Analysis of the changes in the attitude of the news comments caused by knowing that the comments were generated by a large language model

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Abstract

This study examined the attitudes of individuals toward texts generated by large language models (LLMs), including social networking service posts and news comments. Recently, the number of people viewing texts generated by LLMs has increased. Because an LLM can generate natural texts that are almost indistinguishable from those written by humans, there is concern that generating such natural texts may cause problems, such as maliciously influencing public opinion. To evaluate the reception of LLM-generated texts, we conducted an experiment based on the hypothesis that the knowledge that a text was generated by an LLM would influence user acceptance. In the experiment, participants were shown news comments that included AI-generated comments. We controlled whether the user was aware that the text had been generated by an LLM, and assessed their viewpoints from four perspectives: perceived friendliness, trustworthiness, empathy, and reference. The results showed that a generated comment imitating the opinion of an expert increased in rank when it was disclosed that the LLM generated the comment. In particular, "reliability" and "informative" were sensitive to this disclosure, whereas "familiar" and "empathy" were not. This result suggests that expert labeling significantly enhances perceived reliability, and the finding raises concerns about the potential for news viewers to be implicitly guided toward a particular opinion.

1 Introduction

As large language models (LLMs) have rapidly developed in recent years, LLM-generated texts have become more natural and less awkward. LLMs

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that can quickly generate high-quality texts have significantly contributed to the development of services that linguistically summarize large amounts of text and enable people to interact using natural language. LLMs not only make summarization and elaboration easier, but can also transform the tone of a text to match the user's intentions, gain their sympathy, and create a friendly impression. This will help to reduce language barriers and promote closer communication.

However, there is concern that generating such natural texts may cause problems for many people because it may be difficult to distinguish between human-written and LLM-generated texts. For example, articles written using LLMs have led to plagiarism[5]. This case was identified because the article's content partially matched that of an existing article. It has also been reported that LLM-generated texts are posted on social networking services, such as X. These posts primarily aim to efficiently generate advertising revenue by generating numerous impressions.

Information, such as social network service posts and news article comments, can influence people's decision-making. Suppose an LLM-generated text is maliciously disseminated with a specific intent. In that case, it will become difficult to guarantee objectivity and fairness, which could negatively impact the decision-making of individuals who rely on this information. If a large number of generated comments are posted, it could hinder the formation of public opinion and distract from the bases of fair discussion. In addition, there are concerns that such information may accelerate the echo chamber [4] and filter bubble [11] phenomena. This problem not only confuses users who know little about the topic at hand but also forces experts with sufficient background knowledge to make more careful decisions.

Based on this background, this study aimed to clarify the acceptance attitudes of users toward LLM-generated texts. We explored whether people become more careful when they know that an LLM posted a text. It has been pointed out that not only the content of the text, but also other factors such as superficial information about the text (e.g., the tone and wording) and information about the sender (i.e., their social position and attributes), affect its reliability. In the community of an illustration sharing website, for example, when the creator of an image is revealed to be a generative AI, the attitudes of viewers toward the image tend to be more negative[2],[9]. In light of this finding, even in the case of textual information, if the attitudes of viewers are negatively affected by knowing that information is generated by a computer, they may be more careful when using the information in their decision-making. This awareness could help them avoid being swayed toward a specific viewpoint, which could contribute to more thoughtful decision-making.

As a first step for this research, we conducted a study based on the hypothesis that LLM-generated texts would affect user acceptance. The comment section of a web news platform was selected as the target of the study. We analyzed the evaluation difference between cases where it was and was not disclosed that the comments posted were generated by an LLM, which clarified the impact of LLM-generated texts.

[5] https://japan.zdnet.com/article/35216436/(ZDnet Japan, 2025/2/12 Confirmed).

2 Related Work

Since the 2020s, the volume of LLM-generated text in cyberspace has increased rapidly. Accordingly, several studies have focused on how people receive LLM-generated texts [3]. To clarify the position of this study in the field of user perception towards LLM-generated text, we review related research from the following perspectives: (1) the technical evolution and impact of LLM, (2) the impression or emotional responses when people face to LLM-generated texts, and (3) the various elements that influence the acceptance of LLM-generated text.

