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ABSTRACT

Increasing significance of the online consumer-to-consumer (C-2-C) auction market has amplified the need for buyers and sellers to engage in transactions with anonymous counterparts. The sequence of paying first and then taking delivery, introduces a great amount of risk for potential buyers. In order to mitigate this risk, online auction markets (OAMs) are employing an assortment of governance mechanisms, of which reputation scoring and reporting systems are the most popular. Researchers have found substantial evidence from theoretical models as well as empirical studies that higher the reputation rating of a seller, higher the bid prices he/she receives. However, a review of the current literature suggests a conspicuous absence of any standard classification of sellers in OAMs. Lack of such a classification hinders systematic research and theory development. Therefore, a comprehensive classification of sellers, based on feedbacks, is proposed to advance our understanding of online C-2-C auction market and to provide a basis for further research. In addition, the proposed classification is hierarchical rather than monothetic in nature and hence, gives greater systemic power to the classification. Toward demonstrating the classification's systemic power, we present a propositional inventory developed from the classification. We also discuss how the proposed classification accommodates current research and furthers theory building in this research area.

Keywords

Online auction market (OAM), reputation, feedback, classification of sellers.

INTRODUCTION

Growth in the online market has increased the need for buyers and sellers to engage in transactions with unknown counterparts [Houser and Wooders 2000]. Often in cases of online B-2-B (Business-to-Business) and B-2-C (Business-to-Consumer) transactions, the buyers are at least familiar with the sellers. However, in case of C-2-C (Consumer-to-Consumer) online auction markets (OAMs), both buyers and sellers are total strangers and their true identity is seldom known [Houser and Wooders 2000; Livingston 2002; Zacharia et al. 2000]. Further, buyers have to solely rely on unknown sellers' description of products, as buyers have no other means of finding the details of products that they are interested in. Moreover, in such markets, it is not uncommon for payments to precede the delivery of products [Livingston 2002; Melnik and Alm 2002]. The sequence of paying first and then taking the delivery of products, often combined with little or no ability to examine the product in advance, introduces a great amount of risk for potential buyers [Zacharia et al. 2000]. Buyers hardly have any means of preventing the sellers from indulging in opportunistic acts [Shapiro 1983] and for most part rely on the information provided by the sellers [Zacharia et al. 2000]. This situation creates asymmetrical distribution of information whereby sellers, when compared to buyers, not only possesses far more information about the product but also have the opportunity to withhold information critical to the transaction [Choi et al. 1997; Fudenberg and Levine 1989; Houston 2003]. Such asymmetrical distribution of information reduces the credibility of the signals (about product quality and other transaction related information) sent by sellers and hence, can lead to market malfunction or even market failure [Akerlof 1970].

Such a situation demands some sort of governance mechanism aimed at mitigating the risks faced by potential buyers [Kollock 1999]. In fact a variety of governance mechanisms such as insurances (provided by the market provider) and warranties do exist in OAMs. However, they impose an additional cost to the buyers, which is often not desired [Shapiro 1983], especially when the worth of the transaction is small. Therefore, reputation systems have been resorted to as a mechanism to reduce information asymmetries [McDonald & Slawson 2002] that can be used by the buyers without incurring significant additional costs [Shapiro 1983]. The term reputation has been defined in different ways in different studies [Houston 2003; Mailath and Samuelson 2001; Zacharia et al. 2000]. For the purposes of this study, reputation refers to buyer's estimation of consistency in seller's behavior over a period of time over any given attribute such as integrity, competence, etc. [Herbig et al. 1994].

