9-2017

Exploring Information Disclosure In Online Auctions

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Research full-length paper

Track 11 Digital Markets

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Abstract

This research examines how a seller's reputation score and auction pre-configuration affects people's participation in communication within online auction communities. A leading horizontal intermediary auction platform is used to conduct this research. Its seller "feedback" mechanism and "ask seller a question" forum are chosen as representatives of post- and intra-transactional information disclosure. A self-developed classification approach is used to classify the buyer-initiated questions. The results of multinomial logistic regression indicate that product quality, shipment and payment issues are aspects that concern buyers the most in the early stages of an auction. Subsequently, their attention is likely to shift to seller credibility and price negotiations as listing durations get longer. In terms of the influence of seller feedback ratings, our findings suggest that lower-rated traders are more likely to be asked questions about product description and seller credibility. Buyer concern about seller uncertainty is only alleviated if the seller has a good reputation. Even medium-rated sellers are suspected of being opportunistic. Moreover, buyers are more willing to discuss transaction-related issues and raise negotiation-associated questions with sellers who have already achieved high reputation scores. Finally, the theoretical and managerial implications are elaborated.

Keywords: online auctions; information disclosure

1 INTRODUCTION

Conventional markets have long been seen as special social constructions that adopt exchange mechanisms to create and transfer value from trade (McMillan 2003). With the unprecedented development of information technology, the past few decades have seen the emergence, advancement, proliferation and consequent consolidation of the electronic markets. It has been observed that, compared to traditional offline trading, electronic markets put more value on information exchange through social networks within a trading community (Murray and Greenes 2006). Online marketplaces not only provide opportunities for all participating trading partners to establish short-term relationships, but also facilitate bi-directional information flow via online word-of-mouth (Bakos 1997). The growth in information disclosure and exchange mechanisms is expected to mitigate information asymmetry between sellers and buyers.

Wang and Chiang (2009) have pointed out that there are two major types of uncertainties that prevail during internet transactions. The first one involves the true quality and condition of the product, especially items with complex attributes, while the second comes from the concern about the seller’s true identity. Fortunately, innovative market mechanisms diminish these uncertainties by providing more information to buyers and sellers. Several mechanisms such as reputation system, customer reviews and intra-transactional Q&A have been adopted to facilitate information exchange, mitigate uncertainties and enhance the overall auction performance. For instance, the widespread utilization of buyers and sellers’ feedback reduces potential frauds as well as establishes trustworthy relationships (Gregg and Scott 2006, Pandit, Chau et al. 2007). While reputation and feedback allows us to measure the performance in prior transactions, live interaction between buyers and sellers during current auction is becoming a popular mechanism to reduce both product and seller uncertainties.

The impact and efficacy of the above-mentioned mechanisms have been investigated in prior literature (Lucking-Reiley, Bryan et al. 2007), however, we are yet to understand how these mechanisms affect and interact with each other. More specifically, how seller reputational ratings drive the formation of buyer-initiated questions and comments during the bidding stage of online auctions.

Since online Q&A are qualitative data, a classification process is necessary to convert textual information into the categorical form for subsequent multinomial logistic regression. Researchers tend to perform text categorization and include the predicted categories in a set of subsequent statistical analyzes to explore external relationships. Specifically in this study, compared to dimly discernible nominal variables, there is no doubt that a set of explicitly distinguishable categories are adequate for a logistic model. Consequently, a compelling and high-quality categorization for intra-transactional buyer-initiated Q&A is of paramount importance to accurately measure and distinguish buyers’ intentions of raising a question or leaving a comment. Research for long document categorization has already obtained fruitful achievements while algorithms for short text classification still need to be perfected due to their unique characteristics. How to reasonably represent and choose salient, invariant and discriminatory features, effectively reduce the spatial dimension and noise, and increase classification accuracy remains to be the major problem of short text classification (Forsyth and Holmes 1996). Previous research has made satisfactory progress on email sorting, microblog subject categorization, movie or product review sentiment analyzes and so on, which are typical examples of short text classification. Be that as it may, this study is looking at an exclusive type of text, the online auction Q&A, which can be extremely short, cryptic, sparse, and ungrammatical. Moreover, it always fails to provide sufficient term occurrences (Sriram, Fuhry et al. 2010) and it is naturally intricate to identify the underlying sentiment information. Therefore, conventional classifiers may fail to get high-quality results. This study uses and compares two methodologies; the first one is the classical Naive Bayes algorithm and the other one is our newly-developed algorithm which integrates a semi-automated feature selection process and a fully-automated classification according to a set of scores that are assigned to extracted features.

With an intention to provide useful insight for sellers on how to design the market to increase returns by exploring how reputation systems and auction pre-configuration change buyers' willingness and participation in raising questions when auctions are in progress, this work uses the outcome of an actionable and persuasive classification method to categorize intra-transactional buyer-posted questions and comments and subsequently examines how numerical seller feedback ratings and listing duration motivates people's choices of asking questions in online auction. Two research questions are listed underneath:

- What is the impact of listing duration on the people's intention of raising intra-transactional questions?
- How are seller feedback ratings associated with the content of questions that people would ask when an auction is in progress?

