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Buyers' Negative Ratings and Textual Comments on eBay: Reasons for Posting Ratings and Factors in Denouncing Sellers

Xubo Zhang [1], Yanbin Tu [2,*], Mark H. Haney [3] and Huawei Cheng [4]

[1] School of Economics, Wuhan Polytechnic University, Wuhan 430048, China; zhangxubo@whpu.edu.cn
[2] Rockwell School of Business, Robert Morris University, Moon Township, PA 15108, USA
[3] College of Business Administration, University of Pittsburgh, Pittsburgh, PA 15260, USA; mhaney@katz.pitt.edu
[4] School of Information Management & Engineering, Shanghai University of Finance and Economics, Shanghai 200433, China; 2021111459@live.sufe.edu.cn
* Correspondence: tu@rmu.edu

Abstract: In this study, we use a dataset collected from eBay to analyze buyers' negative feedback ratings and associated textual comments. By using text mining and sentiment analysis, we identify seven key reasons why buyers post negative ratings: communication problems, shipping issues, product defects, payment refund problems, customer service issues, fraud, and product packaging. These seven reasons can be classified into three categories: (1) sellers' malicious fraudulence toward buyers, (2) factors likely under the control of sellers, and (3) factors not likely under the control of sellers. Drawing on these categories, we discuss how sellers can effectively reduce the likelihood that buyers post negative ratings. The most important things sellers can do to avoid negative ratings are to improve communications with buyers and to handle product shipping issues properly. In addition to posting the reasons for their negative ratings of sellers, the textual comments associated with negative feedback ratings may also include direct denouncements of sellers, such as buyers explicitly claiming a seller is a liar and warning other buyers to be cautious of the seller. We collectively call these actions buyers' denouncements against sellers. These denouncements have significant negative impacts on sellers' reputations. In this study, we use correlation analysis and logistic regression to investigate the factors that motivate buyers to denounce sellers. We find that, of the three categories of reasons why buyers post negative ratings, sellers' malicious fraudulence toward buyers and factors likely under the control of sellers are more likely to lead to buyers' denouncements of sellers, while factors not likely under the control of sellers are not likely to lead to buyers' denouncements of sellers. In addition, buyers' strong negative sentiment is also more likely to lead to their denouncement of sellers. Managerial implications of these findings are discussed.

Keywords: e-commerce; negative ratings; textual comments; buyers' denouncements; sentiment analysis

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1. Introduction

eBay's feedback rating system or reputation system is an important and successful mechanism to boost online users' trust [1–4]. eBay's rating system invites the winning bidder/buyer to rate their purchase experience as positive, negative, or neutral. A positive feedback rating (+) indicates that the buyer was satisfied with the auction transaction. A neutral feedback rating (0) indicates that the buyer was not fully satisfied with the auction transaction and has some reservations. A negative feedback rating (−) indicates that the buyer is strongly dissatisfied with the auction transaction. Buyers can only rate a transaction as positive, neutral, or negative. Buyers can also write brief textual comments that will be posted with their feedback ratings. These comments typically include content such as the buyer's reasons for their rating of the transaction and the buyer's evaluations of the seller. The comments also reflect the buyer's sentiments, ranging from appreciation and pride

to frustration and anger. Once posted, these comments, along with the positive, negative, or neutral ratings, are publicly available to eBay users. For an eBay user, feedback ratings are aggregated into a summary score displayed next to their ID. Over time, an eBay user develops a feedback profile, or reputation, based on other users' comments and ratings. The feedback score is an essential piece of a feedback profile. The higher an eBay user's feedback score is, the more likely potential customers will want to do business with the user [5]. Potential eBay buyers could use this information to judge sellers' reputations and decide if they should bid for their auction listings. Compared with a positive feedback rating, the marginal impact of a negative feedback rating is more significant [1,2,6,7]. Therefore, after completing auction transactions, sellers want to receive positive feedback with positive comments and avoid receiving negative or neutral feedback from buyers. A large amount of feedback and a high percentage of positive feedback distinguish experienced sellers with good reputations [8–10]. A good reputation could result in the seller receiving a price premium for their products listed on online auction marketplaces [6], while negative or neutral feedback could prevent the seller from gaining customer trust, and even force a new seller to exit the online auction markets on eBay [11]. Therefore, studies on negative feedback, particularly those that help to clarify buyers' complaints and pain points, will be useful in helping sellers improve their service and build their reputation.

There are many studies on online auctions in the literature. These studies can be classified into four streams: (1) online auction transactions and their determinants; (2) online auction mechanisms and designs; (3) online trust and information asymmetry; and (4) online reputation and its role [12]. In the literature, studies on buyers' behavior after online auction transactions are limited. While there are some studies on buyers' feedback ratings, few studies provide in-depth investigations of the buyers' textual comments associated with their negative feedback ratings. In their textual comments, buyers not only explain their reasons for posting negative ratings, but sometimes also make strongly negative claims about the seller, such as alleging that the seller is a liar or cheater, or warning new buyers to "be aware of this guy". We define these extremely negative claims and allegations as buyers' denouncements against sellers. These extremely negative e-WOMs might have serious negative impacts on a seller's image and reputation [13]. To our best knowledge, few studies have investigated the determinants of these denouncements in the literature. This study aims to fill this gap in the literature. We focus on the following two research questions:

- What are the major reasons that buyers post negative ratings?
- What factors lead to buyers' denouncements against sellers?

Answers to these questions can help online auction sellers understand buyers' behavior and improve their service. They can also help sellers avoid negative feedback ratings and buyers' denouncements against them. All these efforts will help enhance the efficiency of online markets. We also contribute to the literature by defining and investigating online buyers' denouncements against sellers.

