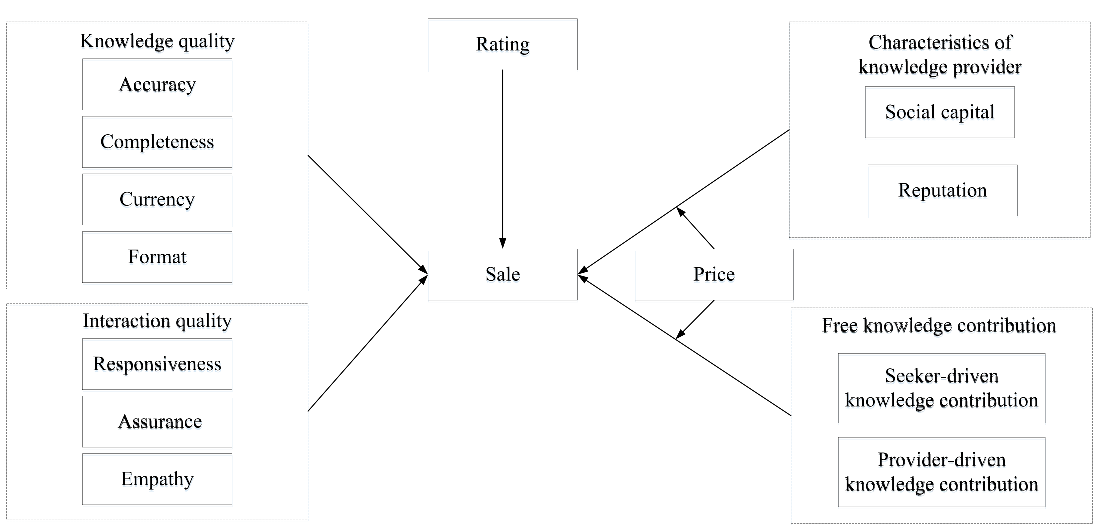

Fig. 1. Theoretical model.

reflects current trends and states (Nelson & Todd, 2005; Kyoon Yoo et al., 2011).

IS research has proved that accuracy, completeness, and currency of information have a significantly positive effect on the performance expectancy of an information system (Nisha et al., 2016) and help to build customers' satisfaction and loyalty (Kumar et al., 2013), so that they are more likely to accept and use the system.

From a representational view, knowledge quality is usually assessed in terms of the extent to which knowledge is presented in a way that helps the receiver's understanding and interpretation (Nelson & Todd, 2005). *Format* is another important dimension of knowledge quality (Yang et al., 2003), and it plays a role in information processing (Tractinsky & Meyer, 1999). Recording or visualizing knowledge in the form of a document, image, or video have been shown to make knowledge more comprehensible and understandable to others (Hendriks, 1999). For these reasons, knowledge with a better format aids in task completion (Nelson & Todd, 2005). In order to learn and complete tasks, consumers evaluate the quality of the knowledge before they make payment, and a live session that is accurate, complete, current, and has a good format sells better. The specific hypothesis 1 (H1) is as follows:

H1. *Accuracy (H1a), Completeness(H1b), Currency (H1c), and Format (H1d) of knowledge has a positive impact on sales of a live session.*

Interaction quality. On paid knowledge-sharing platforms (i.e., Zhihu Live), providers of a live session not only provide the keynote talk but answer listeners' questions about its content. For this reason, the knowledge providers of a live session play a service role. During the broadcast customized personal interactions take place between customer and service provider (Pitt et al., 1995), to the extent to which interaction quality is regarded as a determinant of perceived service quality (Brady & Cronin Jr, 2001). In this study, interaction quality refers to the quality of interaction in a live session between knowledge provider and consumer.

For knowledge service providers, since customers expect to learn or perform certain tasks after accessing the knowledge that they have paid for, this learner-instructor interaction in the online learning environment is an extremely important part of the learning experience (Woo & Reeves, 2007). Through interaction, knowledge providers and customers can exchange knowledge that helps them to achieve better learning outcomes (Kang & Im, 2013).

Interaction quality has three dimensions: responsiveness; assurance; and empathy (Lin, 2012; Nisha et al., 2016). *Responsiveness* refers to the willingness of knowledge provider to assist knowledge customers and provide rapid and agile support (Akter et al., 2010), which enhances their loyalty (Lau et al., 2013). *Assurance* refers to a provider's ability to keep their promises about their product's quality, which helps to build customer trust and confidence in the product (Akter et al., 2010). *Empathy* represents the ability to understand knowledge customers' demands and to offer a personalized service (Akter et al., 2010), and has been found to relate positively to customer satisfaction (Lau et al., 2013). All three dimensions are found to affect customers' performance expectations towards the product (Nisha et al., 2016), for example the information system's utility in task completion (Venkatesh et al., 2003). Hypothesis 2 (H2) is as follows:

H2. *Responsiveness (H2a), Assurance (H2b), and Empathy (H2c) of interaction has a positive impact on sales of a live session.*

Characteristics of knowledge providers

On a knowledge-sharing platform, knowledge seekers are more likely to turn to experts who can provide satisfactory answers (Zhu et al., 2011). In e-commerce the credibility of the information source positively influences a potential customer's acceptance of information such as user comments (Hu et al., 2019). Specifically, in this study we focus on knowledge providers' social capital and reputation.

