A Causal Configuration Analysis of Payment Decision Drivers in Paid Q&A

Wenyu Chen, Yan Cheng[†], Jia Li

School of Business, East China University of Science and Technology,
Shanghai 200237, China

Abstract

Purpose: This paper examines factors of payment decision as well as the role each factor plays in casual configurations leading to high payment intention under systematic and heuristic information processing routes.

Design/methodology/approach: Based on heuristic-systematic model (HSM), we propose a configurational analytic framework to investigate complex casual relationships between influencing factors and payment decision. In line with this approach, we use fuzzy-set qualitative comparative analysis (fsQCA) to analyze data crawled from Zhihu.com.

Findings: The number of previous consultations is a necessary element in all five equivalent configurations which lead to high intention in payment decision. The heuristic processing route plays a core role while the systematic processing route plays a peripheral role in payment decision-making process.

Research limitations: Research is limited in that moderating effect of professional fields has not been considered in the framework.

Practical implications: Configurations in results can assist managers of knowledge communities and paid Q&A service providers in the management of information elements to motivate more payment decision.

Originality/value: This paper is one of the few studies to apply HSM theory and fsQCA method with respect to the payment decision in paid Q&A.

Keywords Payment decision; Paid Q&A; Dual-process theory; Configurational paradigm; Fuzzy-set qualitative comparative analysis (fsQCA)

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[†] Corresponding author: Yan Cheng (Email: yancheng@ecust.edu.cn).

1 Introduction

The information age emphasizes the economic value of knowledge. As a typical representative of the knowledge economy, the emergence and development of paid Q&A provide a new way for knowledge sharing and knowledge diffusion. Paid Q&A is a knowledge payment operation mode based on voice chat launched by online Q&A communities. Users with professional knowledge and trading willingness can apply to become knowledge contributors and command a price for each consultation. Paid Q&A provides a list of knowledge contributors along with some detailed information on its interface. Users with corresponding consulting needs can browse the list to filter and select suitable knowledge contributors and quickly obtain answers by asking questions and paying for the consultation. Meanwhile, knowledge contributors can trade their expertise and build self-reputation through paid Q&A. Paid Q&A service highlights the value of knowledge and improves the efficiency of knowledge acquisition. However, users in paid Q&A generally do not know each other, which makes it difficult for askers to judge knowledge contributors' abilities and make payment decision. Furthermore, paid Q&A does not provide a refund service as long as answers are given within the maximum response time (usually 48 hours) in order to protect knowledge contributors' rights and interests. Askers have to pay the consulting fee first but can only judge the answer quality afterwards. Information asymmetry, uncertainty of answer quality, and other factors may present obstacles to askers in decision-making. At present, it seems only a few head knowledge contributors who are considered as backbone of paid Q&A can continually receive consultations from askers. Remaining knowledge contributors are usually unattractive in motivating payment decision. The sustained and healthy development of knowledge payment service is facing a bottleneck.

Under such a dilemma, the public information provided by Q&A communities may motivate askers to make payment decision, such as (1) knowledge contributor's profile; (2) knowledge contributor's interactive behavior data generated in communities; (3) previous askers' feedback including comments and rating scores; (4) price askers need to pay for answers. When faced with various reference information above, askers spontaneously choose different information processing routes to make an evaluation of knowledge contributors' abilities. Some askers tend to spend more time in analyzing all relevant pieces of information to ensure that they have chosen the most appropriate knowledge contributor, while some other askers pursue efficiency in decision-making and only concentrate on information available. Information elements contained in different processing routes can be combined into multiple configurations to achieve equally high payment intention.

Askers can minimize the information asymmetry by processing related information and thus make sensible payment decision. Paths leading to high payment intention are important for Q&A communities to rationally configure various information elements on the web interface so that an increase can be facilitated in askers' searching efficiency as well as payment willingness. Therefore, how to make multiple configurations of factors to achieve high payment intention according to askers' information processing routes is a research problem awaiting further attention.

The rest of this paper is organized as follows: in Section 2, we offer a literature review of related works and introduce some theories used in our study. In Section 3, we conceptualize our research framework and develop propositions. In Section 4, we describe our research methodology, including the data collection and fsQCA. In Section 5, we present the fsQCA results and compare in detail the configurations that lead to high payment intention at different price levels. Analysis of sufficiency for low/medium intention in payment decision as well as the test for predictive validity is also performed. Finally, we discuss implications and limitations of this paper in Section 6.

2 Literature review

2.1 Payment decision

Payment decision in paid Q&A refers to the purchase behaviors askers carry out to get professional answers. The records of payment decision are important information for Q&A communities to do personalized recommendation. Different from traditional e-commerce, knowledge contributors' expertise traded is intangible. Askers cannot get any objective information about answers other than price while making payment decision. Considering the characteristics of paid Q&A service, existing literature on payment decision mainly studied influencing factors from three aspects: knowledge contributors' ability and credibility, askers' perception about answers, and price.

