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Is Text Mining on Trade Claim Studies Applicable? Focused on Chinese Cases of Arbitration and Litigation Applying the CISG*

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Abstract

Purpose – This is an exploratory study that aims to apply text mining techniques, which computationally extracts words from the large-scale text data, to legal documents to quantify trade claim contents and enables statistical analysis.

Design/methodology – This is designed to verify the validity of the application of text mining techniques as a quantitative methodology for trade claim studies, that have relied mainly on a qualitative approach. The subjects are 81 cases of arbitration and court judgments from China published on the website of the UNCITRAL where the CISG was applied. Validation is performed by comparing the manually analyzed result with the automatically analyzed result. The manual analysis result is the cluster analysis wherein the researcher reads and codes the case. The automatic analysis result is an analysis applying text mining techniques to the result of the cluster analysis. Topic modeling and semantic network analysis are applied for the statistical approach.

Findings – Results show that the results of cluster analysis and text mining results are consistent with each other and the internal validity is confirmed. And the degree centrality of words that play a key role in the topic is high as the between centrality of words that are useful for grasping the topic and the eigenvector centrality of the important words in the topic is high. This indicates that text mining techniques can be applied to research on content analysis of trade claims for statistical analysis.

Originality/value – Firstly, the validity of the text mining technique in the study of trade claim cases is confirmed. Prior studies on trade claims have relied on traditional approach. Secondly, this study has an originality in that it is an attempt to quantitatively study the trade claim cases, whereas prior trade claim cases were mainly studied via qualitative methods. Lastly, this study shows that the use of the text mining can lower the barrier for acquiring information from a large amount of digitalized text.

Keywords: Semantic Network Analysis, Text mining, Topic Modeling, Trade Claim
JEL Classifications: F14, K12, M16

1. Introduction

Changes in the international trading environment, such as new trade protectionism, bilateralism, the Fourth Industrial Revolution, and climate change, increase not only

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uncertainty in international commerce but also the possibility of trade claims being caused. In international commercial practice, preventing and managing trade claims is critical not only for the contracting parties but also for the national economy. For the contracting parties, trade claims increase the transaction costs and a cancellation of contracts results in direct losses to the company's profits and reputation as well as hurting the company's competitive advantages due to potential loss of future contracts. At the macroeconomic level, trade claims can negatively affect the balance of international payments and foreign debts and may induce international trade conflicts between countries (Shin Koon-Jae, 2007). Therefore, with such high amounts of uncertainty, trade claim management is crucial for companies to secure economic performance.

One of the ways to effectively manage trade claims is to identify and respond to the frequent trade claims at the national level. The trading parties interpret and apply the contents of the contract based on their country's legal system, economic environments, commercial practices, cultural values, and beliefs (La Porta et al., 1998; Zhou and Peng, 2010). This implies that trading parties of the same nationality will have comparable commercial behavior patterns and trade claims may appear similar. If a country's trade claims appear in a specific pattern, a trading party planning or carrying out exports or imports for the country may have useful implications for claim management. However, since previous research on trade claims is mainly conducted on individual cases, research on trade claim patterns at the national level is insufficient.

The following academic and practical contributions are expected to be gained by understanding trade claims patterns at the national level and analyzing their characteristics through statistical techniques. First, it is possible to secure objective and reproducible research results. A study on the interpretation of individual cases has the advantage that it informs the interpretation of the theory of law applied to the case. However, it has a limitation from being derived from single cases, which places considerable restrictions on generalization. Therefore, there is a need for a methodology that identifies the overall pattern, connects internal concepts, and organizes them into a form that can be interpreted. It is expected that this study will be able to substantially satisfy this goal.

Second, the statistical approach is highly scalable compared to studies focused on individual cases and legal interpretation. This is because the statistical approach allows analysis of the importance of content as well as interpretation of the regulations of the law. Furthermore, if specific patterns can be analyzed by country, it is possible to check the differences between national patterns due to various macroscopic influences such as culture and economic systems. In practice, this provides a basis for judging which regulations and trade claims should be observed by individual companies in accessing foreign markets. Also, identifying the differences between countries can help to set the market expansion strategies for different markets.

The following two elements are needed to clarify the characteristics of trade claims at the national level. One is to secure data on trade claims across the country. Legal cases are mainly used as the source of the subject of research on claims between trading parties in international business transaction. Claims arising during business transaction are a kind of business secret. Because it is not publicly disclosed, it is more dependent on legal cases. This study aims to secure trade claims data for the entire country through the trade claims legal cases applied to the United Nations Convention on the Contract for the International Sale of Goods of each country published on the website of the United Nations Commission on International Trade Law. The UNCITRAL discloses trade claims legal cases of member countries for the purpose of raising the awareness of CISG as an international trade norm and for the purpose of unified interpretation and application.

The other is the analysis method of the collected large-scale text data. As the content of trade claims data across the country is vast, traditional methods not only take a lot of time to analyze, but have a high probability of error during the analysis process. This study intends to perform analysis by applying a data mining technique that has been actively used for unstructured text data. Text mining is a methodology for structuring input texts and finding patterns in unstructured data, and has the advantage of automatically processing large amounts of text (Ponweiser, 2012). Validity needs to be confirmed to adopt the results of trade claims analysis using text mining (Newman et al., 2010). In this study, the internal validity is confirmed by comparing the analysis results derived through text mining with the analysis results derived through the traditional method.