This paper is organized as follows: after this introduction, we provide a literature review. Then, we conduct data analysis and present our research findings. We also discuss the findings and their managerial implications. Finally, we conclude the study and discuss its limitations and potential future studies.

2. Literature Review

Prior studies on online auctions suggest that eBay's online feedback system is generally effective at improving trust between buyers and sellers, which leads to higher sale rates and higher sale prices. The authors of [14] empirically investigated a large data set from eBay's feedback system from 1999. They found that the feedback profile of a seller on eBay had predictive ability for the seller's future performance and helped buyers to avoid problematic transactions. Using controlled experiments, ref. [6] found that eBay's online feedback system was effective at inducing trust of buyers and produced higher price premiums for sellers with more positive buyer ratings. The authors of [7] investigated

the effects of reputation, as measured by a seller's feedback rating, on the selling price of auctions on eBay. They found that a seller with an extremely high reputation (established identity) had a higher probability of sale and earned on average a 7.6% price premium compared to a newcomer identity.

Ref. [10] found that after sellers received negative feedback for the first time, the sellers experienced a decline in sale growth rate and selling price. The sellers were also substantially more likely to receive subsequent negative feedback from buyers. Their findings suggest that negative feedback damages sellers' reputations and decreases their effort level. Their empirical evidence also indicates that among sellers receiving negative feedback, the ones with a worse feedback score are more likely to exit the market while sellers with a relatively good feedback record are more likely to improve their feedback record.

Based on an analysis of a large panel of sellers on eBay, ref. [15] found that sellers were more likely to stop listing items on eBay right after receiving negative feedback, which was attributed to a psychological impact of feeling unappreciated more than an economic impact. Sellers tend to receive more negative feedback after receiving the first piece of negative feedback if they continue listing items, suggesting that buyers are more inclined to give negative feedback to sellers who recently received negative feedback. In addition, buyers read and study many other pieces of detailed information provided by the feedback system. Specifically, buyers pay more attention to the number of unique negative feedback comments for a seller than to the number of unique positive ones. This suggests that negative feedback harms a seller's reputation more than positive feedback augments it [16]. Ref. [17] found that an eBay seller's number of positive feedback ratings and number of neutral and negative feedback ratings had a significant effect, both in the economic and statistical sense, on the selling price received by the seller. Ref. [18] provided empirical evidence validating the findings in prior research. They showed that a seller's feedback rating on eBay was positively associated with bidding prices for goods in auctions. They also indicated that negative feedback was associated with lower final auction prices on eBay, and potential buyers were more sensitive to negative feedback when buying used or refurbished products. Ref. [19] indicated that a seller's selling reputation (feedback rating from sales) was positively associated with probability of sale and selling prices, while a seller's buying reputation (feedback rating from purchases) had no effect on them. This study also showed that negative selling feedback was weighed more heavily by potential buyers than positive feedback. Ref. [20] examined the factors that affect the long-term survival rate of auction ventures on eBay. Using data collected from eBay's feedback system for 2004, 2009, and 2013, they found that eBay ventures' size, age, total number of feedback ratings, and percentage of positive feedback ratings had a significantly positive effect on the likelihood of their long-term survival.

Although eBay's online feedback system works well overall, there are some challenges and issues, which include retaliation and subsequent revoking of feedback, reciprocation, changing of online identity, purchasing fake positive feedback, and the "market for feedback" with the sole purpose of manufacturing positive feedback [9]. Ref. [3] found that the feedback system could be manipulated for strategic or reciprocation motives. They suggest that a simultaneous rating system, as opposed to sequential endogenous and exogenous systems, can effectively reduce retaliation and strategic ratings and lead to higher trust. Ref. [4] found that the two-way feedback system of eBay enabled certain sellers to engage in the opportunistic behavior of retaliation, subsequently compelling the buyers to revoke their negative feedback. Ref. [21] reviewed fraud on eBay and discussed limitations of eBay's feedback system for preventing fraud such as seller retaliation, changing of online identity, and purchases of fake positive feedback.

As shown above, there are many studies investigating the effects of feedback ratings on sellers. The literature on factors motivating buyers to post negative ratings or even to make strong denouncements of sellers is, in contrast, relatively sparse. Ref. [22] studied the factors motivating consumers to post their reviews online. As part of e-words of mouth (e-WOMs), these online reviews along with textual comments impact consumer behavior

and vendors' sales [23]. In the case of online auctions, an existing study showed that buyers posted negative ratings on eBay due to various reasons [24]. However, the sample size was small (totaling only 1132 negative ratings), and no ranking of the reasons was proposed. In this study, we use a large dataset and apply text mining techniques to shed more light on users' reasons for their negative feedback ratings. In addition to negative feedback ratings, the literature suggests that customers who are extremely unhappy, dissatisfied, or disappointed may post strong denouncements of sellers that may include expressions of anger and hatred [25]. These denouncements spread with contagious effect, which results in negative outcomes for sellers [26]. The literature on understanding and properly handling this kind of negative word-of-mouth in the past four decades has been surveyed by [27]. However, the factors driving online customers' expressions of anger, hatreds, and curses toward sellers (we collectively call them denouncements against sellers) have not been studied thoroughly in the literature. This study helps to fill this gap in the literature.