Social capital. Knowledge providers' social capital can be regarded as a sign of quality, referring to their investment in social relations for an expected return (Stevenson & Radin, 2009). In this study, we conceptualize this investment as the extent to which an individual connects with others, and the return on social capital in terms of an individual's influence in their social network (Stevenson & Radin, 2009).

In previous studies on knowledge-sharing community, social capital has been found to have significant influence on knowledge exchange among participants (Wasko & Faraj, 2005). It has been shown that individuals with more followers often attract attention and favors from others in the virtual community (Wang et al., 2013). This shows the benefits of social capital in a monetary transaction to reducing information asymmetry (Greiner & Wang, 2009). Before making a loan decision, lenders need cues to evaluate whether a borrower can pay back the loan on time. Since borrowers' social capital signals their creditworthiness to potential lenders, those with high social capital are more likely to be funded (Greiner & Wang, 2009). Similar to the lending market, knowledge providers' social capital provides empirical evidence of potential consumers' purchasing behavior (Wang et al., 2016).

Scholars have explored the benefits of social capital to knowledge providers on paid platforms. For example, on medical payment platforms those doctors with higher social reputation and status receive more virtual gifts and monetary returns (Guo et al., 2017). For these reasons, we propose hypothesis 3a (H3a):

H3a. *Knowledge providers' social capital has a positive impact on sales of a live session.*

Reputation. On knowledge-sharing platforms, reputation is defined as the extent to which one is respected and recognized by others (Cai et al., 2020). In research into e-commerce, seller reputation is a critical element in trust building (Cai et al., 2014). It is a positive signal of quality both for the seller (Chu, 1994) and the product (Coff, 2002). The seller's reputation helps to reduce both customers' uncertainty towards their products (McKnight et al., 2002) and the perceived purchase risk (Weiss, 2008). It has been shown that seller reputation significantly influences product sales in the online market (Park & Lee, 2014). Specifically, Cai et al. (2020) found that knowledge providers' reputation refers to approval of a speaker's answers to questions (including the times thanked, upvote count and times 'favorited') in the free Zhihu community, which has proved to boost product sales. We propose hypothesis 3b (H3b):

H3b. *Knowledge providers' reputation has a positive impact on sales of a live session.*

Normative influencing factor: ratings

In contrast to informational influence, which relates to achieving the best possible decisions, normative influence for individuals tends to align with that of other group members (Henningsen, 2003). If there is consensus in the group, namely a shared belief, attitude, or behavior of the majority of members, the other group members are influenced by this consensus and comply with it (Winquist & Larson, 1998). Ratings reflect member congruence in the virtual community (Chou et al., 2015). The rating of a product directly reflects customers' overall usage experience (Wang & Yu, 2017) and encourages potential purchasers to give up to inspect a product's detailed information, which is informational influence (Speier, 2005). Ratings influence potential consumers' decisions by reducing purchase uncertainty (Pavlou et al., 2008) and the cost of their information search (Li et al., 2014), and directly affect purchase behavior (Hsu et al., 2017).

Moreover, for knowledge, it has been proved that knowledge adoption is directly influenced by the normative power of the ratings (Qiu & Dong, 2010). Therefore, for a knowledge-sharing service with high-level ratings, most customers recognize and agree with them. We propose the following as hypothesis 4 (H4):

H4. *Rating has a positive impact on sales of a live session.*

Free knowledge contribution

Knowledge contribution refers to the production and provision of knowledge content (Deng et al., 2020). In the internet age people have a 'free' mentality, thinking that everything online should have no charge (Lin et al., 2013; Chou & Hsu, 2018). Accordingly, although some businesses have been forced to charge users when it became difficult for them to sustain the free business model, few people are willing to pay for what used to be free (Lin et al., 2013; Anzenbacher & Wagner, 2019). For knowledge seekers faced with the choice of purchasing knowledge or getting it free, according to the standard economic theory the rational choice is to pay nothing (Santana & Morwitz, 2011). Moreover, if a knowledge provider makes further contributions of free content, it is likely that potential customers will identify this free substitute for the paid knowledge service. Since knowledge seekers often believe that their needs can be met by the free knowledge, they do not pay to obtain knowledge on a similar topic (Zhu & Zhang, 2019). For these reasons, sales of knowledge-sharing services may be negatively influenced by the sheer volume of relevant free knowledge that is available.