This is an exploratory study to apply text mining techniques to legal cases of trade claims as a quantitative approach. The content of the legal cases is identified using word frequency and centralities generated by semantic network analysis on the corpus because the text contains information and includes words and sentences to convey that information (Laver, Benoit and Garry, 2003). The occurrence and frequency of a particular word is representative of the characteristics of the text (Evans et al., 2007). And centralities generated by semantic network analysis shows the meaning of the content by deriving the role of each word and the relationship between words by representing words as nodes and links (Freeman, 2005).

The subjects of analysis are the Chinese cases published on the UNCITRAL website wherein CISG is applied. The CISG is a universal governing law that determines imputation for claims to international business transaction. This is an international treaty signed by 94 countries and applies to the international sale of goods in preference to domestic law (UNCITRAL website). This study focuses on the fact that the cases are textual documents that contain the contents of claims between the trading parties.

The remainder of the paper is organized as follows: Section 2 reviews the theoretical background and related works of text mining techniques, Section 3 develops the framework for applying text mining on the trade claim analysis, Section 4 presents and explains the results of text mining, and Section 5 concludes the paper and discusses the implications not only theoretically but also practically.

2. Theoretical Background and Literature Review

2.1. Extracting Information from the Text

Text contains information (Laver, Benoit and Garry, 2003) and includes words and sentences to convey that information. Information can be obtained by reading and understanding the words and sentences that make up the text. A well-known method of acquiring information from text is content analysis. Content analysis is a research method that uses a series of procedures to derive valid inferences from text. It is useful for quantitatively transforming the unstructured text to understand its characteristics (Berelson, 1952; Holsi, 1969; Weber, 1990). Content analysis can quantitatively classify and verify the contents of the document using a structured system when research data exists as documentation. In this regard, it is useful in studies of communication, tourism, marketing, and law. That is, if you use the same method with the same data, anyone can replicate the same results (Hall and Wright, 2008).

Despite the usefulness of content analysis, it is time-consuming and expensive for massive text analysis, which has limited its use. However, due to the advancement of information technology, the time and cost of quantifying information contained in digital texts has drastically lowered, increasing its use in various fields. For example, in the financial sector, it is used to predict changes in asset prices or to estimate the effect of new information through extracted text from news, social media, and available data published by a company. In the macroeconomic sector, text analysis is used to predict inflation and unemployment, or to estimate the effects of government policies (Gentzkow, Kelly and Taddy, 2019). Text mining, content analysis using data mining techniques, is a representative methodology for acquiring information from dizitalized text (Evans et al., 2017).

The meaning in a text is not understood by a single word. Since the meaning of a word is determined by other words distributed together with it, several words must be considered simultaneously to interpret and accept meaning. Thus, the meaning of a word is determined by the context, which is the environment for the word, and this environment is structured by other words (Harris, 1954). Therefore, interpreting the context allows understanding of the meaning of the word and measuring the similarity between words (McDonald and Ramscar, 2001). According to the distributional hypothesis, words used in similar contexts have similar meanings (Deerwester et al. 1990; Harris, 1954; Weaver, 1955).

Vector space models (hereafter VSMs) enable statistical processing of digital texts by positioning words in a geometric space. This is a method of substituting the dimensions of the semantic space with words and then placing them in the space according to their degree of appearance together. Two words with similar linguistic contexts are placed in a closer semantic space, allowing the similarity of a corpus of text to be analyzed (McDonald and Ramscar, 2001). That is, VSMs derive co-occurrence frequency information and statistically estimate the similarity of meaning between words, phrases, and documents.

Trade claims are a type of business secret and are not publicized often, so judicial decisions are the main source of information on them. Legal documents are in text form and reading and understanding them can help obtain information about the claims. For example, if the word 'non-conformity' appears frequently along with 'quality' and 'goods', it can be seen that the ruling is related to product quality non-conformity. This implies that content analysis of legal documents is possible through the application of text mining.

2.2. Related Works

Research on applying text mining to digital texts is being carried out in many fields for descriptive and causal analysis. These studies are largely divided into three categories. The first are studies that interpret the meaning through frequency analysis of the words that appear. Evans et al. (2007) regarded the occurrence and frequency of a particular word as representing the characteristics of the text to present a methodology for automatically classifying legal documents. Lee Ju-Yeon, Han Seung-Hwan and Kwon Ki-Seok (2015) analyzed the keywords of 24,019 legal papers from 2004 to 2013 to divide contents of the study into tangible issues such as consumer protection and default on debt, and ideological issues such as freedom of expression and human rights. Iselin and Siliverstovs (2013) attempted to verify to what extent the R-word index proposed by The Economist can predict GDP growth. The R-word index was the frequency of the word 'recession' that appeared in articles in the Financial Times and the Wall Street Journal.

The second are studies that compare the similarity of words that appear and interpret their meaning. Allee, Elsig and Lugg (2017) demonstrated through text mining that the incompatible preferential trade agreements (hereafter PTAs) and the World Trade Organization (WTO) were strongly linked to each other. To this end, they analyzed how often individual country PTAs refer to the WTO. The result showed that 90% of new PTAs refer to the WTO, confirming that the WTO still remains a focal point. Ghani et al. (2006) proposed the use of text mining as a method to estimate the expected sales of new products by extracting products with similar properties and values through it and predicting sales by analyzing those products data. This is a study based on the assumption that products with similar occurrence words will have similar properties. Laver, Benoit and Garry (2003) conducted a study to identify the policy position by analyzing the text generated by politicians. Laver, Benoit and Garry (2003) began their study from the assumption that text contains information. They demonstrated a method of comparing and analyzing texts from politicians based on reference texts regarding past policy positions.