Yin et al. investigated whether AI could generate responses that made people feel that their messages had been heard, with a focus on conversations between people and chatbots [13]. Their study revealed that AI-generated messages made recipients feel more heard than human-generated messages and that AI was better at detecting emotions. However, recipients felt less heard when they realized that a message came from AI.

Ranade et al. asked participants to distinguish between LLM-generated and human-written texts, and reported that as early as 2021, 78.5% of the LLM-generated articles were misidentified as human-authored [12]. Jakesch et al. also reported that people tend to misidentify self-introduction sentences generated by LLM as being written by a human [6]. Considering the rapid technical advancements and widespread adoption of LLMs, it is presumed that accurately distinguishing between LLM-generated and human-written texts has become even more difficult. In fact, a 2025 study by Jones et al. reported that when GPT-4.5 was prompted to adopt a human-like persona in the Turing Test, it was judged to be human 73% of the time [7]. This result was significantly more often than the interrogators selected the real human participant.

However, several studies have reported that LLM-generated texts exhibit certain linguistic features. Matsui investigated how the vocabulary used in cyberspace changed after the introduction of chatGPT, which is a text generation service developed by OpenAI [10]. This study found that in the medical field, words such as “elve,” “underscore,” “meticulous,” and “commendable” appeared more frequently in the ChatGPT-generated content. These findings suggest that texts generated by an LLM exhibit identifiable characteristics at the lexical level.

Research focusing on the influence of linguistic features on human impressions predates the emergence of LLMs, particularly in the fields of mathematical linguistics and natural language processing [1]. For example, Iseki et al. investigated the relationship between the impression of a reader and the modifier–verb ratio (MVR), which is a widely used index for assessing the stylistic features of Japanese text in terms of its part-of-speech composition [5]. Similarly, Yokoyama et al. analyzed the answers labeled as “the best answer” at online Q&A services to identify the linguistic features. They adopted various parts of speech and word choices as document features and estimated the contributing factors based on their appearance frequency and proportionality within the documents [14]. These studies shared the common perspective that the vocabulary used in a text and how it is used can influence how readers evaluate the quality and reliability of the writing. This perspective suggests that people's perceptions of the text could be manipulable if AI-generated text reflects these characteristics.

In addition, there is also concern that LLM-generated texts may contain social biases such as those based on race, gender, or religion. Ma et al. reported that such biases are not embedded in the model as a single concept, but are dependent on individual contexts [8]. They stated that it is difficult to remove the bias contained in the generated sentences using a uniform method, as the bias that LLM is likely to output differs depending on the topic. This suggests that people need to be careful about the sentences generated by LLM when determining whether the information is reliable.

In this study, we focused on how the evaluations of readers on the quality and reliability of a text are affected when they are informed that the text was generated by an LLM. Previous research has shown that lexical choice and frequency can affect document evaluation. However, the potential influence of the awareness that a text is LLM-generated on the evaluations of readers remains underexplored. This study aimed to clarify this issue, thereby making it possible to infer how the knowledge that a text has been generated by an LLM affects its evaluation by a reader. To investigate how such attributes of a comment affect users' impressions, we conducted a user experiment as detailed in the next section.

3 Experiment

To evaluate how labeling a comment as LLM-generated influences its perceived impression, we examined how participants ranked comments based on four impression-related viewpoints. We presented participants with a set of comments collected from web news media, including LLM-generated comments ("AI-comments"). We asked participants to rank the comments based on the given points of view.

3.1 Preparing comments for the experiment

We collected news articles and associated comments from Yahoo! News. Yahoo! News is one of the largest news aggregators in Japan. Yahoo! News aggregates many articles from various news media to provide users with a wide range of news sources. The platform is used by approximately 85 million users per month and attracts users across various age groups and genders. Based on this, we collected news articles along with their comments from Yahoo! News platform. We selected four articles, as shown in Table 1, based on the following conditions: (1) mixed approval and disapproval; (2) a complicated discussion, where the topic is familiar to most users; and (3) a discussion from multiple perspectives. Because the length of a comment influences opinion formation, we collected comments with a limit of approximately 220–280 characters from the top-ranked comments section.