2. LITERATURE REVIEW

2.1 The Role of Textual Word-of Mouth in Online Auction

Previous research on social learning and consumer behaviour indicates that consumers may emulate each other through vicarious interactions (Mothersbaugh, Best et al. 2007), however, more essentially they rely on experience and opinions sharing. Therefore, online word-of-mouth (WOM) has exterted far-reaching influence on interpersonal communications and information transmissions with its capability of reaching thousands of individuals globally and its sheer power of persuasion. This kind of online user-generated content has not only affected consumers' purchase decision, but also encouraged organizations to adjust their marketing strategies. Compared to its offline counterparts, online WOM has remained to be a dominant research interest since online environment makes it possible for reseachers to record, store, organize and analyze WOM content. This paper concentrates on a unique kind of WOM information – the buyer initiated questions and seller responses posted online, we define online word-of-mouth as the disclosure and exchange of information over the internet among consumers and sellers concerning a certain product or service in order to mitigate risks and make informed decisions.

The dissemination of online reviews not only affects individual behaviors but also companies. As reported by an intriguing finding from a 2014 study by "BrightLocal", approximately 88 percent of online consumers will turn to online reviews when they intend to shop over the internet, which is 3 percent higher than a year before (BrightLocal, 2014). Additionally online product reviews represent a potentially valuable tool for enterprises. Organizations are able to take advantage of them to analyze and simulate consumer attitudes toward their products in real time, and adapt their manufacturing, distribution and marketing strategies accordingly (Dellarocas, Zhang et al. 2007). The influence of online WOM on customers' buying decision-making process (Hennig-Thurau, Walsh et al. 2003) as well as enterprises' marketing strategy (Trusov, Bucklin et al. 2009) has been addressed extensively in the academic literature.

2.2 Information Disclosure in Online Auctions

Pre-bidding seller-initiated Information Disclosure: Extensive studies have investigated the information that has been revealed by sellers during the early stage in an online auction before the bidding processes formally start. One of the most general and necessary pre-bidding information disclosure is the product description, which is regarded as mandatory and decisive for customers to evaluate an item.

Textual depictions are essential for diagnoses since certain information such as historical utilization, previous maintenance and inside structure is helpful to mitigate perceived risk but is difficult to be visually represented. Research into the textual product description indicates that more detailed descriptions which delineate the previous personal use of second-hand items will catch more consumers' attention (Kauffman and Wood 2006) and the length of the qualitative file is positively related to the final closing price achieved ultimately (Lewis 2007). Apart from sheer item descriptions, the disclosure of sellers' private experiences also captures scholars' attention. Lewis (2011) delved into the impact of enforced seller private details using eBay Motors data. He argued that a specific listing web page of a seller is deemed to be a contract among the auction parties, and the disclosure of sellers own involvement with the product, be it positive or negative, will assist to reinforce this kind of contract, thus further alleviate the information asymmetry problems and enhance market performance (Lewis 2011). For instance, if a seller takes the initiative to show a scratch on his car, he is likely to benefit from being genuine and straightforward rather than hiding the truth (Srinivasan and Liu 2014).

Another category of information revealed in the early phase is the third party assurances including specialized inspection, performance test, historical check and warranties (Wolf and Muhanna 2005). Such information is regarded as more effective and advantageous over the descriptions created by sellers themselves for the sake of objectivity, specialty and ability to disclose the product's true conditions. Previous studies demonstrated that second-hand car sellers who are reluctant to display history checks or vehicle reports are associated with higher probabilities of defects (Emons and Sheldon 2009) and that warranties provided by an independent third-party offer unbiased functional test and reliable future performance prediction of used cars so as to let buyers gain more confidence and learn true characteristics (Milgrom and Weber 1982).

Except for diagnostic information disclosure that we talked about above, the overall structure of website design and characteristics of identity are also critical. Gregg (2008) conducted an experiment to examine the effect of a seller's professional online electronic image, including username, web page presentation, content organization and reputation counts (Gregg and Walczak 2008). Sand's (2007) study suggested that people are more likely to intentionally and deliberately select an online identity which is unique and appealing (Sand 2007), but he failed to explore the commercial value behind it. Based on Sand's (2007) theoretical conclusion, Gregg (2008) found that customers who perceive a listing's electronic appearance as unfavorable are less willing to engage in further negotiations and transactions with the seller, and additionally, the website characteristic as well as username selection are positively associated with price premium achieved (Gregg and Walczak 2008).

Bidding-stage Information Disclosure: In a second-hand goods market, sellers are the major party who publish various kinds of information and buyers are passive receivers (Dellarocas 2003). However with the evolution of online auction mechanisms, real-time interaction has drawn greater attention in the past few years and it facilitated the buyers to ask for more information according to their own needs. Information disclosure during bidding stage mainly includes real-time winning or losing information sharing (Isaac and Walker 1985, Persico 2000) and question-and-answer-based (Q&A-based) interactions (Hsieh and Counts 2009).

