# Developing a ChatGPT-based text extraction model to analyze effective communication elements in pandemic-related Social Q&A responses

1[th] Hyunwoo Moon
*Department of MetaBioHealth*
*Sungkyunkwan University*
Seoul, Republic of Korea
jdmunpso@g.skku.edu

2[nd] Beom Jun Bae
*Department of Communication Arts*
*Georgia Southern University*
Statesboro, GA, USA
bbae@georgiasouthern.edu

3[th] Sangwon Bae
*Terry College of Business*
*University of Georgia*
Athens, GA, USA
sbae0101@gmail.com

*Abstract*— The present study attempts to use the large language model (LLM) to create a model that identifies Aristotle's rhetorical principles - ethos (source credibility), pathos (emotional appeal), and logos (logic) - in response to COVID-19 information on a question-and-answer community (social Q&A platform). The model differentiates between the most upvoted and random answers to analyze the presence of subdimensions of these rhetorical principles. The research utilized answers to COVID-19 questions on Naver Knowledge-iN, the most popular social Q&A platform in South Korea. A set of 193 answer pairs was randomly selected for training (135 pairs) and testing (58 pairs). These answers were coded for the three rhetorical principles and their subdimensions by researchers, which were used to refine models based on GPT 3.5 technology. The F1 scores were improved to .88 (ethos), .81 (pathos), and .69 (logos).

The fine-tuned models were employed to analyze 128 newly drawn answer pairs of the most upvoted answers and random answers. The paired sample t-tests indicated that rhetorical elements of logos such as factual information and logical reasoning were positively associated with health consumers' preference of information (answers) while the other rhetorical principles of ethos and pathos were not associated with consumer preference of health information. By utilizing the LLM for the analysis of persuasive content, which has been typically conducted manually with much labor and time, this study not only demonstrates feasibility of using the LLM in studies of the humanities and social sciences, but also contributes to expanding the horizon in the field of AI text extraction.

**Keywords—COVID-19, artificial intelligence, machine learning, Aristotle's rhetoric, ChatGPT, social Q&A, persuasion, question and answer community**

## I. 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 that can have severe and adverse consequences [2]. Despite these concerns, the health information-seeking and sharing in the realm of social media continues to be a pervasive global trend.

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 [3], [4], [5]. 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 as persuasive strategies, this study aims to use the large language model (LLM) to construct a model that can autonomously identify and extract the three fundamental elements of persuasive strategies: ethos (credibility of the source), pathos (emotional appeal), and logos (logical appeal) from responses to questions about COVID-19 on social question-and-answer platforms [6], [7], [8], [9]. Furthermore, we apply this model to both the most upvoted and randomly selected non-upvoted answers and compare differences between the answer groups.

## II. Theoretical 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 [10]. Ethos can also refer to borrowing from authoritative sources to express the reliability of information, 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 [10]. Logos appeals to logic and thereby employs reason and evidence to support an argument, thus appealing to the audience's rationality [10]. Table 1 presents the coding scheme that illuminates the definitions and the examples of the sub-dimensions for the three rhetorical modes of appeal.

In the context of social Q&A communities, the following are hypothesized based on Aristotle's rhetorical principles:

Hypothesis 1: the most upvoted answers will use ethos more frequently than 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 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 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.

## III. METHOD

### A. 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 stage 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 were randomly selected among the other answers utilizing Python's built-in 'sample' function from its 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) of them for training and 30% (58) for testing of the model.

Table I presents the definitions with examples of subdimensions and 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 I. 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 specialty [11], [12] | The World Health Organization declares masks effective in reducing COVID-19 transmission. |
| | Expertise | .95 | Use of respondents' professional background [11][12] | 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 [13] | 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 [15] | We've seen remarkable recoveries even in severe COVID-19 cases, showing 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 [14] | Without widespread vaccination, COVID-19 continues 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 presenting a possible menacing future scenario [16], [17] | 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 [18], [19] | COVID-19 primarily spreads through respiratory droplets from coughs and sneezes. |
| | Logical reasoning | .93 | Logical explanation based on causality [18], [19] | Increasing testing capabilities can help track the spread of COVID-19 and contain outbreaks more effectively. |
| | Statistics | .88 | Use of numbers and statistics [20] | COVID-19 vaccines have shown a 95% efficacy rate in preventing severe illness. |

[a]: Cohen's Kappa

## B. 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 and information. It can be utilized in a wide array of natural language processing tasks, 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 generalization ability while learning various information.

## C. Model Training Overview

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

TABLE II. 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 |

Model {Ethos, subclass} was developed to predict the subdimensions of Ethos. Fine-tuning was conducted with the training data on the GPT-3.5-Turbo model. Model {Pathos, subclass} and Model {Logos, subclass} were developed in the same process.

# IV. RESULTS

## A. 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 III. 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 III. 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) |

## B. 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 answer groups: the group holding the most upvoted answers and the group of random answers.

As presented in Table IV, 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 IV. 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) |

## C. 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 V presents the results.

TABLE V. RESULTS OF PAIRED SAMPLE T-TEST

| | Subdimension | Upvoted | Random | 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.