Next, comments were generated using chatGPT-4o[6]. To blend the

[6] `https://chatgpt.com/` (2025/4/8 confirmed).

Table 1: News article used in the experiment. One article was used in Experiment 1, and three articles were used in Experiment 2.

ID	article, source, URL
1	Mr. Shiro Tasaki said "The hasty step... It is questionable" on the "Morning show" in response to the DPFP tax policy chairman's "leaving the room" during the "10.3 million yen barrier" discussion (Sprts Hochi) `https://hochi.news/articles/20241223-OHT1T51024.html`
2	South Korean authorities fail to detain President Yoon. Entering into the presidential residence to execute a warrant was "not permitted" (Kyodo News) `https://www.tokyo-np.co.jp/article/377101`
3	The 2024 birth rate is expected to fall below 700,000, a new record low (Asahi Shinbun Digital) `https://www.asahi.com/articles/DA3S16113715.html`
4	"If the ruling party's plan is adopted, the tax cut will be between 5,000-20,000 yen" Yuichiro Tamaki analyzes the income ceiling, "The increase in spending cannot be covered" (Sankei News) `https://www.sankei.com/article/20241221-A7ZTQPZRXJAVFKQU5EAN52GEMY/`

generated comments into the comments section of the experiment, we attempted to mimic the style and tone of the original comments on Yahoo! News. First, we fine-tuned the prompts by feeding approximately 2,000 characters of user comments such that the generated comment would be perceived as a human-written comment.

In addition, we considered the influence of external information on the impression of comments; we generated comments with features that could be perceived as characteristics of comments from an "expert" or "diversity AI." Yahoo! News has unique characteristics compared to other news sites on the web. The platform certifies real-world experts (e.g., scholars, journalists, and creators from various fields) as "experts," and their comments are displayed at the top of the comment section. In addition, to reduce bias and provide users with diverse perspectives, a diversity AI system ("AI diversity") selects comments from multiple viewpoints for placement. In the experiment, we generated three types of comments: general, "expert," and "AI diversity" comments designed to mimic the original user comments. The prompts used in the attributes are described below: the "expert" and "AI diversity" explanations were cited from the official Yahoo! website[7].

> 1: These comments were posted on Yahoo! News. A user comment with the #expert attribute is sometimes posted on Yahoo! News. Please describe the opinion of "experts" about this news. Please use a gentle and polite tone.
>
> #experts' overview: Yahoo! News experts provide content from a unique perspective, such as explanatory articles and experience reviews. The purpose is to offer users new perspectives and discoveries, which may help address social issues and everyday problems. Our purpose

[7] `https://news.yahoo.co.jp/newshack/inside/news_comment2023diversity.html` (2025/4/7 confirmed).

is to notice new points and discoveries from users. This connects the problems of society and a user's life.

2: These comments were posted on Yahoo! News. Please describe the opinion of "experts" about this news. You generate a frank opinion like a user's comment.

#AI-diversity overview: The comment diversify model is a function that displays a variety of comments preferentially with different perspectives at the top of the comment section when users view the comments in the "recommended" order. The purpose is to create the opportunity to have different perspectives, and it is expected to decrease the echo chamber phenomenon, which increases particular opinions.

3.2 Experiment procedure

We conducted a user experiment using the original comments we collected and the LLM-generated comments mentioned in the previous section. The experimental procedure was as follows. We designed a set of comments comprising both LLM-generated and human-written comments. We asked participants to rank each comment according to the four impression perspectives. We then analyzed the changes in order, depending on whether the writer was a human or an LLM.

Figure 1 shows the appearance of the interface. We placed the comment list below the article. Participants could intuitively change the order of the comment list by dragging and dropping. We displayed the attributes of each comment to the left of the displayed comment for use as a reference (e.g., expert comment: "expert," AI comment: "AI"). We asked the participants to order the comments based on the four perspectives: "familiar," "reliability," "empathy," and "informative." Each comment can be reordered by dragging it with the mouse as shown in Figure 2. For example, if participants thought that a comment was the most "familiar," they would place it first in the "familiar" section. Participants ordered comments according to all four perspectives and moved on to the next article. This process was continued until all the articles were completed. The perspective section could be switched with the tabs at the top of Figure 1.