All leading online auction sites currently provide up-to-the-minute text or email outbid alerts services, thus bidding participants will receive instant messages as soon as others outbid them (Cason 1994, Zacarias, Ahmed et al. 2013). Previous research has figured out the correlation between bidder's behavior and the revelation of losing bids information by an experiment and the results demonstrated that the losing bid information is essential in this competitive environment (Dufwenberg and Gneezy 2000). The ultimate closing price tends to be higher if the historical bids information is available to all bidders, in contrast, if participants are not kept informed of the outbids signaling, the competition will be more fierce, but the price spread is more likely to be narrower (Dufwenberg and Gneezy 2002).

Nowadays major online auction websites all introduce online Q&A forums where buyers can post questions to a specific seller concerning a particular listing and sellers are required to respond. This interactive mechanism will soon establish relationships "between any pair of question issuers and answer providers in the public space" (Wang and Chiang 2009). It has also been argued that buyer-initiated questions will force the timely interactions among auction participants and that social WOM network carries more favorable resources and occupies a more advantageous position, rather than unidirectional information delivery (Lin 1999). Therefore, in a typical transaction-oriented community it is of paramount importance to understand and make the most use of this verifiable information disclosure to choose trustworthy trading partners and to avoid unnecessary monetary losses (Godes and Mayzlin 2004). Consumers tend to rely increasingly on Q&A-based communications to explore more about seller trading history and personal experiences with the item (Wang and Chiang 2009).

Post-transactional Information Disclosure: Reputation system is acclaimed to be one of the most pragmatic and influential categories of information disclosure after a transaction is finalized. It has been broadly recognized that online auction participants suffer from uncertainties concerning sellers' integrity as well as product quality (Vishwanath 2003). Fortunately, the emergence and advancement of post-transaction feedback mechanisms benefit customers with an effective and promising solution to the problems of detecting potential frauds as well as building trust by publishing earlier business records which include personal feelings and opinions of past buyers (Resnick, Kuwabara et al. 2000).

The first channel through which consumers can express their satisfaction level with a seller or a transaction is the numerical feedback ratings (Kim and Phalak 2012). The reputation systems adopted by the world's leading auction websites suggest an avenue to quantify the general satisfaction degree of bidders (Chen and Singh 2001, Ba and Pavlou 2002) and empirically investigate how this type of powerful social force affects people's bidding behavior in the future (Bajari and Hortacsu 2003). It has been accepted that auction participants are pleased to raise their bids for a higher rated seller considering that sellers with higher scores are prone to actively pay more attention to maintaining or improve their reputations in repeated interactions rather than jeopardize previous efforts by fraudulent behaviors in a current transaction (McDonald and Slawson 2002). Another study in that period also illustrated that a seller's e-commerce score acts as a decisive element affecting people's willingness to take part in bidding. Nevertheless, when it comes to its impact on the auction closing price, the reputational rating seemed not that informative (Melnik and Alm 2002).

Complementary to these results, Standifird (2001) delved into the influences of positive and negative scores respectively. The statistical outputs highlighted that the adverse impacts of negative feedback counts are highly significant while positive ratings failed to exert powerful effects except when reaching a relatively high threshold (Standifird 2001). This idea is also supported by Zhang's (2006) research, which informed that negative ratings are regarded as far more helpful than their positive counterparts; thus online auction platform providers would better substitute the net score with unique positive and negative separately (Zhang 2006). Notwithstanding the strong effects of negative comments, an unanticipated finding by Wald and Muhanna (2005) ran counter to previous investigations. They asserted that positive feedback ratings are firmly interrelated with the price premium gained whereas the impacts of negative scores on the likelihood of a successful auction turned out to be irrelevant (Wolf and Muhanna 2005). Correspondingly, work from Resnick et al. also suggested that no significant correlation had been spotted between negative comments and auction closing price (Resnick, Zeckhauser et al. 2006). From my point of view, one of the reasons is the bias of sample selection. Drawing upon already ended auctions, negative feedback should not be as crucial as their positive counterparts since sellers with negative scores are less likely to succeed in the end. Unfortunately, these auctions were not added in the samples.

Another collection of information disclosure that consistently accompanies the numerical rating is the textual feedback comments, which is relatively overlooked by studies in the field of the reputation system. It has been widely accepted that past transaction experience is one of the most influential factors that is related to consumer purchase intention (Weisberg, Te'eni et al. 2011) and that buyers are apt to bank on other people's points of view to alleviate risks and engender trust beliefs (Banerjee 1992). Under this circumstances, the feedback mechanism provides an apparent and friendly platform for buyers to share collectively their prior purchase or bidding experiences in a particular community.