Although a study has already investigated how free knowledge on a relevant topic has a significant and negative effect on the purchase of information (Zhu & Zhang, 2019), for a live session this type of free content contribution can be ignored. This is because we are investigating the influence of the focal knowledge provider's free knowledge contributions on the sales on specifically their live sessions. We propose hypothesis 5:

H5. *Free provider-(H5a) and seeker- (H5b) driven knowledge contribution of the knowledge provider has a negative impact on sales of a live session.*

The moderating role of price

Price is regarded as the most useful information on a service that users can obtain in advance of payment on a paid knowledge-sharing platform, and is critical to the purchasing decision (Yang et al., 2018). It has been studied as a moderator of the relationship between non-monetary factors and the purchase (Kim & Gupta, 2009; Zhu & Zhang, 2019). Since price refers to the actual amount of money that the consumer has to pay (Horton, 1976; Völckner, 2008), it serves as a measure of the cost of a purchase (Völckner, 2008). Since a high price leads customers to perceive high cost, they are more cautious and rigorous about the quality of that provider (Kim, 2005), their integrity, and reputation (Yang et al., 2018). This phenomenon confirms that, upon a price increase, to protect themselves from potential risks potential customers respond with stronger demands on their knowledge providers' social capital and reputation. We propose hypothesis 6 (H6):

H6. *The price reduces the positive influence of providers' social capital (H6a), and providers' reputation (H6b) on sales of a live session.*

Moreover, considering free knowledge contributions, it has been shown that the negative effect of relevant free knowledge on sales is intensified for an expensive knowledge-sharing service (Zhu & Zhang, 2019). In detail, potential customers tend to choose similar free knowledge on free knowledge-sharing platform as an alternativ (Zhu & Zhang, 2019). We propose hypothesis 7 (H7):

H7. *The price strengthens the negative influence of free providers' (H7a) and seekers' (H7b) driven knowledge contribution by the knowledge provider on sales of a live session.*

Data and Method

Research context and data

Since our research is to investigate the impact of free knowledge contributions, knowledge quality, interaction quality, and ratings on sales of paid knowledge-sharing services, comprehensive data on both free and paid providers are required. *Zhihu* (www.zhihu.com) is one of the largest knowledge-sharing communities in China: it has more than 7 million active users (Research, 2018) and huge influence (Sootoo, 2017). It also provides both a free knowledge-sharing platform (*Zhihu*) and a paid knowledge-sharing platform (*Zhihu Live*). In terms of paid knowledge, in 2016*Zhihu* introduced live courses known as *Zhihu Live* (www.zhihu.com/lives). Any user who wants to hold or buy a paid live course in *Zhihu Live* must have a *Zhihu* account. Both platforms share the same user base (that is, there are both free and paid knowledge-sharing platforms in *Zhihu* and *Zhihu Live*) (Zhang et al., 2019); therefore, it is an appropriate and representative provider to serve as our research background.

For a live session, the transaction data, content description, and reviews can be retrieved from *Zhihu Live*, while information on knowledge providers can be retrieved from *Zhihu*. In the Zhihu community, the knowledge providers may answer questions without payment or rewards, publish articles or column articles free of charge, and demonstrate attention to fellow users in various ways. Based on these features of *Zhihu*, we selected seven attributes relevant to our social influence-sales model, making them match as closely as possible the basic measures in the model. Table 2 presents the information on these properties in detail.

In this study, a public data set of 795 live sessions broadcast from October 1, 2016 to September 30, 2017, as well as their 30,891 reviews, was crawled from *Zhihu Live* by network spiders. Since we focused on the influence of individuals' free knowledge-sharing behaviors on sales of knowledge service, live sessions held by organizational accounts were beyond the scope of this research, and we removed them. Some 777 live sessions with a total of 27,223 reviews became our study sample. For each live session, with the speakers' identification, we crawled data about knowledge providers in *Zhihu*. Finally, we combined the information on live sessions with their knowledge providers' characteristics and content contributions according to the speakers' identification.

Measurements

The dependent variable of this research is *sale (S)*, which is measured by the total number of product transactions; that is, the sum of

Table 2
Description of the dataset.

Item of behavior data	Explanation
Upvote count	The number of positive votes the user has received.
Times favorited	The number of this user's replies, threads, and articles collected by other users.
Times thanked	The number of times this user's answers have been marked as appreciated by other users.
Answers posted	The number of answers that this user has posted.
Articles posted	The number of articles that this user has posted.
Columns posted	The number of column articles that this user has posted. Zhihu has set several specific article topics, if an article is related to one of these topics, it is a column article, while others belong to the article.
Follower count	The number of people following this user's contributions.

transactions before and after broadcast. *Price (P)* is the moderating variable, measured by how much money a potential customer must pay for access to the knowledge service. Since knowledge transfer is socially influenced in virtual communities (Chou et al., 2015), the independent variables of this research fall into three categories: informational determinants (i.e., characteristics of knowledge providers, knowledge quality, and interaction quality); normative influence (i.e., ratings), and the free content contributions.