We conducted the experiment in two sessions and recruited participants using the Yahoo! crowdsourcing service[8].

In this experiment, participants were asked to sort article lists and respond to a user questionnaire. However, because the crowdsourcing service targets an unspecified number of people across a wide range of ages and genders, it is known that some participants may provide inaccurate or insincere responses in order to obtain rewards. Therefore, we excluded the following types of responses: (1) those containing only meaningless characters such as "aaa"; and (2) those that clearly ignore the question instruction. For example, when asked to answer a question only if they had

[8] `https://crowdsourcing.yahoo.co.jp/` (2025/4/7 confirmed).

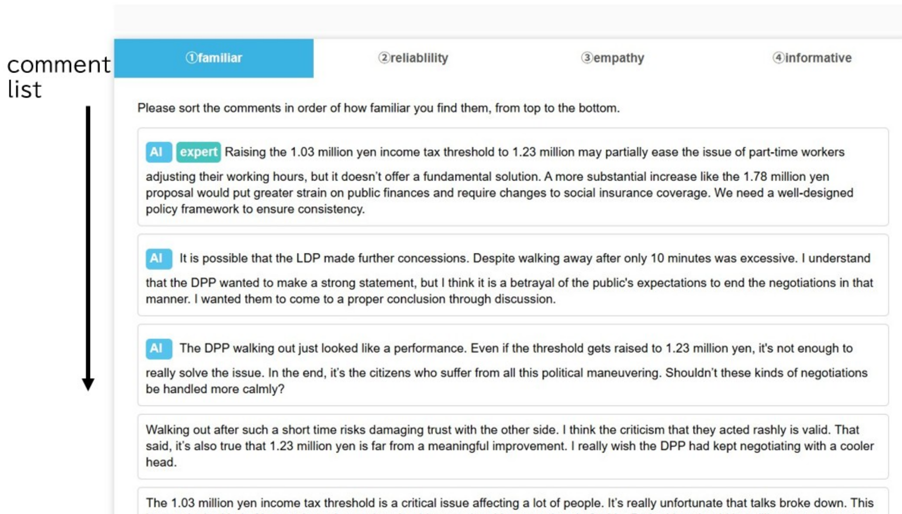

Figure 1: Overview of the interface (presented to Group B). Participants could switch the perspective section. Note that the experiments conducted in this paper were performed using articles written in Japanese.

selected "Others" in the previous question, some participants wrote "?" or submitted unrelated complaints about the survey. These responses were considered insincere and were excluded from the analysis. As a result, 13% of participants were removed. A total of 223 participants took part in this experiment, with 105 in Group A and 117 in Group B. The participants in each group were mutually exclusive. Group A was not informed that some comments were LLM-generated, whereas Group B was notified.

Four articles were selected for this review. Article 1 contained two LLM-generated comments, including one LLM-generated "expert" comment. Article 2 included two LLM-generated comments and one comment by a human expert posted on the Yahoo! News platform. Articles 3 and 4 contained three LLM-generated comments, including one LLM-generated "expert" comment. The LLM-generated "expert" comment was generated based on the procedure mentioned in section 3.1. The interface presented the following message to participants in group B: "Some comments were generated by AI. A comment labeled with the "expert" and "AI" tags was trained using an actual expert's comment." We labeled the applicable comments with both the "expert" and "AI" tags as shown in Figure 3.

3.3 Results

The average ranking of each comment was calculated from each perspective. We compared the changes in the rankings between groups A and B. As a result, the average ranking for both groups A and B was approximately 5th place (see Table 2). A similar trend was observed in the human-written comments, and we compared the average rankings between

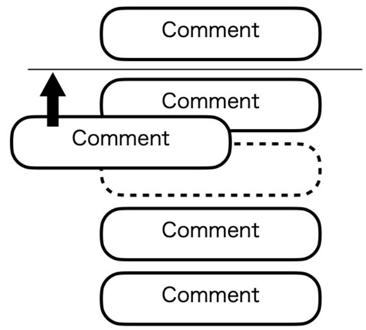

Figure 2: ranking manipulation

Table 2: Changes in the average rankings of all generated comments with or without disclosure

	Group A	**Group B**	**p-value**
familiar	5.021	5.187	0.399
reliability	5.477	5.358	0.513
empathy	5.226	5.504	0.112
informative	5.563	5.284	0.097

groups A and B for each perspective. We did not confirm a statistically significant difference in all the perspectives (significance level: 5% using the Mann-Whitney U test).