Extant literature on trust building divided the trust into two dimensions – benevolence and credibility. Benevolence denotes the buyer's belief that a seller will act honestly with empathy despite the chance to exploit opportunities with little regard to principle (Bhattacherjee 2002) while credibility describes the buyer's belief that a seller is dependable and trustworthy based on contractual obligations (Barber 1983). Based on this theoretical foundation, Pavlou and Dimoka (2006) explore the role of textual feedback in online auctions through a content analysis; the results indicated that online qualitative comments, rather than numerical ratings, benefit consumers with rich and valuable information to make a distinction among sellers in spite of the fact that dealing with those contents may require a large amount of time and energy. Additionally, trustworthy sellers are rewarded with price premiums (Pavlou and Dimoka 2006). However, the comments that had been captured for this research all convey remarkable evidence regarding sellers' trust building, thus may create systematic biases in light of the ignorance of ordinary opinions that may still be contributive and effective (Ghose, Ipeirotis et al. 2009). Trying to control the error, Yang et al. (2007) also examined the impact of eBay's reputation system on internet auctions by introducing a game-theoretic framework. The study suggested that the feedback forum is essential to enhance auction market performance by cultivating a healthy and reliable trading environment. Honest sellers are more likely to earn more money while ill-behaved auctioners will be punished with a decline of gains and a loss of customers (Yang, Hu et al. 2007). Nonetheless, the majority of previous studies discussed above assume that all auction participants play only a single role. As a matter of fact, the roles of sellers and bidders are completely interchangeable, and a seller's reputation can also be separated into selling and buying reputation (Cabral and Hortacsu 2010). With an intention to investigate this role-switching characteristic in repeated games, Zhang (2006) collected and analyzed the iPod MP3 auction data on eBay and stated that prudent bidders are supposed to distinguish and evaluate separately sellers' buying reputation from selling reputation when they aiming to figure out their true credibility (Zhang 2006).

Although reputation mechanisms are deemed to have exceptional effects on establishing trust relationships and fostering positive cooperation in online environments, there still exist certain challenges that we cannot afford to overlook ((Jøsang, Ismail et al. 2007, Jøsang and Golbeck 2009). As reported by a survey conducted by Dellarocas (2006), offline reputational WOM acts as a more reliable source of information disclosure owing to familiarity within the network. On the contrary, users of online feedback platforms are burdened with the effort to assess and evaluate the comments of strangers (Dellarocas 2006). Furthermore, due to the disembodied nature of the economic marketplace, it is effortless for people to alter their online identities. Thus, a con artist is able to take advantage of a high-reputation account to swindle money out of customers and subsequently blank out that identity and reappear with a clean one (Resnick 2001). Likewise in business competition, organizations are likely to strategically manage buyer feedback. Fake online identities are manipulated in order to post extraordinary good comments to reinforce their reputation as well as scatter imputations to damage competitor images (Dellarocas 2006). Hence, the feedback systems which are poised to enhance faith in credible transactions are currently confronted with trust issues in themselves.

Consistent with existing theory and extant literature, we agreed that reputation system act as an active and dominant transaction-commit information disclosure which assists to alleviate, but do not eliminate, the prevalent information asymmetry issues in online marketplace.

2.3 Conceptual framework

The influences of pre-configuration (Lucking-Reiley, Bryan et al. 2007) and information disclosure including pre-transactional passive voluntary disclosure, post-transactional feedback and intra-transactional live interaction on online auction outcome have been extensively discussed in previous literature. Undoubtedly, all those disclosures serve the goal of alleviating the adverse selecting issues and building trust among auction participants. Despite the large aggregation of research in how auction pre-set and information disclosure impact on auction site performance, studies seldom investigated how these different types of disclosures affect each other and how pre-configuration of the auction affect the tendency of online WOM. It is not likely for potential buyers to make bidding decision as soon as they open the listing site; normally an item will be listed for a fixed period of time thus people can consider, compare and then make up their minds. Voluntary item descriptions and previous feedback rating or qualitative reviews are deemed to be conventional channels for buyers to collect information, and recently live interaction auction running time gradually becomes a popular format (Srinivasan and Liu 2014). It is reasonable to hypothesize that buyers' interests and choices of questions will be triggered by the already existing information. People may ask more questions regarding aspects that are not mentioned in the product description and explore further explanations concerning certain information that has already been revealed by the seller. It is argued that the seller feedback postings is closely associated with buyers' concern about adverse selection as well as moral hazard issues (Dellarocas 2005), therefore, it is understandable to make the most of the intra-transactional interaction to gather as much information as possible so as to mitigate risk and establish trust (Pavlou and Dimoka 2006, Ghose 2009). This work obviously acknowledges the significant impact that online WOM exerts on other kinds of information disclosure, and that pre-sets of the online auction have on the intra-transactional information revealing, more specifically, how buyer-initiated questions during the online auction are affected by previous seller ratings and auction duration. However, due to the fact that the intra-transactional information belongs to textual data, quantification is necessary for further analyzes. The conversion from qualitative data to quantitative data is undertaken by classifying the buyer-initiated questions according to given rules. Prior studies have obtained great achievements in long document classification, but online auction Q&A is short, cryptic, often ungrammatical and is very different from typical long grammatically correct text, thus traditional classifiers usually fail to achieve a satisfactory correct classification rate. This study is also an attempt to bridge this gap by designing and using a new classification method. The method is based on an n-gram scoring algorithm and is shown to outperform more traditional text classification approaches such as the Naïve Bayes classifier and unsupervised K-Medoids Clustering.