From typical studies in Table 1, we can see that influencing factors of payment decision are diverse and numerous. The selection of factors is based on research aims and service features. Knowledge contributors' characteristics such as number of followers and personal information integrity (Zhao et al., 2018) can help convey information about their ability and credibility. These factors usually have a positive effect on the final payment decision since they are helpful in building trust. Askers' perception about answer quality, answering speed and so on (Zhao et al., 2020) constitutes their subjective estimation about service. These factors are proved to be important for payment decision. Some studies pay attention to the effects of monetary

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incentives on payment decision (Zhang, Zhang, & Zhang, 2019). It is necessary for communities as well as knowledge contributors to proactively adopt flexible operation strategies according to different prices to motivate payment decision.

Table 1. Selected studies on payment decision in paid Q&A.

Scholar	Method	Conclusion
1. Perspective: knowledge contributors' ability and credibility		
Zhao, Zhao, Yuan, & Zhou (2018)	Negative binomial panel regression	Knowledge contributors' reputation, ability and personal information integrity play a positive role on askers' willingness to pay while price plays a positive regulatory role.
Yan, Leidner, Benbya, & Zou (2019)	Granger causality test	Knowledge contributors' structural capital and relational capital, such as personal information integrity and followers, have a positive influence on askers' payment decision.
2. Perspective: askers' perception about answers		
Morris (2010)	Survey study	Answering speed and quality of answers can be valued as influencing factors when making payment decision.
Zhang, Hu, & Fang (2019)	Semi-structured interviews	Askers participate in paid Q&A for answerers' heterogeneous resources, credible answers and cognition of questions.
3. Perspective: price		
Harper et al. (2008)	Field study	Higher price will lead to askers' trust in answer quality, which will encourage their payment intention.
Zhang, Zhang, & Zhang (2019)	Text mining; Hierarchical OLS regression	The influence of price on askers' motivation in making payment decision might differ according to their knowledge levels. Expert askers are less sensitive to price.

Most of these studies are all based on theories such as perceived value (Li et al., 2017), trust (Zhao et al., 2018), and social capital (Ghahtarani, Sheikhmohammady, & Rostami, 2020), concentrating on the influence of single variable. However, none of these factors works separately on the final payment decision. Instead, complex interactions may exist between factors. We lack studies that explain how and under what conditions such factors will combine up to achieve high payment intention. This study aims to fill this gap in payment decision literature.

2.2 Heuristic-systematic model

The heuristic-systematic model (HSM) proposed by Chaiken (1980) is a widely recognized communication model that attempts to explain how individuals receive and process persuasive messages, establish validity assessments, and later form decision. HSM includes two broad information processing routes. The systematic processing route indicates that individuals use a lot of cognitive efforts to process all relevant pieces of information and form judgments (Todorov, Chaiken, & Henderson, 2002). On the contrary, the heuristic processing route suggests that individuals consider relatively few superficial informational cues and adopt heuristic

decision rules to quickly form judgments (Tam & Ho, 2005), such as “consensus implies correctness”. Systematic processing method depends on reason while heuristic processing method depends on individuals’ mental shortcuts. Wirth et al. (2010) found that experienced users tend to adopt the heuristic processing route when using search engines in order to save cognitive efforts and quickly form decision. However, when the risk of incorrect decision is high, users will process information in a more effortful manner. Son et al. (2020) found that heuristic processing prevails as it reduces cognitive workload needed to make retweet decision when time for processing information is limited. The premise of HSM is that people rarely process information in perfect conditions due to constraints of environment and cognition. When askers process information for decision-making in paid Q&A, they will also face constraints coming from environment (i.e. asker’s urgency for an answer) and cognition (i.e. asker’s own knowledge level). These two information processing strategies can occur separately or sometimes concurrently and affect each other in a complex way.

HSM has been widely used in studies on individuals’ behaviors in the business field. Li, Lee, and Yang (2019) investigated the influence of heuristic factors such as recommender’s identity disclosure, reputation on the popularity of tourist attractions in online travel communities. Lucassen, Noordzij, and Schraagen (2011) pointed out that students who trust Wikipedia tend to adopt the heuristic processing route and pay more attention to quantity of information. On the contrary, students with a low degree of trust are likely to adopt the systematic processing route and concern about information quality. However, there are few studies using HSM to investigate payment decision in paid Q&A. Compared with customer satisfaction model and technology acceptance model, the advantage of HSM is that it is not a structurally fixed model composed of several specific variables, but a general framework and behavioral paradigm for decision-making research. HSM has a strong theoretical expansion and explanation ability. The application of HSM helps avoid the limitation of inherent variables and identify the key influencing factors of payment decision in paid Q&A.

