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A Method for Extracting Multifaceted Information from Free Descriptions in Questionnaires

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Abstract

In Japanese universities, student questionnaires completed in class are used to collect various types of information with two main objectives: students' impressions of classes and finding areas of improvement. The advantage of a class evaluation questionnaire with numerous questions is that detailed information can be collected; however, contrarily, the number of questionnaires collected and the rate of collection can decrease. This study proposes and tests university students a method to extract relevant information from a simple questionnaire. The proposed questionnaire comprises only five items on students' impressions of the classes and free descriptions. Text mining techniques were used to analyze the free descriptions and extract the positive or negative feelings expressed by the students. The results were classified according to the questionnaire score. This analysis method efficiently extracts information to identify the factors affecting students' comprehension, achievement, and satisfaction, which can improve classes. Text mining techniques were used to analyze the free descriptions and extract the positive or negative feelings the students expressed.

Keywords: questionnaire analysis, text mining, emotion analysis, intention understanding

1. Introduction

Class evaluation questionnaires answered by students provide valuable information to improve class quality. According to the Japanese Ministry of Education, Culture, Sports, Science, and Technology (MEXT, 2015), approximately 97% of national, public, and private universities in Japan conduct class evaluation questionnaire surveys among students. Such questionnaire surveys and studies on class evaluation (Terence, 1988) are also conducted in American universities (Stecklein, 1960).

Class evaluation questionnaires serve various needs, such as collecting information to improve classes and students' sense of accomplishment. Consequently, it is necessary to set many questions, for example, to clarify students' attitudes to conducting the class, attendance rate, the preparation and review situation, what the students obtain from the classes, and whether they understand the content of the classes, obtain the expected results, and are satisfied with the quality. To obtain information on ways for improvement, it is imperative to ask questions at different times, such as clarifying the content, textbooks, matters to be prepared in advance, and relationships with other subjects before the class. Furthermore, it also assesses whether it is easy for students to read the handouts, blackboard and hear and understand the instructor after the class. It is further necessary to investigate whether the methods of conducting classes, such as auditing, practical training, and exercises and of learning outside the class, such as homework and reports, are appropriate. Finally, after the class, it is important to check whether there is an appropriate means of measuring students' comprehension post their class.

However, setting multiple questions cause the collection rate of the questionnaire to decrease. University curricula are often designed such that first-year students take approximately 30 classes. To capture the true intentions of students who take many classes, it is necessary that the number of questions in a questionnaire is as few as possible to prevent answering fatigue. Under such circumstances, Y University designed a questionnaire on "Evaluation of class questionnaires" to collect data from all students. Specifically, the questionnaire narrowed down the information obtained to clarify the student's approach to the class and what they obtained from attending the class. Consequently, the time required for students to answer the questionnaire was reduced to a few minutes, making it easier to answer.

To understand the experiences of students, more effective information can be obtained if the factors that universities want to focus on in the future and those that require improvement are clarified. Therefore, this study aimed to extract information on what the students comprehended, what they were satisfied with, and what they felt they had achieved based on the free descriptions of the questionnaire by applying text mining technology.

2. Analysis of Class Evaluation Questionnaires

2.1 Introduction of the Current Situation Regarding Class Evaluation Questionnaires

Class evaluation questionnaires by students are no exception in Japan, and have been developed as class improvement activities in Faculty Development activities (Horoki, 2007; Takashi, 2007). These questionnaires collect data on how teaching activities are perceived by students. Based on the collected data, teachers can inspect and evaluate their teaching activities, thereby improving their skills. This section introduces previous research on item settings for class evaluation questionnaires. Based on the government report "Status of Reform of Educational Content others at Universities 2013" (MEXT, 2015), the results of the question item categories in the class evaluation questionnaire in Japan conducted in universities are summarized in Figure 1. As mentioned earlier, many universities in Japan conduct class evaluation questionnaires, and the questions they ask vary widely, as shown in Figure 1.