## V. Conclusion

This study compared the classification of rhetorical elements in COVID-19 information conducted by researchers with the one by the LLM. After being trained with coding data by the researchers, the classifications 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 and random answers. It was found that only logos elements including evidence and factual information were more frequently presented in the most upvoted answers than the random answers while there were no differences between the answer groups in 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 LLM can correctly identify the persuasive elements of Aristotle's Rhetoric from the natural language. Moreover, the results revealed how much fine-tuning of the 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 the LLM in studies of the humanities and social sciences but also contributes to expanding the horizon in the field of AI text extraction.

## References


[1] Y. J. Yi, "Sexual health information-seeking behavior on a social media site: Predictors of best answer selection," *Online Information Review*, vol. 42, no. 6, pp. 880–897, Sep 2018.

[2] S. H. Jang, K. E. Jung, and Y. J. Yi, "The Power of Fake News: Big Data Analysis of Discourse About COVID-19–Related Fake News in South Korea," *International Journal of Communication*, vol. 17, pp. 5527–5553, Aug. 2023.

[3] B. J. Bae and Y. J. Yi, "What answers do questioners want on social Q&A? user preferences of answers about stds," *Internet Research*, vol. 27, no. 5, pp. 1104–1121, Oct 2017.

[4] N. Hirvonen, A. Tirroniemi, and T. Kortelainen, "The cognitive authority of user-generated health information in an online forum for girls and young women," *Journal of Documentation*, vol. 75, no. 1, pp. 78-98, Jan 2019.

[5] W. Zhao, K. Meng, L. Sun, J. Ma, and Z. Jia, "Language style and recognition of the answers in health Q&A community: Moderating effects of medical terminology," *Journal of Information Science*, vol. 0, no. 0, May 2023. [Online serial]. Available: https://journals.sagepub.com/doi/full/10.1177/01655515231171367. [Accessed Jul. 15, 2023].

[6] A. D. Brown, S. Ainsworth, and D. Grant, "The rhetoric of institutional change," *Organization Studies*, vol. 33, no. 3, pp. 297-321, Feb 2012.

[7] G. Iob, C. Visintini, and A. Palese, "Persuasive discourses in editorials published by the top-five nursing journals: Findings from a 5-year analysis," *Nursing Philosophy*,vol. 23, no. 2, Dec 2022. [Online serial]. Available: https://onlinelibrary.wiley.com/doi/10.1111/nup.12378/. [Accessed Jul. 13, 2023].

[8] I. J. Hall and A. Johnson-Turbes, "Use of the persuasive health message framework in the development of a community-based mammography promotion campaign," *Cancer Causes & Control*, vol. 26, pp. 775-784, Apr 2015.

[9] N. M. Brennan and D. M. Merkl-Davies, "Rhetoric and argument in social and environmental reporting: the Dirty Laundry case," *Accounting, Auditing & Accountability Journal*, vol. 27, no. 4, pp. 602-633, Apr 2014.

[10] J. J. Murphy, Rhetoric in the Middle Ages: A History of Rhetorical Theory from Saint Augustine to the Renaissance. vol. 277, Berkeley, CA, USA: University of California Press, 1981.

[11] Y. J. Yi, B. Stvilia, and L. Mon, "Cultural influences on seeking quality health information: An exploratory study of the Korean community," *Library & Information Science Research*, vol. 34, no. 1, pp. 45–51, Jan 2012.

[12] E. R. Buhi *et al.*, "Quality and accuracy of sexual health information web sites visited by young people," *Journal of Adolescent Health*, vol. 47, no. 2, pp. 206–208, Aug 2010.

[13] M. Hanauska and A. Leßmöllmann "Persuasion in Science Communication: empirical findings on scientific weblogs," *Interaction studies*, vol. 22, no. 3, pp. 343-372, Dec 2021.

[14] S. A. Rains and R. Tukachinsky, "An examination of the relationships among uncertainty, appraisal, and information-seeking behavior proposed in uncertainty management theory," *Health Communication*, vol. 30, no. 4, pp. 339–349, Jun 2014.

[15] G. A. Auger, "Rhetorical framing: Examining the message structure of nonprofit organizations on Twitter," *International Journal of Nonprofit and Voluntary Sector Marketing*, vol. 19, no. 4, pp. 239-249, Sep 2014.

[16] J. Bronstein, "Like me! Analyzing the 2012 presidential candidates' Facebook pages," *Online Information Review*, vol. 37, no. 2, pp. 173-192, Apr 2013.

[17] Z. Iqbal, M. Z. Aslam, T. Aslam, R. Ashraf, M. Kashif, and H. Nasir, "Persuasive power concerning COVID-19 employed by Premier Imran Khan: A socio-political discourse analysis," *Register Journal*, vol. 13, no. 1, pp. 208-230, Jun 2020.

[18] L. Bos, C. Schemer, N. Corbu, M. Hameleers, I. Andreadis, A. Schulz, D. Schmuck, C. Reinemann, and N. Fawzi, "The effects of populism as a social identity frame on persuasion and mobilisation: Evidence from a 15-country experiment," *European Journal of Political Research*, vol. 59, no. 1, pp. 3-24, May 2020.

[19] K. English, K. D. Sweetser, and M. Ancu, "YouTube-ification of political talk: An examination of persuasion appeals in viral video," *American Behavioral Scientist*, vol. 55, no. 6, pp. 733-748, Mar 2011.

[20] H. Osborne, *Health Literacy from A to Z: Practical Ways to Communicate Your Health Message*. Lake Placid, NY: Aviva Publishing.