3. Research Methodology and Analytical Outcomes

To study the research questions mentioned in the Introduction Section, we used PHP, APACHE, MSSQL Server, and other software applications to build an Internet spider. PHP is used to access and save Web pages, and then parse the pages to capture the data points of interest. APACHE is used as a server, and MSSQL Server is used to manage and wrangle the data. Many other software applications such as Python, MySQL, and others can also be used to build Internet spiders to collect online data. The use of Internet spiders to harvest data from eBay is well-established in the business literature [28–31]. We randomly selected thousands of sellers and collected their auction listings on eBay. Then, we collected feedback and comments posted by buyers. Among the millions of feedback instances of all kinds (positive, neutral, and negative), our filtering yielded 43,404 instances of negative feedback with associated text comments posted by buyers for this study. The dataset is summarized in Table 1.

Table 1. Summary of the dataset.

Total #(Number) of Negative Ratings	**43,404**
# of Unique Sellers	8490
# of Unique Buyers	40,408
Average Comment Length in Words	70
Minimum Comment Length in Words	4
Maximum Comment Length in Words	100
Comment Length Standard Deviation	14.7
# of Ratings with Buyers' Denouncements Against Sellers	11,090
Examples of Textual Comments with Negative Ratings	
Terrible Seller. Never received item. Never replied to my emails. *** AVOID ***	
I haven't received the DVD yet. If you forgot or something, please let me know.	
EBAY SENT ALERT NOT TO PAY HE WAS NO LONGER A MEMBER	
NEVER RECEIVED ITEM, TOOK MY $	
refuse to make contact on wrong item mailed	
Tried to contact/pay for 2wks, no response, then I received strike? horrible seller!!	
shipped late, wrong item, no help, by my dime they sent replacement, miss parts.	
I'm very upset the cd player is broken and won't play CDs	

3.1. What Reasons Trigger Buyers to Post Negative Ratings?

The process of buyers posting their negative feedback ratings is described in Figure 1 [24]. After sellers and buyers make a deal on a transaction, sellers will fulfill the deal

through actions such as product packing, shipping, insurance, and more. However, many issues can occur, such as late shipping, shipping the wrong product, poor communication, bad customer service, and even sellers' fraudulence. These issues bring about buyers' unhappiness, dissatisfaction, and even anger, which results in their choice to post negative ratings. Buyers might also include reasons to explain their choice of posting negative ratings. Some buyers also express their anger, warnings, negative opinions, hatred, allegations, or curses. We collectively call these actions customers' denouncements against sellers. It is worth mentioning that the reasons used to justify buyers' ratings are different from customers' denouncements against sellers. Denouncements are even more concerning to sellers because buyers who post seller denouncements are likely to abstain from future transactions with the sellers they denounce, and their allegations negatively impact the sellers' images and reputations [26,32,33].

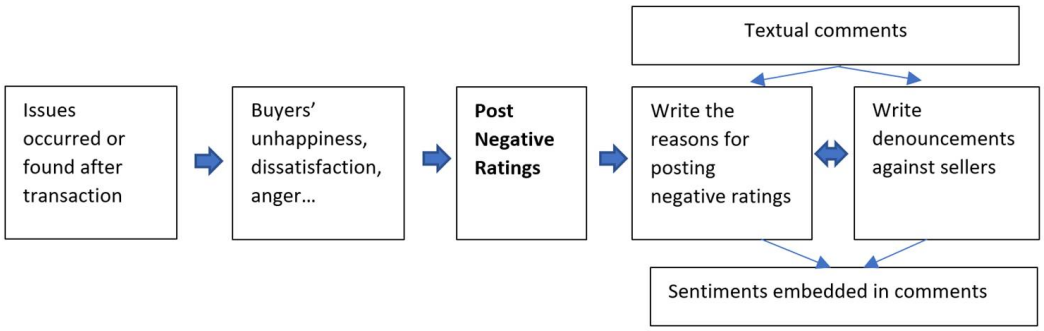


Figure 1. Brief flowchart of buyers posting negative ratings and comments.

Existing studies [11,24] have identified several key reasons associated with negative feedback ratings: items not as described, shipping issues (e.g., wrong shipment, late shipping, no shipping, and shipping damage), poor customer service, bad communication, payment issues (e.g., no refund, credit card rejection), product issues (e.g., wrong items, damaged item, used item instead of new, and no accessories), and fraud. However, these studies have certain limitations, which motivated us to conduct the current study. The limitations can be summarized as follows: (1) The feedback rating datasets used in these two studies are mainly from specific products. Ref. [11] used feedback ratings from Sony PlayStation Consoles, and [24] used the ratings from Sony PlayStation, Xbox, and Nintendo game consoles, and Texas Instruments calculators. For this study, we collected feedback data from eBay covering a variety of product categories. (2) The sample size of negative feedback ratings in the two previous studies was very small. Ref. [11] used 381 negative ratings, and [24] used 1132 negative ratings. In this study, we use a large dataset of more than 43,000 negative ratings, which could be used to generate more robust insights about negative ratings. (3) The two previous studies focused on identifying the main reasons for posting negative ratings, but neither included in-depth analysis to further categorize the reasons. In this study, we categorize the reasons for negative ratings into three categories, which we introduce in detail later. (4) The two previous studies did not address the association relationships among the reasons for negative ratings. For example, a majority of buyers who complain about product damage also complain about shipping. In this study, we investigate the associations between the reasons for negative ratings. (5) The two previous studies did not provide recommendations to sellers on how to avoid receiving negative ratings. We provide recommendations in this study. (6) The two previous studies did not address the sentiments embedded in textual comments posted by buyers. We address this issue in this study. (7) The two previous studies did not study buyers' denouncements against sellers. This study explores this topic in the context of online auctions.