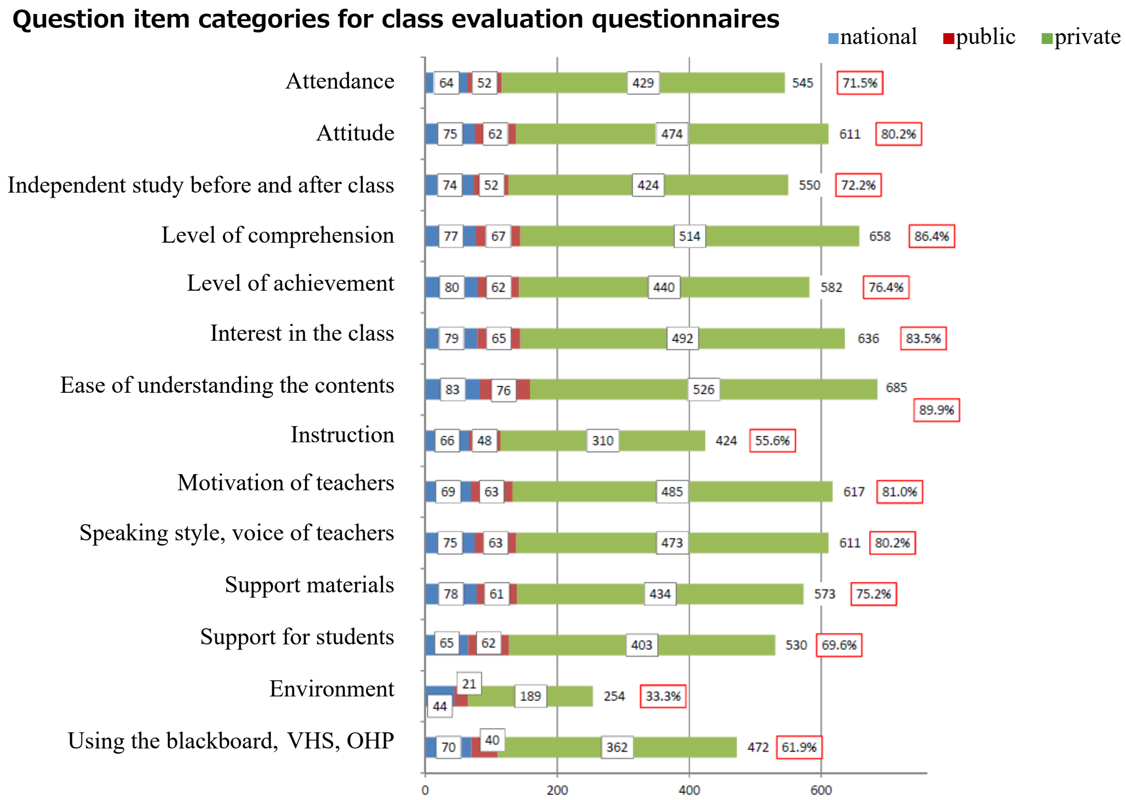

Figure 1. Summary of the report, Status of Reform of Educational Content others at Universities 2013 (MEXT, 2015)

Class evaluation questionnaire surveys are being conducted in many universities, and the number of such studies is increasing. Horoki (2007) argues that the question items of the class evaluation questionnaire are shown in seven target areas: "learning," "students," "environment," "teaching materials," "class," "teacher," and "assessment." In their study on question perspectives, Marsh (1983) and Makoto (2002) each dealt with nine such items. Some studies have classified specific questions. For example, Takeshi (2005) analyzed 100 different questionnaires consisting of 1,675 question items and classified them into six areas: "educational methods," "learners," "teacher qualifications," "teaching and learning outcomes," "educational content," and "classes." Thus, there are various ways of thinking about questions in class evaluation questionnaires.

Yoshiro (1992) analyzed the class evaluation questionnaire questions and extracted two factors: “Teacher’s teaching style and attitude” and “Students being influenced by the class,” while Yukimasa and Yahachiro (2004) mention “overall satisfaction” and explain its significance. Takashi et al. (2006) investigated the class evaluation questionnaires of 29 universities and organized the purpose of the questions. According to this study, the purpose of the questions can be classified into four categories: “Self-evaluation,” “Class evaluation,” “Overall evaluation,” and “Free descriptions.” Research on the question items of class evaluation questionnaires is declining. The question items are classified and categorized to some extent. From among them, each university and teacher select the questions that they think are necessary. In recent times, there has been an increase in research on the analysis of class evaluation questionnaires, such as the relationship between grades and questionnaires (Kiichiro, 2004; Ruriko, 2013).