With the growth in the OAMs, online C-2-C websites such as ebay.com, yahoo.com, and other market providers have set up reputation mechanisms where by buyers and sellers provide feedbacks and rate each other based on their transaction related experiences [Livingston 2002; Resnick and Zeckhauser 2001]. Feedbacks are specific to the parties involved in a particular transaction and are classified into positive, negative or neutral feedbacks and the difference between the total number of positive and negative feedbacks forms the seller's net reputation rating [Standifird 2001]. Future buyers examine the feedbacks and the net reputation ratings of sellers, with the objectives of reducing existing information asymmetries and making better-informed decisions [Livingston 2002]. While extensive literature exists on the differential treatments received by sellers with high and low reputation [Allen 1984; Klein and Leffler 1981; Livingston 2002; McDonald and Slawson 2002; Melnik and Alm 2002; Shapiro 1983;], no study has systematically developed a classification of sellers in OAMs. Absence of a comprehensive classification of a phenomenon being studied so widely restricts the prospects for systematically studying the phenomenon and the opportunities for developing related theories. Therefore, in this paper we present a hierarchical classification of sellers in OAMs that can facilitate systematic research. Subsequently, we (i) assess the classification using the evaluative criteria provided by Hunt (1991), (ii) demonstrate the systemic power of the classification by providing a sample propositional inventory, and (iii) discuss how the proposed classification can facilitate further theory building, while accommodating current research.

SELLERS IN ONLINE AUCTION MARKETS: A CLASSIFICATION

Past research on the role of reputation in OAMs has focused on a number of important issues some of which have been summarized in Figure 1.

While different groups of sellers such as new comers, sellers with positive or negative reputation, have been individually identified in the literature, a review of the relevant literature reveals no standard classification of OAM sellers based on feedbacks or reputation scores. Since classification schemata play a significant role in organizing phenomena into classes that are amenable to systematic investigation and theory development (Hunt, 1991), we propose a classification of OAM sellers that could potentially lead to substantive theoretical development, facilitate meaningful comparisons between different groups of sellers, help in developing a holistic perspective about the impact of reputation on bid prices, and provide other research opportunities. While recognizing that sellers can be categorized on the basis of product types, price range of the products, homogeneity and heterogeneity of products, innocence and malice in intentions, etc., in this paper, we present a parsimonious but adequate classification scheme of sellers based on feedbacks, since feedbacks and the reputation ratings calculated based on feedbacks have been extensively studied as determinants of the prices and number of bids received by an OAM seller. Since we are developing the classification " a priori", i.e., before analyzing any specific set of data, the procedure employed here is called logical partitioning (Harvey 1969). Though the classification is not based on empirical data, it is strongly based on past literature and findings in this area of research. This way of classifying schema is also called "deductive classification" or "classification from above" (Hunt 1991).

Developing a classification schema involves three main steps: (i) specifying the phenomena to be categorized, (ii) delineating the categorial term(s), which are properties of the phenomena on which the classification schema is to be based, and (iii) labeling the various categories that emerge from applying the categorial terms to the phenomena (Hunt 1991). The phenomenon that we are attempting to categorize is OAM sellers, based on feedback provided by unique registered users, which is then used to calculate reputation ratings as the difference between the number of positive and negative feedbacks (McDonald & Slawson 2002). More specifically, the classification is based on (i) type of feedbacks (positive, negative, or neutral) that can be aggregated to obtain the reputation ratings of sellers, (ii) proportion of negative feedbacks, and (iii) nature of negative feedbacks (feedbacks suggesting total loss or partial loss) that can be aggregated into proportion of negative feedbacks suggesting partial or total loss. Based on the reputation ratings, sellers can be categorized into five different groups: 1. Sellers with high positive reputation, 2. Sellers with average reputation, 3. Sellers with low positive reputation, 4. Sellers with zero reputation, and 5. Sellers with negative reputation. However, we contend that reputation, as a simple number may not tell the complete story. For example, if two sellers have a high positive reputation score of 100, they may be perceived very differently by customers because seller A might have received 150 positive feedbacks and 50 negative feedbacks while seller B might have received 1100 positive feedbacks and 1000 negative feedbacks. Hence, proportion of negative feedbacks received should be included in the classification and therefore, each category in the classification can be

1. A stringent reputation mechanism works effectively towards alleviating information asymmetries and facilitating a market for quality products [Diamond 1989; Houston 2003; Klein and Leffler 1981; McDonald and Slawson 2002; Shapiro 1983;].