Refs. [11,24], because of their small sample sizes, performed qualitative analysis in which they manually processed the textual comments associated with the negative

ratings. The current study utilizes both text mining and sentiment analysis to efficiently and effectively process a much larger sample of textual comments. In the literature, there is support for the use of both text mining [34–36] and sentiment analysis [37–39] to conduct qualitative or quasi-qualitative studies. This kind of qualitative analysis with text or sentiment mining uses computer algorithms instead of human beings to read, analyze, and identify sentiment or patterns in the textual comments. Along with the trend of analyzing larger datasets, the applications of text mining and sentiment analysis are expected to continue to grow.

Our study data consist of 43,404 instances of negative feedback with associated text comments, which were collected with computer spiders from eBay. To more efficiently and effectively identify the issues buyers mention most frequently in their textual comments and to investigate the sentiment expressed in the comments, we used two analytics tools: text mining and sentiment analysis. To identify the common topics that buyers frequently mention in their comments, we mined the most frequently used common words and sentiment words. The combination of common word and sentiment analyses produces more solid clues from textual comments and helps to determine the most common reasons for buyers posting negative ratings. For the text mining, we used R along with the R package *tm*. For the sentiment analysis, we used R along with the R package SentimentR and the lexicon *BING*. After we analyzed the most frequently used words or phrases, we divided the reasons for posting negative feedback ratings into seven categories: communication (comm), claimed fraud victim (victim), shipping delay (shipping), customer service (service), product damage or defect (defect), refund (refund), and product packing (pack). Figure 2 shows the flowchart for the data analysis process.

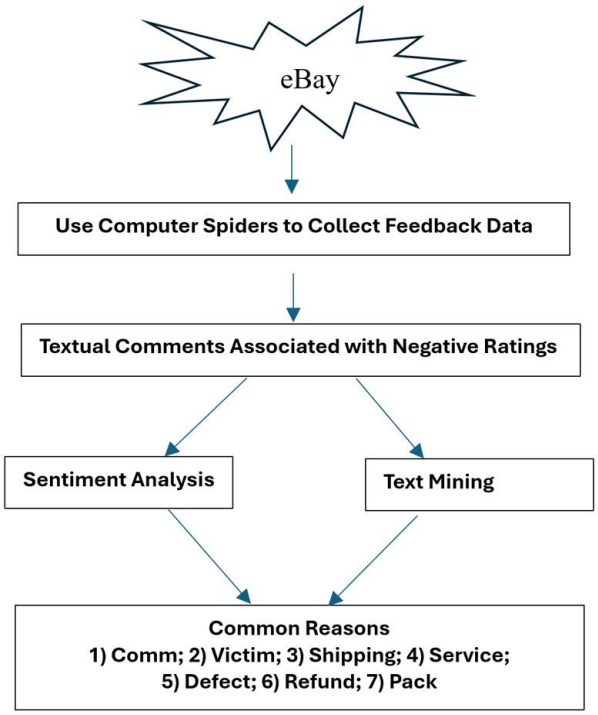


Figure 2. Flowchart for deriving common reasons from text comments.

Of these reasons for negative ratings, we understand that fraudulence is a sellers' purposeful malicious behavior which is intended to cheat buyers in order to gain a financial benefit. Of the remaining six reasons, some of them are likely under the control of sellers: customer service, communication, and refund. The other reasons are likely not directly under the control of sellers: shipping logistics, package damage, and product damage/defect. We rank the reasons from highest frequency to lowest frequency in Figure 3.

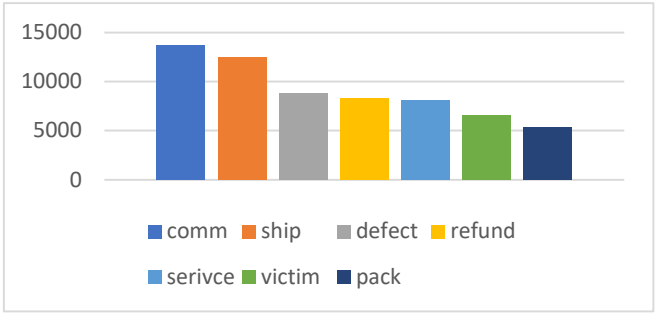


Figure 3. The ranking of reasons for negative ratings.

We can see that the most frequent reason for buyers posting negative ratings is communication issues, which sellers can improve themselves. The second most frequent reason is the shipment. If the shipment delay is the fault of the sellers, the sellers can improve this to avoid receiving negative feedback. If the shipment delay is the fault of the carrier, sellers need to choose different carriers with higher-quality service. We offer our suggestions for each reason in Table 2. Because fraudulence is a crime, eBay as a platform provider needs to work to fight against it. Regular sellers need to work with eBay to fight against fraud and will benefit from cleaning cheaters out of the auction platform. As for product defects, sellers need to accurately describe the products with photos or videos, so that buyers have more accurate expectations of the products. This effort will reduce issues of information asymmetry. If defects are due to shipment damage, sellers may need to choose a better carrier. For refund requests, sellers need to respond promptly to buyers, and refund the buyer if their request is legitimate and justified. For customer service, sellers need to improve it by all means. For packing issues, sellers need to use solid and secure packaging. If package damage is due to abnormal logistics, sellers may need to choose a better carrier. It is worth mentioning that auction fraud is still a big issue, as 15% of the negative ratings in our study dataset relate to malicious seller behavior. It goes without saying that sellers should maintain integrity and honesty when doing business with buyers and avoid any fraudulent behavior.

Table 2. Seven reasons and suggestions to sellers.