3 Research framework and propositions

Research framework in this paper is conceptualized based on HSM. In paid Q&A, askers try to find a balance between efficiency and accuracy when they need to process information and make payment decision. If an asker is under great time pressure, there is a great chance that he will choose the heuristic processing route based on some external cues of information to save time. However, if an asker is

willing to get a credible answer and make the consulting fee worthy, he is more likely to choose the systematic route which takes more cognitive efforts to explore internal cues of information. Due to the heterogeneity of askers and the diversity of payment scenarios, these two information processing routes can occur at the same time and together affect the final decision. As is shown in Fig. 1, we consider the effect of information elements in different information processing routes as well as the effect of price on the final payment decision. The factor of price does not belong to any information processing route, but it will influence configurations that lead to high payment intention. In this model, changes in the number of paid questions are used to represent the payment decision, which mean how many paid questions one knowledge contributor received in a period of time. The greater the numerical changes in the number of paid questions, the higher the willingness of askers to pay. Variables that represent influencing factors can be calculated based on raw data crawled from Zhihu.com.

Figure 1. Research model of payment decision drivers based on HSM.

3.1 Systematic processing route

Latent factors such as the central cues of behavior and the internal characteristics of information are divided as systematic variables (Zhang & Watts, 2008). In paid Q&A, judging the value of answers that will be provided by knowledge contributors costs more cognitive resources. One important reference for askers to comprehensively evaluate the ability of knowledge contributors as well as usefulness of future answers is previous askers’ feedback towards knowledge contributors’ performance in free knowledge sharing and paid Q&A. Incorporating askers’ feedback into quantification of usefulness of answers can make research results more reliable. Usefulness of past consultations can be measured through rating scores left by askers (Natour & Turetken, 2020). While value of free knowledge sharing can be measured through

average number of likes each free answer received. Here, perceived usefulness of answers provided by knowledge contributor is classified as an influencing indicator in the systematic processing route, which contains two variables of effective rating score and average number of likes.

Effective rating score and average number of likes refer to the attitude and feedback previous askers left to knowledge contributors for their free and paid knowledge sharing. It is easier for knowledge contributors to attract askers' attention when they have more positive feedback. Effective rating score is calculated through previous askers' rating stars in a period of time in equation (1). If askers do not comment in time after receiving service, the platform designates a default five-star rating. These automatic comments have been excluded in the calculation. The higher the rating score, the more satisfied previous askers feel about the service. The number of likes has the similar significance as the rating score to show users' cumulative recognition of public answers (Shi, Zheng, & Yang, 2020). We use average number of likes each public answer receives in a period of time (in equation (2)) as another variable of perceived usefulness. These two variables cannot be obtained directly from the community, so askers need to spend more cognitive efforts to make an evaluation according to the available information.

$$\text{Effective_RatingScore} = \text{sum of RatingScore} / \text{number of RatingScore} \quad (1)$$

$$\text{AvgLike_Num} = \text{number of likes} / \text{number of public answers} \quad (2)$$

3.2 Heuristic processing route

Dominant factors such as external cues of behavior and formal characteristics of information are considered as heuristic variables, which do not involve deep cognitive thinking (Zhang & Watts, 2008). Perceived credibility of knowledge contributor is intuitive in saving cognitive resources and helps askers quickly form judgments. Four variables are considered to represent perceived credibility, including the number of previous consultations, network centrality, personal information integrity, and the number of honor labels.

When askers want to devote fewer cognitive resources and less time to making payment decision, the first thing to confirm is knowledge contributors' activeness in paid Q&A. The number of previous consultations can be regarded as the symbol of knowledge contributors' participation in paid Q&A (Zhao et al., 2018). Askers tend to raise questions towards knowledge contributors with more consultation records, because they believe these knowledge contributors are more credible.

Since the transaction goods is intangible knowledge, askers cannot accurately judge the exact value of answers while making decision. It is important to build up askers' trust towards knowledge contributors. Users can establish their own

relationship network in online communities, where they can interact and communicate with others. Network centrality that contains in-degree (followers) and out-degree (followees) indicates the size of users' social relationship network. Followers and followees both influence users' engagement in communities through affecting social capital (Hofer & Aubert, 2013). In general, knowledge contributors with higher popularity are more favored by askers (Zhang, Lu, & Zheng, 2020). Network centrality (summing the number of followers and followees in equation (3)) is chosen to represent perceived credibility.

$$\text{Network_Centrality} = \text{Followers} + \text{Followees} \quad (3)$$

Besides network centrality, personal information integrity and honor labels can also represent perceived credibility. Personal information integrity (Zhao et al., 2018) refers to whether the personal information such as sex, self-introduction, residence, and education experience has been filled in the profile. Personal information can help askers learn more about knowledge contributors and help enhance trust when they are strangers. If a knowledge contributor is an expert or has contributed much useful knowledge in a certain field, Q&A platform will offer him with honor labels as a certification. Askers can judge the credibility of knowledge contributors through the number of honor labels. They may give priority to knowledge contributors with specific professional skills when making payment decision.

3.3 Differences between configurations under different price levels

Knowledge contributors ask for different prices for each paid Q&A service. Price represents knowledge contributors' perceived value of their professional knowledge sharing. Some studies concluded that price has a variable effect on payment decision based on askers' segments (Zhang, Zhang, & Zhang, 2019). Considering that price can influence askers' choices of information processing routes while making decision, our research model views price as an element in configurations leading to high payment intention to investigate how other elements in different information processing routes will configure to influence askers' payment decision under different price levels.