Lastly, there are studies using semantic network analysis. This is a method of analyzing the meaning of the content by deriving the role of each word and the relationship between words by representing words as nodes and links. This is the use of co-occurrence in which a specific word is mentioned along with other words shared with it, and concepts with a similar context (Freeman, 2005). Lee and Jung (2019) applied semantic network analysis to current social sustainability literature over time. Ruiz and Barnett (2015) conducted a semantic network analysis to determine how HPV vaccine information is presented online and what concepts co-occur. Zarei, Sharifi and Chaghouee (2017) conducted a semantic network analysis to examine the delay causes of complex construction project in the Oil-Gas-Petrochemical sector. Jiang, Barnett and Taylor (2016) used a semantic network analysis to understand the national political environment affecting the formation of news frames on international political issues.

2.3. Prior Studies on the Application of CISG in China

China has introduced and utilized the CISG since 1988. The CISG not only had a major influence on the formation of domestic contract law in China but is also evaluated as taking an important position in China's international transactions and legal practices. This is due to the fact that the CISG was used as a reference to enact the Contract Law of the People's Republic of China on October 1, 1991 to unify the existing economic contract law, foreign economic contract law, and technology contract law (Yongping and Weidi, 2008). Accordingly, the Supreme People's Court and the China International Economic and Trade Arbitration Commission (CIETAC) pay close attention to the CISG, and there are studies being actively conducted on the Chinese trade claims in which the CISG is applied. Related studies mainly include Chinese CISG reservations (Wang and Andersen, 2004), their impact on domestic law (Zeller, 1999), the comparison between the Contract Law of the People's Republic of China and the CISG (Shen, 1997; Wang, 1989a/1989b/1989c; Yang, 2004), and the application of CISG in arbitration practice (Jacobs and Huang, 2005; Mohs and Zeller, 2006; Wu, 2005).

A representative study on cases of CISG application in China was done by Yongping and Weidi (2008). This study was conducted on the scope of the CISG, the CISG and party autonomy, the CISG and trade customs, formal validity of the contract, product nonconformity and notification obligation, buyer inspection obligation, etc. based on China's CISG legal cases published by the Pace Law School. Shulman and Singh (2010) argued that China's CIETAC judged foreign companies without prejudice through an analysis of the Chinese arbitration cases applying the CISG. Ramaswamy (2017) conducted a study through legal case analysis on the applicability and limitations of the CISG in the sale of goods in China and Brazil. Yu Cheon (2018) studied the application of the relational contract theory by using the mutuality-flexibility frame targeting the decisions of applying CISG in China.

The preceding studies above have adopted the method of deriving issues and presenting implications based on the legal interpretation of provisions on the application of the CISG's governing laws, obligations of the trading parties, contract violations and compensation for damages, etc. and related legal cases. This is effective for application to individual cases, but has limitations in the analysis of overall trade claims trends. Therefore, the goal of this study is to analyze the contents of trade claims by applying text mining for the all cases in China in which the CISG was applied.

3. A Text Analytic Framework

3.1. Text

The subjects of this study are 81 cases of arbitration and court judgments from China published on the website of the United Nations Commission on International Trade Law where the CISG was applied. Individual legal cases can be found on the website of the United Nations Commission on International Trade Law. The total number of words is 36,848. The document structure for legal cases where the CISG was applied consists of case identification, UNCITRAL abstract, classification of issues present, citation, and case text. The subject of analysis in this study is the content of the claim and the content of the judgment on the claim. Therefore, data was collected excluding the general information of the case.

The contents of the case text first introduce the contract and the process of the transaction, and the items to be traded, the nationality of the trading party, the payment method, whether or not it was a split transaction, and incoterms are presented. Subsequently, the process and cause leading to the claim are presented, and the arguments of the trading parties are described. In the second half, a case text is presented which describes the results of the dispute between trading parties and the provisions on which the judgment is based. Lastly are the contents of the decision of the responsible party and compensation for damages.

3.2. Analytic Procedure

The goal of this study is to analyze the content characteristics of 81 trade claims cases at the national level and verify validity by applying a text mining technique. Validation is performed by comparing the manually analyzed result with the automatically analyzed result (Evans et al., 2007; Laver, Benoit and Garry, 2003). The manual analysis result is the cluster analysis wherein the researcher reads and codes the case. The automatic analysis result is an analysis applying the text mining technique to the result of the cluster analysis.

The cluster analysis result is used as a standard for comparison of the internal validity of content analysis through text mining. Internal validity compares the similarity between the content identified through manual work and the content estimated through topic modeling. In other words, the content validity of text mining results can be verified by comparing the result of topic modeling derived through text mining with the result of cluster analysis derived manually (Newman et al., 2010). The degree of agreement between the manual analysis result by the author and the automatic analysis result by computer means the degree of applicability of the text mining technique.