Informational determinants can be subdivided by whether they have a provider or product perspective. Characteristics of knowledge providers include reputation and social capital. *Social capital* (*Qsc*) is measured by the number of followers in the knowledge-sharing community (Wang, 2016). *Reputation* (*Qrep*) refers to the ability of a user to influence others, and is measured by the sum of the upvote count, number of times thanked, and the number of 'favorited' items collected (Deng et al., 2020). As for knowledge providers' free content contributions, we considered both the provider- and seeker-driven modes. The *Seeker-driven knowledge-contribution* (*Qsdkc*) is measured by the number of free answers that a user has posted to questions initiated by other knowledge seekers, while the *provider-driven knowledge-contribution* (*Qpdkc*) is measured by the sum of articles posted and columns posted that this user has posted that are not in response to questions.

As mentioned above, in this study knowledge-sharing service quality can be disaggregated into knowledge quality and interaction quality. Based on prior work considering the intrinsic, contextual, and representative dimensions of knowledge quality (Nelson & Todd, 2005), we extracted the core features of knowledge quality: accuracy, completeness, currency, and format (Wand et al., 1996; Wang & Strong, 1996; Nelson & Todd, 2005; Kyoon Yoo et al., 2011).

We measured the first three dimensions through reviews. From a total of 27,223 reviews, we selected 2503 comments and manually annotated each sentence in relation to the dimensions of *accuracy, completeness,* and *currency*, and applied a deep learning approach, XGBoost, to predict the labels for the remaining reviews (see Appendix A for details). To discriminate between the influence of the review counts, the measurement items of *accuracy, completeness,* and *currency* were as follows: number of reviews about accuracy divided by the review count for the product (*Racc*); number of comments about completeness divided by the review count for the product (*Rcom*); and number of comments about currency divided by the review count for the product (*Rcur*).

Since format is regarded as the extent to which knowledge is represented in a way that contributes to knowledge receivers' understanding and interpretation (Nelson & Todd, 2005), *format* is measured by the number of attachments uploaded in the *Live* (*Qfor*).

Interaction quality has three dimensions of responsiveness, assurance, and empathy. *Responsiveness* is measured by the number of replies to answers during the broadcast (*Qres*). *Assurance* is a binary variable *(Qass)* of 1, which means that this knowledge service is guaranteed to be refunded within seven days with no need for explanation. *Empathy (Qemp)* is measured by the knowledge services' comments (see Appendix A for details), namely the number of comments about empathy divided by the review count for the product.

For a normative determinant, in this study we focused on *rating (R),* which is measured by the mean of the rating scores by customers. For each live session, customers can rate for them from 1 to 5 in integer scores. In Table 3 we summarize the descriptions and measurement sources of all variables.

Descriptive statistics

Data from 777 live sessions, covering 17 professional fields, were selected as the study sample. Education (145, 18.66 %), Career (102, 13.13 %) and Internet (91, 11.71 %) were three of the most active themes on the *Zhihu Live* platform. For each live record we collected 14 variables, and Table 4 describes the statistics for all variables in this study, including minimal, maximal, mean value, and standard deviation.

Empirical model and analysis

Empirical model

To investigate the influence in the online learning environment by the knowledge-sharing service's quality, knowledge providers' characteristics, and ratings on sales of services, we used a hierarchical regression model to test the hypotheses in three steps. In the first, 12 independent variables were included in the regression equation to form model 1. Based on model 1, model 2 adds *price (P)*. In model 3, four interaction terms were added to the regression equation. Equations (1), (2) and (3) for these three models are shown in the following, where subscript i indicates i^{th} *Live* in our dataset.

In these equations, multipliers of two variables represent the interaction effect. Since variables have differing scales in this study, before regression analysis we standardized all variables. We reported partial F tests on the significance of the added variables. For the moderating effect, if *R*-square of model 3 was significantly greater than that of model 2 and coefficients for interaction items were significant, we concluded that price moderates some main effects.

Analysis method

In this study, multiple OLS regression analysis was applied to test the validity of our model (Trenz et al., 2018; Zhang et al., 2019, 2023). Regression analysis is often used to explore relationships within data, especially causal relationships. If the predictor variable was set be to a function of multiple independent variables, multiple regressions were used (Keith, 2019).

According to Wen et al. (2005), when independent variables and moderating variables are continuous, hierarchical regression can verify the moderating effect.

Results

STATA 15 was used to analyze the data. To ensure that the variables are independent of each other, we conducted Pearson correlation analysis. The correlations between the independent, the dependent, and moderating variables are shown in Table 5. Since all correlation coefficients are less than 0.8, there is no strong linear correlation (Hinkle et al., 2003).

The results for the regression analysis are reported in Table 6.

Model 1 includes all 12 independent variables, and *sale (S)* as the dependent variable for regression analysis. The value of adjusted *R*-square is 0.237, indicating that 24.9 % of sales can be explained by changes of the variables in Model 1. The value of the F test is 21.14 ($p < 0.001$), indicating that the regression effect is significant. For variables about knowledge quality, coefficients of four dimensions are not significant, so that H1a to H1d are not supported. For interaction quality, the coefficient of responsiveness is both positive and significant ($\beta_{9,\ \mathrm{model1}}$= 0.096, $p < 0.001$), so that only H2a is supported.