However, the decline in the collection rate and the burden on students has become a concern. According to Takashi et al. (2006), the average number of questions for 29 universities is 16. This describes how the number of questions increases when a large amount of information is collected. Universities have several questions to ask students, and this number is increasing over time. With the spread of class surveys in Japanese universities, students are required to answer one questionnaire for each class; thus, the more classes they take, the greater the number of questionnaires. In general, response rates tend to decrease when students are required to answer the same question multiple times. In response to this issue, Davis (2009) pointed out that the questions should be simple because students need to complete the survey for all faculty members. Consequently, Japanese universities have also begun to reduce the number of questions to reduce the burden on students and improve the response rate. According to Davis (2009), by informing the students of the purpose of the questionnaire, it is possible to obtain important information, such as accurate evaluations and opinions. Therefore, many researchers, such as Kazuo et al. (2011) and Takanobu et al. (2003), conducting research to reduce the number of questions.

Reducing the number of questions inevitably reduces the information available. Therefore, many universities have provided free descriptions, and research on the analysis of free descriptions has increased. According to Takashi et al. (2006), 27 out of 29 universities provided free descriptions. Koji et al. (2015) and Hideya et al. (2017) have investigated the analysis of free descriptions using text mining technology, but the analysis is more arduous to tabulate than score evaluation. However, the analysis of free descriptions is becoming increasingly important because it can collect unexpected information instead of expected information from questions.

Thus, although there are studies on text mining, most of them aim at understanding the whole class in terms of frequent words and co-occurrence networks. Therefore, it is difficult to understand the object to be improved, and it takes time to propose an improvement. For example, it is necessary to determine what to improve and carry out activities to enhance low levels of comprehension, achievement, and satisfaction and further extend to high levels. In other words, since the question items are not detailed, it is necessary to subdivide the content to be improved from the free description. The 5-point scale, a quantitative evaluation, is more effective when analyzed with binary values (Maya & Kazuhiko, 2022). Conversely, some techniques can extract positive and negative sensitivities toward an object to analyze free descriptions. By clarifying improvement targets by objective, it is possible to know which ones to initiate improvement actions and efficiently conduct improvement activities for teaching activities. Combining these two studies, there is no significant concern in interpreting that objects rated as positive in the free description have a deep relationship with objects of items rated as good on the 5-point scale, and objects rated as negative in the free description have a deep relationship with objects of items rated as bad on the 5-point scale.

2.2 Emotional Analysis from Free description (Text mining to understand emotions)

Sentiment analysis algorithms that extract emotional information from various free descriptions have been studied for many years (Anil et al., 2017; Johnson-laird & Oatley, 1989; Saif, 2016; Yla & James, 2010). The accuracy of these tools has improved gradually. Recent emotion analysis algorithms have shown adequate performance in grasping positive and negative tendencies. There are many sentiment analysis algorithms for Japanese (Alexandra, 2018; Michal et al., 2009). Its analysis accuracy is similar to that of English, and it has sufficient performance to grasp positive and negative tendencies. In particular, the emotion information acquisition method using the polarity dictionary proposed by Nozomi et al. (2005) is a simple algorithm. First, a polarity dictionary, a set of words with emotional information, is constructed and compared with the words in the document to be analyzed (Ryuichiro et al., 2014).

In traditional natural language processing technology, morphological analysis divides a document into words and assigns part-of-speech information to each word (Ryohei & Sadao, 2011). Furthermore, syntactic analysis analyzes dependencies between words from the results of the morphological analysis (Daisuke & Sadao, 2006). Using this technology, it is possible to identify objects that generate emotional information.

Therefore, in this study, we aim to acquire positive or negative emotional information from the students based on the free description sections of the class questionnaire. Using syntactic analysis, we acquire an object that emits emotional information. An <object> is an event or item that causes <emotion>. In this study, two pieces of information, <emotion> and <object>, were extracted from the free description of the questionnaire as a pair of <object, emotion>. The <emotion> to be extracted is a binary value of positive or negative emotion.

2.3 Aim of this Study

Based on our literature survey, the most important objective of the class evaluation questionnaire is to clarify whether the class was meaningful for the students. A questionnaire with few questions has a higher collection rate; however, the problem is that less information is obtained.

The university in this study, Y University, has been considering and standardizing the question items for implementation in all classes and reducing the number of questions owing to concerns about the burden on students and the decreased collection rate. Here, the question design was narrowed to focus on students' self-evaluation. The questionnaire content was reduced to a 5-point rating of six question items and free descriptions. However, one item was excluded from the scope of this evaluation because it covered online classes temporarily conducted during the COVID-19 pandemic.

