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Abstract: Cross-border e-commerce (CBEC) has become an important channel to help a firm to go into the international market in China. The recent influx in development of CEBC has caused a simultaneous influx in accumulation of text data such as consumer feedback. To better understand consumer feedback, we collected data from a leading CBEC firm in China to explore the topics of feedback posted directly by their customers. We employed the Latent Dirichlet Allocation (LDA) model to explore the potential topics focused on most by consumers. We found 35 primary topics are mentioned by both sellers and buyers. For the seller's perspective, we found that the topics such as commission, product audit, communication between seller and buyer, order management and traffic are most important. On the buyer's side, we found that return and refund, product tracking, product description, shipping time, and seller performance are the most mentioned topics. This study will help contribute to the understanding of how consumer feedback will help firms in many ways, including but not limited to recovering service and product failures, audit internal functions, and improve product quality.

Keywords: Cross-border e-commerce, Latent Dirichlet Allocation, text mining, consumer feedback, LDA

1. INTRODUCTION

Cross-border e-commerce (CBEC) has become an important channel to help a firm to go into the international market. This phenomenon has been highly recognized, especially in China. Many CBEC firms have emerged in the past decade, including both AliExpress (launched 2010) and Lightbox (2012). The recent influx in development of CEBC has caused a simultaneous influx in accumulation of big data. Among the vast majority of big data, text data is particularly useful. Namely, text data containing consumer feedback has been noted as a significant resource. Successful techniques can identify consumers' feelings, both before and after the purchase stage. Indeed, text mining can help businesses to better understand consumer behavior, helping to expand a firm's brand into an international market.

To begin, text mining is a lot like it sounds. Computer algorithms can sort through a body of text for certain key words and phrases. Consumer feedbacks published publicly can influence other consumer's purchase decisions [16]. As expected, the negative sticks more than the positive. Dissatisfied consumers are more likely to post negative feedback, which may threat a firm's reputation for a longer period of time than positive feedback [7] [14]. Consequently, managing consumer feedback is important for CBEC firms.

A majority of the existing papers studying consumer feedback behavior focuses on the context of social media [6]. This is because social media is a revolutionarily crucial communication channel to share individuals' opinion on a brand or company. The feedback published on social media, including Facebook, Yelp, and Trip Advisor, is easy to see among any user with an account. Hence, CBEC firms benefit immensely from managing their brand on social media. Often, unsatisfied consumers want to disseminate their unsatisfied shopping experiences from some firm by voicing their intention to refrain from continuing to shop, and to caution other consumers not to buy from that firm as well. Other consumers may remain loyal consumers despite experiencing

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unsatisfactory service, but they still let the firm know about their bad experience by expressing their feelings publicly, hoping the firm will thus attempt to fix the service failure. On the other hand, some consumers prefer their reviews not be published for anyone to see (e.g., some embarrassing or private products). Such consumers may send their feedback to the firm directly. Therefore, the feedback published on social media may not properly represent all customers' perspectives. As a firm, both public and private feedback are important to obtain in order to fully understand their consumer's feelings. Therefore, it is also important for a firm to collect both types of feedback using social media as well as their own feedback collection system(s).

Previously, the research of consumer feedback that generated on social media has been studied in the tourism and hospitality area [7] [26] [34], e-commerce setting [16] [28], and social media [14]. There remains a lack of study focusing on consumer feedback in CBEC context. CBEC is different with domestic e-commerce. This is because the nature of CBEC results in more complex transactions (i.e., the complex return and refund process). In CBEC, additional uncertainties such as asymmetric product information, privacy concerns, after-sales quality uncertainty, confiscation risk and delivery risk, all of which may detract from the use of CBEC [21] [27]. In our study, we used consumer feedback from a leading CBEC firm. On its official website, there are several incentives for customers to give feedback. For example, multiple open questions (i.e., *what are your suggestions for our firm*?) lead to links which allow customers to post their opinions. This offers an up-to-date view of consumers' suggestions and feedback. Only the accumulated feedbacks are analyzed by a firm. This may gain more insight to recover the service failures or to improve consumer satisfaction.