3.4 Research propositions

Our research model suggests that different information processing routes occur concurrently and affect the payment decision in an interactively complex way under different price levels. Based on the research model and detailed analysis above, several propositions are advanced as follows:

Proposition 1: No single configuration of variables in perceived usefulness, perceived credibility or price is sufficient to explain high intention in making payment decision; instead, multiple, equally effective configurations of causal factors exist.

Proposition 2: Single causal condition in perceived usefulness, perceived credibility and price may have opposite effects on payment decision, depending on how it combines with other causal conditions to form a solution.

Proposition 3: The number of previous consultations is a core causal element for motivating askers to make payment decision.

Proposition 4: The heuristic processing route plays a dominant role while the systematic processing route plays a peripheral role in making payment decision.

Proposition 5: When knowledge contributors have a large number of previous consultations and high network centrality, askers will show high intention in making payment decision.

Proposition 6: Effects of systematic and heuristic processing routes on payment decision vary under different price levels. Askers tend to use the heuristic processing route when price is high. Meanwhile, askers are more likely to process information in the heuristic route with the systematic route playing a peripheral role when price is low.

4 Methodology

4.1 Data collection

Zhihu.com is the largest online Q&A community in China, which provides social function so that users can discuss their interested topics together through building up relationship network. The empirical data used in this paper are crawled from paid Q&A module in Zhihu.com. There are rough field classifications and corresponding lists of knowledge contributors on the web interface. As is shown in Fig. 2, information such as number of previous consultations, overall average rating score, tags and consulting fee can be directly verified. If askers want to learn more detailed information such as the number of likes, the number of followers and followees, the number of public answers, they have to click the target knowledge contributor and go to his homepage.

This paper crawled two sets of cross-sectional data through a python-based procedure on August 25th, 2020 and September 25th, 2020. We traced and collected observational data of 216 knowledge contributors who come from different knowledge fields, including their interactive behavior data and personal information in community. There is a one-month interval between two time points for crawling data to ensure that behavior data have significant changes but the webpage structure remains the same. First of all, we need to remove duplicate information and check data consistency. After data cleaning, dataset for empirical research is selected according to our research framework (ensuring information elements of each knowledge contributor are complete and the change in the number of paid questions is not zero during the observation period). Despite the number of previous consultations and price which can be directly viewed on the webpage, there are

Figure 2. A Snapshot of Paid Q&A Page.

some raw data need to be preprocessed to calculate variables contained in the research model. First, the variable *Pay_Num* indicates the increase in the number of paid questions within one month. It is calculated by subtracting the number of paid questions in dataset of August 25th from that in dataset of September 25th. Second, the variable of effective rating score refers to the average rating score left by previous askers during observation period. Third, the number of likes, followers, followees, public answers are cumulative numerical data. We need to calculate the increment in likes and free-shared answers, then the variables of average number of likes and network centrality can be calculated following equations (2) and (3). Finally, personal profile and honor labels are text data, which should be converted into numeric data. Based on such selection and calculation rules, we choose 95 knowledge contributors along with their datasets to investigate the configurations of payment decision drivers. Table 2 presents the variable description.

4.2 fsQCA

Based on the set theory, fuzzy-set qualitative comparative analysis (fsQCA) can effectively handle exponentially increasing complexity of a configurational perspective (Fiss, 2007; Ragin & Fiss, 2008). Different from regression-based techniques which mainly focus on the net effect of explanatory variables, fsQCA

Table 2. Variable Description.

Dimension	Variable	Definition
Consequent variable	Pay_Num_i	The increase in the number of paid questions knowledge contributor i has answered within one month
Antecedent variables in the systematic processing route	$Effective_RatingScore_i$	The effective average rating score that knowledge contributor i got during one month
	$AvgLikes_Num_i$	The average number of likes for each public answer knowledge contributor i shared for free during one month
Antecedent variables in the heuristic processing route	$Consulting_Num_i$	The number of consultations that knowledge contributor i has answered at the start of observation period
	$Network_Centrality_i$	The network centrality (sum up out-degree and in-degree) of knowledge contributor i at the start of observation period
	$Info_Integrity_i$	The personal information integrity of knowledge contributor i
	$Honor_Label_i$	The number of honor labels that knowledge contributor i owns
Public antecedent variable	$Price_i$	The consulting fee that knowledge contributor i asks for

can integrate multiple interdependent causality into a coherent framework to analyze the influence of combination mode of independent variables (Fiss, 2011). What's more, fsQCA can explain the influencing results when preconditions are absent and is suitable for dealing with small sample sets (15–80). Recently, fsQCA method has been widely used in the field of business in case of several different paths leading to one certain result (Oyemomi et al., 2019; Pappas et al., 2016). Antecedent variables contained in two information processing routes along with price have asymmetrical and complex causal relationships with the consequent variable in this paper. It is suitable to adopt fsQCA to explore how these information elements combine into configurations to motivate payment decision.