Specifically, two items were set to measure students' attitude toward the class–attendance rate and time spent studying outside of class–and three items were set as the gains from attending the class–comprehension, achievement of the class objectives in the syllabus, and satisfaction. The information obtained is usually scarce for such factors. To solve this problem, this procedure was considered to extract a large amount of information, specifically by analyzing the free description of the questionnaire, where students identify objects with positive or negative emotions.

3. Extraction and Classification of Emotional Objects

3.1 Outline of Processing Procedure

The questionnaire used in this study, detailed in Subsection 3.2, measures comprehension, achievement, and satisfaction obtained by the students. To clarify the objects of comprehension, achievement, and satisfaction, the free description of the questionnaire was analyzed in the following four steps.

1. Selecting only questionnaires with free descriptions
2. Applying text mining technology to free descriptions in questionnaires and extracting <object, emotion>
3. From the <object, emotion> extracted from the numerical evaluation of the questionnaire and the free description, determining whether <object> belongs to a factor of comprehension, achievement, or satisfaction
4. Performing logical operations on the set of <object> belonging to each factor of comprehension, achievement, and satisfaction to clarify the position between < object> and factors.

Based on the above, the link data of <object> of comprehension, achievement, and satisfaction were created, and subsequently, the created data were analyzed and discussed.

3.2 Questionnaire Data

The questionnaire, "Evaluation of class questionnaires," was administered at the end of the classes in the first semester of 2021 (April–September) for 58 liberal arts courses at Y University. It was answered by first- and second-grade university students who attended the classes. The seven questions in the survey are listed in Table 1.

Table 1. "Evaluation of class questionnaire" Questions

	Questions	Response options
Q1	What was your attendance for this class? (the numbers in parentheses are estimates for classes that meet 15 times)	5. Over 90% (14 classes or more) 4. 80–90% (12–13 classes) 3. 60–80% (9–11 classes) 2. 40–60% (6–8 classes) 1. Less than 40% (Less than 6 classes)
Q2	How much time did you spend doing work outside of class, such as previewing and reviewing materials, writing reports, and self-studying? Please circle the average time per class period.	5. 3–4 hours or more 4. Around 2 hours 3. Around 1 hour 2. Around 30–50 minutes 1. Less than 30 minutes
Q3	I understood the contents of this class.	5. Strongly Agree 4. Agree 3. Neutral 2. Disagree 1. Strongly Disagree
Q4	I achieved the goals outlined in the syllabus.	5. Strongly Agree 4. Agree 3. Neutral 2. Disagree 1. Strongly Disagree
Q5	Overall, I was satisfied with this class.	5. Strongly Agree 4. Agree 3. Neutral 2. Disagree 1. Strongly Disagree
Q6	[Please respond to Question 6 if any one or more of the lectures in this class was held remotely (Student Support System, Moodle, Zoom)] How easy was it for you to understand the online classes?	5. Very easy 4. Easy 3. Neutral 2. Difficult 1. Very difficult
Q7	Please write any comments that you may have about the class.	

The descriptive statistics for questions 1–5 and 7 (free description) of the "Evaluation of class questionnaires" used in this study are shown in Table 2. Question 6 was not used in the study because it was to the COVID-19 pandemic period.

The questionnaire was kept simple to increase the collection rate. In total, 21,896 valid responses were obtained (Table 2). The distribution of the questions on a 5-point scale ranged from 1 to 5 for extracurricular learning. However, for the three factors that students gained from the class, the number was skewed toward 4 and 5, with 4 and 5 accounting for more than 80% of the total number of questions.

Table 2. Summary of Analysis Data

		Response options (Number of responses)					
		5	**4**	**3**	**2**	**1**	**Total**
Questions	Q1 Attendance rate	19,999	1,264	288	114	231	21,896
	Q2 Study time outside class	2,966	3,371	6,278	4,142	5,139	21,896
	Q3 Comprehension	8,857	9,528	2,313	825	373	21,896
	Q4 Achievement	7,807	9,956	3,203	618	312	21,896
	Q5 Satisfaction	10,597	7,684	2,333	824	458	21,896

As Table 3 shows, 2,517 of the 21,896 questionnaires collected had free descriptions, and the free description response rate was 11.50%. The results of the 5-point scale for the comprehension, achievement, and satisfaction factors and the free-response rate are shown in Table 3, where the scale is biased toward 4 and 5. However, the free-response rate has a high probability of 1 and 2. Therefore, opinions with low scores could be extracted sufficiently, although the absolute numbers differed.