#	Reason	Example	Under Sellers' Control	Suggestion
1	Communication	seller was not returning phone call and didn't accept PayPal like was stated	More likely	Timely response to buyers' email or phone call
2	Shipping	Shipment was slow,	Less likely	Choose a better carrier if needed
3	Product defect	Item defective. When contacted seller back peddled. I filed a complaint	Less likely	Accurately describe the products, and choose a better carrier if needed
4	Refund	condition was worse than described in description wouldn't refund money	More likely	Timely response to buyers' refund request
5	Customer service	terrible customer service	More likely	Improve customer service
6	Fraud victim	paid but never received the shirt FRAUD	More likely	Be honest to do business with buyers
7	Shipping packing	packaged horribly, and one of the controllers is cracked	Less likely	Solid and secure package, and choose a better carrier if needed

Above, we have analyzed each of the main reasons for buyers to give sellers a negative rating. In fact, for one negative rating there might be several reasons mentioned by buyers in their text comments. We list the frequency of the number of reasons mentioned for one rating in Figure 4. The figure shows that over half of total ratings have just one reason provided in the text comments.

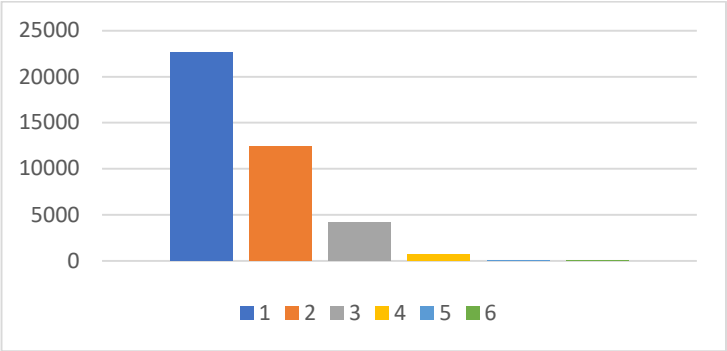


Figure 4. The frequency of negative ratings with the number of reasons.

It is very interesting to investigate the distribution of reasons for the negative ratings with only one reason. That is, among the negative ratings that only have one reason mentioned in the textual comments, what does the reason distribution look like? Table 3 shows this distribution. Issues related to shipping and communication are the most common reasons that trigger buyers to post negative ratings where the buyer only mentions on reason in their textual comments.

Table 3. Distribution of reasons for one-reason negative ratings.

#	Only One Reason	Numer of Cases	%
1	Shipping	6115	26.94%
2	Communication	4257	18.76%
3	Product defect	3209	14.14%
4	Refund	3189	14.05%
5	Fraud victim	2865	12.62%
6	Customer service	1939	8.54%
7	Shipping packing	1123	4.95%

In a similar fashion, we investigate negative ratings with only two reasons mentioned in the textual comments. The two-reason negative ratings made up 15% of the total negative ratings. Table 4 lists the two-reason combinations along with the number of cases represented by each pair and the percentage of total negative ratings. The data in the table suggest that many shipping issues are related to communications, refunds, and customer service. Communication issues are most frequently related to customer service, shipping, and refund. The victim reason most commonly co-occurs with communication, refund, and shipping, suggesting that many claimed fraud victims attempt to communicate with the respective seller for refunds or shipment concerns. For refund, sellers have mainly communication and shipment issues. Defect occurs most frequently with product packing, communications, and shipment. It is reasonable to say that product defects might be related to packing and shipment. The service reason most frequently co-occurs with communications with sellers, shipping issues, and buyer-claimed fraud victim issues.

Table 4. Distribution of reasons for two-reason negative ratings.

Reason1	Reason2	Cases	%	Reason1	Reason2	Cases	%
Shipping	**Comm**	1176	9.42%	**Comm**	**Service**	1950	15.63%
	Refund	806	6.46%		Shipping	1176	9.42%
	Service	653	5.23%		Refund	1129	9.05%
	Pack	506	4.05%		Victim	851	6.82%
	Victim	463	3.71%		Defect	599	4.80%
	Defect	457	3.66%		Pack	178	1.43%
Victim	**Comm**	851	6.82%	**Refund**	**Comm**	1129	9.05%
	Refund	575	4.61%		Shipping	806	6.46%
	Shipping	463	3.71%		Victim	575	4.61%
	Service	301	2.41%		Defect	372	2.98%
	Defect	187	1.50%		Service	283	2.27%
	Pack	58	0.46%		Pack	119	0.95%
Defect	**Pack**	1386	11.11%	**Service**	**Comm**	1950	15.63%
	Comm	599	4.80%		Shipping	653	5.23%
	Shipping	457	3.66%		Victim	301	2.41%
	Refund	372	2.98%		Defect	297	2.38%
	Service	297	2.38%		Refund	283	2.27%
	Victim	187	1.50%		Pack	134	1.07%

3.2. What Factors Drive Buyers to Denounce Sellers?

Why do customers complain or not complain? The current literature shows that customer experience [40], customer characteristics, and association with relevant situational factors play an important role in initializing customers' complaints [41,42]. It was estimated that the correlation between customer complaints and customer satisfaction is negative, and a one-unit increase in customer satisfaction results in a 0.76-unit decrease in customer complaints [43]. Compared with off-online shopping, customers are more dissatisfaction-sensitive when purchasing online [44]. As we stated previously, if buyers are not satisfied with transactions, they are more likely to post a negative rating, and they may also describe the reasons or explanations in textual comments. These textual comments help both sellers and new buyers understand the issues behind negative ratings. In addition, some buyers become angered or frustrated enough to explicitly denounce sellers [25,45]. In the dataset used in this study, 25.5% of buyers not only list the reasons or explanations for their negative rating of the seller, but also further explicitly denounce the seller. These denouncements have more serious impacts on potential buyers than common WOMs (words of mouth) [26,32,33]. Therefore, denouncement is more worrisome to sellers who want to build their reputations and customer relationships at eBay.

