Exploring the Impact of Artificial Intelligence-Mediated Communication on Bias and Information Loss in Non-academic and Academic Writing Contexts

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Abstract

Artificial Intelligence-Mediated Communication (AI-MC) is reshaping message construction, dissemination, and interpretation. This dual-study examines AI-MC's impact on positivity bias and information retention in non-academic and academic writing. Findings show nuanced bias effects across large language models (LLMs), with ChatGPT 4.0 reducing perceived bias in non-academic texts and no significant information loss between original and AI-refined texts. These results support cautious AI integration in academic publications and highlight the need for further research on AI-MC's limitations and implications across diverse languages and cultures.

Keywords: Artificial Intelligence-Mediated Communication (AI-MC), Large Language Models (LLMs), Bias perception, Information loss, Non-academic writing, Academic writing

Introduction

In an era marked by rapid digital transformation, the fusion of artificial intelligence (AI) with communication has ushered in a novel paradigm known as Artificial Intelligence-Mediated Communication (AI-MC). This emerging field blends technological advancements with human discourse, fundamentally reshaping the construction, dissemination, and interpretation of messages. The influence of AI-MC extends beyond mere technological evolution; it signifies a profound transformation in interpersonal interactions and communication practices.

As AI technologies, particularly large language models (LLMs) such as ChatGPT, Claude, and Gemini, become increasingly prevalent in various forms of writing, including academic and scientific endeavors, their implications warrant careful examination. Research highlighted by Hancock et al. (2020), Hohenstein and Jung (2018), and others, underscores AI's role in enhancing, altering, or generating messages to meet specific communicative goals. These studies delve into AI's integration into communication, examining its impact on efficiency, linguistic norms, and social dynamics. The influence of AI-MC on human cognition and interpersonal relations points to its potential to both enrich and complicate human interactions, calling for a nuanced understanding of its ethical, cultural, and policy implications.

While there has been considerable discussion on the broader implications of AI-MC, specific studies addressing its impact on both non-academic and academic/scientific writing are less frequent. This gap is important given the widespread application of AI-MC in these areas and the ongoing ethical debates surrounding authenticity and academic integrity. The potential of AI to transform scholarly communication—by enhancing writing efficiency, overcoming language barriers, and promoting diversity—brings to light pressing concerns related to ethics, accuracy, and plagiarism. These concerns highlight the necessity for a measured approach to AI's integration in scholarly endeavors.

This paper seeks to bridge this research gap by exploring the role of LLMs in refining, rewriting, or directly composing texts within academic and non-academic contexts as instances of AI-MC. It argues that the use of LLMs for writing assistance represents a critical AI-mediated stage in the communication process. This involvement of AI engages with fundamental issues within AI-MC research, including technology design, effectiveness, and its ethical and societal ramifications.

Through a dual study investigating AI-MC's influence on positivity bias and information loss, this research contributes to the evolving discourse on AI's role in scholarly communication. It supports the cautious use of AI for language polishing in academic publications, while emphasizing the importance of further research to elucidate current limitations and explore the implications across different linguistic and cultural contexts. This paper aims to provide an examination of how LLMs like ChatGPT, Claude, and Gemini influence bias perception and information loss in both academic and non-academic writing, discussing the ethical, cultural, and technological considerations of AI-MC in scholarly communication.

Literature Review

AI-MC stands at the confluence of technological innovation and human discourse, heralding a significant shift in the construction, transmission, and interpretation of messages. As delineated by Hancock et al. (2020), AI-MC emerges as a pivotal force in mediated communication, capable of enhancing, altering, or generating messages to fulfill distinct interpersonal or communicative objectives. This framework accentuates the intricate role of AI in both facilitating and complicating human interactions, wherein computational agents undertake actions on behalf of communicators to achieve varied communicative ends.

The progression of AI-MC from elementary text-based enhancements, such as auto-correct and predictive text, to sophisticated applications including smart replies and auto-completion (Hancock et al., 2020), underscores the depth of AI's integration into communicative practices. This evolution not only showcases the technological finesse involved but also prompts critical reflection on AI's impact on linguistic norms, interpersonal trust, and the ethical contours of communication. The advent of functionalities like Gmail's smart replies, which provide pre-generated email responses, illustrates AI-MC's dual impact by offering efficiency and potentially reshaping linguistic patterns and social dynamics (Hancock et al., 2020).

Moreover, the interplay between AI-MC and human cognition is profound. The interactive alignment model suggests that AI-generated text can significantly influence linguistic alignment, potentially altering not just lexical choices but also semantic content and social interactions (Pickering & Garrod, 2013; Hancock et al., 2020). This effect is further complicated by AI-MC systems' tendency towards a positivity bias, as evidenced by Hohenstein & Jung (2018), where suggestions for smart replies in text messaging exhibited an overly positive tone, potentially inducing shifts in language norms and interpersonal dynamics.

The exploration of AI-MC's role in interpersonal dynamics underscores its capacity to both complicate and enrich human interactions. Li, J., Chu, Y., & Xu, J. (2023) underscore the profound influence of AI's fairness within AI-MC contexts on human impression formation, indicating that AI behavior, when aligned with social norms of fairness, can significantly improve interpersonal perceptions and relationships. Conversely, Glikson & Asscher (2023) highlight the challenges AI-MC poses to perceived authenticity and forgiveness in multilingual work contexts, emphasizing the delicate equilibrium between leveraging AI's capabilities and preserving the authenticity of human expression.

Accessibility and equitable adoption of AI-MC tools surface as critical concerns, with Goldenthal et al. (2021) identifying barriers to AI-MC access and literacy that could impede the widespread and equitable utilization of AI technologies. This issue highlights the necessity of formulating inclusive strategies to ensure the benefits of AI-MC are accessible across all societal segments.

Thus, the integration of AI into mediated communication signifies a notable advancement with extensive implications for language usage, interpersonal relationships, and the ethical framework of communication. Although AI-MC presents unparalleled opportunities for enhancing communication efficiency and effectiveness, it concurrently demands meticulous consideration of its potential to modify social norms, affect interpersonal trust, and introduce ethical quandaries. Consequently, the scholarly examination of AI-MC must persist in evolving, tackling these challenges while exploiting AI's potential to enrich human communication.

The primary challenges encompassing AI-MC involve:

1.The Impact on Human Language and Cognition: AI-MC has the potential to transform human language usage and cognitive processes, guiding specific grammatical and semantic responses through functionalities like Gmail's smart replies, which could lead to shifts in language norms and expectations.

2.Complexities in Interpersonal Dynamics and Impression Formation: AI's intervention in human communication can affect interpersonal trust and the authenticity of expressions. Utilizing large language models may diminish the authenticity of communications, engendering skepticism towards AI-mediated apologies and impacting relationships.