4.2.1 Calibration

FsQCA allows the representation of each antecedent condition and the outcome of interest in the form of sets. Each case is represented as a complex entity according to the degree of membership. Calibration includes the value of an interval-scale variable that corresponds to three qualitative breakpoints that structure a fuzzy set: the threshold for full membership (fuzzy score = 0.95), the threshold for full non-membership (fuzzy score = 0.05), and the cross-over point (fuzzy score = 0.5). These three benchmarks are used to transform the original counting numerical or interval-scale values into fuzzy membership scores (Ragin, 2006). One widely used method to calibrate data is based on percentiles (Speldekamp, Knoben, & Helmhout, 2020). We can identify 95%, 50%, and 5% as three benchmarks according to features of our data sample, respectively. Appendix 1 presents the calibration of variables.

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Fuzzy scores range from 0 to 1 after calibration, which show the degree of membership of cases in the dataset.

4.2.2 Truth table analysis

The truth table algorithm is applied to identify combinations of elements that produce the outcome of interest after calibration. The truth table gives out all possible combinations of causal conditions, the number of cases displaying the combination of conditions (frequency) and the proportion of cases in each truth table row that displays the outcome (raw consistency). After deleting rows that have not met the frequency threshold (here we set the threshold as 1), we set a cutoff of 0.86 for raw consistency, which means that only combinations with a raw consistency over 0.86 are considered as reliably resulting in high payment intention. After truth table is constructed, it is applied to reduce the numerous combinations into a smaller set of configurations in the form of complex, parsimonious and intermediate solutions based on the QM algorithm and counterfactual analysis (Park, El Sawy, & Fiss, 2017). Set-theoretic indices of consistency and coverage are used to estimate and interpret the results. Consistency measures the degree to which solution terms and the solution as a whole are subsets of the outcome, while coverage measures how much of the outcome is covered or explained by each solution term and by the solutions as a whole (Ragin, 2006). Results help identify multiple equivalent configurations associated with an outcome.

5 Result

5.1 Data analysis

Table 3 presents descriptive statistics of variables, which can provide references for data calibration. Table 4 presents correlations of variables. Result confirms that there is no symmetrical relationship between these variables because all coefficients are below 0.8 threshold (Woodside, 2014).

Table 3. Summary statistics of variables.

Variable	Count	Mean	Std.	Min	Max
<i>Pay_Num</i>	95	22.074	77.262	1.000	696.000
<i>Effective_RatingScore</i>	95	4.745	0.427	2.000	5.000
<i>AvgLikes_Num</i>	95	486.745	689.375	3.950	3899.620
<i>Consulting_Num</i>	95	379.358	1171.699	3.000	10673.000
<i>Network_Centrality</i>	95	134364.421	163643.105	387.000	805492.000
<i>Info_Integrity</i>	95	6.032	1.165	2.000	7.000
<i>Honor_Labels</i>	95	1.726	1.469	0.000	6.000
<i>Price</i>	95	57.105	53.393	1.000	268.000

Table 4. Correlations of variables.

	<i>Pay_Num</i>	<i>Effective_RatingScore</i>	<i>AvgLikes_Num</i>	<i>Consulting_Num</i>	<i>Network_Centrality</i>	<i>Info_Integrity</i>	<i>Honor_Labels</i>	<i>Price</i>
<i>Pay_Num</i>	1.000							
<i>Effective_RatingScore</i>	-0.014	1.000						
<i>AvgLikes_Num</i>	0.060	0.034	1.000					
<i>Consulting_Num</i>	0.542	-0.024	0.097	1.000				
<i>Network_Centrality</i>	-0.027	0.032	0.477	0.022	1.000			
<i>Info_Integrity</i>	-0.089	0.131	-0.044	-0.014	0.054	1.000		
<i>Honor_Labels</i>	-0.158	-0.003	-0.024	-0.148	0.238	0.073	1.000	
<i>Price</i>	-0.115	0.098	0.132	-0.025	0.396	0.151	-0.140	1.000

Note: correlations greater than 0.30 are significant at the 0.01 level; those greater than 0.23 are significant at the 0.05 level.

5.2 Identifying sufficient solutions for high intention in payment decision

In this part, we will analyze casual recipes sufficient for askers' high intention to pay for consultations and investigate research propositions in section 3.4. Necessary conditions are identified in Appendix 2 along with the consistency and coverage scores for individual conditions and specified substitutable conditions. Analysis results are depicted by using the notation system from Ragin and Fiss (2008).

5.2.1 Configurations under systematic and heuristic processing routes

Table 5 shows five solutions that sufficiently explain askers' high intention in payment decision and the specific consistence of each solution. Results leading to high scores for payment decision have an overall consistency of 0.823 and a coverage of 0.515. No single condition is sufficient to explain high payment intention. Different configurations of conditions will make the same result in encouraging askers to make payment decision. The same variable may have opposite effects on payment decision in different solutions (i.e. the effect of *Effective_RatingScore* in solution 2 and 3).