2. Anecdotal evidence strongly suggests that reputation greatly matters in OAM and that buyers in this market do actually pay attention to the sellers' reputation [Friedman and Resnick 2001].

3. In OAMs, reputation building is not free of cost. It occurs at a cost to the players, i.e., players with low reputation are treated poorly when compared to players with high reputation [Rao and Ruekert 1994; Shapiro 1983].

4. In the long run participants are rewarded for building reputation and the rewards thus received far outweigh the costs incurred in the process of reputation building [Kreps and Wilson 1982; Milgrom and Roberts 1982].

5. Several empirical studies have examined the impact of reputation on buyers bidding behaviors and have found that there is a significant relationship between sellers' reputation and the bid prices received by them [Friedman and Resnick 2001; Houser and Wooders 2000; McDonald and Slawson 2002; Melnik and Alm 2002; Shapiro 1983].

6. While the magnitude of impact has differed from study to study, it is evident from theoretical models as well as empirical studies that higher the reputation of a seller higher the number of bids and prices that he receives [Allen 1984; Camarer and Weigelt 1988; Houser and Wooders 2000; Kalyanam and McIntyre 2001; Klein and Leffler 1981; Livingston 2002; Lucking-Reiley et al. 1999; McDonald and Slawson 2002; Melnik and Alm 2002; Shapiro 1983;].

7. Negative ratings have a highly significant impact on the bid prices, i.e., negative ratings considerably reduce the bid prices received by the seller [Shapiro 1983; Standifird 2001].

8. New comers or sellers with no reputation or negative reputation are treated poorly during their initial transactions i.e., they receive low bids or no bids irrespective of the quality of the product they are offering for sale [Friedman and Resnick 2001; Resnick and Zeckhauser 2001; Shapiro 1983; Zacharia et al. 2000].

Figure 1: Summary of some of the important findings from the past literature on sellers in OAMs

further classified as sellers with high and low proportion of negative feedbacks. In addition, we propose that the nature of negative feedbacks can affect the reputation of sellers. Within negative feedbacks, there could potentially be information relating to total loss or partial loss. For instance, a negative feedback could be, “Sent money but did not receive the product” or “product was totally damaged and was of no use to me!” Such feedbacks suggest that the buyer perceived total loss from the transaction. On the other hand feedback could have been, “Received the book on time but one page was torn!” In this case, the feedback does not suggest total loss but signifies buyer's perception of partial loss, i.e., not getting everything he/she expected from the transaction. Therefore, sellers can be further classified based on the nature of the feedbacks received by them, and hence sellers can be with high or low proportion of negative feedbacks suggesting total loss or partial loss. The procedure employed to create the classification has resulted in a hierarchical classification represented in figure 2. The advantage of such a classification is that it has greater power in systematically organizing the phenomenon under investigation (Hunt 1991). We now describe each category in the classification that was briefly introduced here.