Previously, consumer-generated feedback has been studied in the purchase decision process, the reliability of the feedback, and the true impact of the feedback [34]. Few studies employ an LDA method to discover the topics which emerged in CBEC context. To better understand consumer's feedback, we collaborated with a leading CBEC firm to explore the topics of feedbacks that posted by their customers. To do so, we employed the Latent Dirichlet Allocation (LDA) model to explore the potential topics, or concerns, raised by consumers. Specially, we aim to answer the flowing research question:

Which types of feedback are mostly commonly voiced via a firm's private feedback collection system?

This study is organized as follows: in next section, the context of CBEC has been introduced, and the term of consumer feedback has been reviewed. Thereafter, to resolve the research question, the research method of LDA has been outlined. Then, the research results are discussed. Finally, drawing on the research results, the conclusion section has been spread out.

2. LITERATURE REVIEW

2.1 Cross-border e-commerce

Chinese e-commerce revolutionary Belt on One Initiative (previously One Belt On Road) brings more opportunities to increasing world economics. Especially for China, it can gain more access to foreign markets by exporting their products and services overseas [18]. It also brings more opportunity for the development of CBEC. According to China Daily (30-10-2017), Chinese CBEC transaction reached 6.7 trillion yuan ($1.01 trillion) in 2016 and it is predicted that by 2018, the value of China's import and export transaction via e-commerce might hit 8.8 trillion yuan [32].

CBEC is a new mode of import and export trade via e-commerce platform. It allows the firm to avoid high competition in their local markets and to seek more markets in abroad [9]. The term of CBEC dervives from the combination of cross-border shopping and electronic commerce. Cross-border shopping refers to the activity wherein a consumer purchases goods abroad, which may need a consumer cross an international boundary into another country [38]. CBEC refers to "an online transaction of buying and selling products and services using

information communication technologies (ICTs), where buyers and sellers are located in two different countries and therefore, different jurisdictions [1]. Due to the definition of CBEC, it includes both import and export transactions. In China, the term of "haitao[1]" has been used frequently to refer Chinese consumers using an e-commerce website for the purchase of goods from abroad [25]. In our study, we only consider one specific type which refers to Chinese firms sell products of services via a CBEC platform.

Different from traditional cross-border (CB) shopping, the characteristics of CBEC are *multilateral*, *direct*, *small amount* and *high frequency* [36]. *Multilateral* in this context specifically refers to the fact that CBEC can integrate different countries or firms' services, such as logistics service and payment services together to perform a transaction. *Direct* refers to CBEC context allows a consumer to buy product directly form a foreign country, while offline cross-border purchase may purchase a large number of quantity products. Further, CBEC are usually in a small amount with a high frequency purchase [36]. CBEC logistics also represents more process linkages, varied channels and wider span of geography [12].

CBEC is more complex that domestic electronic commerce due to the uncertainty among international market environments and the shipping of product across countries [38]. Meanwhile, cross-border shopping features the economic advantages, quality, service and variety of product selection [38]. The advantages of shopping abroad additionally include more competitive prices, warranties, access to latest products and a pleasant shopping environment [33]. Cross-border shopping may also motivate value perceptions, such as relaxation, pleasure, or dissatisfied with their local shopping environment e.g., currency rates, and government policies [33].

Although CBEC brings potential benefits, consumers still concern the legal enforcement, culture barriers and high shipping costs [9]. Further, import duty has also been recognized as a barrier for CBEC, this is because consumers may face an additional cost when purchasing a product from a foreign country [23]. Turban et al. [35] also emphasized that CBEC website should provide multiple languages, currencies, payment systems and input devices. To reduce the complex checkout process, it should eliminate the detailed user profiles and offer free shipping and rewards to encourage repeat traffic.