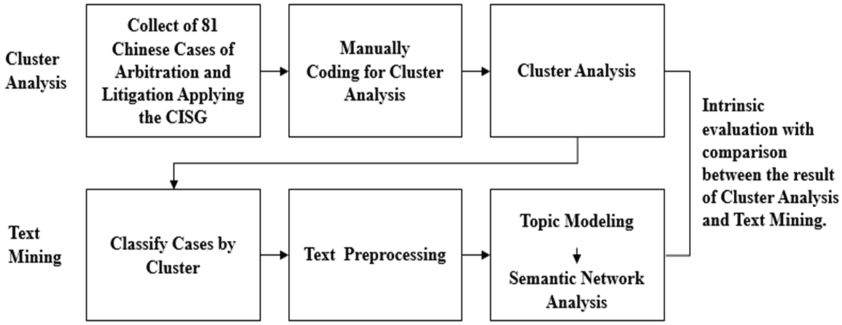
The detailed analysis procedure is as follows. First, 81 cases collected are individually documented. For cluster analysis, data is converted by coding based on the contents of the claims in individual cases. The trade claim content is identified based on the information contained therein after reading the case. For example, the keywords such as ‘seller, buyer, goods, L/C, failure, breach of contract, damage’ indicate that the content of a trade claim in the case is related to payment. In this way, they are coded as ‘Refusal of Product Acceptance=1’, ‘Failure of Product Acceptance=2’, ‘Refusal of Payment=3’, ‘No Issuance of

L/C= 4', 'Nonpayment=5', 'Delay of Delivery=6', 'Failure of Delivery=7', 'Refusal of Delivery=8', 'Product Nonconformity=9'. At this time, the refusal and failure of receiving goods are classified based on the words used in the judgment while filing a claim, and delay, failure, and refusal of delivering goods are also classified based on the words used in the judgment. The party at fault is coded by classifying it into 'seller=1' and 'buyer=2'.

After developing the coding manual, two cross-checks are conducted on each piece of research with one researcher who majored in international commerce to secure the validity.

Cluster analysis is conducted based on the trade claims and party at fault to classify cases. To determine the number of clusters, a hierarchical cluster analysis is performed using the squared Euclidean distance, and the appropriate number of clusters is determined based on the coefficient growth rate according to the average linkage method. K-means cluster analysis is performed using the number of clusters determined through hierarchical cluster analysis.

Fig. 1. Analytic Procedure



Prior to text mining for each cluster, data pre-processing is performed for all cases. A thesaurus list is created by searching for words used in the text, and a defined words list is created so that proper nouns composed of several words can be recognized as a single word. After that, words that are not applied to the topic, such as specific items and units of the product, and words that are judged not to be directly related to the content of trade claims such as CISG, case, court, arbitration, etc., are included in the exception list. After that, all of the cases go through a process of review via word frequency analysis to determine whether words that match the research purpose appear.

After conducting topic modeling to derive detailed topics for each cluster, the internal validity of the topics is verified through comparison with the cluster analysis results by reviewing the high ranking words. After that, semantic network analysis is conducted to analyze the contents of each topic. At this time, the length of the word is set to 2 or more, the window size indicating the formation of links of adjacent words is set to 2, and a semantic network is formed using the top 50 words. The learning method uses Markov Chain Monte Carlo, and the number of iterations is set to 1,000. Based on the semantic network analysis results, the network centrality index for each topic is calculated and analyzed.

3.3. Analytic Strategy

3.3.1. Cluster Analysis

This study categorizes trade claims cases by the cluster analysis. Individuals within classified clusters are classified so that they have as similar characteristics as possible and are different between clusters (Hair et al., 2006). In particular, cluster analysis is often used in the case of grouping in exploratory situations like this study because grouping is based on the characteristics revealed without prior information about the group (Hardiman et al., 1990). For the data composed of the entire sample, the number of clusters 'K' is determined, and the central point is calculated for the corresponding variable in each cluster so that all subjects are assigned to the cluster for analysis. Here, K is the number of clusters derived via hierarchical cluster analysis. The goal of the cluster analysis result is to confirm the internal validity of the text mining result.

3.3.2 Text Mining Techniques

This study is designed to explore the applicability of text mining techniques to digitalized trade claims cases using topic modeling and semantic network analysis.

a) Topic Modeling

Topic modeling is a probability modeling algorithm to extract topics that are hidden latent variables through text analysis. This is possible because words are used to describe a particular topic. The topic modeling technique can derive meaningful topics by mechanically analyzing the contents of the entirety of the text data according to a certain algorithm, so its use in content analysis research is increasing rapidly. Topic modeling is a text mining technique based on a probabilistic framework, and has the advantage of automatically constructing and understanding large amounts of text data, enabling search and summarize (Hornik and Grün, 2011). A topic is a latent variable in the text, meaning the context revealed through the connection of words appearing in the document (Tong and Zhang, 2016). In other words, it is a method that allows the topic to be estimated via words classified through machine learning and natural language processing. Topic modeling assumes that words in the document are not randomly selected, but they are generated by combining the word distribution of the topic and the topic distribution of the document. Accordingly, it is possible to estimate the distribution of topics and the distribution of topics within the document. Topic modeling does not require pre-determining the category of code or meaning, and it is automatically classified by specifying the number of topics. In this regard, it is considered more inductive than traditional text mining methods (Nahm Choon-Ho, 2016). This is because the process of deriving the topic is clear, so it is highly replicable by other researchers and does not depend much on prior knowledge.