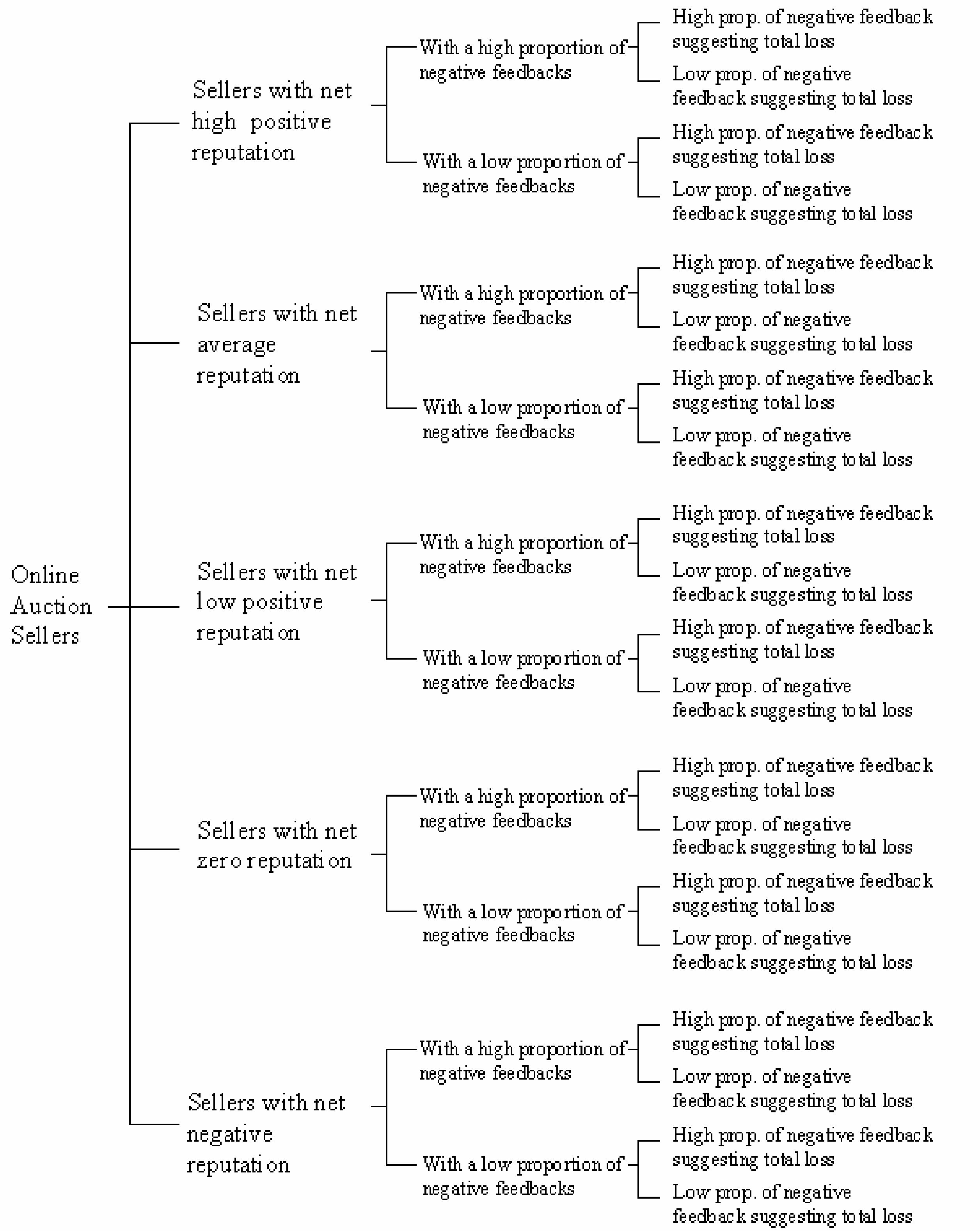

Figure 2: Classification of Sellers in OAM based on Feedbacks

Level I: Categorization Based on Reputation Ratings

Most research in this research area has displayed a historical bias towards sellers with high and low reputation ratings. Given that OAMs are relatively immature, there is a conspicuous presence and a constant influx of sellers with (i) low positive reputation, (ii) zero reputation, and (iii) negative reputation. In this section, we discuss the various categories of sellers based on their reputation ratings.

2.1.1 Sellers With High Positive Reputation

This group of sellers refers to those whose reputation ratings are greater than the average rating of sellers in a specified product market. For example, if average ratings of sellers in a market for a particular product is 75, and a seller S has a rating of 200, he will be considered as a seller with high positive reputation. Past research has shown that this group of sellers is the most desired one and often receives high bids for their products [Livingston 2002; McDonald and Slawson 2002; Melnik and Alm 2002].

2.1.2 Sellers With Average Reputation

Sellers with average reputation are those whose reputation ratings equal to the average ratings of sellers in that product market. For example, if average ratings of sellers in a market for a particular product is 75, and a seller S has a rating of 75 or a rating close to that number, he will be considered as a seller with average reputation. Average ratings can probably act as the reputation ratings that a buyer can commonly expect in that particular product market.