Cross-border trade research has been gradually attracting attention in recent years. For example, just this year, Huang and Chang [19] empirically examined the determinants of a consumer purchase on a CBEC platform. They found that any consumer transaction on a CBEC platform is mostly influenced by trust beliefs and value perceptions. The determinants of cross-border shopping have been classified as market-based factors and consumer-based factors [22]. Market factors relate to price level, shopping environment, shopping facilities, product variety and product/service quality. Consumer factors focus on consumer demographics and motivational characteristics, such as pleasure bargaining and social experience [22]. Singh et al. [31] state that localization also plays an important role in CBEC setting, which may affect consumers' usability, accessibility and interactivity. Utilizing this knowledge can help a firm increase the relationship between their products and consumer. For instance, language serves as a cultural indicator, and can help shape ideas for a target consumer [23] [24]. In addition, Liu and Hong [25] emphasized the importance of online payment facilities and cost-efficiency of parcel delivery systems. Further, Guo et al. [10] studied the impacts of chargeback fraud on CBEC seller's intention to use CBEC platform.

2.2 Consumer feedback

Given consumer feedbacks include both positive and negative, we define consumer feedback as the favorable and unfavorable experiences and a consequent recommendation of a product or service to an online platform [26]. The benefits of managing consumer feedback have been summarized as impacting on customer

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[1] Haitao means Chinese consumers purchase products from abroad.

retention rates, deflecting the spread of damaging word-of-mouth, promoting more positive word-of-mouth, increasing customer perception of quality, improving marketing intelligence, and promoting a positive company image [15].

Consumer feedback affects both the seller and the buyer side. Since consumer feedback reflects consumers' online shopping experience, it can help other consumers to evaluate a seller's reputation on the buyer side, and therefore potentially increase (or decrease) sale performance for the seller [13]. On the other hand, it also can help sellers to better improve their service and product quality [11]. Consumer reviews are more focused on online stores and their goods as well as services. Reviews regarding a specific purchase are more likely to occur just after that purchase. General consumer feedback that are more focused on the suggestions for the platform and its services may occur at any time.

Wu and Huang [28] argue that while consumer complaint behavior can help online vendors develop innovative products and services, it also can help consumers to solve transaction issues. However, as a new firm, it may also hinder consumers' ability to share their negative experience on social media [15]. Given the high cost of finding a new customer, firms are fully aware that it is imperative to maintain customer satisfaction whenever and wherever possible. Therefore, it is important to redress the problems to satisfying the complained customers.

When a consumer experiences a problem with a product, three types of consequent actions have been summarized by Harrison-Walker [15], which are listed below:
Disassociating themselves with the company and/or spreading negative word-of-mouth
posting a complaint directly to the company, and taking indirect public action on a social media.
Negative word-of-mouth and feedbacks than are posted on social media have been widely studied in marketing and information systems fields [3] [5] [14] [17] [20] [30].

However, feedback that have been posted directly to the company has been paid little attention. This study aims to discover the topics from the feedbacks that have been posted by the customers to the CBEC firm directly.

Online service reviews have been emphasized its two primary functions. The first is to assist the decision-making of service consumer; the second, to assist service providers in service quality improvement [11]. The context of this study focuses on online feedback to assist service providers in service quality improvement. This is because customer service teams need to be particularly sensitive to customer needs and expectations when they attempt to recover from service failures. Prior studies have merely explored data from online review websites, e-commerce website and tourism website are often examined the numeric ratings rather than extensive exploring the textual comment data. The current study extends the current literature by focusing on the topics and tones of the textual feedbacks given by cross-border consumers, and discussing the benefits for both the buyer and seller side.

Because both public and private feedback plays an important role in studying consumer satisfaction, organizations must manage consumer feedback appropriately [29]. Currently, firms usually collect consumer feedback constantly via customer satisfaction surveys, online reviews, e-mails, as well as in-person, for both praises and complaints [34]. Consumer feedback can also serve as a benchmark, internal audit for a firm [34]. Moreover, by studying consumer feedback can help an organization to resolve the problems caused by service failures [2].

3.   RESEARCH METHOD

3.1 Topic Extraction Using Latent Dirichlet Allocation (LDA)

Topic modeling has become an increasingly important method for extracting useful topics from vast amounts of textual data. Among all topic modeling methods, Latent Dirichlet Allocation (LDA) [4] is one of the most widely used [25]. It helps to capture both explicit and implicit topics, including the relative words for each topic. The entire process is based on Bayesian networks.