3.Reassessment of Online Self-presentation and Trust: AI's involvement in crafting online profiles and messages adds complexity, potentially eliciting concerns over deceit and manipulation. Profiles considered to be AI-generated may be deemed untrustworthy, affecting impression formation and trust in online environments.

4.Ethical, Cultural, and Policy Implications: The replication of existing biases in AI systems could reinforce societal power structures and normalize certain modes of communication while marginalizing others. Additionally, balancing the need for transparency in AI-MC and protecting freedom of speech against ensuring the ethical use of AI-MC technologies presents significant ethical considerations.

5.Positivity Bias: AI's propensity to use overly positive language forms a core concern, as this positivity bias, exemplified by Hohenstein & Jung's study(2018) on "smart reply" suggestions in text messaging revealed that they were overly positive ("sounds great!"). could lead to overly positive perceptions of scientific articles, thereby influencing reader perceptions.

However, the chanlleges of AI-MC involvement in writing and academic/scientific writing are much less discussed in the field of communication studies, despite AI-Mediated writing is quite an important topic in recent scholarly literature.

This paper argues that employing large language models (LLMs) such as ChatGPT and Claude for refining, rewriting, or directly composing articles or academic papers should be recognized as instances of AI-MC. AI-MC involves the use of artificial intelligence systems to modify, enhance, or generate content to achieve communication and relational goals. The use of LLMs for writing assistance exemplifies an AI-mediated stage in the text-based communication process between human writers and readers, raising concerns over the quality and efficiency of information expression and sparking profound discussions on how AI impacts human communication methods, content creation quality, and recipient perception.

Moreover, AI-MC research focuses on the design of these technologies and their psychological, linguistic, interpersonal, policy, and ethical impacts on human communication. Thus, utilizing LLMs for writing or editing tasks not only embodies the definition of AI-MC but also engages with the core issues of concern within AI-MC research, such as technology design, effectiveness, and accompanying ethical and societal impacts (Hancock, Naaman, & Levy, 2020).

Despite extensive discourse on AI-MC's broader implications, there remains a notable scarcity of research specifically targeting its role in facilitating the writing of articles and academic papers. This gap is peculiar, considering the widespread recognition and application of AI-MC in these domains, even amid ethical dilemmas concerning authenticity and academic integrity (Fitria, T. N., 2023; Chen, T.-J., 2023; Miao et al., 2024).

AI-MC has transformed various facets of human interaction, especially in writing and scholarly activities. While research in communications and human-computer interaction often emphasizes the challenges and ethical concerns associated with AI-MC, such as its influence on language and thought, ethical and policy implications, and the reevaluation of trust and authenticity online, there is a notable discrepancy in the embrace of AI tools like ChatGPT in academic writing Fitria, T. N., 2023; Chen, T.-J., 2023; Miao et al., 2024).

Studies highlight AI's efficacy in enhancing writing efficiency, overcoming language barriers, and generating diverse text versions (Chen, T.-J., 2023; Kacena, M. A. et al., 2024). However, these advancements are accompanied by ethical concerns, accuracy doubts, and plagiarism risks, advocating for a cautious yet open approach to AI integration in scholarly endeavors (Miao et al., 2024; AlAfnan et al., 2023).

The ethical challenges and implications of AI integration in academic settings are profound, with discussions on academic integrity, transparency, and the formulation of ethical guidelines taking precedence (Miao et al., 2024; Thorp, 2023). Furthermore, AI's potential to exhibit a positive bias raises questions about its impact on scholarly discourse and the integrity of scientific communication.

The trust in AI-MC, particularly in academic writing, necessitates a reevaluation. The acceptance of AI tools in scientific writing, in spite of known challenges, indicates a significant paradigm shift in the scholarly community's perception of trust and credibility. This shift demands a thorough understanding of AI's capabilities and limitations to ensure responsible usage (Herbold et al., 2023; Balel, 2023).

The divergent perspectives on AI-MC in communication studies versus academic writing underline a complex interplay of ethical, cultural, and technological considerations. The widespread acceptance of AI tools like ChatGPT in academic settings, despite existing challenges, suggests an evolving landscape of scholarly communication. This scenario underscores the importance of ongoing research, ethical deliberation, and policy development to navigate effectively the future of AI-MC in academic discourse (Dwivedi et al., 2023; Thorp & Vinson, 2023).

Research Gaps and Research Hypothesis

The exploration of AI-MC in academic settings, particularly concerning the role of LLMs like ChatGPT, Claude, and Gemini, introduces a complex paradigm shift in scholarly communication. Following the foundational insights provided in the lierature review section on the diverse implications and challenges of AI-MC, this chapter delves into positivity bias and information loss within writing and academic writing aspects of AI-MC.

Positivity bias, a concern previously flagged in various communicative contexts (Hohenstein & Jung, 2018), warrants a reevaluation in the context of advanced LLMs' application to academic writing. The optimistic stance of the academic community towards LLMs in scholarly writing, as indicated by the relative absence of concern for positivity bias in previous research, prompts an inquiry into whether advancements in AI capabilities have mitigated this issue.

Diamond (2024) argues that systems like autocorrect, autocomplete, and smart replies have become cornerstones of modern text communication. While these systems provide significant assistance day-to-day, they primarily focus on simple tasks like response prediction, spelling corrections, or sentence completion. With the sudden rise in advanced generative AI—namely large language models (LLMs) like GPT-4 and LLaMa 2—the door has opened for smarter and more capable AI assistance systems for digital writing composition.

However, the question remains: Does the advanced technology of LLMs perpetuate or mitigate positivity bias and its associated risk of information loss in academic/scientific writing? This concern is crucial because academic/scientific writing demands precision and objectivity, with any form of bias potentially skewing reader perception and distorting the author's intended message.

Moreover, the challenge of information loss in text-based communication—a phenomenon well-documented in literary and communication studies—gains a new dimension with the intervention of LLMs. Studies have shown that discrepancies between authorial intent and reader interpretation are commonplace, leading to varied understandings of the same text (Pisanty, 2015; Gibbs, 2001; Rosebury, 1997; Katz & Lee, 1993; Horváth, 2015).This discrepancy, termed in this paper as information loss in text-based communication, raises pertinent questions about LLMs' role in either exacerbating or alleviating this fundamental challenge of communication.

To address these concerns, this chapter proposes two research questions aimed at critically examining the impact of LLMs like ChatGPT, Claude, and Gemini on writing and academic writing:

Research Questions 1 (RQ1)

RQ1: Does texts generated by LLMs, such as ChatGPT 4.0, Claude 3 Opous, and Gemini Advanced, significantly increase or metigate biases when compared to the original texts?

This research question and its null counterpart allow for an empirical test of whether LLM-generated texts are characterized by a tendency towards more positive or negative language compared to original human-authored texts. This is grounded in the observation of potential positivity bias in AI-generated content, as noted in prior research.