In order to verify the validity of the topic extracted through topic modeling, internal or external validity can be used. The purpose of internal validity is to compare the similarity between the content identified through manual work and the content estimated through topic modeling. In this study, after the researcher clusters the manually coded data, topic modeling is performed for each cluster to review the words constituting each topic to verify the internal validity of each topic. When the topic derived through text mining and the contents of cluster analysis coincide with each other, it is considered that the validity is secured.

b) Semantic Network Analysis

Semantic Network Analysis is an application of Social Network Analysis to text (Wasserman and Faust, 1994). SNA uses an object as a connection point while semantic network analysis sets the word as a node and analyzes the structural relationship of the words that make up the message in the text. Semantic Network Analysis is a research method used to identify potential topics by identifying the relationship between words in the corpus. In particular, each word in the corpus is set as one node, and the form and strength of the relationship between each node, as well as the location of the node on the network, are presented using the centrality index. By doing so, it reveals the context of the words more clearly (Jang and Barnett, 1994).

SNA uses indices such as density, centrality, and centralization in order to understand structural characteristics (Hansen, Shneiderman and Smith, 2009). Density refers to the overall connection strength between nodes in the network. This is measured by the number of connected lines, and a high density means a network with a strong relationship. Centrality is an index that explains what position a node occupies in the overall network structure, and refers to the relative importance of a node. Representative centrality indices include degree centrality, between centrality, closeness centrality, and eigenvector centrality (Freeman, 2005).

In this study, degree centrality, between centrality, and eigenvector centrality are used to understand the characteristics of word networks within a cluster of cases applying the CISG. This is because degree centrality can identify words that play a key role in the cluster of cases and between centrality is useful for grasping the topic of the network by connecting key words. Eigenvector centrality reveals the content that is important to the topic.

4. Results

4.1. Descriptive Statistics

The results of the analysis of the descriptive statistics of the Chinese cases applying the CISG are as follows. First, there were 42 cases (51.9%) of sellers and 39 cases (48.1%) of buyers as claimant. For the contents of claims, 25 cases (30.9%) were Product Nonconformity, 14 cases (17.3%) were Nonpayment, 9 cases (11.1%) were Refusal of Product Acceptance and Refusal of Payment respectively, 8 cases (9.9%) were No Issuance of L/C. For party at fault, 35 cases (43.2%) were attributable to the seller and 46 cases (56.8%) were attributable to the buyer.

4.2. Result of Cluster Analysis

In order to determine the number of clusters, a hierarchical cluster analysis was conducted based on the trade claim content and party at fault. K-means cluster analysis was performed by applying four, which is the number of clusters determined. The party at fault and claim contents by cluster are shown in Table 1 below. Cluster 1 is the Buyer at fault, Product Acceptance group, and 10 cases are clustered. Cluster 2 is the Seller at fault, Delivery group, and 14 cases are clustered. Cluster 3 is Buyer at fault, Payment and L/C group, and 31 cases are clustered. Cluster 4 is Seller at fault, Product Nonconformity group, and 26 cases are clustered. The differences between groups in each cluster for party at fault were verified using Duncan when homogeneity of variance was secured according to Levene's test and Dunnett T3 was used when homogeneity of variance was rejected. The difference between clusters' claim content was verified through Fisher's Exact Test. It was clustered so that differences between clusters occur at 99%.

Table 1. Result of Cluster Analysis

Item		Cluster 1	Cluster 2	Cluster 3	Cluster 4	Post hoc (F Value)
Party at Fault	Seller	1	11	0	23	Cluster 1,3 > Cluster 2,4 (F=60.641***)
	Buyer	9	3	31	3	
Claim Content	Refusal of Product Acceptance	9	0	0	0	Fisher's exact Test = 164.068***
	Failure of Product Acceptance	1	0	0	0	
	Refusal of Payment	0	0	9	0	
	Issuing L/C	0	0	8	0	
	Nonpayment	0	0	14	0	
	Delay of Delivery	0	2	0	0	
	Failure of Delivery	0	6	0	0	
	Refusal of Delivery	0	6	0	0	
	Product Nonconformity	0	0	0	26	
No. of Cases		10	14	31	26	

Notes: 1. Fisher's Exact Test conducted due to the existence of low expected frequency.
2. *** P<0.01.

4.3. Result of Text Mining on Each Cluster of Trade Claim Collections[1]

4.3.1. Result of Word Frequency

Prior to topic modeling analysis, word frequency analysis was performed for the entire text. Among the 36,848 words, a total of 15,855 words were extracted by excluding similar words, designated words, and exception words. The most frequently used word in all judgments was buyer, 1286 times (8.11%), followed by seller (1078 times, 6.80%), good (684 times, 4.31%), payment (319 times, 2.01%), order (265 times, 1.67%), deliver (261 times, 1.65%), claim (240 times, 1.51%), price (210 times, 1.32%), breach of contract (192 times, 1.21%), L/C (157 times, 0.99%). The top 20 words are presented in Table 2.

Table 2. Result of Word Frequency

Rank	Word	Freq.	Ratio	Rank	Word	Freq.	Ratio
1	buyer	1286	8.11	11	damage	154	0.97
2	seller	1078	6.80	12	interest	132	0.83
3	goods	684	4.31	13	loss	128	0.81
4	payment	319	2.01	14	request	122	0.77
5	order	265	1.67	15	issue	111	0.70
6	deliver	261	1.65	16	quality	109	0.69
7	claim	240	1.51	17	time	105	0.66
8	price	210	1.32	18	inspect	104	0.66
9	breach of contract	192	1.21	19	shipping	102	0.64
10	L/C	157	0.99	20	obligation	101	0.64

[1] As a result of conducting topic modeling for each of the four clusters, it was found that all of the four clusters were composed of two topics, and topics related to 'damage compensation' were common within all clusters. This study aims to derive the contents of trade claims through text mining, and the presentation of the results on the topic of 'damage compensation' is omitted.

