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Application of ChatGPT text extraction model in analyzing rhetorical principles of COVID-19 pandemic information on a question-and-answer community

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Abstract

This study uses a large language model (LLM) to identify Aristotle's rhetorical principles (ethos, pathos, and logos) in COVID-19 information on Naver Knowledge-iN, South Korea's leading question-and-answer community. The research analyzed the differences of these rhetorical elements in the most upvoted answers with random answers. A total of 193 answer pairs were randomly selected, with 135 pairs for training and 58 for testing. These answers were then coded in line with the rhetorical principles to refine GPT 3.5-based models. The models achieved F1 scores of .88 (ethos), .81 (pathos), and .69 (logos). Subsequent analysis of 128 new answer pairs revealed that logos, particularly factual information and logical reasoning, was more frequently used in the most upvoted answers than the random answers, whereas there were no differences in ethos and pathos between the answer groups. The results suggest that health information consumers value information including logos while ethos and pathos were not associated with consumers' preference for health information. By utilizing an LLM for the analysis of persuasive content, which has been typically conducted manually with much labor and time, this study not only demonstrates the feasibility of using an LLM for latent content but also contributes to expanding the horizon in the field of AI text extraction.

Keywords: *Artificial Intelligence, Machine Learning, Aristotle's Rhetoric, ChatGPT, Persuasion, Question and Answer Community, COVID-19*

1. INTRODUCTION

In the age of readily available health information, both laypeople (referred to as consumers) and professionals are taking advantage of social question-and-answer (social Q&A) platforms to swiftly share health and medical knowledge [1]. This trend has been met with enthusiasm for its potential to enhance access to health information, but it is also fraught with concerns about the dissemination of misinformation, which

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can have severe and adverse consequences [2].

The pervasive influence of social media in health communication is further complicated by the rapid spread of misinformation, as highlighted by Tasnim, Hossain, and Mazumder [3]. They advocate for the use of advanced technologies like natural language processing (NLP) to mitigate the spread of unfounded rumors, a method that aligns closely with the aims of this study. Moreover, Fang & Wang (2022) discuss the critical role of effective influencers in using NLP during the COVID-19 pandemic to disseminate accurate health advisories, emphasizing the importance of ethos in health communication [4].

Hasan et al. (2021) demonstrate the potential of an NLP pipeline for diagnosing COVID-19 through the analysis of patient-authored social media posts, reinforcing the utility of AI in public health communication [5]. Similarly, Luccioni et al. (2021) stress the need to extend the reach of NLP to include low-resource languages and diverse modalities, expanding the demographic and linguistic accessibility of these technologies [6].

Previous studies predominantly discuss the information-seeking behaviors of health information consumers. They delve into various aspects, including identification of information needs, exploration of information sources, and establishment of criteria for assessing the quality of information [7-9]. However, there is a lack of research identifying the specific elements of health information that render it more easily accepted by consumers. To facilitate the dissemination of accurate health information, this gap between the previous studies and the current need in health communication should be filled.

Following Aristotle's rhetorical principles, which are widely employed for persuasive communication strategies, this study aims to use a large language model (LLM) to autonomously identify and extract the three fundamental principles of persuasive strategies—ethos (source credibility), pathos (emotional appeal), and logos (logical appeal)—from responses to questions about COVID-19 on social question-and-answer platforms [10-13]. Furthermore, we apply this model to both the most upvoted answers and randomly selected less-upvoted answers before comparing the differences between the answer groups.

2. THEOREICAL FRAMEWORK AND HYPOTHESES

Aristotle's Rhetoric introduces the concepts of ethos, pathos, and logos, which are keys to understanding persuasive communication. Ethos refers to the speaker's own expertise, profession, and experience [14]. Ethos can also refer to borrowing from authoritative sources to express the reliability of the supposed information provided, influencing how an audience perceives the speaker's authority and reliability. Pathos, on the other hand, pertains to the emotional appeal to the audience, aiming to evoke specific feelings to persuade [14]. Logos appeals to logic and thereby employs reason and evidence to support an argument, thus appealing to the audience's rationality [14]. Table 1 presents the coding scheme that illuminates the definitions and examples of the sub-dimensions for the three rhetorical modes of appeal.

With respect to social Q&A communities, the following assertions are hypothesized based on Aristotle's rhetorical principles:

Hypothesis 1: the most upvoted answers will use ethos more frequently than the random (less-upvoted) answers. This suggests that answers that are perceived as more credible and coming from a source of authority or expertise are more likely to be upvoted.