Consequently, the qualitative features of intra-transactional interaction during an auction and the quantification of textual auction Q&A are considered along with the role of different genres of information disclosure and their impacts on auction outcomes in the comprehensive conceptual framework (Figure 1). The dotted part of the diagram outlines the specific focus of this research.

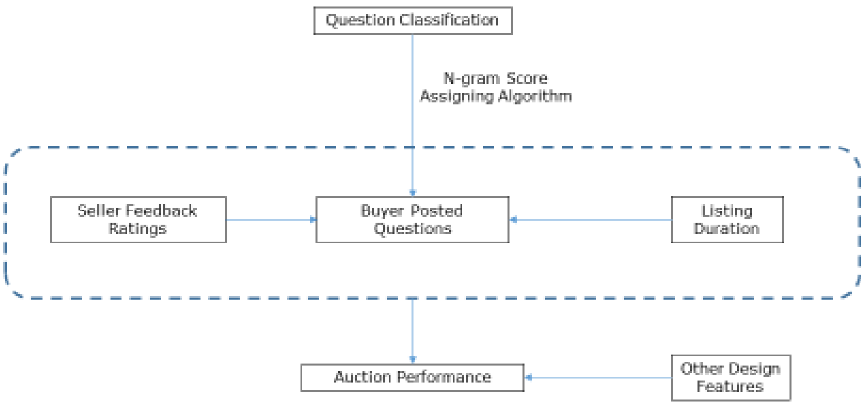

Figure 1. The Conceptual Model

3. PREDETERMINED CLUSTERS

Classification involves developing pre-determined clusters. This belongs to the supervised learning where group labels are defined as the first step. Discriminatory and meaningful predetermined categories are an essential prerequisite for classification, whose importance has always been overlooked since an overwhelmed majority of problems are limited to binary classifications. Additionally, for some difficult problems with more than two categories, the clusters are determined based on common sense. For instance, the groups of movie review opinion mining are naturally pre-defined as positive, negative and neutral without doubt (Tang, Tan et al. 2009, Li and Wu 2010) while the classes of library document titles categorization is adopted following a real-world cataloging system (Mitra, Wang et al. 2007). Nevertheless, for problems that require a new set of categories, reasonable determination and explicit clarification are imperative. In this section, we pre-determined the categorization clusters which are also used as categorical dependent variables for the quantitative analysis afterward. The question categories of this work are inspired and motivated by Srinivasan and Liu's (2014) previous paper, which classified buyer-posted questions with content analysis approach (Srinivasan and Liu 2014). The questions initiated by the buyers are classified into six categories, namely exploratory questions, confirmatory questions, comment implying possible frauds, the intention for inspection, price enquiries and other general questions. This classification method is quite suitable to be addressed by content analysis that puts more emphases on objective evaluations on the content and is more capable of handling people's underlying intentions which are far more difficult for machines to recognize, but it is hard to process large text unit. This work proposes a set of categories which present the online auction intra-transaction questions in a more thorough fashion, and are easily processed by computers. The question categories are listed below:

Cluster 1: Product Description and Quality Inspection

Questions and comments regarding asking more/detailed information of used car auction listing and the intention of looking or inspecting the vehicle. On the one hand, seller-initiated item descriptions are to some extent subjective and incomplete and they are more likely to make the best use of strong points and circumvent weaknesses to foster competitive strength; on the other hand, customers' expectations and requirements might vary widely from each other. Posts in this category tend to concentrate on vehicle's previous usage and maintenance. Depending on the current condition evident in the listing, customers may request more visual information to make better decisions. This type of question allows customers to explore product information on which they focus or arrange a time with the owner for "kicking the tires".

Cluster 2: Seller information and credibility

Questions and comments asking for more information of the sellers such as contact number or email address to access the sellers' characteristic and furthermore mitigate the seller uncertainty. Dimoka et al. (2012) defined the seller uncertainty as potential bidders' predicaments of examining the seller's moral standing and anticipation whether the seller is willing to offer true information and behave collaboratively (Dimoka, Hong et al. 2012). This kind of question assists buyers to establish certain relationships with owners and lower the possibilities of seller opportunism.

Cluster 3: Transaction and shipment

Questions and comments which involve discussions on payment method and shipment issues. In terms of selecting a payment method, for instance, some customers are only cash buyers while others may require an installment payment rather than pay in full at once. Concerning the handover of a car, some people prefer collecting it themselves whereas others would like it to be delivered. Hence, this kind of questions allows sellers and buyers to discuss what kind of transaction method they are going for and corresponding shipment details if they win the bid.

Cluster 4: Negotiation

Questions and comments concerning price negotiation and swapping enquiries. Some genuine buyers may inquire if there is a buy now price or reserve price while others may go straight to bargaining with the owner. In addition, a large quantity of people would like to ask if the owner is willing to do a trade-in with their own car even with extra money added. These kinds of questions and comments are dealing with price enquiries and personal swapping negotiation.