For variables about characteristics of knowledge providers, the coefficients of reputation (*Qrep*) and social capital (*Qsc*) are both positive and significant ($\beta_{1,\ \mathrm{model1}}$=0.568, $p < 0.001$; $\beta_{2,\ \mathrm{model1}}$= 0.270, $p < 0.001$). H3a and H3b are supported. The coefficient of rating is significant but negative ($\beta_{12,\ \mathrm{model1}}$= −0.031, $p < 0.01$), so that H4 is contradicted supported. As for the free knowledge contribution, the coefficient of provider-driven knowledge contributions (*Qpdkc*) is significantly negative ($\beta_{4,\ \mathrm{model1}}$= −0.108, $p < 0.01$), while the coefficient of the seeker-driven knowledge contribution (*Qsdkc*) is not significant. H5a is supported, while H5b is not supported.

Based on model 1, price is added to form model 2. The significance of the price variable (P) is shown both by its t-statistic ($\beta_{13,\ \mathrm{model2}}$= −0.097, $p < 0.01$) and by the significance of the partial F test

Table 3
Construct, measurement and variable.

Theoretical construct	Dimension	Sub-dimension	Definition	Measurement	Variable
Quality of Paid Knowledge-Sharing Services	*Knowledge Quality*	Accuracy	The degree to which the knowledge is correct, unambiguous, objective, meaningful and reliable (Wang & Strong, 1996; Kyoon Yoo et al., 2011).	Number of reviews about accuracy divided by the review count for the product	*Racc*
		Completeness	The degree to which knowledge is sufficient and the extent to which all relevant contents are covered within the task (Becerrafernandez & Sabherwal, 2001; Kyoon Yoo et al., 2011)	Number of comments about completeness divided by the review count for the product	*Rcom*
		Currency	Currency refers to the degree to which knowledge is latest, effective, or to what extent knowledge can accurately reflect the current trends and states (Nelson & Todd, 2005; Kyoon Yoo et al., 2011).	Number of comments about currency divided by the review count for the product	*Rcur*
		Format	How knowledge is presented in a way that helps knowledge receivers' understanding and interpretation (Nelson & Todd, 2005).	Number of attachments uploaded in the Live	*Qfor*
	Interaction Quality	Responsiveness	The willingness of knowledge providers to assist knowledge customers and provide rapid and agile support (Akter et al., 2010)	Number of replies to the answers during the broadcasting	*Qres*
		Assurance	The providers' ability to keep their promise about products' quality, which will help customers to build trust and confidence in the product (Akter et al., 2010)	A binary variable, which values 1 means that this knowledge service is assured to be refunded within seven days without reasons	*Qass*
		Empathy	The ability to understand knowledge customers' demands and the ability to offer personalized service (Akter et al., 2010)	Number of comments about empathy divided by the review count for the product	*Qemp*
Knowledge contribution	Provider-driven knowledge contribution		For provider-driven mode, knowledge providers actively design content themselves for one-to-many promotion, and only seekers who pay for it can get the shared knowledge (Zhang et al., 2019).	Sum of articles posted and columns posted that this user has posted initially without responding to the questions	*Qpdkc*
	Seeker-driven knowledge contribution		Initiated by knowledge seeker's need to solve the specific problem with paying, and knowledge providers answer questions and get monetary returns (Zhang et al., 2019).	Number of free answers that this user has posted to questions initiated by knowledge seekers	*Qsdkc*
Rating			Member congruence in the virtual community (Chou et al., 2015). Rating score of a product directly reflects the overall usage experience of customers (Wang & Yu, 2017)	Mean of rating scores given by customers	*R*
Price			The actual amount of money the consumer has to pay for the product (Horton, 1976; Völckner, 2008)	How much money potential customers should pay to get the access to the knowledge service	*P*

(ΔF=9.006, $p < 0.01$). Also, the adjusted R-square increases to 0.245. In the third level regression, model 3 introduces 12 interaction items about price (P) into the regression equation, such as $Qrep * P$, as independent variables. The results show that model 3 performs better than model 2, with adjusted R-square increases to 0.272, and the ΔF value is 8.04 ($p < 0.01$), indicating an interaction effect. In model 3, the coefficient of interaction item ($P * Qsc$) is negative and significant ($\beta_{15,\ \text{model3}}= -2.43$, $p < 0.01$), while the coefficient of $P * Qpdkc$ is positive and significant ($\beta_{17,\ \text{model3}}= 0.934$, $p < 0.05$). Other coefficients of interaction terms are not significant, so price moderates only the main effect on sales by social capital and provider-driven content-contribution. H6a is supported, while H6b and H7b are not supported. Moreover, H7a is contradicted.

Discussion

Based on social influence theory, this study investigates the impact of three groups of factors on the sale of paid

Table 4
Descriptive statistics.