Research Questions 2 (RQ2)

RQ2: Does LLM-generated texts, such as those from ChatGPT 4.0, Claude 3 Opous, and Gemini Advanced, in comparison to original texts, exacerbate the problem of information loss in text-based communication?

This research question is designed to investigate the effect of LLMs on the fidelity of information transmission in text-based communication. Specifically, they aim to determine if texts generated by LLMs lead to greater or lesser information loss compared to original texts, addressing concerns about the accuracy and integrity of AI-mediated communication.

Methods

The Methods are separated as Study 1 and Study 2.

<insert Table 1. here>

Methods of Study 1

Participants and Sample Size

Study 1 recruited participants online through the Credamo platform, regardless of their background. The initial sample size was determined using the formula $n=Z^2 \cdot p \cdot (1-p)/E^2$, yielding a required maximum sample size of 385. To accommodate this, 400 samples were chosen, with 100 each for the control group and three experimental groups.

After conducting post hoc power analysis based on the effect sizes of the ChatGPT 4.0 Edited (f=0.173) and Gemini Advanced Edited (f=-0.200) groups, the sample size was adjusted to 143 per group to achieve a desired power of 0.80, resulting in a total of 572 participants across four groups.

Materials and Procedure

Step 1: Content Creation.

Part 1 involved six writers writing short text messages (100-500 words each) conveying specific emotions: happiness, anger, sadness, disgust, surprise, or worry.

Part 2 involved three writing experts, each with at least one year of experience in their respective fields (fact description, opinion expression, and emotional expression), writing three articles (1000-3000 words each) on these themes.

Step 2: Questionnaire Development.

Part 1: A 5-point Likert scale questionnaire was developed to measure the intended emotional intensity in the short messages, with six questions designed for each emotion.

Part 2: A questionnaire with five multiple-choice questions was created to assess clarity in expressing the writing's purpose, central idea, and preferences for the three articles. The correct answers for both questionnaires were determined by the authors

Step 3: AI Enhancement.

The short messages and articles, along with their corresponding questionnaire responses, were used as the prompts for refinement by ChatGPT 4.0, Claude 3 Opous, and Gemini Advanced. The AI models were instructed to refine the texts to more accurately convey the intended emotions and central ideas by the same prompts.

Experimental Group A (AI-Enhanced Group)

1.AI-enhanced articles and short messages were distributed to readers, with each AI version assigned to a different group of 143 samples, totaling 429 samples.

2.Readers responded to the same questionnaires filled out by the authors after careful reading.

3.Reader responses were compared with author responses to determine accuracy rates for emotional and idea conveyance.

Control Group B (Unenhanced Group)

1.Unenhanced original articles and short messages were distributed to a random set of 143 readers.

2.Readers answered the questionnaires after reading.

3.Reader responses were compared with author responses to determine accuracy rates.

Methods of Study 2

Participants and Sample Size

Following the insights from Study 1, the sample size for Study 2 was set at 140 samples per group, with one control group and two experimental groups, totaling 420 participants. Native Chinese speakers aged 18 years or older were selected regardless of sex, gender, or educational background.

Materials and Procedure

Step 1: Content Creation.

Part 1 involved six authors of published academic papers in Chinese, spanning economics, psychiatry, agriculture (translated into Chinese by the author who wrote it), psychology, communication, and management. Select authors from their published works and rate them on a scale of 1-5 for academic contribution, timeliness, scope, novelty, significance of conclusions, and neutrality of data presentation. The authors provided correct answers.

Part 2 involved three authors of published academic papers in Chinese, from the fields of sociology, sports education, and health medicine, extracting sections (Introduction, Literature Review, and Conclusion) from their works and collaboratively creating five multiple-choice questions for each section.

Papers involved in both Parts 1& 2 were all published in peer-reviewed journals and the authors were all first authors of the paper.

Step 2: Questionnaire Development.

Part 1: A 5-point Likert scale questionnaire was developed to assess academic contribution, timeliness, scope, novelty, significance of conclusions, and neutrality of data presentation.

Part 2: Multiple-choice questions were created to elucidate the author's writing purposes and central ideas for each of the three detailed academic sections.

Step 3: AI Enhancement.

The same with Study 1 but Gemini Advanced was excluded due to its inability to interpret the required instructions.

Experimental Group A (AI-Enhanced Group)

1.AI-enhanced texts were distributed to random readers, with separate groups of 140 samples each for ChatGPT 4.0 and Claude 3 Opous.

2.Readers answered the same questionnaires completed by the authors after reading.

3.The accuracy rates of readers' responses were compared with the authors' original answers.

Control Group B (Unenhanced Group)

1.Unenhanced original texts were provided to a random set of 140 readers.

2.Readers responded to the questionnaires after reading.

3.Accuracy rates of readers' responses were compared to the authors' answers.

<insert Figure 1. here>

Scoring Criteria

The assessment questionnaires consist of two main sections: bias and information loss. The bias section includes questions 4.1-4.6, while the information loss section includes questions 6.1-6.5, 8.1-8.5, and 10.1-10.5.

Bias (Questions 4.1-4.6): For non-academic texts (Study 1), the bias questions assess the degree of happiness, disgust, surprise, anger, worry, and sadness on a 1-5 scale. For academic texts (Study 2), the bias questions evaluate the level of academic contribution, timeliness, scope, novelty, significance of conclusions, and neutrality of data presentation, also on a 1-5 scale. Each question in the bias section is a single-choice question.

Information Loss (Questions 6.1-6.5, 8.1-8.5, 10.1-10.5): The information loss section consists of single-choice questions that assess the extent of information lost in the text by asking the participants questions related to the contents to see whether they have the same level of understanding of what the authors intended to express.

Scoring: The authors provides standard answers for each question, with each correct answer receiving one point. The bias section contains a total of 6 questions, with a maximum score of 6 points. The information loss section consists of 15 questions, with a maximum score of 15 points. The total score for both sections combined is 21 points.

Data Inclusion and Exclusion Criteria

Native Chinese speakers of 18 years old are selected regardless of sex. gender or educational background etc. Samples that provide incorrect responses to control (trap) questions are considered invalid and excluded from the analysis.

Data Interpretation

To investigate the influence of AI-MC on positivity/negativity bias and information loss in the interaction between authors and readers in the context of academic text comprehension, a comparative analysis is conducted on the accuracy rates of readers in groups of Experimental and Control. If the accuracy of readers in the experimental group is found to be lower than that of the control group, it would suggest that the occurrence of bias and information loss is intensified. Conversely, if the accuracy rate of readers in the experimental group is essentially comparable to that of the control group, it would indicate that AI-MC has a negligible impact on bias and information loss. Furthermore, if the accuracy of readers in the experimental group surpasses that of the control group, it would imply that AI-MC not only does not exacerbate bias and information loss but, rather, possesses the capability to convey the author's intended meaning more effectively and accurately than the author themselves, thereby attenuating the prevalence of bias and information loss.