Take a collection of seller or buyer reviews, $R = \{r_1, r_2, \dots r_{|R|}\}$. Each review, call it r, is represented as a collection of words $r = \{w_{1r}, w_{2r}, \dots w_{Nr}$, here $r_{|R|}$ denotes the $|R|$th review in the collection R, and w_{Nr} denotes the Nth word in review r. The latent topics are denoted by $K = \{\Phi_1, \Phi_2, \dots \Phi_{|K|}\}$, where $|K|$ is the topic number.

The underlying principle of the LDA model is that it allocates words from multiple, separate reviews to a new, single document, assigning a probability to each word. Consequently, each new document represents a topic consisting of some highly-related co-occurring words (i.e., top words). The generative process for each new document is described as follows:

(1) For each review, choose the topic distribution $\theta_r \sim Dirichlet(\alpha)$

(2) For each word w_{Nd} in the review r

(a) Choose a topic $z_{Nr} \sim Multinomial(\theta_r)$

(b) Choose a word w_{Nr} from $p(w_{Nr}|z_{Nr}, \beta)$ (i.e., $\Phi_{r,N}$)

In the generative process, two Dirichlet priors α and β are endowed to determine the document-topic distribution θ and the topic-word distribution Φ, respectively, where we assume both θ and Φ follow multinomial distribution. We estimate the parameters for θ and Φ using the Variational Inference [4] and Gibbs sampling [8] methods. Given α and β for a single review, the joint distribution of θ, z, and w is computed as follows:

$$p(\theta, z|w, \alpha, \beta) = \frac{p(\theta, z, w|\alpha, \beta)}{p(w|\alpha, \beta)} \tag{1}$$

where:

$$p(\theta, z, w|\alpha, \beta) = p(\theta|\alpha) \prod_{n=1}^{N} p(z_n|\theta) \, p(w_n|z_n, \beta) \tag{2}$$

p (w|α, β) in Equation (1) denotes the weigh, or probability, of each extracted word. The probability represents relative importance of one word in one topic. The higher the probability, the more relevant the word.

$$p(w|\alpha, \beta) = \frac{\Gamma(\sum_i \alpha_i)}{\prod_i \Gamma(\alpha_i)} \int \left(\prod_{i=1}^{k} \theta_i^{\alpha_i - 1} \right) \left(\prod_{n=1}^{N} \sum_{i=1}^{K} \prod_{i=1}^{V} (\theta_i \beta_{i,j})^{w_n^l} \right) d\theta \tag{3}$$

Once we have the probabilities per word, it is often still difficult to determine the topic number K from a given collection for the LDA model [37]. To obtain an appropriate topic number, Blei et al. [4] suggests calculating the perplexity for a held-out test set to evaluate the performance of the trained models. For example, if given the topic number collection $K = \{1, 2, 3, 4, 5\}$, we could select one appropriate topic number by calculating the perplexity for the five trained models, wherein each topic number from the Ks can be used to train a single LDA model. The lower perplexity, the better generalized performance will be obtained for the trained model. The entire process is to find the lowest perplexity from the given topic number set Ks, and use this to determine the topic number K from a given collection. The perplexity is given by

$$Perplexity = \exp\left\{-\frac{\sum_{r=1}^{|R|} \log p(w_{Nr})}{\sum_{r=1}^{|R|} N_r}\right\}$$

(4)

It is typical to calculate a multiple-fold validation method and use an average perplexity.

3.2 Data Analysis and Results

In this study, we adopted the data from a large CBEC firm in China. The data ranges between January 2016 to December 2016, containing 21,852 total posts from both buyers and sellers. The seller feedback makes up 11,816 posts, and the buyer feedback, 10,036 posts.

We employed a five-fold validation method to calculate an average perplexity for each trained model. We observed the change of perplexity by setting the number of topics ranging from 5 to 100, with an interval of 5. It is sufficient to capture the number of topics from the feedback in real life. We found that it obtains the smallest average perplexity for both seller and buyer data when the number of topics approximate to 35. Therefore, the appropriate number of topics is 35 for the seller and buyer data. Note the similarity in shape; it is safe to assume there is a drop before the perplexity begins to increase as the number of topics also increases. However, it occasionally obtained the identical number of topics for the seller and buyer in our study. Because these 35 topics can be summarized into several broader topics (i.e., dimension) for the buyer and seller respectively, it does not make any sense with the identical number of topics. Rather than the identical number of topics, it is more important to exploit the common topic they pay attention to.