Table 3. Summary of Analysis Data for Free Descriptions

		Response options (Number of responses)					
		5	**4**	**3**	**2**	**1**	**Total**
Questions	Q3 Comprehension	8,857	9,528	2,313	825	373	21,896
	Free description available	1,070	1,012	243	109	83	2,517
	Description rate	12.08%	10.62%	10.51%	13.21%	22.25%	11.50%
	Q4 Achievement	7,807	9,956	3,203	618	312	21,896
	Free description available	901	1,087	366	86	77	2,517
	Description rate	11.54%	10.92%	11.43%	13.92%	24.68%	11.50%
	Q5 Satisfaction	10,597	7,684	2,333	824	458	21,896
	Free description available	1,332	707	227	127	124	2,517
	Description rate	12.57%	9.20%	9.73%	15.41%	27.07%	11.50%

3.3 Free-Text Analysis Algorithm (Text mining to determine emotions)

This section determines how to analyze free descriptions in questionnaires.

First, morphological analysis was performed on the free description sentences of the questionnaire. Morphological analysis divides a sentence into words and assigns a part of the speech to each word. Syntactic analysis is performed on the output result of this morphological analysis, and morphological dependencies, objects, and predicates are extracted. In this study, JUMAN/KNP, developed by the Kurosaki Laboratory at Kyoto University, was used as the morphological and syntactic analysis engine.

Then, the emotional information and object of the sentence were extracted from the syntactic structure of the sentence. Many polar dictionaries express the relationship between words and emotion, such as those developed by the Inui laboratory at Tohoku University. For example, a sentence containing the word “beautiful,” regardless of its object, is generally positive.

Similarly, sentences containing “be easy” tend to have a positive emotion. However, if the object is an event that should not occur, such as “missing,” “leakage,” or “broken,” it indicates a negative emotion. Thus, instead of relying on word-matching with polarity dictionaries, a more precise extraction of emotional information can be achieved by considering dependencies. Consequently, the objective of this study was to extract emotional information from the free description responses to the questionnaires. However, the existing polarity dictionaries and knowledge for emotion extraction based on dependencies were not optimized or available for use in this study.

Furthermore, while referring to the existing polarity dictionary, we constructed a knowledge dictionary for emotion extraction that acquires emotional information from free descriptions in past questionnaires. Consequently, we constructed a knowledge dictionary for emotion information extraction that consists of 1,188 matching rules, including 577 word-matching rules and 611 dependency-matching rules. Requests, complaints, questions, and other items were added as emotional information in the knowledge dictionary for emotional information extraction. Table 4 presents examples of word-matching and dependency-matching rules.

Table 4. Examples of Word-Matching Rules and Dependency-Matching Rules

Acceptance		Word	
feel annoyed	negative	it was bad	negative
low level	negative	Abnormal	negative
I don’t know what that means	negative	it was disappointing	negative
I was often confused	negative	it was painful	negative
there was a lot of noise	negative	Confused	negative
don’t come in time	negative	it was a pity	negative
I couldn’t deny the pressure	negative	it was hot	negative
I was able to do what I wanted	positive	feel relieve	positive
I was motivated	positive	easy to understand	positive
I found it interesting	positive	Improved	positive
helpful answer to the question	positive	I like	positive
I liked the naming	positive	Best	positive

Using a knowledge dictionary for emotional information extraction and syntactic analysis, <object, emotion> was extracted from the free description of the questionnaire. In this study, the “Evaluation of class questionnaires” conducted in 2021 at Y University was analyzed. Of the 2021 questions, 2,517 allowed free descriptions and to extract <object, emotion> from the questionnaire with the free description. There are cases in which multiple <object, emotion> can be obtained from the free descriptions in a single questionnaire. The number of objects and emotions that could be extracted was 2,590. Among them, 1,595 were positive, 650 were

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negative, and 345 had no emotions.