This result shows that a corpus properly reflects the characteristics of trade claims because trading partners, goods, the price of the goods, payment conditions, orders, and payments are in the top rank. Also, words such as delivery time, product quality and nonconformity, as well as inspection, damage and loss, cost, and interest are ranked next.

4.3.2. Results of Text Mining on Cluster 1: 'Buyer at fault - Product Acceptance' Cluster

According to cluster analysis based on the manual work, Cluster 1 appeared as a trade claim related to 'Buyer at fault - Product Acceptance'. Ten of the 81 cases fall into this. And topics that were latent in the 10 cases in Cluster 1 were extracted using topic modeling techniques. As a result, Cluster 1 was divided into two topics. The words mainly used in the target topic were in the order of 'buyer, seller, goods, shipping, payment, deliver, loss, claim, cost, obligation' showing that it is related to the shipment and delivery of goods by buyers and sellers.

Semantic network analysis was conducted to more clearly understand the content of the target topic of Cluster 1. As a result, the network showed high degree centrality in 'buyer, goods, seller, payment, shipping, cost, deliver, obligation, data, defect'. On the other hand, between centrality was high in 'B/L, shipping, inspect, payment, error, reasonable, data'. At this time, words such as 'refuse, request, loading, notify' did not appear in degree centrality or between centrality, but appeared in eigenvector centrality. The text mining analysis result shows that Cluster 1 is about 'Product Acceptance', which is consistent with the cluster analysis result. The cases where the buyer refuses to accept the goods are generally document nonconformity, quality nonconformity, and noncompliance with the delivery date. This can be inferred from words such as 'refuse, error, date, request, notify'.

Table 3. Results of Text Mining on Cluster 1

Rank	Result of Topic Modeling (Words Ratio=52%)		Result of Semantic Network Analysis					
			Degree Centrality		Between Centrality		Eigenvector Centrality	
	Word	Freq.	Word	Index	Word	Index	Word	Index
1	buyer	138	buyer	0.688	buyer	0.323	buyer	0.488
2	seller	129	good	0.583	seller	0.185	good	0.467
3	good	85	seller	0.563	good	0.168	seller	0.454
4	shipping	34	payment	0.313	BL	0.089	deliver	0.289
5	payment	30	shipping	0.292	shipping	0.060	payment	0.248
6	deliver	25	cost	0.271	inspect	0.048	shipping	0.215
7	loss	24	deliver	0.229	payment	0.045	refuse	0.153
8	claim	18	obligation	0.188	error	0.042	request	0.136
9	cost	17	date	0.167	reasonable	0.037	loading	0.106
10	obligation	14	defect	0.167	date	0.023	notify	0.096

4.3.3. Results of Text Mining on Cluster 2: 'Seller at fault – Delivery' Cluster

According to cluster analysis based on the manual work, Cluster 2 appeared as a trade claim related to 'Seller at fault – Delivery'. 14 of the 81 cases fall into this. Topics that were latent in the 14 cases in Cluster 2 were extracted using topic modeling techniques. As a result, Cluster

2 was divided into two topics. The words mainly used in the target topic were 'buyer, seller, deliver, goods, L/C, order, breach of contract, payment' showing that it is related to the delivery and payment.

Semantic network analysis was conducted to more clearly understand the content of the target topic of Cluster 2. As a result, the network showed high degree centrality in the order of 'seller, buyer, goods, deliver, payment, L/C, claim, breach of contract, agreement, time'. Between centrality was in the order of 'buyer, seller, goods, deliver, L/C, payment, claim, date, breach of contract, cost', and eigenvector centrality was in the order of 'seller, buyer, deliver, goods, claim, payment, order, breach of contract, L/C, date'. In the semantic network of the target topic of cluster 2, words with high degree centrality have high between centrality and high eigenvector centrality. At this time, the high degree centrality and eigenvector centrality of 'seller' and 'deliver' indicates that the network is mainly composed of contents related to seller delivery. The text mining analysis result shows that Cluster 2 is about 'Deliver & Payment'. This is consistent with the cluster analysis result. The main causes of claims related to Deliver include seller's refusal of delivery or non-compliance with deliver data by seller due to buyer's non-payment. This can be inferred from the co-occurrence words 'payment, L/C, date'.

Table 4. Results of Text Mining on Cluster 2

Rank	**Result of Topic Modeling (Words Ratio=67%)**		**Result of Semantic Network Analysis**					
			Degree Centrality		**Between Centrality**		**Eigenvector Centrality**	
	Word	**Freq.**	**Word**	**Index**	**Word**	**Index**	**Word**	**Index**
1	buyer	171	seller	0.837	buyer	0.263	seller	0.513
2	seller	161	buyer	0.796	seller	0.258	buyer	0.491
3	deliver	64	good	0.612	good	0.110	deliver	0.376
4	goods	62	deliver	0.551	deliver	0.060	good	0.330
5	L/C	46	payment	0.408	L/C	0.040	claim	0.172
6	order	39	L/C	0.347	payment	0.036	payment	0.168
7	breach of contract	35	claim	0.306	claim	0.020	order	0.148
8	payment	32	breach of contract	0.286	date	0.020	breach of contract	0.136
9	claim	30	agreement	0.265	breach of contract	0.020	L/C	0.132
10	damage	21	time	0.265	cost	0.010	date	0.111

4.3.4 Results of Text Mining on Cluster 3: 'Buyer at fault – Payment and L/C' Cluster

According to cluster analysis based on the manual work, Cluster 3 appeared as a trade claim related to 'Buyer at fault – Payment and L/C'. 31 of the 81 cases fall into this. Topics that were latent in the 31 cases in Cluster 3 were extracted using topic modeling techniques. As a result, Cluster 3 was divided into two topics. The words mainly used in the target topic were in order of 'buyer, seller, goods, payment, order, delivery, price, obligation, fail, resell' showing that it is related to payment between trading parties.