Table 1: Top 5 topics out of 35 topics (seller dataset)

Topic	Dimension	Top 10 words
1	佣金 (Commission) 0.925	佣金(Commission) 0.467 太高(Too High) 0.174 手续费(Handling Charge) 0.052 收取(Charge) 0.049 利润(Profits) 0.044 比例(Proportion) 0.039 过高(Too High) 0.035 降低(Decrease) 0.033 支付(Pay) 0.020 接受(Accept) 0.013
2	产品审核(Product Audit) 0.877	审核 (Audit) 0.516 速度 (Velocity) 0.137 太慢 (Too Slow) 0.107 快点 (Quicker)0.026 快速(Fast) 0.025 比较慢(Slowish) 0.022 加快(Accelerate) 0.019 通不过 0.009 快些(Quicker) 0.008 用品(Article) 0.008
3	买卖家沟通 (Communication) 0.863	客户(Customer) 0.541 沟通(Communication) 0.108 朋友(Friend) 0.081 介绍 (Introduction) 0.062 评价(Evaluate) 0.019 喜欢(Like) 0.016 不上(Offline) 0.012 机制(Mechanism) 0.010 第二天(The Next Day) 0.007 延迟(Delay) 0.007
4	订单管理 (Order Management) 0.821	订单(Order) 0.461 发货(Shipping) 0.094 取消(Cancel) 0.053 成交(Make a Deal) 0.038 付款(Payment) 0.037 单号(Order Number) 0.033 下单(Place The Order) 0.032 错误(Error) 0.028 风控(Risk Control) 0.027 地址(Address) 0.015
5	流量 (Traffic) 0.803	流量 (Traffic) 0.377 太少 (Too Little) 0.148 曝光 (Exposure) 0.084 整体 (Overall)0.035 提高(Improve) 0.034 有待(Remain) 0.030 引流(Drainage) 0.027 浏览量(Page View) 0.024 提升(Promote) 0.024 太低(Too Low) 0.021

To move toward a better understanding of seller and buyer feedbacks, we extracted the top words over the top topics utilizing the LDA model. Table 1 reports the top 5 topics and each respective top 10 words (and phrases) from the seller perspective. The top 5 topics are commission, product audit, communication between seller and buyer, order management and traffic. Each topic's top ten discussed words can see detailed in Table 1. Note that it does not yet associate each top 10 words or phrases with some degree of quality (i.e., good or bad). We also presented the relative weight of each word that calculated in Equation (3). A sum of the weights of the top 10 words, represents the relative importance of each topic. We found that the most important topic for the sellers was "commission" (0.925), which refers to the commission that the cross-border platform charges when a transaction occurs. In addition, many sellers pointed out that the product audit processing time needs to decrease. Further, the communication between buyer and seller needs more ease of use and user friendly platforms. The other topics, interestingly, are related with these primary issues. For instance, the sellers complained that order

management is difficult to use. Indeed, the function of order management needs improvement.

Further, we also considered the LDA results for buyer feedback when setting the number of topics as 7. The extracted topics include the shipping, goods, ease of use, return and refund, product description, Customer Relationship Management (CRM), and seller performance. By comparing the relative importance of topics, we found that buyers were more concerned about the shipping time with a total weight of 0.210. A too-long duration of shipping may cause the consumers' complaints, while a fast shipping, conversely, may increase the favorable impression to the product. Interestingly, the positive topic (e.g., Good) has been found from the buyer's dataset. On one hand, CBEC buyers are posting some complaints to the firm, on other hand, CBEC buyers are also praise firms for their excellent product and services. This can significantly help CBEC firms to better understand their problems and benefits for current buyers.

Table 2 depicts the top 5 topics and key words of each topic by setting the number of topics as 35 according to the perplexity. The top 5 topics are return and refund, product tracking, product description, Shipping time, and Seller performance. Give the complex nature of CBEC, the process of return and refund becomes critical for the CBEC success, where the more simplistic, the better. In addition, the difficulty of tracking products is another topic for CEBC transaction. Further, product description, shipping, and seller performance are also recognized as principal issues for CBEC.