3.4 Connection Between Objects and Factors

To assess which factors (comprehension, achievement, and satisfaction) are closely related to the <object, emotion> extracted from the free description, an algorithm was applied to determine which of the three factors the object of the extracted emotion is related to, using a 5-point scale of the three factors.

First, out of the 3 factors in this questionnaire, a 5-point scale for 2 factors was used. If the emotion extracted from the free description was positive, the object was judged as the object of the factor with a good score. If the emotion extracted from the free description is negative, the object was judged as the object of the factor with a poor score.

Figure 2 displays some examples to explain this. The emotion in Example 1 is positive because it is judged that the object "sound quality" belongs to the high comprehension level of 5 points. The emotion in Example 2 is negative because the object "assignment" is judged to have a low achievement level of 5 points. Examples 3 and 4 are processed in the same way. However, as shown in Example 5, when the 5-point levels are the same, the relevant factor cannot be determined. Therefore, it was treated as not belonging to either factor. Consequently, the object belonging to comprehension is judged as {sound quality, explain}, and the object belonging to achievement is judged as {assignment, employment}.

	Comprehension	Achievement	Object	Emotion	Judgment
Example 1	5	3	sound quality	positive	comprehension
Example 2	5	4	assignment	negative	achievement
Example 3	3	4	employment	positive	achievement
Example 4	3	5	explain	negative	comprehension
Example 5	4	4	knowledge	positive	×

Comprehension
= {sound quality, explain}

Achievement
= {assignment, employment}

Figure 2. Examples of Emotion, Object, and Judgment from the Free Description

The above processing was performed for three sets: "Comprehension & Achievement," "Comprehension & Satisfaction," and "Achievement & Satisfaction." The maximum difference was 4 on a 5-point scale. In each factor set, emotions were distributed according to the score difference. Table 5 lists the number of assigned <object, emotion>. In any combination of factors, more than half of the respondents had the same score on a 5-point scale. However, a difference of 2 or more on the 5-point scale is less than 10%, which is extremely rare. Therefore, we decided to not consider the difference in scores and count based only on which factor is greater or lesser.

Table 5. Scores Assigned to Sensitivities per Point Difference

Factor	Sub.	Neg.	Pos.	Non	Factor	Sub.	Neg.	Pos.	Non	Factor	Sub.	Neg.	Pos.	Non
	4	1	0	2		**4**	0	1	0		**4**	0	1	0
Achievement	**3**	3	1	2	**Comprehension**	**3**	0	0	2	**Satisfaction**	**3**	0	0	2
	2	16	5	3		**2**	6	17	14		**2**	10	44	14
	1	68	77	24		**1**	106	339	47		**1**	109	453	68
-	**0**	454	1,242	258	-	**0**	345	1,158	187	-	**0**	340	1,036	179
	1	94	255	44		**1**	133	65	62		**1**	122	52	47
Comprehension	**2**	13	15	9	**Satisfaction**	**2**	35	12	28	**Achievement**	**2**	50	8	27
	3	0	0	2		**3**	22	3	4		**3**	17	1	6
	4	1	0	1		**4**	3	0	1		**4**	2	0	2
	Total	650	1,595	345		**Total**	650	1,595	345		**Total**	650	1,595	345

The objects corresponding to each factor were counted. For comprehension, 450 objects were extracted, of which there were 252 types. The average number of overlaps was 1.79. Regarding achievement, 264 objects were extracted with 144 types of objects. The average number of overlaps was 1.83. In terms of satisfaction, 1,174 objects were extracted, with 309 object types. The average number of overlaps was 3.80.

Table 6 shows the top 20 object frequencies corresponding to comprehension, achievement, and satisfaction. Naturally, all factors include things that are innate in classes, such as “class” and “teacher.”

Table 6. Top 20 Objects of Each Factor

Comprehension	Achievement	Satisfaction
class, lecture, teacher, content, talk, assignment, knowledge, how to use, voice, microphone, report, life, psychology, example, history, pronunciation, interest, contact, online class, remote	class, report, lecture, voice, teacher, life, online class, remote class, practical skill, question, slide, face-to-face, face-to-face class, experience, interact, system, speaker, fieldwork, report assignment, English conversation	class, assignment, content, lecture, voice, video, time, face-to-face, meaning, textbook, slide, teacher, word, report, document, knowledge, discussion, opportunity, story, air conditioner

3.5 Logical Operation of Objects and Factors

As shown in the previous section, many objects are included in multiple factors. Therefore, to clarify the characteristics of the object corresponding to the factor, logical operations are performed on the object included in each factor. Figure 3 presents an outline of the logical operation results, where comprehension is indicated by (C), achievement by (A), and satisfaction by (S). The numbers shown in the figure are assigned according to the logical operations. The number of objects shown in the figure is the sum of the object frequencies corresponding to the factors included in each factor. Therefore, the number of objects shown in the figure is greater than the number of objects for each factor.