Standardized Analysis

In both Studies 1 and 2, the assessment of bias and its perception relies on the deviation of scores from predetermined set points, reflecting specific levels of emotional intensity and academic attributes. These set points, such as 'surprise at level 4' or 'worry at level 2', were established by the authors themselves. The rationale for these set points, along with their validation, stems from the need to standardize measurements across different texts and contexts to ensure consistency in the evaluation of AI-mediated modifications. To address potential concerns about the variation in bias assessment, it is crucial to understand that these deviations—such as scoring a '5' instead of a '4' for disgust—are not merely arbitrary. Each point difference represents a shift in perceived intensity or attribute as predetermined by the study's design. Furthermore, it is inherent that discrepancies between reader comprehension and author intent—encompassing bias and information loss—will occur, a phenomenon also reflected in this study. However, the central focus of our analysis is to ascertain whether AI-mediated editing exacerbates or mitigates these disparities, thereby critically evaluating the influence of AI on the integrity of communication.

Data Analysis

Data was analyzed through SPSS software Version 27.01, SPSSAU online and ChatGPT 4.0.

Ethical Considerations

Participants were informed about the academic use of their work and compensated accordingly. Informed consent was obtained, and a single-blind approach was adopted to ensure participants were unaware of the experiment's purpose. Measures were in place to protect participants' personal information and ensure anonymized data handling.

Data availability

Data collected during this study has been treated with strict adherence to ethical guidelines and participant consent, resulting in different accessibility levels for the datasets. Data concerning non-academic texts is made publicly available on Figshare under the Creative Commons Attribution license (CCBY 4.0), allowing for free access, use, and citation by other researchers. However, access to data concerning academic texts, including participant responses and AI-modified versions, is restricted due to certain original academic text authors' refusal to consent to open sharing due to privacy concerns (they cannot be anonymous in this research). Researchers wishing to access the academic text data are required to contact the corresponding author via email to request permission. Such requests will be evaluated individually, with access granted based on compliance with ethical and privacy considerations.

Code availability and AI Versions

The AI modifications were implemented using the standard, publicly available versions of ChatGPT 4.0, Claude 3 Opus, and Gemini Advanced, accessed through individual subscription-based plans from April to May 2024. No custom modifications or proprietary code were applied.

Supplementary Materials

For detailed experiment procedures, please refer to the Supplementary Materials: Detailed Experiment Procedure

Results

The results are separated as Study 1 and Study 2.

Results of Study 1

Study 1 (n=572) investigated the influences of AI-mediated communication on bias perception and information loss in non-academic texts, examining the text refinement abilities of three distinguished large language models (LLMs): ChatGPT 4.0, Claude 3 Opous, and Gemini Advanced. A mixed-methods approach was adopted for this investigation, with nonparametric statistical analyses to scrutinize data from a control group (original texts) and three experimental groups (texts edited by each LLM).

Information Loss

The evaluation of information loss was conducted using the Independent-Samples Mann-Whitney U Test across the control and experimental groups. Results indicated no significant differences in the perception of information loss between groups ($p>0.05$ for all LLM comparisons), suggesting that the act of refining texts with these LLMs neither significantly detracts from nor adds to the preservation of information content in non-academic texts from the readers' perspective.

<insert Figure 2. here>

Bias Perception

Bias perception was assessed through the Independent-Samples Mann-Whitney U Test, comparing the median scores of responses across the original and AI-edited texts. The findings presented a varied impact on bias:

Texts refined by ChatGPT 4.0 demonstrated a significant reduction in perceived bias (p=.002) compared to the control group, highlighting ChatGPT 4.0's effectiveness in mitigating bias within non-academic text contexts.

For Claude 3 Opous, no significant difference in bias perception was detected (p=.824) when compared with the control group, indicating that edits made by Claude 3 Opous do not significantly alter readers' perceptions of bias.

•Gemini Advanced edits resulted in a significant finding (p=.010), pointing towards a slight enhancement of perceived bias for certain contexts, contrasting with other instances where no significant bias alteration was noted.

<insert Figure 3. here>

Emotional Bias Influence

Further exploration into emotional biases revealed differentiated effects contingent on the specific LLM's text editing actions:

Gemini Advanced was found to slightly enhance both negativity and positivity biases in certain cases, signifying a nuanced alteration in emotional tone due to its refinements (Mann-Whitney U: 8479.50).

Conversely, ChatGPT 4.0 was generally effective in reducing these biases, demonstrating its capacity to convey more accurate emotional tones within texts than those originally from writers/authors(Mann-Whitney U: 12304.00).

The effect sizes observed were modest across the board, indicating that while LLM modifications can influence emotional biases, the overall impact remains subtle, causing only slight deviations from the anticipated emotional perceptions.

<insert Figure 4. here>

Demographics

The normality test conducted on variables including total scores, duration of total response time, gender, education level, occupation, age, daily reading duration and reviewing experiences for scholarly journals revealed that these variables did not follow a normal distribution ($p<0.05$) in the control group and all three experiment groups. This finding suggests that robust non-parametric methods should be employed for subsequent analyses to ensure accurate and reliable results.

Impact of Response Time on Scores Robust regression analysis showed that the duration of total response time had a significant positive impact on total scores in the control group ($\beta=0.003$, $p<0.01$), Claude 3 Opus edited group ($\beta=0.003$, $p<0.01$), and Gemini Advanced edited group ($\beta=0.002$, $p<0.05$). This indicates that longer response times were associated with higher scores in these groups. However, in the ChatGPT 4.0 edited group, the duration of total response time had no significant effect on total scores ($\beta=0.001$, $p=0.182>0.05$), suggesting that the editing by ChatGPT 4.0 might have weakened the association between response time and scores, potentially making the text more readable and understandable.

Influence of Demographic Variables In all four groups, gender, education level, occupation, age and reviewing experiences for scholarly journals had no significant influence on total scores ($p>0.05$). Only in the Gemini Advanced edited group, daily reading duration had a weak positive impact on total scores ($\beta=0.491$, $p<0.05$). The influence of reading duration was not significant in the other three groups. These findings indicate that AI editing did not substantially change the relationship between demographic factors and readers' comprehension of non-academic texts.

Explanatory Power of the Models Where significant effects were found, the duration of total response time had the strongest explanatory power on total scores, with adjusted R^2 ranging from 0.047 to 0.155. The model fit for other variables was generally low, with most adjusted R^2 values less than 0.01. This suggests that response time is a more reliable predictor of scores compared to demographic variables and reading duration.