Table 2: Top five topics out of 35 topics (buyer dataset)

Topic	Dimension	Top 10 words
1	Return and Refund 0.815	item 0.340 refund 0.248 return 0.059 purchased 0.038 asked 0.033 full 0.031 reason 0.018 request 0.018 receive 0.018 lied 0.012
2	Tracking 0.787	tracking 0.246 number 0.194 information 0.118 provide 0.066 post 0.038 package 0.036 correct 0.030 shipped 0.025 update 0.020 stated 0.015
3	Product Description 0.771	product 0.409 description 0.106 pictures 0.096 photo 0.048 details 0.023 actual 0.019 advertised 0.018 include 0.017 match 0.015 image 0.018
4	Shipping Time 0.761	time 0.280 long 0.121 delivery 0.088 ship 0.075 takes 0.060 survey 0.041 delivered 0.031 arrive 0.031 date 0.020 promised 0.015
5	Seller Performance 0.742	make 0.317 purchase 0.221 customers 0.056 clear 0.031 coupon 0.029 easier 0.026 merchandise 0.019 part 0.014 mistake 0.014 returns 0.013

4.   DISCUSSION AND CONCLUSION

CBEC has become an important channel to help local firms to increase abroad market share. With the development of CBEC, there has been accumulated many consumer feedbacks. Through managing consumer feedback, CBEC firms can increase customer retention rates, deflect the spread of damaging word-of-mouth, promote more positive word-of-mouth, increase customer perception of quality, improve marketing intelligence, and promote a positive company image. Given aforementioned advantages, CBEC firms are eager to know their consumer feedback. To better understand the types of feedback are mostly commonly voiced, we employed an LDA technique to track the topics from a large CBEC firm's private feedback collection system. Our study makes both practical and theoretical contributions.

Our study makes the practical contributions for both CBEC platforms and business consulting firms. Through analyzing consumer feedback, the CBEC platforms can be more easily to understand their firm's disadvantage and advantage, and therefore help them to build a better consumer relationship. The firms may choose the most important issues and resolve such issues to significantly improve consumer's satisfaction. In addition, CBEC firms should handle consumer feedbacks appropriately to correct the failed service and thereby transform it into a satisfactory encounter. For example, CBEC may develop a better consumer feedback system to contact with non-satisfied consumers to improve the level of consumer's post-purchase satisfaction. This can be used for CBEC firm to better mining their consumer's suggestions, and for complaints websites to deeper management their text data. Business consulting firms may track different CBEC platform's consumer feedbacks. As a benchmark to guide the newly entered CBEC to better management their consumer relationship.

Indeed, it is important to understand both the seller and buyer feedback for both platform developers and managers. A better understanding the feedback, is beneficial for the platform developers to understand the difficulties, barriers for users, both buyers and sellers. For example, many sellers have difficulties in the store design (including of that online), order management, and product function setting. In addition, the platform managers can also learn the sellers' complaints (e.g., complaints on the expensive commission, slow product auditing, and dispute arbitrament). A better understanding the buyer feedback, is beneficial for the sellers to understand the buyers' complaints, including product defects, speed of delivery. Moreover, by analyzing the buyers' complaints, the platforms can effectively detect products with poor quality, and fake products, as well as the fraudulent retailers. Rather than the numerical rating, the text mining process acts as a kind of regulation mechanism.

Our study also makes several theoretical contributions. Based on the theoretical underpinning of the consumer complaint behavior, we explored the 35 topics from consumer feedbacks are important for cross-border buyers. Importantly, for a seller perspective, we found that store related issues were ranked as the most important issue that is mentioned by CBEC sellers, while for a buyer perspective, we found that shipping related issue is the most important for international buyers. The factors we determined which may significantly improve consumer's satisfaction, and therefore develop the theoretical of consumer complain behavior and satisfy consumers.

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Given the page limitations, we only listed a part of our citations. Remains citations may request from the corresponding authors.

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