Cluster 5: General questions and comments

This category includes all the general questions and comments which cannot be classified into any other clusters above. Some questions and comments may include spelling mistakes or abbreviation forms which have no effect on understanding but are hard to be recognized by the machine, whereas some other posts may not appear in proper language. Also, some sellers may add some notes which they want people to know. To ensure the integrity of this research, all the questions in the dataset are included in these five clusters, regardless whether the post makes sense.

4. DATA COLLECTION

Data was collected from a leading internet auction operator as the example of the online marketplace and concentrate on used-car auctions. Given our motivation to investigate how seller numerical feedback ratings and listing duration affect the intra-transactional information disclosure during an online auction, the second-hand car auction is selected as the research focus category considering its unique features.

Initially, “Motors” is one of the most striking and recognizable product categories operated in the online auction marketplace we choose. Secondly, compared to new cars, second-hand car trades may incur more information asymmetry between sellers and buyers. In the new car trading market, there is relatively low-quality uncertainty for the buyers since all the automobiles are from a standardized manufacturing process. There is no doubt that a car owner is able to form a comprehensive idea about the quality of the vehicle and differentiate if the car is good-functioning (peach) or defect-ridden (lemon) after using it for a period of time. Conversely, it is more difficult for potential buyers to examine latent mechanical problems of used cars since they are not experts and know little about the previous use of the car. Given the information asymmetry developed between sellers and buyers, people tend to participate more in live interaction forums in order to facilitate information disclosure and overcome adverse selection. Thirdly, second-hand car is a category of complex technical features. There are a wide array of attributes that buyers may consider and different people may concentrate on different parts according to their specific needs and previous experiences. Consequently, the quality of information exchange between auction participants is essential for potential buyers to check out whether a car is worthy of bidding, and the high level of vehicle attribute would further enhance buyers’ willingness to raise their own questions and look for assistances from other useful live conversations. Ultimately, used vehicle is a typical high-involvement product with relatively high value. Potential bidders may think twice and spend a long time to evaluate it before making the final decision. In order not to buy a lemon, the buyer is trying to get as many clues as possible before bidding in high prices. Given this four critical characteristics of second-hand cars, we can conclude that it is an appropriate product category for the purpose of this research.

5. ANALYSIS AND RESULTS

The purpose of this quantitative analysis is to investigate how seller feedback and listing duration drive the formation of buyer-initiated questions. Thus the dependent variable should be a categorical variable which is set to represent the different genres of questions or comments that buyers post online. Through a self-designed text-classification algorithm which successfully achieved averagely 85.67% accuracy, we categorized the buyer-initiated questions given the above-mentioned five predetermined clusters. Totally, 5130 questions and comments from 24th October 2012 to 16th January 2013 were randomly selected to conduct the multinomial logistic regression. The corresponding sellers were separated into three groups according to their numerical feedback achieved in previous transactions, which comprised one of the independent variables of this study. Specifically, the numerical ratings were arranged in order of size from smallest to largest and then divided into three equal parts. The first one-third of sellers were placed into a “low-rating” group (feedback ranged from 0 to 26), the second part were categorized as “medium-rating” (feedback ranged from 27 to 121) whereas the remaining observations were absolutely “high-rating” traders (feedback ranged from 122 to 12361). In addition to the nominal independent variable which allows contrasts among different groups of seller feedback ratings, a continuous independent variable was also included as a covariate to examine how listing duration affects people’s behavior of asking questions. This scale variable was captured by calculating the number of running days from the beginning to the end of listings.

Analyses on how numerical feedback ratings and listing duration motivate people’s choices of raising intra-transactional questions are carried out through a quantitative methodology; more specifically, multinomial logistic regression. In this research, buyer-initiated question types and seller reputation ratings are both nominal; they are utilized as our dependent variable and one of the independent variables respectively, listing duration is regarded as a metric covariate. Since multinomial logistic regression models choose one of the outcome variable categories as the baseline comparison group (base), we ran five models with different categories treated as the reference level in each case.

Regarding the whole model fitting information, the likelihood ratio chi-square value of 52.056 with a p-value smaller than 0.0001 informs us that our entire model fits significantly better than an empty model. Considering the overall effect of a nominal variable, Table 1 also shows which of the independent variables are statistically significant. We can see that both “Listing_duration” and “Feedback_Rating” are highly significant in this case, which indicates that the overall effects of the model (predictor variables) are favorable.

	Chi-Square	P-value
Final	52.056	.000
Listing_Duration	24.169	.000
Feedback_Rating	26.218	.001

Table 1. Model fit information

The “Parameter Estimates” shown in Table 2 below presents the coefficients of the model. The categorical variables are automatically dummy-coded, and each dummy variable has a coefficient for the “Feedback_Rating” variable. As there are five categories of the dependent variable, we can see that there are four sets of logistic regression coefficients (also called logits). The coefficient B represents the log odds (logits) of that particular independent variable. Further, each coefficient represents the comparison of the category in that set to the reference level. In this example, the reference group for the dependent variable is the “Transaction and Shipment” category. Coefficients are therefore interpreted as relative to the particular reference group under consideration. We conducted similar analysis using each of the five categories as reference groups; however we show only one of the results in this table for illustrative purposes.