Implications of AI Editing on Non-Academic Texts The ChatGPT 4.0 edited group showed some differences compared to the other three groups, mainly in terms of the non-significant impact of response time duration on total scores. This finding suggests that the editing by ChatGPT 4.0 might have weakened the association between response time and scores to some extent, potentially making the text more readable and understandable. However, further research is needed to verify this interpretation.

Moreover, after applying the Benjamini-Hochberg method to control the false discovery rate for the multiple testing of bias perception across the three AI models (ChatGPT 4.0, Claude 3 Opous, and Gemini Advanced), here are the adjusted results:

- ChatGPT 4.0 (p-value = 0.002): The effect remains significant under the FDR adjustment.
- Gemini Advanced (p-value = 0.01): This also remains significant after adjustment.
- Claude 3 Opous (p-value = 0.824): The high p-value indicates no significant effect, which is consistent with not adjusting for multiple testing.

This adjustment confirms that both the reductions in bias by ChatGPT 4.0 and the slight enhancement of bias by Gemini Advanced are statistically significant findings when considering multiple comparisons, while the result for Claude 3 Opous remains non-significant. This analysis helps in accurately interpreting the impacts of different AI models on bias perception without overstating the findings due to multiple tests.

Results of Study 2

Study 2 (n=420) explored the influence of AI-MC on bias perception and information loss within academic texts, focusing specifically on the text refinement effects of LLMs: ChatGPT 4.0 and Claude 3 Opous. Given that Gemini Advanced was unable to interpret the prompts, it was not included as part of the experimental groups. This phase of the research utilized a mixed-methods design, employing nonparametric statistical analyses to evaluate data collected from a control group (original texts) and two experimental groups (texts edited by ChatGPT 4.0 and Claude 3 Opous, respectively).

Information Loss

The analysis of information loss was conducted using the Independent-Samples Mann-Whitney U Test across the control and experimental groups. The findings revealed no significant differences in information loss among the groups ($p>0.05$ for all LLM comparisons). This outcome suggests that text refinement by the LLMs under study does not significantly impact the preservation or degradation of information content in academic texts as perceived by the readers.

ChatGPT 4.0 Edited Texts: The mean rank comparison between control (original texts) and ChatGPT 4.0 edited texts showed minimal differences, with a significance level of .660, indicating no significant information loss.

Claude 3 Opous Edited Texts: Similarly, the comparison between control texts and those edited by Claude 3 Opous demonstrated no significant difference in information loss, with a significance level of .573.

<insert Figure 5. here>

Bias Perception

In terms of bias perception, the Independent-Samples Mann-Whitney U Test was employed to analyze the median scores across the original and AI-edited texts. The tests concluded that:

ChatGPT 4.0 Edited Texts: No significant difference in bias perception was observed between the control group and the ChatGPT 4.0 edited group ($p=.797$), suggesting that

ChatGPT 4.0's interventions in academic text refinement do not significantly alter the perceived bias.

Claude 3 Opous Edited Texts: The results were similar for texts edited by Claude 3 Opous, with no significant difference in bias perception compared to the control group ($p=.502$), indicating that Claude 3 Opous's text refinements do not significantly influence bias perception among readers.

However, the discrepancy in understanding between readers and authors of academic texts is a significant issue that warrants further investigation. This study reveals that both positivity and negativity biases are substantially more pronounced in academic texts compared to non-academic texts, with differences often spanning 1-2 levels of bias. These findings suggest that readers and authors may have divergent perceptions of the six key aspects of scientific research examined in this study: contribution, timeliness, scope, novelty, significance, and objectivity.

Notably, the application of AI editing tools, specifically Claude 3 Opous and ChatGPT 4.0, does not appear to significantly influence readers' understanding of the text. This observation implies that the perception of these six aspects may be primarily influenced by other factors and is largely subjective in nature, potentially explaining the high number of responses that deviate from the authors' intended meaning.

Figure 6 presents a comparative analysis of the average and total scores for bias across the control group and two AI-edited groups (Claude 3 Opous and ChatGPT 4.0). The total scores for each aspect are normalized to 1. The data reveals that the average scores for each aspect are relatively consistent across the three groups, further supporting the notion that AI editing did not substantially alter the overall bias pattern. However, it is important to note that all four average scores are comparatively low in relation to the total scores, indicating a general tendency towards bias.

The distribution of bias error answers for each aspect provides additional insights, with the correct answer level indicated by red lines. In the case of the contribution aspect (correct answer level 2), the majority of responses across all three groups fall within levels 3 and 4, suggesting the presence of a positive bias. Similarly, for timeliness (correct answer level 5), most responses are concentrated in levels 3 and 4, indicating a negative bias.

The scope aspect (correct answer level 3) exhibits a slightly different pattern, with the highest number of responses in level 2 for the control group and Claude 3 Opous, while ChatGPT 4.0 has a greater proportion of responses in level 3. This suggests that ChatGPT 4.0 editing might have marginally reduced the negative bias for this particular aspect.

For novelty (correct answer level 4) and significance (correct answer level 3), the distribution of responses is more evenly spread across levels 2 to 4, with a slight positive bias observed in the AI-edited groups. Lastly, the objectivity aspect (correct answer level 4) demonstrates a relatively accurate perception, with the majority of responses falling within level 4 for all groups.

The findings of this study underscore the presence of bias in readers' perception of academic texts, with positivity and negativity biases being more pronounced compared to non-academic texts. The minimal impact of AI editing on these biases suggests that other subjective factors may be at play. These results raise important questions regarding the evaluation of scientific papers' overall contribution and the need for objective and accurate assessment methods. The varied perceptions revealed in this study highlight the complexity of this issue and the necessity for further research to develop robust and impartial evaluation frameworks. By addressing these challenges, the scientific community can work towards ensuring that the true value and impact of academic research are accurately recognized and communicated.

Moreover, after applying the Benjamini-Hochberg correction to control the false discovery rate in Study 2, both adjusted p-values remain unchanged at 0.797. This indicates that the original findings — no significant difference in bias perception between control and AI-edited groups for both ChatGPT 4.0 and Claude 3 Opous — hold under this more stringent correction for multiple comparisons.

<insert Figure 6. here>

<insert Figure 7. here>

Demographics, Responding Time, and Reading Habits

Study 1 and Study 2 recruited a total of 992 valid participants from various provinces and cities across China. The sample considerably consisted more of cis-gender females compared to their cis-gender male counterparts, with ages mostly ranging from 20 to 40 years old. The majority of the participants held a bachelor's degree. Specifically for Study 2, it included a diverse sample of readers from various academic backgrounds and levels of expertise. By controlling for the potential confounding effects of domain-specific knowledge, the study seeks to exclusively analyze the impact of language on reader perception. This approach allows for a more comprehensive understanding of how the linguistic features of academic texts contribute to the observed positivity and negativity biases, independent of the readers' familiarity with the subject matter. Specifically, total socres here and below are the total scores obtained by the readers for correct answers, which represent the alignment of the readers' and authors' understanding.