In contrast, we compared the average rankings of groups A and B for each comment. As a result, we confirmed a significant rise in rankings as follows: perceived "reliability": four comments, "informative": two comments, "familiar" and "empathy": one comment. Significant differences were observed in eight comments. We observed commonalities in those eight comments; 7 out of 8 comments were labeled with the "expert" tag. Table 3 lists the average rankings of the "expert" comments. Table 4 lists the comments with significant differences.

Those results indicate that the acceptance of LLM-generated comments can shift depending on the comments' label information, such as expert label or AI-label. In the next section, we offer some perspectives on what we can understand from those results.

4 discussion

Based on the results of the experiment discussed in section 3, this section discusses the effects on human impressions of disclosing whether a comment was generated by an LLM. In addition, the tendencies of the comments are discussed.

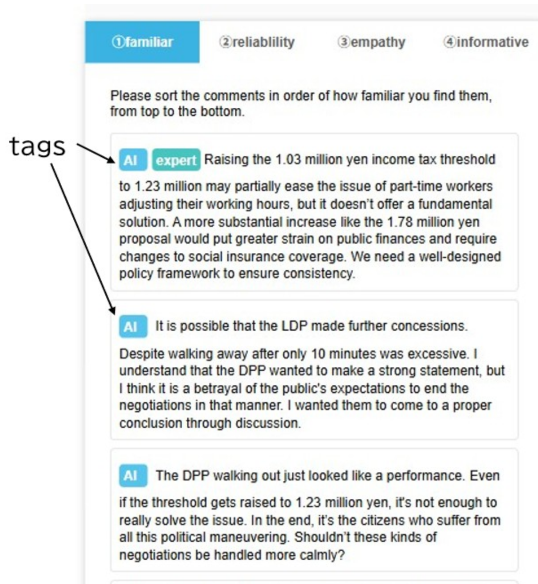

Figure 3: Comments with both the “expert” and “AI” tags (presented to Group B).

Table 3: Changes in the average rankings of “expert” tagged generated comments with or without disclosure

	Group A	**Group B**	**p-value**
familiar	5.163	4.894	0.321
reliability	5.254	3.666	2.97×10^{-7}
empathy	4.975	4.883	0.543
Informative	5.206	4.044	6.08×10^{-5}

4.1 Impact of disclosing source of generated comments on impressions

The average ranking of the comment order in the previous experiment showed no notable effects of disclosing whether the comment was LLM-generated. However, observing the average ranking for each comment, especially comments with the “expert” tag, revealed that the ranking tended to rise. In the set of comments in the experiment, there was no significant difference in the average rankings of human-written and LLM-generated comments. There is a possibility that the explicit disclosure of LLM-generated data contributed to capturing user trust. With recent information gathering using LLM, we can obtain the source of information, which could be a part of decision-making. As these examples suggest, an attempt to guarantee the transparency of responses may contribute to user acceptance of generated comments.

Table 4: Examples of generated comments tagged with "expert" that showed a significant difference (metric:"reliability").

Article No.	Comments	A	B
1	**[Expert]** Mr. Tasaki, you are still too pro-Liberal Democrat in your viewpoint. The fact that the LDP proposed the 1,230,000 again is a problem in itself. The fact that the LDP ignored the KDP's proposal and took only hard-line measures is the reason why the talks are not progressing. The premise that it is wrong to leave the table during talks is also questionable. If the LDP had been more flexible, the talks would have gone smoothly. It is obvious that the LDP wants to proceed according to its own agenda.	5.872	4.392
3	**[Expert]** With the birthrate declining, there is an urgent need to rethink policies. In particular, the key is to improve the environment to make it easier for the younger generation to get married and raise children at the same time. For example, we need to create opportunities to meet people in order to increase the number of marriages, and to provide housing support for the child-rearing generation.	5.237	3.338
4	**[Expert]** When discussing tax cut policies, the question is not only the width of the "wall" increase, but also the balance of the overall policy. The 1.23 million yen proposed by the ruling party is a challenge in terms of the composition of deductions, and it lacks fairness if only salaried workers benefit from it. On the other hand, the KDP's proposal of 1.78 million yen is a bold proposal, but sustainability of financial resources and measurement of effectiveness are essential. What is important is that the tax cut will be felt in daily life and lead to economic revitalization. We look forward to measures that will revitalize society as a whole, centered on stimulating consumption through tax reductions.	4.779	3.338