Hypothesis 2: the most upvoted answers will use positive pathos elements of optimistic information and empathy more frequently than the random (less-upvoted) answers while the negative pathos elements of pessimistic information, fear and cynicism, will be less frequently found in the most upvoted answers than the random answers. This hypothesis implies that answers that effectively appeal to the emotions of the audience, possibly by being more empathetic or emotionally resonant, are more likely to receive upvotes.

Hypothesis 3: the most upvoted answers will use logos more frequently than the random answers. This suggests that answers that present logical arguments, which are supported by evidence and clear reasoning, are more likely to be favored by health information consumers.

3. METHOD

Data and Preprocessing

The data was collected using Python 3.10.12 on Naver Knowledge-iN, the leading social Q&A platform in South Korea, with over 500 million accumulated responses. In this study, answers published in 2020 (from January 1 to December 31) were collected. In the early stages of COVID-19, there was a lack of consistent terminology for the disease, resulting in a variety of terms being used across media outlets. Hence, to ensure comprehensive data collection, the search keywords were set as 'Corona', 'Coronavirus', 'Corona19', 'Corona-19', 'COVID', 'COVID19', 'COVID-19', 'New Coronavirus', 'Novel Coronavirus', 'Novel Coronavirus Infection', 'Novel Coronavirus Infectious Disease' (the official term by the WHO), 'Wuhan Pneumonia', and 'Wuhan Corona' – a total of 13 keywords.

Initially, the data collection amounted to a total of 192,261 sets where each set consisted of a question, the most upvoted answer, and an answer, which was randomly selected among the other answers utilizing Python's built-in 'sample' function from Python's random data collection module. After excluding duplicate posts and irrelevant topics such as 'Corona beer' and 'Corona cats', the dataset consisted of 91,772 answer pairs. Researchers randomly selected 193 pairs of answers from the dataset and used 70% (135 pairs of answers) of them for training and 30% (58 pairs of answers) for testing the model.

Table 1 presents the definitions with examples of the subdimensions as well as their inter-coder reliability. Due to the nature of the content analysis, coding for the rhetorical elements can be subjective. To overcome this limitation, multiple training sessions and discussions were conducted among the coders, and the inter-coder reliability of each subdimension was greater than 0.80 (Cohen's Kappa), which is considered a high level of agreement among coders.

Table 1. Definitions and Inter-coder Reliability of Subdimensions

Term		k^a	Definition	Example
Ethos	Borrowed authority	.93	Reference to opinions of experts or expert groups to prove an answer's credibility [15-16].	The World Health Organization declares masks effective in reducing COVID-19 transmission.
	Expertise	.95	Use of respondents' professional background [15-16].	As an epidemiologist, I've seen first-hand the impact of social distancing in controlling the spread of the virus.
	Personal experience	.84	Information that represents empirical authority from non-experts [17].	I've been working in a COVID-19 ward for a year now and have seen how critical vaccination is.

Pathos	Optimistic information	.86	Hopeful evaluation and description of a questioner's situation, diagnosis, treatment method, etc., regardless of the outcome of the phenomenon [19].	We've seen remarkable recoveries even in severe COVID-19 cases, which shows the resilience of the human body.
	Pessimistic information	.86	Pessimistic evaluation and description of a questioner's situation, diagnosis, treatment method, etc., regardless of the outcome of the phenomenon [18].	Without widespread vaccination, COVID-19 will continue to be a significant threat to global health.
	Empathy	.85	Value individuals place on simply having someone acknowledge their feelings as real and reasonable.	I also suffered a lot from COVID symptoms, which I've found regrettable.
	Fear	.86	Attempt to persuade the audience by creating fear or by presenting a possible menacing future scenario [20-21].	Without proper measures, we could face another wave of the pandemic that is potentially worse than the last.
	Cynicism	.94	Sneering at a phenomenon or person in a sarcastic manner.	Sure, let's just ignore social distancing and hope the virus magically disappears.
Logos	Evidence	.87	Use of example(s). This may include personal experience, historical information, etc.	Quarantine: isolating people exposed to a contagious virus, such as COVID-19, to prevent its spread. For instance, someone with symptoms like fever, cough, and difficulty breathing may be quarantined to avoid infecting others.
	Factual information	.97	Use of basic knowledge or incontrovertible facts in answers [22-23].	COVID-19 primarily spreads through respiratory droplets from coughs and sneezes.
	Logical reasoning	.93	Logical explanation based on causality [22-23].	Increasing testing capabilities can help track the spread of COVID-19 and contain outbreaks more effectively.
	Statistics	.88	Use of numbers and statistics [24].	COVID-19 vaccines have shown a 95% efficacy rate in preventing severe illnesses.