In this section, we investigate the factors that lead buyers to denounce sellers. We classify the reasons for posting negative ratings into three categories: (1) sellers' malicious fraudulence; (2) factors likely under the control of the sellers, such as communication, customer service, and honoring refund requests; (3) factors not likely under the control of the sellers, such as shipping logistic delay, shipping product damage, and improper packaging. The first category, seller's fraud, would result in the buyer's loss, which would typically trigger the buyer's anger and strong denouncements of the seller [21,46,47]. Some victims might file a complaint or report fraudulence to eBay. Some frauds with a significant loss to victims might lead to the cheaters' eBay membership suspension and serious crime investigations [47,48]. Combining these studies and our research questions, we list our first hypothesis as follows:

Hypothesis 1: Buyers who claimed themselves fraud victims are more likely to denounce sellers.

An important assumption in modern economic theory is that consumers are rational [49]. Generally speaking, the assumption of consumer rationality assumes that people seek to maximize their own utility by making optimal choices based on all the information available to them. Rational consumers can discern the main reasons or causes for the issues in their complaints. If service failure happens, for example, customers do not tolerate it and they start to complain, even though sellers try to change customers' decision control [50]. It was observed that customer complaints directed towards employees might trigger employees' anger and even make buyers estranged [51]. In this study, the second category of reasons for complaints consists of issues that are likely caused by behavior that is under the seller's control. For example, sellers can control the timing of their communications with buyers. So, if there is a delay in communication, it is likely to be caused by the seller's behavior. For the issues in this category, rational buyers are inclined to blame the seller because the issue was one over which the seller had control. Thus, buyers will be more likely to denounce sellers [52]. This leads to the following hypothesis:

Hypothesis 2: The factors likely under the control of sellers are more likely to drive buyers to denounce sellers.

Existing studies show that even though customers complain, sellers still can achieve a recovery–loyalty relationship if they properly manage customers' expectations and satisfaction [53–57]. Even more, sellers might have the opportunity to turn complaining customers into loyal customers if they spend substantial resources responding to customer complaints [58]. This implies that not all the complainers would denounce sellers. For the third category of complaint reasons in this study, shipping delay and damage are likely to be attributed to the carrier, as they are unlikely to be directly under the control of the seller. Sellers sometime ship products a bit late, but buyers might still feel it is a carrier problem. For the issues in this category, even though buyers give a negative rating to sellers, they might not strongly denounce sellers with rationality [59,60]. Thus, we have the following hypothesis:

Hypothesis 3: The factors not likely under the control of sellers are less likely to drive buyers to denounce sellers.

Ref. [61] identified five categories of negative emotions: shame, sadness, fear, anger and frustration. Among them, the negative emotion of frustration is the strongest driver for complaint behavior towards sellers. Customers' frustration might lead to them rejecting the loyalty program, and even rejecting the firms [62]. Ref. [63] studied three types of negative emotions, anger, fear, and sadness, and showed they have impacts on other reviewers. Ref. [64] showed that consumer review sentiment correlates positively with consumer online review ratings. Stronger negative sentiments more likely lead to stronger negative ratings. Ref. [65] found that the types of feedback ratings (+, 0, and −) are consistent with the sentiments (positive, neutral, and negative) embedded in the textual comments on eBay. In the context of cyberspace, the sentiments embedded in textual comments can be taken as an important clue to explain buyers' denouncements against sellers. Following these theoretical considerations, we set up the following hypothesis:

Hypothesis 4: Buyers who have more negative sentiments are more likely to denounce sellers.

The research framework is depicted in Figure 5. To proceed, we needed to obtain sentiment scores from the text comments for each negative rating. Sentiment analysis can be used to retrieve sentiments from text comments posted by buyers. Sentiment analysis

(also called opinion mining) is a text mining technique to process language-related content. The authors of [66–68] pointed out that sentiment analysis could help managers understand consumers and develop effective marketing strategies and decision-making policies. Sentiment analysis is an important tool for tracing customers' or investors' sentiments, which may significantly impact product sales and stock markets. As the volume of user-generated content rapidly increases, with big data available on social media, sentiment analysis has become popular in the fields of sales, marketing, hospitality management, and financial investment. Computer sentiment applications can produce accurate sentiment classifications at high efficiency as they can handle big data [69]. Ref. [70] conducted social media analytics using Twitter data on cruise travel. Ref. [71] used sentiment changes to predict movie box-office revenues. Ref. [72] used Twitter sentiment analysis to capture visitors' sentiments on resorts.