Study 1

The normality test conducted on variables including total scores, duration of total response time, gender, education level, occupation, age, and daily reading duration revealed that these variables did not follow a normal distribution ($p<0.05$) in the control group and all three experiment groups. This finding suggests that robust non-parametric methods should be employed for subsequent analyses to ensure accurate and reliable results.

Robust regression analysis showed that the duration of total response time had a significant positive impact on total scores in the control group ($\beta=0.003$, $p<0.01$), Claude 3 Opus edited group ($\beta=0.003$, $p<0.01$), and Gemini Advanced edited group ($\beta=0.002$, $p<0.05$). This indicates that longer response times were associated with higher scores in these groups. However, in the ChatGPT 4.0 edited group, the duration of total response time had no significant effect on total scores ($\beta=0.001$, $p=0.182>0.05$), suggesting that the editing by ChatGPT 4.0 might have weakened the association between response time and scores, potentially making the text more readable and understandable.

Variables In all four groups, gender, education level, occupation, and age had no significant influence on total scores ($p>0.05$). Only in the Gemini Advanced edited group, daily reading duration had a weak positive impact on total scores ($\beta=0.491$, $p<0.05$). The influence of reading duration was not significant in the other three groups. These findings indicate that AI editing did not substantially change the relationship between demographic factors and readers' comprehension of non-academic texts.

Where significant effects were found, the duration of total response time had the strongest explanatory power on total scores, with adjusted R^2 ranging from 0.047 to 0.155. The model fit for other variables was generally low, with most adjusted R^2 values less than 0.01. This suggests that response time is a more reliable predictor of scores compared to demographic variables and reading duration.

The ChatGPT 4.0 edited group showed some differences compared to the other three groups, mainly in terms of the non-significant impact of response time duration on total scores. This finding suggests that the editing by ChatGPT 4.0 might have weakened the association between response time and scores to some extent, potentially making the text more readable and understandable. However, further research is needed to verify this interpretation.

Study 2

The normality test conducted on variables such as total scores, duration of total response time, gender, education level, occupation, age, and daily reading duration revealed that these variables did not follow a normal distribution ($p<0.05$) in the control group and both experiment groups (ChatGPT 4.0 edited and Claude 3 Opus edited). This finding indicates that robust non-parametric methods should be employed for subsequent analyses to ensure accurate and reliable results.

Robust regression analysis showed that the duration of total response time had a significant positive impact on total scores in all three groups. In the control group ($\beta=0.002$, $p<0.01$), ChatGPT 4.0 edited group ($\beta=0.002$, $p<0.01$), and Claude 3 Opus edited group ($\beta=0.003$, $p<0.01$), longer response times were associated with higher scores. This suggests that regardless of the type of text (original or AI-edited), individuals who spent more time responding to the questions tended to achieve better results.

In the control group, occupation had a significant positive influence on total scores ($\beta=0.520$, $p<0.01$), while other variables such as gender, education level, age, and reading duration had no significant impact. However, in both the ChatGPT 4.0 edited group and Claude 3 Opus edited group, all demographic variables and reading duration had no significant effect on total scores ($p>0.05$). This finding implies that AI editing may have reduced the impact of certain demographic factors on the comprehension of academic texts.

The duration of total response time demonstrated a relatively large explanatory power on total scores, with an adjusted R^2 of 0.114 in the ChatGPT 4.0 edited group and as high as 0.228 in the Claude 3 Opus edited group. In contrast, the model fit for other variables was generally low, with most adjusted R^2 values less than 0.05. This suggests that response time is a more reliable predictor of scores compared to demographic variables and reading duration.

The results indicate that AI editing did not weaken the association between response time and scores but rather slightly strengthened it, particularly in the Claude 3 Opus group. This may imply that AI editing did not significantly simplify the comprehension of academic texts, as it did for non-academic texts. The professional nature and complexity of academic texts may still require readers to invest more time in understanding the content.

In the control group, occupation had a positive impact on total scores, but this effect disappeared in the AI-edited groups. This finding suggests that AI editing may have somewhat reduced the differences in understanding academic texts among individuals with different occupational backgrounds. However, given the relatively crude measurement of the occupation variable, further evidence is needed to support this interpretation.

Limitations and Future Directions

This paper, while shedding light on the implications of AI-MC in text refinement, encounters certain limitations that pave the way for future exploratory avenues. A primary constraint lies in the exclusive use of Chinese texts for analysis. Given that the underlying algorithms of the LLMs examined—ChatGPT 4.0, Claude 3 Opous, and Gemini Advanced—are predominantly trained on datasets comprising English language material, the proficiency of these models may inherently skew towards English. The comparatively lesser volume of Chinese data in training may have nuanced implications on the performance and efficacy of these models in handling Chinese texts. Consequently, it is hypothesized that the performance of these LLMs might exhibit enhanced accuracy and subtlety in refining texts written in English or other languages more prevalently represented in their training corpora.

Furthermore, the demographic homogeneity of the participant sample, confined to Chinese respondents, introduces another limitation. This restriction curtails the generalizability of the study's findings across different cultural contexts. Future research endeavors should thus incorporate a broader, more culturally diverse participant base. By doing so, researchers can ascertain the universality of the observed effects of AI-mediated text refinement on bias perception and information loss, offering insights into whether these impacts are consistent across varied cultural and linguistic landscapes or if they manifest differently.

Addressing these limitations, future research should extend the linguistic scope of text samples, encompassing English and other languages to provide a more comprehensive understanding of LLMs' text refinement capabilities. Moreover, expanding the study's geographical and cultural participant range will enrich the findings, allowing for a more nuanced exploration of AI-mediated communication's effects across diverse global contexts. These directions not only promise to broaden the empirical foundation of AI's role in communication but also to elucidate the interplay between language, technology, and culture in shaping text comprehension and perception.

Discussions

This paper aims to contribute to the existing body of knowledge on text-based communication in the context of bias and information loss.

This paper approaches to studying bias and information loss in text-based communication by objectively comparing readers' and authors' perspectives, which may serve as a framework for analyzing bias and information loss in text-based communication in future research. Furthermore, this approach may be useful in evaluating the performance of AI systems in the context of communication.

Moreover, this paper empirically confirms the existence of bias and information loss in both academic and non-academic texts. It also demonstrates that LLMs can have both positive and negative impacts on bias, with the specific effects varying across different AI tools. Thus, it might be better for future research to explicitly indicates the AI tools they use. In addition, this research investigates both positivity and negativity biases, aiming to provide a more balanced analysis of the role of AI in text-based communication.