The coefficients of the Listing Duration variable are positive and significant for the first three categories of questions. Every one unit increase in Listing Duration increases the log odds of the Product Description, Seller Information, and Negotiation categories by 0.033, 0.067, and 0.057 relative to the Transaction and Shipment category. With respect to the impact of feedback ratings on question category we observe the following. For the Product Description and Seller Information categories, lower feedback ratings increase the log odds of those categories compared to the reference category.

By repeating this analysis by rotating the reference category in each iteration, we get a more complete picture of the influence of listing duration and feedback ratings on the likelihood of each type of question being posed by potential buyers. In the next section, we summarize these observations and develop a general level of understanding of the nature of this discourse.

Cluster		B	*p*	Exp(B)
Product description and inspection	Intercept	1.381	**.000****	
	ListingDuration	.033	**.040***	1.033
	[Feedback_Rating=low]	.337	**.027***	1.401
	[Feedback_Rating=medium]	.230	.122	1.259
	[Feedback_Rating=high]	0^b	.	.
Seller information and Credibility	Intercept	-.565	**.013***	
	ListingDuration	.067	**.001****	1.069
	[Feedback_Rating=low]	.497	**.007****	1.644
	[Feedback_Rating=medium]	.441	**.015***	1.555
	[Feedback_Rating=high]	0^b	.	.
Negotiation	Intercept	.836	**.000****	
	ListingDuration	.057	**.001****	1.058
	[Feedback_Rating=low]	.025	.874	1.025
	[Feedback_Rating=medium]	-.009	.951	.991
	[Feedback_Rating=high]	0^b	.	.
General questions	Intercept	1.019	**.000****	
	ListingDuration	.020	.221	1.021
	[Feedback_Rating=low]	.111	.487	1.118
	[Feedback_Rating=medium]	.058	.710	1.060
	[Feedback_Rating=high]	0^b	.	.

Table 2. Parameter Estimates: Transaction and Shipment as Reference Group

[b: Parameter estimate set at 0 due to redundancy]

6. DISCUSSION

Using multinomial logistic regression, this study examines how listing duration and sellers' reputation rating affect buyer's preference of raising intra-transactional-stage questions in online auctions. According to the outputs that we listed in the last section, we will draw some conclusions and discuss the underlying reasons correspondingly. Initially, in relatively shorter length auctions, buyer attention focuses more on collecting comprehensive information about the past use and maintenance of the item. Also they tend to talk about payment method and shipment issues in early stages of an auction. As listing duration gets longer, bidders are apt to be concerned about seller uncertainty, and they are more willing to discuss price and swap negotiation. This is justifiable if we explicitly reconsider the whole trading process. Regardless of how long an item will be listed, the central concern of consumers is whether the vehicle is generally in good condition and whether a majority of attributes meet their expectations. Normally buyers will start with searching for vehicles they appreciate and slotting some in their private "candidate pool" with the assistance of product descriptions and attached images. However, the fact is that seldom seller-initiated information disclosure is all-inclusive and well-rounded. It is not uncommon for sellers to accentuate the strengths of an item while obscuring or even keeping silent about the deficiencies. Moreover, some mechanical aging problems and other internal defects due to long-term utilization or absence of maintenance are difficult to be identified even by the users themselves since they are not automobile experts (Dimoka, Hong et al. 2012). All these factors will dampen the quality of seller-initiated information disclosure. Bearing that in mind, an efficient and effective way is raising questions to collect further information about the listing. Consequently, questions regarding comprehensive product description and quality inspection are the first and foremost issues to be addressed even though the listing duration is short. Another aspect that people concentrate on in earlier stages of a listing is the payment and shipment issues, which relate directly to buyers' final decision. Use-vehicle is not a kind of item whose physical location does not need be considered. Even though a car is exactly what he or she wants, a customer is unlikely to cast a bid if shipment is unavailable. Thus most buyers are willing to check payment method and shipment issues at the very first in order to avoid wasting more time and energy on a “mission impossible”. After making sure that a vehicle has already met all the requirements and that no problems in paying and collecting processes, buyers’ focus will be shifted to collect more information about the sellers such as contact number or address to estimate the sellers’ characteristics and further mitigate the seller uncertainty. Whether a seller will act opportunistically is also a major concern for buyers. Our finding suggests that buyer anxiety about opportunistic conduct become more serious if the listing duration is longer. When it comes to negotiation-related questions, the statistical outputs indicate that the number of these inquiries is expected to experience an increase as the seller prolongs the listing period, which is reasonable since the intention of negotiation is based on sufficient satisfaction about a used-vehicle after generating a penetrative understanding about its previous use and overall quality. Regardless of what kind of negotiation it is, this situation happens only when a trader is indeed interested in a listing and is willing to trade. Even if a trader wants to swap the listing with his own car, he also needs to check the listing first. Therefore, the likelihood of interactions regarding negotiation is higher if traders have sufficient time.