Variable type	Variable	Min.	Max.	Mean	Std.
Independent variable	***Qrep***	0.00	6,177,643.00	150,592.41	315,876.01
	Qsc	35.00	1,489,540.00	51,406.61	108,002.57
	Qsdkc	0.00	4531.00	223.51	393.90
	Qpdkc	0.00	1526.00	52.56	150.91
	Racc	0.00	0.50	0.74	0.69
	Rcom	0.00	0.67	0.12	0.88
	Rcur	0.00	0.43	0.06	0.06
	Qfor	0.00	181.00	19.53	22.29
	Qres	0.00	258.00	29.36	33.76
	Qass	0.00	1.00	0.38	0.49
	Remp	0.00	0.57	0.08	0.07
	R	4.00	5.00	4.54	0.26
	P	RMB 5.99 (US$0.92)	RMB 199.00 (US$30.59)	RMB 22.69 (US$3.52)	RMB 18.69 (US$2.87)
Dependent variable	***S***	50.00	31,445.00	1554.54	2966.82
	Number of effective cases	777.00			

knowledge-sharing services: knowledge quality; interaction quality; and knowledge provider. The empirical results show the following.

First, knowledge providers' social capital, reputation, free provider-driven knowledge contributions, and ratings directly influence sales of paid knowledge-sharing services, consistent with the findings of Ghahtarani et al. (2020). However, unlike previous studies (Qiu & Dong, 2010), higher ratings are not necessarily good for knowledge service sales. In online shopping, potential buyers may prefer niche products that are less popular with customers (Brynjolfsson et al., 2011). Specifically, on paid knowledge-sharing platforms knowledge customers opt not to change their behaviors to fall into line with member congruence (i.e., ratings).

Second, free provider-driven knowledge contributions by the knowledge provider have a negative impact on the sales of a live session, yet free seeker-driven knowledge contributions do not have the same effect. One reason may be that both the keynote talk aspect of a live session and the free articles are provider-driven knowledge sharing. Besides, since both are well organized around a specific topic (Zhang et al., 2019), free articles can be regarded as a good substitute for a keynote talk at a live session.

Third, price weakens both the positive influence of providers' social capital and the negative influence of free provider-driven knowledge contributions on the sales of a live session. It happens because, besides the cost signal, price can be regarded as an indicator of quality (Erdem et al., 2008). Since low prices lead to less perception of the product's value (Zhu & Zhang, 2019), customers are more likely to turn to substitutes such as free knowledge.

Theoretical and practical implications

Theoretical implications

From the theoretical view, this study focuses on a new knowledge-based services and contributes to the paid knowledge-sharing service in the three ways. First, we discriminate between the role of knowledge quality and interaction quality on sales of a paid knowledge-sharing service. Unlike the other three knowledge-sharing services (i.e., paid subscriptions, one-to-one consultations, and paid Q&As), a live session is a combination of provider-driven and seeker-driven knowledge-sharing. The interaction between the speaker and customer is an important feature of emerging knowledge-sharing services, distinguishing them from other virtual goods (Cai et al., 2020). Although some studies on paid knowledge-sharing have focused on customer satisfaction (Zhang et al., 2019; Fu et al., 2020) to explain sales of knowledge-sharing services, the frequency of a customer's payments (Shi et al., 2020), the number of times that a knowledge provider is paid (Yang et al., 2018), and other factors about the interaction are underexplored.

Our results show that a live session's sales are boosted by the quality of the interaction, while its quality of knowledge has no significant influence. Moreover, by exploring the detailed sub-dimensions of the interaction's quality (i.e., responsiveness, empathy, and assurance, we find that what leads to further sales of a live session is its responsiveness.

Second, we extended the application of social influence theory to paid knowledge-sharing service research. In detail, we implied a

Table 5
Pearson correlation analysis.

	Qrep	Qsc	Qsdkc	Qpdkc	Racc	Rcom	Rcur	Qfor	Qres	Qass	Remp	R	P	S
Qrep	1	.795**	.421**	.340**	−0.111**	−0.106**	−0.084*	−0.013	.139**	−0.191**	−0.123**	.026	.059	.443**
Qsc	.795**	1	.315**	.322**	−0.125**	−0.109**	−0.109**	−0.049	.083*	−0.201**	−0.108**	.000	.156**	.422**
Qsdkc	.421**	.315**	1	.302**	−0.046	−0.077*	−0.098**	−0.062	.217**	−0.088*	−0.065	.074*	−0.012	.145**
Qpdkc	.340**	.322**	.302**	1	−0.048	−0.038	−0.034	.018	.047	−0.119**	−0.103**	−0.007	.172**	.060
Racc	−0.111**	−0.125**	−0.046	−0.048	1	.544**	.686**	.119**	−0.080*	.300**	.400**	.311**	−0.049	−0.122**
Rcom	−0.106**	−0.109**	−0.077*	−0.038	.544**	1	.497**	.106**	−0.081*	.350**	.567**	.281**	−0.060	−0.113**
Rcur	−0.084*	−0.109**	−0.098**	−0.034	.686**	.497**	1	.133**	−0.076*	.331**	.337**	.262**	−0.102**	−0.080*
Qfor	−0.013	−0.049	−0.062	.018	.119**	.106**	.133**	1	−0.043	.063	.085*	.208**	−0.008	−0.024
Qres	.139**	.083*	.217**	.047	−0.080*	−0.081*	−0.076*	−0.043	1	−0.132**	−0.036	.094**	−0.055	.175**
Qass	−0.191**	−0.201**	−0.088*	−0.119**	.300**	.350**	.331**	.063	−0.132**	1	.306**	.217**	−0.210**	−0.148**
Remp	−0.123**	−0.108**	−0.065	−0.103	.400**	.567**	.337**	.085*	−0.036	.306**	1	.257**	−0.072*	−0.117**
R	.026	.000	.074*	−0.007	.311**	.281**	.262**	.208**	.094**	.217**	.257**	1	.059	−0.078*
P	.059	.156**	−0.012	.172**	−0.049	−0.060	−0.102**	−0.008	−0.055	−0.210**	−0.072*	.059	1	−0.064
S	.443**	.422**	.145**	.060	−0.122**	−0.113**	−0.080*	−0.024	.175**	−0.148**	−0.117**	−0.078**	−0.064	1