So proposition 1 and 2 are supported according to five solutions listed in Table 5.

Consulting_Num constitutes core causal condition in each pathway, which means this condition is essential and plays a key role in encouraging payment decision. Askers are likely to show higher payment intention towards knowledge contributors who have provided more paid Q&A service before. So proposition 3 is supported according to the role *Consulting_Num* playing in all five solutions.

Solution 1 and 5 give out configurations for high payment intention with the high membership of price. Solution 1 indicates that askers tend to consult knowledge contributors with a larger number of consultation records and other elements absent. A larger number of consultations combining with more average number of likes and larger network centrality will also attract more askers to make payment decision (solution 5).

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Table 5. Configurations for achieving high intention in payment decision.

Condition		Configuration				
		1	2	3	4	5
Perceived Usefulness	Effective_RatingScore	⊗	●	⊗	⊗	⊗
	AvgLikes_Num	⊗	⊗		●	●
Perceived Crebidity	Consulting_Num	●	●	●	●	●
	Network_Centrality	⊗	●	●	⊗	●
	Info_Integrity			●	⊗	⊗
	Honor_Labels	⊗		●	⊗	⊗
Knowledge Information	Price	●	⊗	⊗	⊗	●
	Raw Coverage	0.250	0.301	0.293	0.220	0.212
	Unique Coverage	0.061	0.064	0.031	0.026	0.019
	Consistency	0.829	0.855	0.861	0.903	0.901
	Solution Coverage			0.515		
	Solution Consistency			0.823		

Note: Large circles indicate core elements, and small circles indicate peripheral elements. Black circles indicate the presence of a condition, and crossed-out circles indicate its absence. Blank spaces in a pathway indicate “don’t care” which means the presence or absence of the condition has nothing to do with the final result.

Remaining solutions show configurations of influencing factors for high scores in payment decision with the absence of price. Variables in heuristic processing route can combine up to motivate payment decision when price is low in nearly three-tenths of cases (solution 3). It means heuristic processing route is frequently used while making payment decision at the expense of low price. Some askers try to find other information cues to evaluate knowledge contributors apart from number of previous consultations when price is low. High payment intention can also be achieved through combining large number of consultations with high effective rating score, large network centrality and many honor labels (solution 2) or with large average number of likes (solution 4).

All in all, information elements in heuristic processing route present are often treated as core elements while those in systematic processing route are often treated as peripheral elements. Askers are more likely to attach importance on heuristic elements which stand for external cues of information. They use heuristic and simple decision rules to save time and cognitive efforts. Heuristic processing route plays a dominant role while systematic processing route plays a peripheral role in information processing and decision making in paid Q&A.

Proposition 4 is supported according to comparison of roles variables in systematic and heuristic processing routes play in the configurations given by fsQCA.

Next, we will identify how defined configuration explains the outcome of high intention in payment decision, and especially for which cases and for how many in our dataset sample. We plot the specific configuration against the outcome of high intention in payment decision (Pappas, 2018).

Figure 3. Fuzzy XY plot for testing proposition 5.

Fig. 3 presents the fuzzy XY plot for testing proposition 5. Twelve cases in red box stand for knowledge contributors with a large number of consultations and high network centrality (scores over 0.7). Among these cases, askers show high intention in payment decision towards 8 knowledge contributors (scores over 0.8 in the blue dotted box). Thus, proposition 5 includes only 12 cases, but 8 out of 12 show high payment intention. The proportion has reached 66.7% with a consistency of 0.823 and a coverage of 0.626. Previous consultations and network centrality work in tandem to motivate the payment decision. So proposition 5 is supported by the results.

5.2.2 Differences between configurations under different price levels

As is shown in Table 5, price is a core or peripheral element in all configurations for achieving high scores in payment decision. The number of previous consultations is the shared core element in different configurations. Askers will pay attention to the number of paid questions knowledge contributors have answered before no matter what the price is. When the consulting price is low, higher effective rating

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score as well as more average number of likes combining with heuristic information cues can encourage askers to make payment decision. Meanwhile, when consulting price is high, askers will concentrate on the frequency of previous paid Q&A service provided.

Results show that price provides important information for askers about the paid Q&A service and is helpful to build trust between askers and knowledge contributors. High price conveys the message that knowledge contributors have a relatively high valuation of shared knowledge. It also provides a guarantee from another perspective since people all believe “you get for what you pay”. So askers tend to consider about some heuristic elements such as the number of previous consultations to help efficiently form decision. On the contrary, low consulting price will decrease the perceived quality of answers and service, so askers determine whether to pay or not based on some other information in addition to the number of consultations. In general, when price is high, askers favor heuristic processing route. However, askers tend to process information in heuristic route with systematic route playing a peripheral role when price is low.

These findings provide support for proposition 6.