2.1.3 Sellers With Low Positive Reputation

Sellers with a reputation rating significantly less than the average ratings of sellers in a specified product market are referred to as sellers with low positive reputation. For example, if average ratings of sellers in a market for a particular product is 75, and a seller S has a rating of 5, he will be considered as a seller with low positive reputation. This group of sellers would include those sellers who are relatively new to the OAM itself, those who are old to the market itself but have sold very few items during that period, those who have often not received feedbacks on the transactions carried over by them, or those who have positive as well as negative feedbacks such that their net reputation rating is relatively lower than others.

2.1.4 Sellers With Zero Reputation

This group of sellers refers to those whose reputation score is equal to zero. This group of sellers might be composed of different types of sellers. It includes (i) sellers with a transaction history but no feedbacks, (ii) sellers with a transaction history but with equal number of positive as well as negative feedbacks, and (iii) sellers who are new comers to the OAM.

2.1.5 Sellers With Negative Reputation

This group refers to sellers whose net reputation score is less than zero, i.e. number of negative feedbacks is greater than the number of positive feedbacks. In case of eBay, the reputation ratings of such sellers might range from –1 to –4. It cannot go any lower as eBay removes sellers with lower scores from their OAM.

It is important to note that the proposed categorization uses the net reputation ratings of sellers to classify them into one of the five categories mentioned above. However, the categorization is specific to a product market. For example, lets assume that a seller's reputation score is 50. When he attempts to sell a book, the average reputation score in that market could be 100 and hence, he could be treated as a seller with low positive reputation in that market. But when the same seller attempts to sell a laptop, he might be considered as a seller with high positive reputation because the average reputation scores in that market is 25. Thus, the categorization is flexible enough to accommodate the changing status of a seller.

Level II: Categorization Based on Proportion of Negative Feedbacks

Each category of sellers in Level I can be further classified based on the proportion of negative feedbacks received by them. This categorization is essential because two sellers with the same reputation rating might be treated differently depending on the proportion of negative feedbacks received by them. That is, two sellers A and B with a reputation rating of 50 will be treated differently if they have significantly different proportions of negative feedbacks, for instance, 1% and 45% respectively. Other things being equal, its reasonable for anyone to choose seller A over B. Therefore, we further classify sellers in each category in Level I, based on the proportion of negative feedbacks, as sellers with high proportion of negative feedbacks and sellers with low proportion of negative feedbacks. Sellers with high proportion of negative feedbacks also refer to sellers with low proportion of positive feedbacks and vice versa. Additionally, sellers with high proportion of positive feedbacks include sellers with no negative feedbacks. Given the significant implications of negative feedbacks (Standifird 2001), we classify sellers in Level I based on proportion of negative feedbacks rather than the proportion of positive feedbacks. For the purposes of this classification we classify sellers with 25% or a greater percent of negative feedbacks as sellers with high proportion of negative feedback and sellers with 1% - 24% of negative feedbacks as sellers with low proportion of negative feedback.

Level III: Categorization Based on Nature of the Feedback

Buyers are not likely to interpret all feedbacks simply as positive, negative or neutral feedbacks. Lets consider for instance two positive feedbacks. 1. “Great seller, great transaction. Thank You!” 2. “Got what I wanted but delivery was late by a week.” Though both are positive feedbacks they clearly do not suggest the same information about the sellers. In the first case, the buyer is totally satisfied and hence perceives “total gain” whereas in the second case the buyer is not totally satisfied and hence, perceives only “partial gain” that might vary in degree from buyer to buyer. Next lets consider two negative feedbacks. 1. “Sent the money, did not get the product.” 2. “Got the product after one month!” In the first case, the buyer perceives “total loss” since he did not get anything in return for his payment. In the second case, the buyer does get the product but is not satisfied due to the delayed delivery and hence perceives “partial loss”. A close observation highlights the similarity between partial loss and partial gain. The only difference between them is how the buyer perceived the case. If the buyer classifies such a feedback as positive, it means he/she perceives the transaction to be a transaction fetching partial gain or else he considers it to be a transaction resulting in partial loss. Therefore, based on the nature of the feedbacks, sellers can be classified as sellers with high or low proportion of positive or negative feedbacks suggesting total or partial gain or total or partial loss. However, according to Standifird (2001, p. 293), “… positive reputational rating emerged as only mildly significant in determining the final bid price … whereas a negative reputational rating emerged as highly significant and detrimental.” Therefore, we further classify sellers in level II as sellers with high proportion of negative feedbacks suggesting total loss or partial loss. Sellers with 50% or more of negative feedbacks suggesting total loss are considered as sellers with high proportion of negative feedbacks suggesting total loss else they are classified as sellers with negative feedbacks suggesting high proportion of feedbacks suggesting partial loss.