A surprising finding is that ChatGPT can reduce emotion-related bias and express emotional intensity more accurately than the authors themselves, leading to better reader understanding. This is a positive signal, suggesting that ChatGPT may have strong capabilities in emotion recognition and processing within texts. This finding raises the possibility that ChatGPT could help people express their emotions more accurately, opening up new avenues for future research.

Moreover, this paper confirms that LLMs do not significantly influence either bias or information loss in academic texts. In the context of non-academic texts, LLMs do not have a significant impact on information loss. Thus, these findings provide some empirical support for the policies of mainstream publishers like Nature, Science, Sage, and Elsevier, which permit the use of AI for language editing in academic articles (Nature Portfolio, n.d.; Thorp, 2023; Sage Publications, n.d.; Elsevier, n.d.). Although this paper focused on Chinese texts, its results lend some empirical backing to such practices. Future research may explore the implications for academic texts in other languages such as English.

Furthermore, the work by Abid et al. (2021) highlighted the potential for bias in LLMs can stem from errors in training data, including gender, racial, or political biases, and reinforcement learning based on user feedback can also introduce biases. However, this paper argues that AI technology, including models like ChatGPT 4.0, Claude 3 Opous and Gemini Advanced etc., has evolved significantly since then, improving measures to mitigate biases and enhance text quality. Moreover, this paper focuses solely on AI's role in language editing and enhancement (AI-AC) for academic and non-academic texts, which involves refining linguistic aspects rather than generating orignial content, thus excluding biases related to gender, race, or politics. Academic writing itself should be devoid of insidious biases, confusing mistakes, irony, and sarcasm, so the concern that LLMs might merely select common synonyms without addressing deeper issues may not be applicable. Additionally, human oversight is required in reviewing AI-enhanced texts ensures accuracy and appropriateness, minimizing potential biases or inaccuracies. While LLMs have limitations, their ability to refine text may be practical in writing contexts for researchers (Gruda, 2024).

In summary, this paper aims to explore the nuanced role of large LLMs in text-based communication, particularly in reducing bias. It also seeks to emphasize the importance of careful, informed use of AI in text editing tasks. The methodological and empirical insights offered here are intended to serve as a stepping stone for further investigations into the effects of AI on communication dynamics. As the integration of AI into communication continues to evolve, futher research for understanding its implications across different languages and cultural contexts may be crucial for harnessing its full potential while mitigating unintended consequences.

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Table 1.

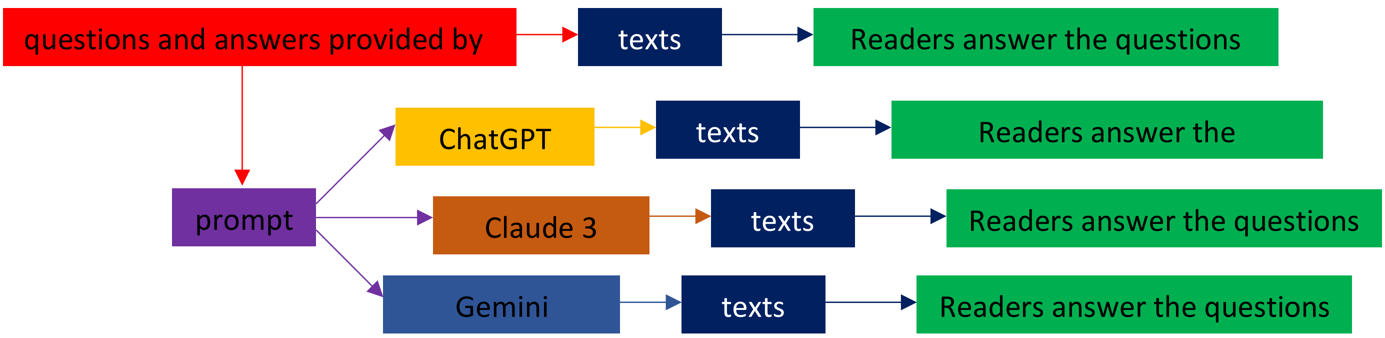
Summary of Key Parameters Analyzed in the Study

Parameter	Study 1: Non-Academic Texts	Study 2: Academic Texts
Participants	572 participants (4 groups: 1 control, 3 experimental)	420 participants (3 groups: 1 control, 2 experimental)
LLMs Used	ChatGPT 4.0, Claude 3 Opous, Gemini Advanced	ChatGPT 4.0, Claude 3 Opous
Sample Size per Group	143 participants per group	140 participants per group
Content Creation	Short messages (100-500 words) and articles (1000-3000 words) on specific emotions	Sections (Introduction, Literature Review, Conclusion) from academic papers in various fields
Questionnaire	5-point Likert scale for emotional intensity; multiple-choice for clarity (content understanding)	5-point Likert scale for academic attributes; multiple-choice for clarity (content understanding)
Bias Measurement	Degree of happiness, disgust, surprise, anger, worry, sadness (1-5 scale)	Academic contribution, timeliness, scope, novelty, significance of conclusions, neutrality of data presentation (1-5 scale)
Information Loss Measurement	Single-choice questions assessing information retention (content understanding)	Single-choice questions assessing information retention (content understanding)
Analysis Method	Independent-Samples Mann-Whitney U Test	Independent-Samples Mann-Whitney U Test
Significant Findings	- ChatGPT 4.0 reduces perceived bias (p=.002) - No significant information loss detected	- No significant bias alteration by ChatGPT 4.0 (p=.797) and Claude 3 Opous (p=.502) - No significant information loss detected

Demographic Variables	Gender, education level, occupation, age, daily reading duration	Gender, education level, occupation, age, daily reading duration, reviewing experiences for scholarly journals
Impact of Response Time	Significant positive impact on total scores in control, Claude 3 Opous, and Gemini Advanced groups; no significant effect in ChatGPT 4.0 group	Significant positive impact on total scores in all groups
Demographic Influence	Minimal influence on total scores; daily reading duration has weak impact in Gemini Advanced group	Minimal influence on total scores; occupation has significant impact in control group only
Explanatory Power	Adjusted R^2 for response time ranges from 0.047 to 0.155	Adjusted R^2 for response time ranges from 0.114 to 0.228

Figure 1

Exemplified Experiment Procedures



note: For detailed experiment procedures, please refer to the Supplementary Material.