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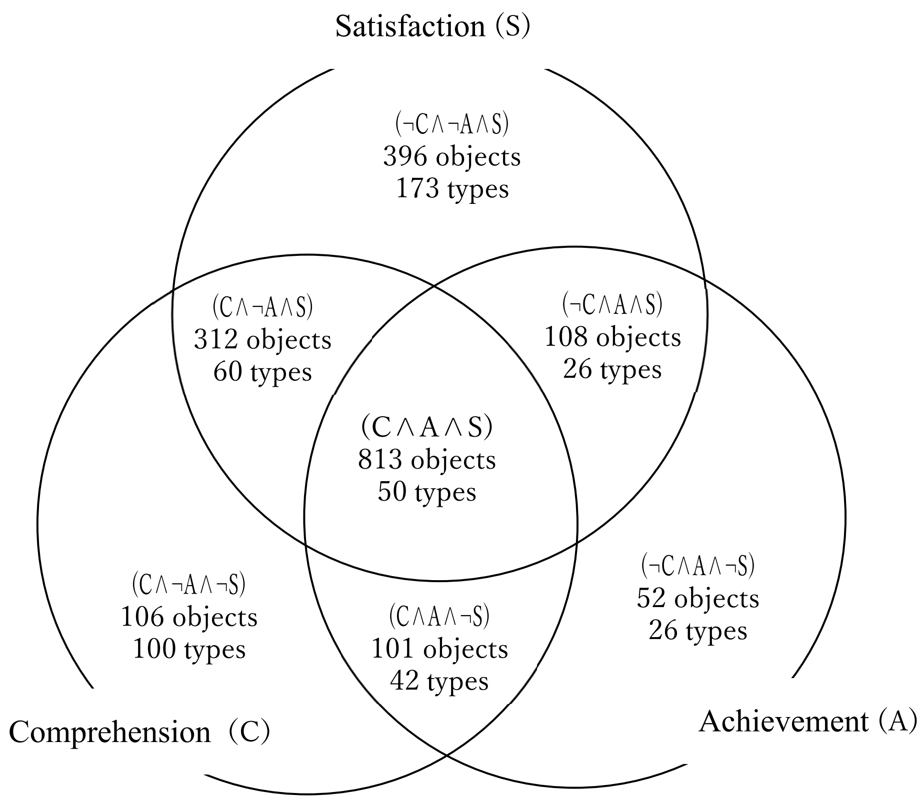

Figure 3. Logical Operation Result

Table 7. Top 20 Objects for the Logical Operation Result of Each Factor

$C \land \neg A \land \neg S$	$\neg C \land A \land \neg S$	$\neg C \land \neg A \land S$	$C \land A \land \neg S$	$C \land \neg A \land S$	$\neg C \land A \land S$	$C \land A \land S$
pronunciation, exercise, operation, ability, unsubmitted, thing, money, meal, subject, education, speaking style, 15 weeks, 1 year, about 2, approach, excel, tips, shortcut keys, sports, training	exchange, system, speaker, fieldwork, report assignment, English conversation, answer, maximum, vocabulary test, long sentence, submission, simultaneous, story, grammar, problem, practice questions, pdf, breakout room	meaning, zoom, video, quiz submission, this matter, zero, high pace, up to members, redo, leader, English conversation, answer, confirmation, point of view, final report, play, second half, seating chart, paper medium, document distribution	online class, distance class, practice, contact, online application, technique, learning, employment, forensics, request, 20 minutes, 2 weeks, URL, announcement, news, font, others, mask, message, ruler	video, textbook, text, discussion, air conditioner, group work, canceled class, lecture material, class content, situation, lecture time, information, example, screen, email, question, verbal, blackboard, class system, score	online learning, summary, paper, class development, life, submissions, number of characters, purpose, field, 1 sheet, data science, practice materials, solution, homework, attendance, mathematics, students, presence, speaking, benefits	class, lecture, content, assignment, voice, teacher, report, time, face-to-face, talk, slide, knowledge, document, microphone, opportunity, explanation, remote, how to use, professor, high school

Table 7 lists the top 20 objects belonging to the logical operation result of each factor. Objects corresponding to only one factor tended to have many words with a relatively narrow meaning, and objects corresponding to three factors tended to have many words with a broad meaning.