In terms of how seller reputation score drives the formation of buyer-initiated intra-transactional questions, the quantitative analysis provides us with several useful conclusions. Firstly, the possibility of being asked product description and quality inspection related questions is the highest in low reputation seller group. As seller reputation score gets higher, the number of these questions is expected to decline. A possible reason is that sellers with higher reputation scores are equipped with richer experience in previous transactions. They grasp better knowledge of how to display a certain listing and how to give a comprehensive introduction that covers the majority of aspects about which customers may have concerns (Melnik and Alm 2005). Srinivasan and Liu’s (2014) research suggests that a main part of intra-transactional questions are exploratory questions where further information is needed due to an incomplete description (Srinivasan and Liu 2014). Even if the seller has mentioned a certain attribute, buyers can still raise confirmatory questions asking for further explanation for a piece of information provided. Therefore, all-rounded and well-organized product descriptions are effective to mitigate the likelihood of questions of this sort. Furthermore, higher rating sellers are regarded as more believable considering their long-term efforts in building personal credibility, thus corresponding doubts that the seller will deliberately hold some back defects in product description will see a proportionate decline when seller numerical score increases.

Secondly, buyers’ concern about seller uncertainty is only alleviated if the seller has built a high reputation in past transactions; even the medium-rated sellers are suspected of being opportunistic. This piece of finding informs that customers are quite cautious about estimating a seller’s true characteristics. The incredible growth and popularity of online auction make it quick and easy for people to trade with people from all over the world, however, it also provides perfect hunting grounds for scam artists. An official statistical survey of the American Federal Trade Commission (FTC) reveals that nearly 500 auction frauds, such as shilling, internet fencing, misrepresentation, or failure to ship the products, are reported every week. Actually online auction fraud comprises approximately 50% of online fraud reported to the FTC, thus there is no doubt that online consumers have all experienced or heard the stories of fraudulent transactions (Gregg and Scott 2006). Given this, it makes sense that buyers are all circumspect about sellers’ opportunistic conducts; only the traders who have achieved a high reputation score are more likely to be thought of as reliable and trustworthy.

Thirdly, potential buyers are more likely to discuss transaction and shipment issues with those sellers who have already achieved high feedback ratings. Additionally, more price and swap negotiations occur among high rating sellers and bidders. Obviously, dealing with a trader who has already achieved a high reputation is pretty much easier since time and energy spent on product and seller investigation are saved for the subsequent processes. Buyers may directly talk about the payment options and shipment method, negotiate prices with the seller or ask if the seller is willing to do a swap.

7. IMPLICATIONS AND FUTURE WORK

Echoing the discussion in the quantitative analysis about the role of auction listing duration and seller's numerical feedback ratings as driving forces behind the formation of buyer-initiated questions and comments while an auction is in progress, this study sheds light on a number of implications for both research and practice. One of the most significant theoretical implications of this work is connecting the reputation system to the intra-transactional information disclosure in online auctions. Previous research has placed more emphases on how feedback mechanisms adopted in online communities affect people's risk perception and purchase intention in the future and how buyer-initiated live interaction influences the outcomes of online auctions. Our study takes the other way around and investigates how current numerical feedback counts impact the information exchange during the auction listing stage; more specifically the buyers' intentions of raising questions and the buyers' choices of question types. Additionally, we also examine the role of listing duration as a key determinant that drives the formulations and arrangements of intra-transactional communications.

The managerial implication of this research is that it provides a guideline for online auction sellers with different ratings to better display their listings and organize the description contents. We recommend that sellers with tentative lower reputation scores should give as comprehensive a description of the item as possible. Photos are a more straightforward and helpful way to depict a product; as the saying goes, a picture is worth a thousand words. Thus we also suggest that sellers upload images allowing customers to see the product from different perspectives. Furthermore, the findings of the data analyses favors our speculation that buyers are quite harsh on sellers in terms of estimating their true characteristics, only high reputational traders are relatively unlikely to be suspected of being opportunistic. This fear is deemed to be a major obstacles in electronic commerce, but it is also demanding and time-consuming for sellers to achieve such high scores. Therefore, the sellers should take measures to calm customers beforehand. For example, the seller can take initiative to reveal contact details (phone numbers or emails) or get address verified by the website, thus making buyers feel that they are dealing with a good-hearted person. Moreover, for items of high value and attribute complexity like vehicles, a third party insurance is also effective to mitigate buyers' risk perception and alleviate the deficiencies of insufficient reputational ratings.

While we have taken some critical initial steps in several directions, we acknowledge that our research is burdened with several limitations, which suggests avenues for further research. Firstly, this study divides the sellers into three group, low, medium and high according to their numerical feedback counts. Future work might only focus on one specific group and investigate the relationship between high feedback rating sellers and the intra-transactional question types. Secondly, this research provides a possible set of dimensions of classification, which are product, seller, and process related. Future studies may create a new typology. A potential way is identifying the questioner's intention of raising a certain question. From this perspective, a question can be a clarification question which enables sellers to describe more fully and helps buyers to eliminate areas of misunderstanding or a question that just casts a doubt on a certain attribute. This is much like, but not really, sentiment analysis where terms implying people's intentions are captured to determine the membership.

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