Semantic network analysis was conducted to more clearly understand the content of the target topic of Cluster 3. As a result, the network showed high degree centrality in the order of 'buyer, seller, goods, payment, deliver, price, order, obligation, agreement, data'. Between centrality of 'buyer, seller, goods, payment, deliver, price' was in the same order as degree centrality but 'agreement, order, fail, present' demonstrated a difference. Eigenvector centrality was the highest in 'payment' followed by 'buyer, goods, seller, deliver, price, order, obligation, fail, agreement' in that order. In the semantic network of the target topic of cluster 3, there was not much difference between words in terms of degree centrality and between centrality. The fact that payment is high in eigenvector centrality indicates that the network is composed of contents related to payment. The text mining analysis result shows that Cluster 3 is about 'Payment'. This is consistent with the cluster analysis result. The main causes of claims related to payment include breach or failure of the buyer's obligation to pay payment at the time of delivery on agreement to supply of goods. This can be inferred from the co-occurrence words 'fail, price, obligation, agreement'.

Table 5. Results of Text Mining on Cluster 3

Rank	Result of Topic Modeling (Words Ratio=46%)		Result of Semantic Network Analysis					
			Degree Centrality		Between Centrality		Eigenvector Centrality	
	Word	Freq.	Word	Index	Word	Index	Word	Index
1	buyer	347	buyer	0.660	buyer	0.222	payment	0.485
2	seller	292	seller	0.638	seller	0.183	buyer	0.475
3	good	185	good	0.617	good	0.177	good	0.448
4	payment	159	payment	0.553	payment	0.131	seller	0.386
5	order	76	deliver	0.468	deliver	0.063	deliver	0.271
6	deliver	72	price	0.362	price	0.047	price	0.205
7	price	59	order	0.298	agreement	0.024	order	0.140
8	obligation	35	obligation	0.255	order	0.021	obligation	0.127
9	fail	32	agreement	0.213	fail	0.013	fail	0.093
10	resell	21	date	0.213	present	0.012	agreement	0.061

4.3.5 Results of Text Mining on Cluster 4: 'Seller at fault – Product Nonconformity' Cluster

According to cluster analysis based on the manual work, Cluster 4 appeared as a trade claim related to 'Seller at fault – Product Nonconformity'. 26 of the 81 cases fall into this. Topics that were latent in the 26 cases in Cluster 4 were extracted using topic modeling techniques. As a result, Cluster 4 was divided into two topics. The words mainly used in the target topic were 'buyer, seller, goods, claim, damage, inspect, quality, breach of contract, defect' showing that it is related to product nonconformity.

Semantic network analysis was conducted to more clearly understand the content of the target topic of Cluster 4. As a result, the network showed high degree centrality in the order of 'buyer, seller, goods, inspect, claim, time, quality, damage, defect, period'. Between centrality was in the order of 'buyer, seller, goods, inspect, quality, time, period, claim, defect, contractual' and eigenvector centrality was in the order of 'buyer, seller, goods, claim, damage, inspect, breach of contract, defect, quality'. The text mining analysis result shows that Cluster 4 is about 'Product Nonconformity'. This is also consistent with the existing cluster analysis. These are cases where trade claims are caused by product nonconformity or defect.

Table 6. Results of Text Mining on Cluster 4

Rank	Result of Topic Modeling (Words Ratio=51%)		Result of Semantic Network Analysis					
			Degree Centrality		Between Centrality		Eigenvector Centrality	
	Word	Freq.	Word	Index	Word	Index	Word	Index
1	buyer	630	buyer	0.792	buyer	0.345	buyer	0.531
2	seller	496	seller	0.583	seller	0.157	seller	0.450
3	good	352	good	0.521	good	0.107	good	0.384
4	claim	142	inspect	0.417	inspect	0.067	claim	0.382
5	damage	88	claim	0.333	quality	0.059	damage	0.229
6	inspect	86	time	0.313	time	0.044	Inspection	0.142
7	quality	78	quality	0.292	period	0.028	breach of contract	0.137
8	breach of contract	76	damage	0.271	claim	0.027	defect	0.118
9	defect	66	defect	0.271	defect	0.022	quality	0.114
10	time	60	period	0.250	contractual	0.020	compensation	0.109

According to the above findings, the results derived through topic modeling and semantic network analysis are consistent with the characteristics of the group derived through cluster analysis based on the manual work. Thus, it can be seen that the content of trade claims of each cluster by the manual method and by the automatic method are very similar.