Empty Classes

An important observation made relating to logical partitioning is the scope for empty classes (Hunt, 1991). According to Hunt (1991, p. 180), “… proper application of categorial terms may generate a class to which no phenomenon belongs.” Our classification has certain empty classes precisely for the reason suggested by Hunt (1991). Sellers with zero reputation can either have equal number of positive and negative feedbacks or have no negative feedbacks. Similarly, sellers with net negative ratings will always have more number of negative feedbacks than positive feedbacks. Therefore, sellers with zero or negative reputation ratings can be further classified as sellers with high proportion of negative feedbacks but not as sellers with low proportion of negative feedbacks and hence, the category of low proportion of negative feedbacks and its subsequent classifications will be empty classes for sellers with zero or negative reputational ratings.

EVALUATION OF THE PROPOSED CONCEPTUAL MODEL

Although alternative classifications of sellers in OAMs are not available, we attempt to validate our classification by evaluating it based on five important criteria provided by Hunt (1991)

Does the schema adequately specify the phenomenon to be classified? As there seems to be a consensus among researchers about the definition of an OAM seller, this schema does well on criterion 1 referring to what is being categorized.

Does the schema adequately specify the properties or characteristics that will be doing the classifying? Throughout the classification, we uniformly use type of reputation scores, proportion of negative feedbacks, and nature of negative feedbacks as categorial terms that form the basis of our classification. Hence, the scheme is structurally sound and does not produce different and inconsistent systems of classes. Also, our classification procedures are inter-subjectively unambiguous, i.e., given our categorial terms different people would classify the phenomena into the same categories.

Does the schema have categories that are mutually exclusive? Since one seller who belongs to one category or class does not fit into any other category or class at a given point in time in a given product market, all categories are mutually exclusive. For example, a seller who belongs to high positive reputation class for one product does not fit into negative reputation class for the same product at a given point in time.

Does the schema have categories that are collectively exhaustive? As every seller that needs to be classified does have a home in our classification, our classification is collectively exhaustive.

Is the schema useful? Our classification is devised to explicate buyer behavior with reference to various sellers that are present in OAMs. To the extent that our classification adequately classifies sellers and generates intellectual discourse for further conceptual and empirical work, it is useful. We encourage researchers to critically evaluate our work toward a better understanding of OAMs. Further, we further demonstrate the usefulness of the proposed conceptual model in the following section.

A DEMONSTRATION OF THE SYSTEMIC POWER OF THE CONCEPTUAL MODEL: A PROPOSITIONAL INVENTORY

An important use of classifications is its ability to systematically generate meaningful propositions. A number of propositions can be put forward based on the proposed classification of sellers in OAMs. Due to space limitations, we put forward five interesting propositions that can be used to study how prospective buyers are likely to treat the different categories of less desirable sellers (sellers with low positive reputation, sellers with zero reputation, and sellers with negative reputation).

Negative reputation increases the risks for potential buyers [Shapiro 1983]. Due to the negative signals sent by the negative ratings, such sellers will have to sell their products at significantly lower prices when compared to new sellers who send no signals about their credibility to the buyers. We propose that sending no signals is better than sending strong negative signals. Thus,

Proposition One: *Sellers with negative* reputation *are likely to receive lower prices on their products when compared to new sellers, ceteris paribus.*

Unlike sellers with negative reputation, sellers with low reputation send mixed signal to the buyers because they have both positive and negative feedbacks. When compared, sellers with low reputation can be expected to send more desirable signals than sellers with negative reputation. That is, other things being equal, buyers are likely to choose sellers with low reputation over sellers with negative reputation.