* : Correlation is significant at the 0.01 level(2-tailed);.

** : Correlation is significant at the 0.05 level(2-tailed).

Table 6
Results of hierarchical regression.

	Sale (S)		
Predictive variables	Model 1	Model 2	Model 3
Reputation (Qrep)	0.568***	0.533***	0.413*
Social capital (Qsc)	0.270***	0.300***	0.666***
Seeker-driven knowledge contribution (Qsdkc)	−0.042	−0.050	−0.024
Provider-driven knowledge contribution (Qpdkc)	−0.108**	−0.092*	−0.245*
Accuracy (Racc).	−0.026	−0.023	−0.028
Completeness (Rcom)	−0.002	0.001	0.004
Currency (Rcur)	0.022	0.017	0.020
Format (Qfor)	0.013	0.012	0.018
Responsiveness (Qres)	0.096***	0.090***	0.087***
Assurance (Qass)	−0.003	−0.007	−0.007
Empathy (Remp)	−0.027	−0.029	−0.033
Rating (R)	−0.031*	−0.025*	−0.027*
Price (P)		−0.097**	0.002
P * Qrep			−1.19
P * Qsc			−2.43**
P * Qsdkc			−0.356
P * Qpdkc			0.934*
R^2	0.249	0.258	0.288
Adjusted R^2	0.237	0.245	0.272
F	21.140	20.411	18.077
ΔF		Model 1 vs. 29.006**	Model 2 vs. 38.040***
ΔR^2		0.009	0.030

* Significant at 0.05 level;.
** Significant at 0.01 level;.
*** Significant at 0.001 level;.

partial explainability of social influence in knowledge service research, where informational influence is supportive and normative influence is not susceptible of explanation. From the social influence perspective, paying for knowledge can be seen as a social process; that is, customer purchases are influence by others.

In this study, we focus on informational and normative social influences as potential predictors of sales of knowledge services. While previous studies have focused on the informational influence of public information (Chou et al., 2015; Ismagilova et al., 2019), we considered the informational influence of private knowledge services. We showed that customers' perception of both the reality of services and the knowledge provider's ability boost sales, in line with informational social influence, but that normative social influence is not suitable to explain purchasing in the context of knowledge-sharing. In opposition to normative influence, on a paid knowledge-sharing platform the ratings actually depress sales, meaning that customers have no tendency to act in line with group members but, instead, pursue individualization.

The results also show that the use of social influence theory is applicable to test individuals' knowledge adoption empirically in virtual communities. Therefore, the model proposed provides a theoretical basis for researchers to explore further knowledge adoption domains, such as online knowledge adoption behaviors or theories of online knowledge adoption.

Third, this study extends our understanding of the free-to-paid phenomenon. We examine both how knowledge providers' free knowledge contributions influence their services' sales on a live session platform and the moderating role of price. We distinguish the influence of two types of knowledge contribution, provider- and seeker-driven, and have explored each.

Previous research has investigated how the popularity and number of free knowledge products relate to the knowledge service's influence over customer purchases (Zhu & Zhang, 2019). However, in studying the substitution effect between free and paid knowledge, the role of the knowledge provider cannot be ignored. If a knowledge provider does not consider the processes of knowledge creation (such as learning and knowledge internalization), their knowledge base is not extended (Rowley, 2010) so they can provide only similar content (such as experience, skills, views, and suggestions) on a specific topic, whether free or paid.

Our results show that the more provider-driven knowledge that a knowledge provider makes available, the fewer the sales of their live sessions. However, price can moderate the negative relationship between free provider-driven knowledge and sales of a live session's sales. This is because price is a sign of quality, and customers on paid knowledge-sharing platforms perceive expensive products to have greater value (Zhu & Zhang, 2019). For this reason, the sales of an expensive live session are diminished less by its provider's free provider-driven content contributions.