[a]: Cohen's Kappa

Model Overview

GPT-3.5-Turbo is the third version of the Generative Pre-trained Transformer and is based on the Transformer architecture. The Transformer was first introduced in a paradigmatic paper entitled "Attention is All You Need," and is currently one of the most influential mega-scale artificial intelligence (AI) models in the field of natural language processing (NLP). GPT-3.5-Turbo has been pre-trained with a large text dataset encompassing a wide range of topics and areas, thereby enabling the model to understand various contexts of information. It can be utilized in a wide array of natural language processing tasks, showing it is capable of demonstrating high performance in sentence generation, question answering, machine translation, text summarization, and more, with various applications in both commercial services and research. Due to its large-scale structure, GPT-3.5-Turbo can significantly reduce the risk of overfitting, meaning it can maintain generalizability while also learning various kinds of information.

Model Training Overview

Table 2 explains how the ethos model was developed as an example.

Table 2. Model Training Tasks

	Model{Ethos, subclass}
Task	Classify sentences in Model{Ethos, subclass} into subcomponents of Ethos
Train	Train only components of Ethos
Classification	Multi-Label Classification
Metric	F1-Score

In the development of the models {Ethos, subclass}, {Pathos, subclass}, and {Logos, subclass}, it was paramount to ensure that each subclass prediction within the multi-label framework was accurate and comprehensive. Utilizing the F1-score facilitated an effective measure of balance between precision and recall across the various subclasses. This balance is crucial because each subclass represents a distinct aspect of the rhetorical dimensions being predicted, and an oversight or misclassification can significantly impact the overall interpretability and utility of the models. Therefore, the F1-score was adopted as a primary performance metric, providing a harmonized view of the predictive performance by penalizing extreme values of precision and recall, which is particularly advantageous in the nuanced field of rhetorical analysis where both missing and spurious predictions can lead to substantial errors in interpretation.

Additionally, during the fine-tuning process, specific instructions were provided for each of the rhetorical elements—Ethos, Pathos, and Logos—to ensure that the models were accurately tuned to the distinct dimensions and the multiclass nature of the classification. These instructions included details on the subdimensions of each rhetorical principle and clarified that the classification was to be treated as multi-label. For example, the instruction for the {Pathos, subclass} model was as follows:

"This model has the function of analyzing a given text or sentence and classifying it under one of the 'pathos' elements in Aristotle's rhetoric. Here, the elements of 'pathos' include 'socialsupport', 'empathysympathy', 'optimisticframing', and 'pessimisticframing' making a total of 5 categories. And it can be multi-labeled."

These detailed instructions were crucial for guiding the models to correctly interpret and classify the complex and nuanced data, especially in a way that would ensure that the aligning would match up with the specific rhetorical analysis required in the study.

Additionally, examples of questions and answers were presented as follows (the questions were provided in Korean, but for convenience, they are translated into English here): The answers listed the applicable labels among 'socialsupport', 'empathysympathy', 'optimisticframing', and 'pessimisticframing'. Here is an example:

User Question: " Is a sauna a high-risk area for the coronavirus? User Answer : “Especially in saunas, the baths can be a breeding ground for viruses and bacteria, which means you could get infected and put yourself at serious risk." Assistant's Response: " pessimisticframing." These examples are crucial for training the model to handle complex emotional content appropriately, especially in a way that guides it to recognize when and how each rhetorical element is represented in user queries.

4. RESULTS

Model Test Result

After fine-tuning Model {Ethos, subclass}, Model {Pathos, subclass}, and Model {Logos, subclass}, improvement was visible in the multi-label classification performance of all three rhetorical principles, as shown in Table 3. For instance, Logos improved the most from 0.45 to 0.69 and Ethos saw a modest improvement from 0.85 to 0.88. This indicates an enhanced classification performance when fine-tuning GPT-3.5 based on training data.

Table 3. Model Accuracy

	F1-SCORE (Precision, Recall)	Ethos	Pathos	Logos
Test Data	GPT 3.5	0.85 (0.85, 0.85)	0.62 (0.61, 0.64)	0.45 (0.49, 0.40)
	Fine_Tuned GPT 3.5	0.88 (0.91, 0.86)	0.81 (0.81, 0.81)	0.69 (0.67, 0.70)

Answer Characteristic Classification

Predictions were made on the newly drawn answers to 128 questions employing the three fine-tuned models. To train the LLM more precisely, content analysis was conducted with each sentence, and the LLM was fine-tuned with the sentence-based classification of the subdimensions of the rhetorical principles. Then, the number of times each rhetorical element was presented in each answer was calculated to examine if there were differences between the most upvoted answers and the random answers.