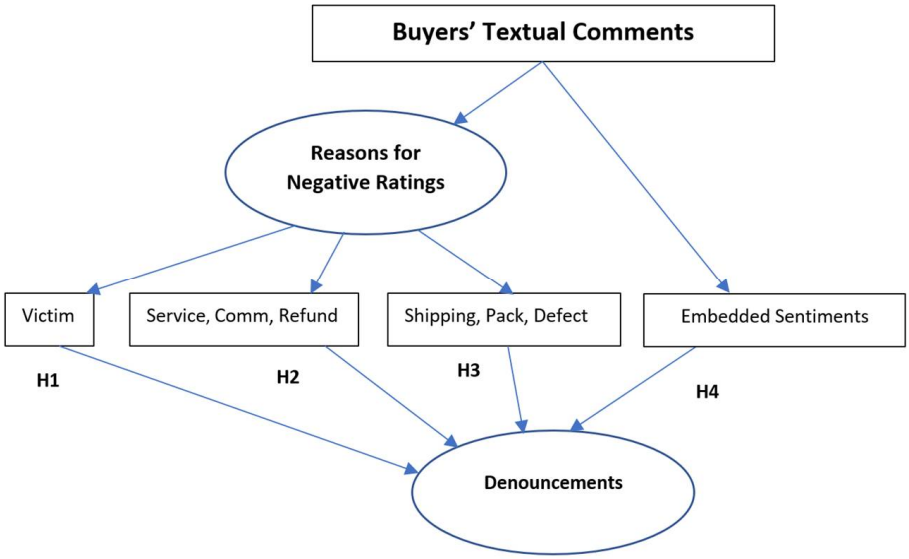


Figure 5. Conceptual research framework of buyers' denouncements.

There are two ways to conduct sentiment analysis: corpus-based and lexicon-based [73]. A corpus-based analysis uses the texts/corpora representing a paragraph to determine the sentiment types (negative, neutral, or positive) derived from text contents. A lexicon-based method uses an existing lexicon or dictionary to determine text contents' sentiment types (negative, neutral, or positive). Ref. [74] showed that the two approaches produce similar accuracy in some cases. There are different lexicon methods available for sentiment analysis. In this study, we use the R package SentimentR to assign sentiment scores to comments associated with each rating. SentimentR is lexicon-based, runs at a fast speed, and handles various sentiment analytical challenges such as negations well. Because of these strengths, SentimentR has been utilized for sentiment analysis in published business research [75–77]. Table 5 lists a few examples of negative ratings with their sentiment scores. For example, for the first row, the textual comment associated with the negative rating has a sentiment score of −0.124.

Table 5. Samples of sentiment scores.

Sentiment Score	Negative Rating
−0.124	"item still not received, paid 9 days ago. run-around on the emails"
−0.080	"This seller did not provide a shipping date and was not punctual not recomended!"
−0.200	"Lost my payment, late shipment, accused of not paying"

To explore the relationship between denouncements and the proposed factors, we conducted a correlation coefficient analysis, as listed in Table 6. The coefficient between denouncements and the variable victim is positive, which suggests support for H1. That is, buyers who claimed themselves fraud victims are more likely to denounce sellers. The coefficients between denouncements and the variables refund and comm are negative, but the coefficient between denouncements and service is positive, suggesting the ambiguity of H2: the factors likely under the control of sellers may or may not motivate buyers to denounce sellers. The coefficients between denouncements and the variables pack, defect, and shipping are all negative. This suggests support for H3. That is, the factors not likely under the control of sellers are less likely to motivate buyers to denounce sellers. The coefficient between denouncements and sentiment is negative. This suggests support for H4. That is, buyers who have strong negative sentiment are more likely to denounce sellers.

Table 6. Correlation coefficients.

Factors	Denouncements	
Victim	0.156 ***	H1 Supported
Refund	−0.005 ***	H2 Undecided
Comm	−0.002 ***	
Service	0.016 ***	
Pack	−0.017 ***	H3 Supported
Defect	−0.019 ***	
Shipping	−0.064 ***	
Sentiment	−0.175 ***	H4 Supported

Note: *** significant at 1%.

The correlation coefficient analysis offers preliminary results. More formally, we test the hypotheses with logistic regression. The dependent variable is the binary variable denouncement (0 for non-denouncement, and 1 for denouncement), and the independent variables are the claimed fraud victim, the factors likely under the control of sellers, the factors not likely under the control of sellers, and buyers' sentiments. The regression outcomes are listed in Table 7.

Table 7. Logistic regression outcomes.

Coefficients:	Estimate	Std.	Pr (>|z|)	
(Intercept)	−1.851	0.032	0.000 ***	
Victim	0.748	0.033	0.000 ***	H1 Supported
Comm	0.020	0.029	0.490	H2 Supported
Refund	0.054	0.034	0.108	
Service	0.192	0.033	0.000 ***	
Shipping	−0.221	0.032	0.000 ***	H3 Supported
Pack	−0.205	0.042	0.000 ***	
Defect	−0.051	0.035	0.150	
Sentiment	−1.747	0.054	0.000 ***	H4 Supported

Note: *** significant at 1%.

The coefficient of victim is positive and statistically significant, which supports H1. This means if buyers claim themselves fraud victims, they are more likely to denounce sellers. For the category of variables likely under control of sellers, the coefficients of comm and refund are not significantly positive. But the coefficient of service is significantly

positive. This suggests support for H2; that is, the factors likely under the control of sellers are more likely to motivate buyers to denounce sellers. For the category of variables not likely under control of sellers, the coefficients of shipping, pack, and defect are negative. This supports H3. That is, the factors that are not likely under the control of sellers are less likely to motivate buyers to denounce sellers. The coefficient of sentiment is negative, which means when one buyer's sentiment becomes more negative, the likelihood of buyers' denouncements against sellers becomes higher. This result supports H4. Briefly speaking, the testing outcomes from the logistic regression are the same as those from the correlation analysis.