5.3 Analysis of sufficiency for low/ medium intention in payment decision

Unlike the assumption of causality symmetry in regression analysis, causes of positive and negative results are not symmetrical in QCA problems. Solutions leading to low/medium payment intention are listed in Table 6.

Table 6. Configurations for achieving low/medium intention in payment decision.

Condition		Configuration				
		1	2	3	4	5
Perceived Usefulness	Effective_RatingScore	●	⊗	⊗	●	●
	AvgLikes_Num	●	●	●	●	⊗
Perceived Crebitility	Consulting_Num	⊗	⊗	⊗	⊗	⊗
	Network_Centrality		⊗	⊗	●	●
	Info_Integrity	●	⊗	●	⊗	●
Knowledge Information	Honor_Labels	●	●	⊗	●	●
	Price	⊗	⊗	●	●	●
	Raw Coverage	0.284	0.138	0.153	0.166	0.213
	Unique Coverage	0.090	0.021	0.047	0.024	0.045
	Consistency	0.993	0.999	0.994	0.999	0.996
				0.444		
				0.993		

Note: Large circles indicate core elements, and small circles indicate peripheral elements. Black circles indicate the presence of a condition, and crossed-out circles indicate its absence. Blank spaces in a pathway indicate “don’t care” which means the presence or absence of the condition has nothing to do with the final result.

Five solutions of antecedent combinations show an overall coverage of 0.444 for low/medium intention in payment decision. Configurations that explain high payment intention are no mirror opposites of those for its negation. The condition of few previous consultations is always part of solutions for low/medium payment intention, but this condition is not sufficient on its own. For example, in order to achieve low/medium scores for payment decision, it should be combined with high effective rating score, large average number of likes, high self-information integrity, many honor labels and low price (solution 1).

5.4 Predictive validity

Validity testing is performed to exam if this model is able to predict the outcome in additional samples (Pappas et al., 2020). For testing predictive validity, the sample is firstly divided into a subsample and a holdout sample. Then both calibration and truth table analysis are carried out for the subsample. Each solution for subsample should be modeled as one variable and be tested against the holdout sample. The samples need to explain the outcome well at a similar level if the model performs well in prediction. Details and instructions on how to perform predictive validity can refer to research of Pappas, Giannakos, and Sampson (2019).

Table 7. Complex configurations indicating high intention in payment decision for the subsample.

Models from Subsample for High Intention in Payment Decision	Raw Coverage	Unique Coverage	Consistency
1. <i>~Effective_RatingScore*~AvgLikes_Num*Consulting_Num*~Network_Centrality*~Info_Integrity*~Honor_Lables</i>	0.230	0.058	0.800
2. <i>~Effective_RatingScore*Consulting_Num*~AvgLikes_Num*~Network_Centrality*~Honor_Lables*Price</i>	0.218	0.034	0.825
3. <i>~Effective_RatingScore*AvgLikes_Num*Consulting_Num*~Network_Centrality*Info_Integrity*~Honor_Lables*Price</i>	0.175	0.046	0.904
4. <i>Effective_RatingScore*~AvgLikes_Num*Consulting_Num*~Network_Centrality*Info_Integrity*Honor_Lables*~Price</i>	0.265	0.130	0.852
solution coverage		0.468	
solution consistency		0.837	

Table 7 shows that the patterns of complex antecedent conditions are consistent indicators of high payment intention for subsample, with overall solution consistency of 0.837 and coverage of 0.468. Each solution in Table 7 represents a model, which should be plotted against the outcome. Here, we take model 1 against high payment intention as an example in Fig.4. The result shows a high consistency of 0.825 and a coverage of 0.218. Tests for all four configurations in Table 7 suggest highly consistent models for subsample have good predictive ability for the holdout sample.

Figure 4. Testing model 1 of the subsample using data from the holdout sample.

6 Discussion

6.1 Theoretical implications

Our study adds to a large body of literature on payment decision in paid Q&A. By constructing a framework that combines two information processing routes, this study examines the impact of information elements on payment decision from a new perspective. Here, we discuss how our findings contribute to prior literature.

First, this paper applies HSM to payment decision in paid Q&A, which is a new commercial scene compared with traditional B2C or C2C transactions where HSM has previously been applied (Ruiz-Mafe, Chatzipanagiotou, & Curras-Perez, 2018). Our study completes the instantiation of variables in the HSM framework for payment decision-making in paid Q&A. Previous researches usually pay more attention to some heuristic elements standing for knowledge contributors' reputation. This study also takes systematic elements which need more cognitive resources such as effective rating score and average number of likes into consideration. Especially, effective rating score is obtained from previous askers' comments, which expands

studies on the influence of comments in decision-making. Deviating from general correlational associations, fsQCA is employed to demonstrate the complex and asymmetrical causal relationships between payment decision and multiple influencing factors, leading to the creation of new propositions. We thus confirm the applicability of fsQCA in paid Q&A. Results indicate how drivers of payment decision form different configurations to achieve equally high payment intention under systematic and heuristic processing routes.