The experiment results for each comment showed that four "reliability" comments increased in rank, two "informative" comments increased in rank, and only one each of the "familiar" and "empathy" comments increased in rank. LLM-generated comments often exhibit a frank and natural tone, as commonly seen on real-world social networking services, such as "it is too chaotic." However, this tone did not make any significant difference to the evaluation of the comments. Both "familiar" and "empathy" are decision-making criteria related to human emotions and personality. Therefore, the significant differences may not be attributable to the disclosure of authorship.

4.2 Impact of displaying expert attributes on impressions

Based on the results for the observation of comments that showed a significant difference between groups A and B, we confirmed that the existence of the "expert" tag with the "AI" tag made a substantial difference in the ranking. This suggested that even when a comment was LLM-generated, the information it has been fine-tuned using expert sources can enhance its perceived trust. This indicated that such information may influence how users evaluate the value of content. Among such relevant information, comments with colloquial expressions tended to show a lower rise in ranking than comments with polite or formal tones. The ranking of human-written comments was not affected by the tone, but the "expert" label appeared to influence the perceived trust of LLM-generated comments. Therefore, it is important to consistently maintain a gentle tone to maintain "reliability."

However, the following effects should be considered regarding the result of a comment tagged as expert: (1) the expert tag and (2) the prompt in the stage of generated comments contribute to the expertise. Indeed, a significant increase in the average ranking was also observed for the real-world "expert" comments included in Article 2 (group A: 6.276, group B: 4.375). It is necessary to conduct additional experiments under controlled conditions to further investigate the effects of each factor.

4.3 Influence of the attributes of the experiment participants on impressions

The participants in this experiment were recruited through the Yahoo! crowdsourcing service. Less than 10% were under the age of 30, 13% were in their 30s, 65% were in their 40s and 50s, and 16% were over the age of 60. We assumed that the participants represented a wide age range. However, younger people were less likely to participate in this experiment, as they tend to be less interested in news compared to older people. Therefore, it is necessary to conduct another experiment, as future work, focused on age groups to analyze differences in the trend. Regarding the LLM usage percentage, 85.2% of the participants used LLMs less than once a week or not at all, 7.1% used them two to three times a week, and 7.6% used them daily. Therefore, it is necessary to consider the possibility that the results might differ if participants utilize LLMs more frequently.

There is a generational gap in LLM usage. Younger people, particularly students, tend to use LLMs more frequently, whereas the usage percentage decreases with an increase in age. Whether people use LLMs daily is likely to significantly affect their attitudes toward acceptance. Therefore, it is necessary to examine this issue by limiting participants to younger adults. There is a generation gap in the use of LLM. Younger students, especially, tend to use LLM more frequently, while usage rates decline with age. Whether people use LLM on a daily basis is likely to significantly influence their perceptions towards acceptance. However, daily use of LLM does not necessarily reflect a deep understanding of how they work, and it is necessary to consider this when designing future experiments.

5 Conclusion

In this study, we investigated the change in the acceptance attitudes of people when comments generated by an LLM were mixed into the comments section of news websites. In the experiments, we divided the participant group according to whether or not they knew that an LLM had generated comments. Four perspectives were considered: (1) familiar, (2) reliability, (3) empathy, and (4) informative. Based on the results, this experiment suggested the following: (1) a generated comment that imitated the opinion of an expert increased in rank when it was disclosed that the LLM generated the comment. (2) In particular, "reliability" and "informative" were sensitive to this disclosure, while "familiar" and "empathy" were not.

In the future, it is necessary to conduct additional experiments that take into account differences in attributes such as age group and gender, in order to further verify the validity and potential of the findings obtained in this study.

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