Proposition Two (a): *Sellers with negative reputation are likely to receive lower prices on their products when compared to low reputation sellers who have received negative feedbacks significantly suggesting partial loss, ceteris paribus.*

Proposition Two (b): *Sellers with negative reputation are likely to receive lower prices on their products when compared to low reputation sellers who have received negative feedbacks significantly suggesting total loss, ceteris paribus.*

Empirical studies on sellers with low reputation show that such sellers receive lower bids because low reputation signals reduced assurance of sellers completing transactions as contracted [Shapiro 1983]. Sellers with negative feedbacks suggesting complete loss can be expected to send stronger negative signals to buyers about the seller's credibility when compared to sellers with negative feedbacks suggesting partial loss. Therefore, the effects of negative feedbacks suggesting total loss and partial loss are predicted to be unequal. Drawing from probability theory, we propose that buyers will place greater negative weights on sellers with feedbacks suggesting total loss when compared to sellers with feedbacks suggesting partial loss. Thus,

Proposition Three: *Sellers with negative feedbacks suggesting total loss to the buyers are likely to receive lower prices when compared to sellers with negative feedbacks significantly suggesting partial loss to the buyer, ceteris paribus.*

While a seller with negative feedbacks suggesting total loss sends strong negative signals to the buyer, a new seller has no means of sending any positive signal. In this case, buyers can either choose between sellers who are more likely to default or choose sellers whose behavior is not much known and hence, there is a possibility that the buyer might honor the agreement. Drawing from prospect theory, we argue that in cases of losses, individuals are willing to take chances and explore the unknown. Therefore,

Proposition Four: *New sellers are likely to receive better prices when compared to low reputation sellers with negative feedbacks significantly suggesting total loss to the buyer, ceteris paribus.*

While comparing low reputation sellers with negative feedbacks suggesting partial loss versus new sellers, buyers need to choose between new sellers and sellers with low reputation. Since sellers with low reputation do have some positive feedbacks and the negative feedbacks do not suggest total loss, it is more likely that buyers will choose them over new buyers. Thus,

Proposition Five: *Low reputation sellers with negative feedbacks significantly suggesting partial loss are likely to receive better prices when compared to new sellers, ceteris paribus.*

Next, with reference to accommodating current research and facilitating further theory building, we discuss some of the other uses of our classification.

DISCUSSION

Given the relative immaturity of OAMs, there is immense scope for both empirical and conceptual work. Our endeavor, we hope provides a small but significant thrust in that direction. Our work could lead intellectually stimulating researchers to come up with newer classifications that could then be validated and to systematic empirical investigations using our classification. Our classification also has important implications for practice. The process of developing the classification highlighted the need for including information such as mean reputation scores in a product market as it can provide buyers with useful information in evaluating a sellers' reputation. It also draws attention towards more closely examining feedbacks in terms of total and partial loss. Empirical studies in this area could have important implications for building more sophisticated and useful reputation reporting systems.

It is important to note that our classification does not undermine the research that has been done so far. In fact, our classification accommodates research that compares sellers with high and low reputation. In addition, our classification highlights the need to pay greater attention to the process of reputation building by introducing sub-classes that could bring greater explanatory power with reference to buyer behavior that reflects in number of bids and bid prices received by a seller.

As we have argued earlier in this article, classifications are important for developing good research traditions in our discipline, because classifications are amenable to systematic investigation and thereby theory development. With our proposed classification we have demonstrated that (i) new propositions and hypotheses concerning various categories can be developed, (ii) a sound foundation that provides the basis for cumulative conceptual and empirical research can be provided, and (iii) last but not the least, concept or theory driven work that could potentially stimulate the intellectual curiosity of researchers can be initiated. Toward an intellectual discourse that can facilitate stronger theory-informed empirical research, *we wait!*

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