Second, the empirical research based on data crawled from Zhihu.com provides several interesting conclusions. This study produces five configurations which can equally achieve high payment intention rather than exploring the quantitative relationship between payment decision and influencing factors as previous researches have done (Zhao et al., 2018). The results identify the core role of the number of previous consultations in motivating askers to make payment decision.

Third, the analysis of five configurations reveals that the heuristic processing route plays a dominant role while the systematic processing route plays a peripheral role. Payment decision in paid Q&A is usually a decision-making process that takes little time. Askers prefer some specific heuristic elements for saving cognitive efforts and efficiently making choices. This conclusion contributes to the theory of information processing in terms that it identifies which route plays a core role in achieving high payment intention. Wirth et al. (2010) proposed that the application of heuristic and simple strategies in decision-making is widespread and sufficiently efficient in many cases. Our results verify this argument in paid Q&A.

Finally, investigation on differences between configurations leading to equally high payment intention under different price levels extends prior studies on the influence of price in paid Q&A. For a high price, askers use the heuristic processing route. For a low price, askers additionally pay attention to some systematic elements based on the heuristic processing route. All these prove that price plays an important role on payment decision as well as the choice of information processing strategies.

6.2 Managerial implications

Findings provide practical implications for managers of knowledge communities and paid Q&A service providers. Results show the important influence of previous consultations on payment decision. Managers can highlight the number of consultations on knowledge contributors' recommendation list and their homepages to attract askers' attention in the shortest time. Managers can also adjust the information layout of web pages. For example, network centrality often combines with the number of previous consultations in configurations leading to high payment intention. These elements can be put together for askers' convenience, helping them

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save time and motivating them to make payment decision. Furthermore, since configurations vary under different price levels, different price ranges can be set for askers to choose. In a high price column, heuristic elements such as knowledge contributors' network centrality should also be conspicuous. Knowledge contributors need to pay attention to their performance in heuristic information elements. While in a low price column, other indications that reflect systematic information elements such as recent rating scores should be provided. Knowledge contributors who ask for a low price can strengthen their attractiveness by sharing more high-quality knowledge in public community and paid Q&A apart from performing well in heuristic elements. Managers can also offer rewards to encourage askers to write comments and express recognition on knowledge contributors' sharing since feedback from askers provides important reference for decision-making.

6.3 Limitations and future study

This study has some limitations. First, the research model in this paper uses the variable of *Pay_Num* which indicates the increase in the number of consultations during observation period to represent changes in payment decision. Future research endeavors may consider different observation intervals for the sake of robustness. Second, paid Q&A in Zhihu provides a classification of knowledge contributors' professional fields. The research model has not considered the moderating effect of professional fields. Since some fields are more popular (i.e. health, law, and education), paid Q&A service in these fields may enjoy more popularity than other fields. In future research, the element of professional fields can also be included in the model.

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Author contributions

Wenyu Chen (cwy902@163.com): Conceptualization (Equal), Data curation (Lead), Formal analysis (Lead), Investigation (Lead), Methodology (Supporting), Software (Lead), Validation (Lead), Visualization (Lead), Writing-original draft (Equal), Writing-review & editing (Equal); Yan Cheng (yancheng@ecust.edu.cn): Conceptualization (Equal), Funding acquisition (Lead), Methodology (Lead), Project administration (Lead), Resources (Lead), Writing-original draft (Equal), Writing-review & editing (Equal); Jia Li (jiali@ecust.edu.cn): Conceptualization (Supporting), Methodology (Equal), Software (Supporting), Writing-review & editing (Supporting).

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Appendix 1: Calibration

Table 8. Calibration of variables.

Variable	full membership (fuzzy score=0.95)	cross-over point (fuzzy score=0.5)	Full non-membership (fuzzy score=0.05)
<i>Pay_Num</i>	101.000	3.000	1.000
<i>Effective_RatingScore</i>	5.000	4.875	3.857
<i>AvgLikes_Num</i>	1652.340	186.378	15.725
<i>Consulting_Num</i>	1446.000	94.000	13.000
<i>Network_Centrality</i>	475946.000	81021.000	7288.000
<i>Info_Integrity</i>	7.000	6.000	4.000
<i>Honor_Labels</i>	5.000	1.000	0.000
<i>Price</i>	199.000	48.000	5.000

Appendix 2: Necessary condition test

Table 9. Analysis of necessary conditions for the presence of payment decision.

Conditions	Consistency	Coverage
<i>Effective_RatingScore+AvgLikes_Num</i>	0.868	0.452
<i>Consulting_Num+Network_Centrality+Info_Integrity+Honor_Labels</i>	0.994	0.455
<i>Effective_RatingScore</i>	0.752	0.474
<i>AvgLikes_Num</i>	0.643	0.538
<i>Consulting_Num</i>	0.823	0.768
<i>Network_Centrality</i>	0.664	0.575
<i>Info_Integrity</i>	0.742	0.464
<i>Honor_Labels</i>	0.706	0.487
<i>Price</i>	0.633	0.575
Outcome variable: <i>Pay_Num</i>