4. Discussion and Managerial Implications

Compared with existing studies that mainly focus on the validation and effectiveness of eBay's feedback ratings [6,14,78,79], this study focuses on the textual comments, and applies both text mining and sentiment analysis to identify seven key reasons why buyers post their negative ratings. The ranking of the reasons from high frequency to low is: comm, shipping, defect, refund, service, victim, and pack. These seven reasons can be classified into three categories: (1) sellers' malicious fraudulence toward buyers (victim), (2) factors likely under the control of sellers (comm, refund, and service), and (3) factors not likely under the control of sellers (shipping, defect, and pack). For malicious fraudulence, the platform provider eBay, all associated stakeholders, and buyers need to work together to fight against it. For the factors likely under their control, sellers need to improve their communications and customer service with buyers, and carefully handle their refund requests. For the factors not likely to be under their control, sellers need to choose qualified third parties such as shipping carriers.

In this study, we find that the most frequent reasons for negative ratings are communications and shipping (please see Figure 3). We also find that 50% of negative ratings are triggered by only one reason. Another 30% of negative ratings are accompanied by two reasons (please see Figure 4). The top five pairs of two-reason combinations are (shipping and comm), (defect and pack), (refund and comm), (service and comm), and (victim and comm). This finding helps us see how important it is for sellers to improve their communications with buyers and arrange shipping properly in order to reduce receiving negative feedback ratings from buyers. By using the dataset in this study, we apply an "if–then" scenario analysis and obtain the flow chart depicted in Figure 6. If sellers can resolve all the communication issues, keeping the others unchanged, the number of negative ratings will be reduced by 18.76%. If sellers can resolve all the shipping issues, keeping the others unchanged, the number of negative ratings will be reduced by 26.94%. If sellers can resolve both the communication and shipping issues at the same time, the number of negative ratings will be reduced by at least 55.12%!

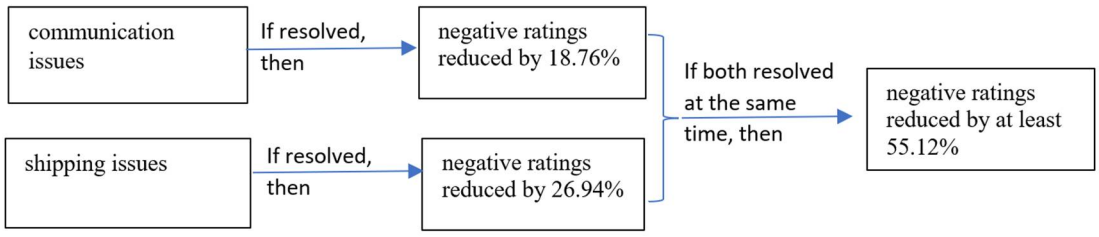


Figure 6. "If–Then" scenario analysis.

Some buyers not only list the reasons for posting their negative ratings, but they also post denouncements against sellers. While a small group of such customers are still likely to do business with denounced sellers (it is called emotional resilience—or the ability to rebound from negative experiences) [80], their allegations have a broader negative impact on other potential users, especially new buyers [13,25,81]. In this study, we find that buyers who claimed themselves fraud victims are more likely to post denouncements against

sellers. This is a positive for the eBay platform because this kind of denouncement helps warn other buyers and assists in getting fraudulent sellers out of the marketplace. The finding that the factors likely under the control of sellers are more likely to motivate buyers to post denouncements against sellers suggests that buyers know what sellers are supposed to do after accepting a bid, and if sellers do not do their duties or do not provide the best service to fulfill the transaction, they will get penalized by receiving negative ratings and possible denouncements against them. This process helps sellers do their best to avoid buyers' denouncements. The finding that the issues not likely under the control of sellers are less likely to motivate buyers to post negative denouncements implies that buyers understand that some responsibilities related to the transaction are handled by third parties, not directly by the sellers. Overall, we can claim that buyers are rational and objective when they post their ratings and textual comments. We also find that buyers who have strong negative sentiment are more likely to post denouncements against sellers. So, buyer sentiment management is also important for sellers to avoid denouncements. In sum, to reduce the chance that buyers post negative ratings and denouncements, sellers need to carefully fulfill transactions with due diligence. Enhancing communication, properly handling shipping, and improving customer service and the refund process will not only reduce the chance of receiving negative ratings, but also reduce the chance that buyers post negative denouncements against sellers.

5. Conclusions and Limitations

In this study, we used a dataset from eBay to analyze negative feedback ratings along with textual comments from buyers. By applying sentiment analysis and text mining analysis, we identify seven key reasons that buyers post negative ratings: communication, shipping, product defect, payment refund, customer service, fraud victim, and product packing. These seven reasons can be classified into three categories: (1) sellers' malicious fraudulence toward buyers (victim), (2) factors likely under the control of sellers (comm, refund, and service), and (3) factors not likely under the control of sellers (shipping, defect, and pack). We discuss what sellers can do to reduce that chance of receiving negative ratings from buyers. The most important tactic for sellers is to improve communications with buyers and resolve issues related to product shipping. Some buyers not only list the reasons for posting their negative ratings, but they also post denouncements against sellers. These denouncements might have potential long-term negative impacts on sellers' reputations. In this study, we study the determinants of buyers posting denouncements against sellers. Sellers' malicious fraudulence is more likely to cause buyers' denouncements. It seems that buyers are acting rationally when they post their denouncements against sellers; the issues likely under the control of sellers are more likely to motivate buyers to post denouncements, and the issues not likely under the control of sellers are less likely to motivate buyers to post denouncements. In addition, buyers who have strong negative sentiments are more likely to post denouncements. We also discuss our findings and their managerial implications.

There are certain limitations in this study. We use a dataset only from eBay. Researchers might use rating datasets from other marketplaces such as Amazon.com in future research. We use sentiment and text mining analysis in this study. Other big data techniques or machine learning might be used in future studies. More studies and discussions are needed to fight against fraudulence. We leave these for future research.

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