4. Discussion of Results for Objects and Factors

In this section, we discuss the correspondence between <object, emotion> extracted from the free description and the three factors of comprehension, achievement, and satisfaction. First, <object, emotion> for each of the three factors of comprehension, achievement, and satisfaction shown in Section 3.4. Objects for satisfaction were extracted overwhelmingly more than those for comprehension and achievement. Comprehension has a threshold of what should be understood and to what extent, and achievement has a threshold of what has been achieved. Achievement goals may be specified in the syllabus. Subsequently, it is necessary to judge whether it has exceeded the threshold. By contrast, satisfaction can be judged only by one's thoughts. Therefore, there are many descriptions of satisfaction, and as a result, it is one of the reasons many objects for satisfaction were extracted.

"Evaluation of class questionnaires" covers one experience of taking a class. Since the area is limited, there is a limit to the number of topics that can be discussed. Therefore, as the number of extractions increases, the overlaps also tend to increase. However, when comparing comprehension and achievement, the number of achievements is a little less than 60%, but the average number of overlaps is slightly high. This is perhaps because the objects are clearly stated in the syllabus, resulting in a concentration. It is even more evident in the results of the logical operations presented in Section 3.5. There were 106 objects and 100 kinds of objects for $C \land \neg A \land \neg S$, which corresponded only to comprehension. The fact that there is almost no duplication this way means that there were few objects shared among the students. Additionally, there were 26 types of 52 objects for $\neg C \land A \land \neg S$, which corresponded only to achievement. The fact that the number of objects was small in this manner indicates that there was little description of achievement in the free description, likely because, in many cases, the goals are stated in the syllabus and therefore assumed.

However, there are only 50 types of objects for $C \land A \land S$, out of 813 objects, which correspond to all the factors. Assessing the contents of the questionnaire, many words indicate the object that means the lesson or the object that is indispensable to the class because it is a questionnaire for those who have attended the class. The 396 objects for $\neg C \land \neg A \land S$ correspond only to satisfaction, excluding those corresponding to all these factors. The number of types was 173, and the average number of overlaps was 2.29, a relatively high value. This is a large number compared to the other two factors, indicating that the objects of satisfaction are diverse.

"Evaluation of class questionnaires" does not include items aimed at improving classes. In this questionnaire, only five evaluation items and free description items were set. There are two items to clarify the attitude of the students toward the class and three factors obtained by the outcome of the class such as comprehension, achievement, and satisfaction. In this study, we could extract the objects that the students were pleased with, or dissatisfied with the form of

<object, emotion> from free description questionnaires. This suggests that useful information can be extracted to improve the classes, especially as student dissatisfaction indicates the possibility of improvement. Thus, it is possible to indirectly obtain information on how to improve classes, even from a brief questionnaire, based on students' opinions and perceptions.

5. Conclusion

This study analyzed free descriptions in questionnaires using text mining technology and clarified what students comprehend, their sense of accomplishment, and what satisfies them. Resultantly, many students were satisfied with a wide range of objects because satisfaction was based only on their feelings. Regarding comprehension, there was little overlap in the objects among the students, and the objects of comprehension differed for each student. Regarding achievement, the object was clarified because of little fluctuation for each student.

This questionnaire was designed to clarify students' engagement with the class and what they obtained. However, the analysis of free descriptions suggests the possibility of extracting information to improve classes.

In this study, the negative emotions in the free description were approximately 40% less than the positive emotions, but the analysis did not consider this fact. There is a possibility that further useful information can be extracted if this point is improved. Additionally, the emotional information extraction dictionary used in this study included the categories of requests, complaints, and questions. If such information is used, there is a possibility that further areas for improvement in the class can be clarified.

The Text Analysis Algorithm used in this study does not focus on compound word extraction. Therefore, many of the extracted objects were general words. More meaningful objects can be extracted by considering compound words. In the future, we aim to investigate these improvements.

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