Table 7. Comparison of Two Approaches in Each Cluster

Result of Cluster Analysis		Results of Text Miming
Cluster 1	Buyer at fault – Product Acceptance	Product Acceptance
Cluster 2	Seller at fault – Delivery	Delivery & Payment
Cluster 3	Buyer at fault – Payment & L/C	Payment
Cluster 4	Seller at fault – Product Nonconformity	Product Nonconformity

Each cluster is named based on the characteristics of the cases included in the cluster: the trade claim content classified by the researchers & the party at fault. Two criteria are named based on information obtained by researchers after reading legal cases. For example, in the legal case, the following sentence means Seller at fault: The tribunal stated that the seller would be liable for latent defects where the buyer had raised a claim within two years after the acceptance of the flanges. And the trade claim content is identified based on the information contained therein after reading the text such as 'seller, buyer, goods, damage, inspect, quality, defect, etc.'. Those keywords indicate that the content of a trade claim is related to Product Nonconformity [2]. Therefore, this case belongs to cluster 4(Seller at fault - Product Nonconformity) according to k-means cluster analysis. Cluster 4 is a group consisting of Seller at fault - Product Nonconformity cases. The word frequency and centrality index of the text mining on Cluster 4 clearly reveal the contents of Cluster 4. The keywords that the researcher obtained manually information to classify the trade claim content appear the same in the text mining results.

Therefore, it is confirmed that text mining technique can be used as a statistical method to typify cases and interpret their meaning. Furthermore, when topic modeling and semantic

[2] The sentence and words are part of case 770 used in the study.

network analysis are applied, it is possible to grasp which concepts have important meanings in the process of calculating the centrality index. There is also an advantage in that the results can be interpreted in a richer manner because the connectivity with other concepts can be considered at the same time.

5. Conclusion

This study is designed to verify the validity of the application of text mining for trade claims research. To this end, 81 cases applying the CISG in China published on the UNCITRAL website were collected and used. First, 81 cases were converted into data by applying the existing method and cluster analysis was then conducted. Finally, text mining techniques were applied to each cluster afterwards.

The summary of the analysis results is as follows. First, the cases applying the CISG were divided into four clusters by the claim content and the party at fault, 'Buyer at fault – Product Acceptance', 'Seller at fault – Delivery', 'Buyer at fault - Payment & L/C', 'Seller at fault - Product Nonconformity'. According to the text mining results for each cluster, Cluster 1, 'Buyer at fault – Product Acceptance', showed high frequency and centrality in 'shipping, deliver, defect, B/L, inspect, notify, etc.' and appeared to be related to trade claims that occurred during the product acceptance process. Cluster 2, 'Seller at fault – Delivery', showed high frequency and centrality in 'deliver, time, date, L/C, payment, etc.' and appeared to be trade claims in connection with product delivery and payment. Cluster 3, 'Buyer at fault - Payment & L/C', showed a high frequency and centrality in 'payment, fail, resell, date, price, etc.' indicating trade claims related to payment. Cluster 4, 'Seller at fault - Product Nonconformity', showed a high frequency and centrality in 'damage, inspect, quality, defect, period, etc.' indicating trade claims related to product nonconformity.

The implications of this study are as follows. First, the validity of the text mining technique in the study of trade claim cases is confirmed. Table 7 shows the comparison of the cluster analysis results and text mining results. Specifically, it was found that the characteristics of the cluster and the details derived through text mining coincide. Also, the degree centrality of words that play a key role in the topic was high as was the between centrality of words that are useful for grasping the topic and the eigenvector centrality of the important words is high in the topic. Therefore, the results of cluster analysis and text mining results are similar to each other and confirm that the results of trade claim analysis through text mining has internal significance. This indicates that text mining techniques can be applied to research on content analysis of trade claims.

Secondly, this study has implications in that it is an attempt to quantitatively study the trade claim cases, whereas prior trade claim cases were mainly studied via qualitative methods. This is because qualitative research is suitable for interpretation of legal texts and case analysis accordingly (Ramaswamy, 2017; Wang and Adnserson, 2004; Yongping and Weidi, 2008; Yu, 2019). However, this approach has a limitation in that it is difficult to identify the common characteristics of multiple cases. In this study, text mining was conducted to quantitatively analyze the contents of trade claim cases. As a result of the analysis, it was possible to secure a result with internal validity. Recently, there have been an increasing number of research cases applying text mining techniques to unstructured text data. Text mining refers to the process of extracting high-quality information from a large amount of text (Ponweiser, 2012). The application of this methodology is expected to provide new implications to the methodologies used for research on trade cases, which have previously remained centered on individual case analysis.

Lastly, the usefulness of text mining techniques for content analysis of trade claims is confirmed. There are 10 trade claim cases in Cluster 1. Reading all 10 cases, grasping and organizing the contents by classifying them requires considerable effort and time. However, if you examine the words with high centrality shown in Table 7, you can easily see that it is made up of claims related to the acceptance of products. The same method can be applied to the remaining the clusters. The traditional method of content analysis is not only time-consuming and expensive, but also limited in its use as it requires skilled labor (Laver, Benoit and Garry, 2003; Evans et al., 2007). This study shows that the use of the text mining can lower the barrier for acquiring information from a large amount of text.

However, this study has the following limitations. First, the application of text mining is useful for understanding the types of trade claims but it appears that additional analysis is needed regarding the legal principles and the presence or absence of the liability of the claim. Second, comparative analysis is necessary to examine the differences in the characteristics of Chinese trade claims and other countries. Since this study was conducted only on Chinese trade claim cases, it is somewhat unreasonable to interpret the results of the study as unique characteristics of Chinese trade claims. Lastly, this study was conducted on only 81 cases published on the website of the United Nations Commission on International Trade Law among cases applying the CISG in China. In order to derive more generalized results, it is necessary to secure a larger amount of data. This limitation can be overcome by research in the future.

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