Practical implications

This study provides suggestions for paid knowledge-sharing platform managers and knowledge providers to increase their knowledge sales. According to the results of our research, knowledge providers' social capital, reputations, and free provider-driven knowledge contributions boost their sales of paid knowledge-sharing services.

To obtain more followers, it can be seen that knowledge providers should improve their social capital by answering questions and interacting with others in the community free of charge. To improve their reputation, they should create high-quality content in the free community. In addition, our research shows that free provider-driven knowledge contributions by knowledge providers depress the sales of a live session. Providers should be careful not to over-provide free knowledge, as it is not good for their product sales. While it may attract new consumers and retain existing ones, consumers may not want to part with their money for knowledge while the free knowledge is readily available. Therefore, providers should be careful about their active content contributions and not post too many articles in the free community.

Our research also shows that it is important for providers to set suitable prices for their knowledge services, as this can relieve the side effects of active free content contribution. This means that when the same degree of free knowledge is obtained, consumers are more likely to buy the dearer products than the cheaper ones. It may be because consumers believe that expensive knowledge products represent better value; that is, the price of paid knowledge products should be appropriate, as cheap is not necessarily good.

Meanwhile, the quality of the interaction between the knowledge provider and consumers is critical. Knowledge providers should help consumers to internalize their content by actively responding to questions, as this helps to stimulate consumers' purchase intentions.

Managers of paid knowledge-sharing platforms should also help to promote the social capital, reputation, of knowledge providers. First, build knowledge communities. Communities can provide opportunities for knowledge providers to participate in social activities. It is easy for knowledge providers to establish social capital and improve reputation in an active knowledge-sharing community so that their knowledge services' sales are also increased.

Second, emerging platforms should design features to promote interaction during the knowledge-sharing process. Beyond the real-time Q&As in a live broadcast, there should be interaction chances afterwards. For example, each live session could have a discussion group comprised of all the speakers and paying customers.

Third, our research suggests that ratings may not be a significant factor in sales of paid knowledge products. Customers prefer an individualized knowledge service to complying with the view of other members, therefore it is critical for platforms to refine their recommendation system. They should recommend knowledge services according to the individual's requirements and preferences, focusing on differences between customers rather than their common interests.

Limitations and future research

This study has several limitations that future research may address. First, it did not categorize the market to explore separately knowledge-sharing services' sales mechanisms. Sub-dimensions of knowledge quality and interaction quality of a knowledge-sharing service in the specific field might have dissimilar influence on sales. For example, customers who purchase knowledge-sharing services in one field (such as stock) may emphasize accuracy and currency more than those purchasing knowledge services in a field such as photography.

Second, this study builds only a static model to explain the sales of knowledge-sharing services. Future studies could use machine learning methods, such as a hidden Markov model, to explore a process model to explain dynamically paid knowledge-sharing platforms.

Conclusion

This study mainly investigated, from a social influence perspective, the influence on sales of knowledge-sharing services by service quality, knowledge providers' characteristics, and ratings. To explain the role of knowledge providers' free knowledge contributions we collected data from *Zhihu Live* and *Zhihu* to test our research model, and this supported some important hypothesized relationships.

Our main findings reveal that there is indeed informational influence on sales of a live session, where there is a negatively normative influence. Overall, from the perspective of social influence, this study reveals the key factors of the sales of paid knowledge-sharing services. The findings add new knowledge to the field of knowledge services and provide useful insights for researchers and practitioners.

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Appendix A

In order to retrieve semantic information from the text of user reviews, these text was projected to a low-dimensional semantic space using Paragraph Vector (Chen et al., 2015), which has proven to be powerful and efficient in multiple text-mining tasks including sentiment analysis (Le & Mikolov, 2014). After training our semantic model with 27,223 reviews from *Zhihu Live*, each was represented by a K-dimensional, real-valued vector. After several trials with different K values for text features, the optimal number of K was found to be 200.

Table A-1
Test results of variable prediction.

	Accuracy	Completeness	Currency	Empathy
Accuracy	0.892	0.770	0.874	0.709
RMSE	0.291	0.435	0.375	0.468

To simplify the training, the variables, including *Accuracy, Completeness, Currency,* and *Empathy*, were considered as dummy variables in our model. Each variable was labeled as either 1 if the review conveys the corresponding meaning, or 0 if it does not mention it. To construct the training set, a portion of the dataset containing 2503 reviews was labeled manually. A deep learning approach, known as XGBoost, was applied to predict the variables of the rest of reviews. To cross-validate the prediction accuracy, all manually labeled data were randomly divided into a training set with 2003 reviews and a cross-validation set with 500 reviews. After training the XGBoost classifier, the prediction for the cross-validation set was compared to the ground truth to validate its reliability. The test result (see Table A-1) indicates acceptable reliability for predictions of variables, with an average accuracy of over 0.7 for each variable.

Although there are some errors in understanding information relating to *Completeness* and *Empathy*, this can be considered to be an acceptable level. Therefore, our method is reliable to retrieve text information and generate variables for further analysis.

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