As presented in Table 4, the models classified logical reasoning and factual information in logos most often. The next most classified were the optimistic and pessimistic information subdimensions in pathos, followed by expertise and borrowed authority in ethos. The models found that personal experience in ethos, cynicism and empathy in pathos, and evidence and statistics in logos were less frequently presented in both answer groups than the other subdimensions.

Table 4. Frequencies of Subdimensions in Answer Groups

	Subdimension	Upvoted Answers	Random Answers
Ethos	Borrowed Authority	14.1% (18)	20.3% (26)
	Expertise	21.9% (28)	15.6% (20)
	Personal Experience	11.7% (15)	7.8% (10)
Pathos	Cynicism/Sarcasm	1.6% (2)	3.1% (4)
	Empathy/Sympathy	7.0% (9)	12.5% (16)
	Fear	8.6% (11)	10.2% (13)
	Optimistic info	44.5% (57)	38.3% (49)
	Pessimistic info	17.2% (22)	32.8% (42)
Logos	Example/Evidence	25.8% (33)	18.0% (23)
	Factual info	59.4% (76)	43.8% (56)
	Logical Reasoning	69.5% (89)	60.2% (77)
	Statistics	10.2% (13)	7.0% (9)

Tests of Hypotheses

The most upvoted answers and random answers to the same questions were analyzed with the paired sample t-test to compare how these answer groups differ in ethos, pathos, and logos. Table 5 presents the results.

Table 5. Results of Paired Sample t-Test

	Subdimension	Most Upvoted Answer	Random Answer	t	df	Sig.
Ethos	Borrowed Authority	.203	.273	-.91	127	.18
	Expertise	.266	.203	.94	127	.17
	Personal Experience	.156	.117	.63	127	.27
Pathos	Optimistic info	.680	.523	1.54	127	.06
	Pessimistic info	.227	.266	-.51	127	.31
	Empathy	.102	.141	-.67	127	.25
	Fear	.102	.110	-.17	127	.43
	Cynicism	.016	.031	-.82	127	.21
Logos	Evidence	.453	.227	1.85	127	.03
	Fact	1.516	.914	2.34	127	.01
	Logical Reasoning	1.617	1.414	.97	127	.17
	Statistics	.102	.086	.38	127	.35

As hypothesized, paired sample t-tests indicated that the most upvoted answers were more likely to have logos elements, such as evidence and factual information, than the random answers. However, there were no differences in ethos and pathos between the answer groups, and research hypotheses regarding these rhetorical principles were not confirmed.

5. DISCUSSION

This study compared the classification of rhetorical elements in COVID-19 information conducted by researchers with the classification by the LLM. After being trained with coding data by the researchers, the classification by the LLM improved to .88 (ethos), .81 (pathos), and .69 (logos). Then, the fine-tuned models were employed to automatically extract rhetorical elements from a new dataset of 128 answer pairs of the most upvoted answers and random answers. It was found that only logos elements, including evidence and factual information, were more frequently present in the most upvoted answers than in the random answers, while there were no differences between the answer groups with respect to the other rhetorical principles of ethos and pathos. The results imply that health information consumers prefer logical elements of the information but do not value the emotional elements (pathos) and the information sources (ethos) of the information regarding COVID-19.

By comparing the analyses of content conducted by researchers and LLM, this study demonstrated how much an LLM an correctly identify the persuasive elements of Aristotle's Rhetoric from the natural language. Moreover, the results revealed how much fine-tuning of an LLM improves F1 scores compared to the base model. Above all, by automating the analysis of persuasive content, which has been typically conducted manually with much labor and time, this study not only demonstrates the feasibility of using an LLM in studies of the humanities and social sciences but also contributes to expanding the horizon in the field of AI text extraction.

6. CONCLUSION

This study used a large language model (LLM) to identify Aristotle's rhetorical principles in COVID-19 information on a social Q&A community. The fine-tuned models showed improved performance in classifying ethos, pathos, and logos compared to the base model. The analysis of 128 new answer pairs revealed that logos elements were more frequently used in the most upvoted answers, suggesting that health information consumers value evidence and factual information. This study demonstrates the feasibility and efficiency of using an LLM for rhetorical analysis, contributing to the field of AI text extraction.

The data that support the findings of this study are openly available in figshare at https://doi.org/10.6084/m9.figshare.25238695.v1

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