Figure 2

Mean and Full Marks for Information Loss in Non-Academic Texts

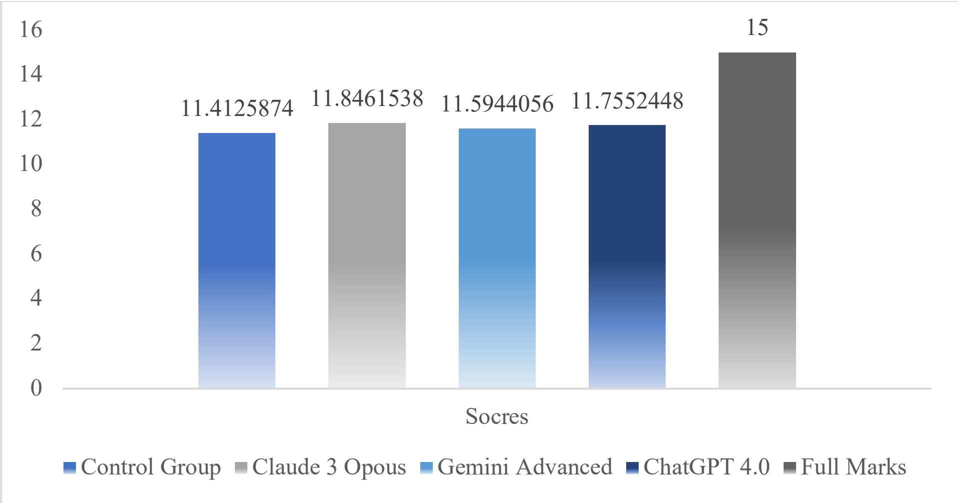


Figure 3

Control VS ChatGPT 4.0 and Gemini Advanced

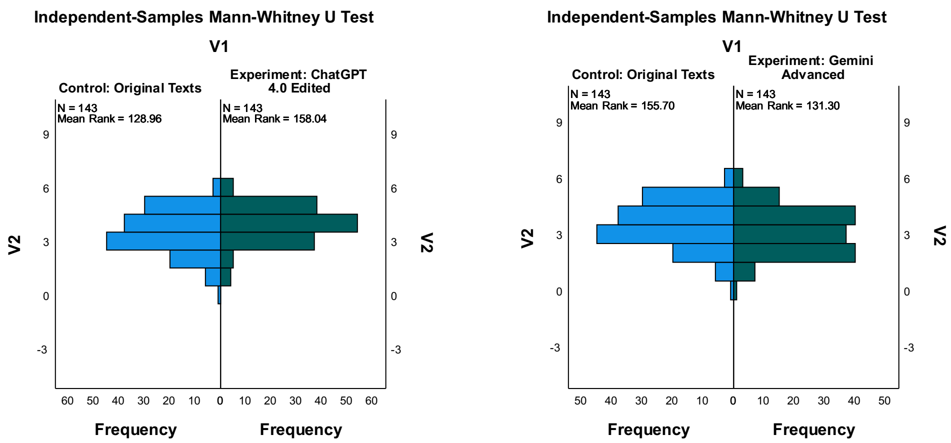
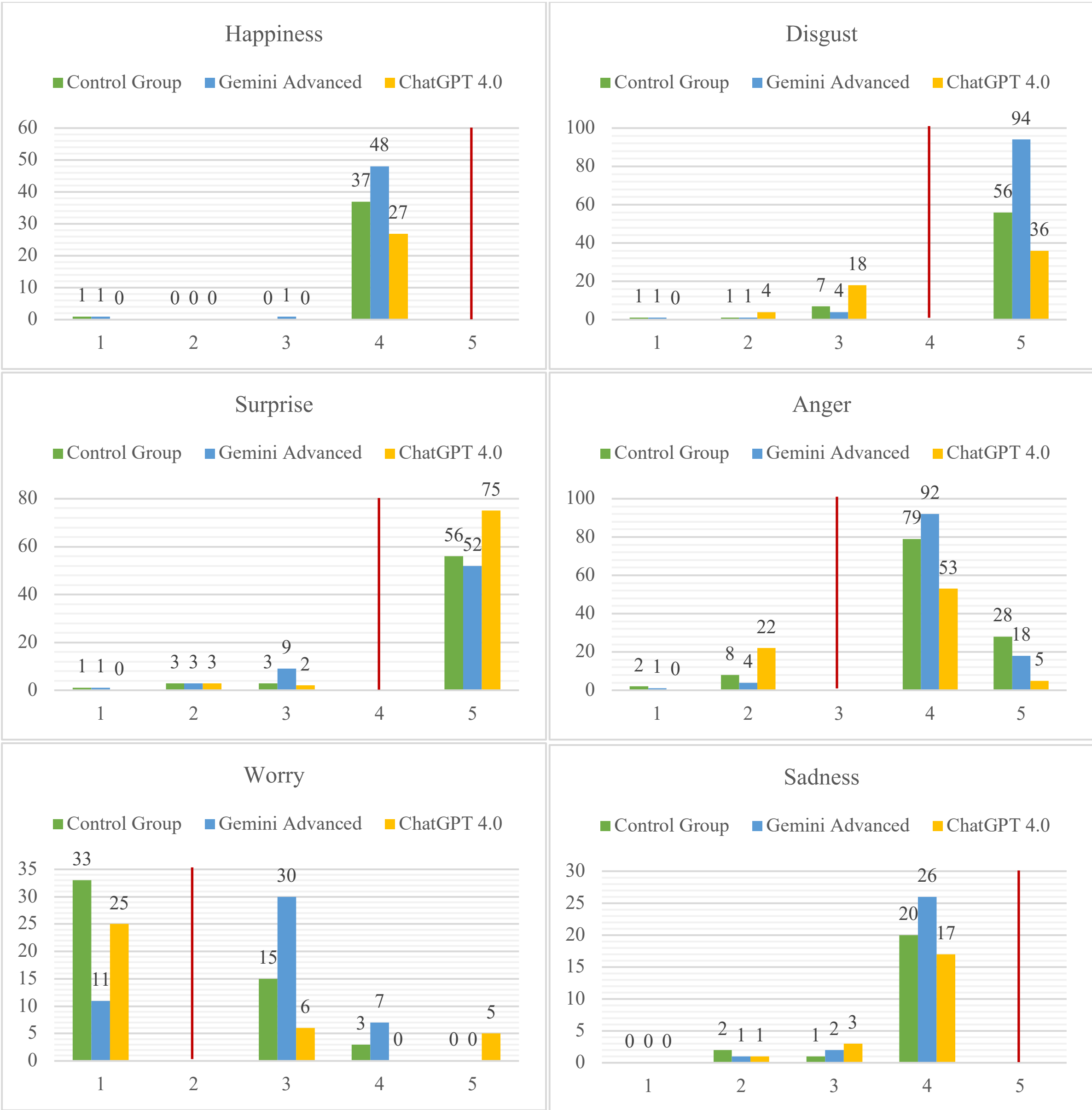


Figure 4

Distribution of Bias Error Answers in Non-Academic Texts (Red Lines Indicate Correct Answers)



Note: The correct answers indicated by the red lines were set by the authors themselves.

Figure 5

Mean and Full Marks for Information Loss in Academic Texts

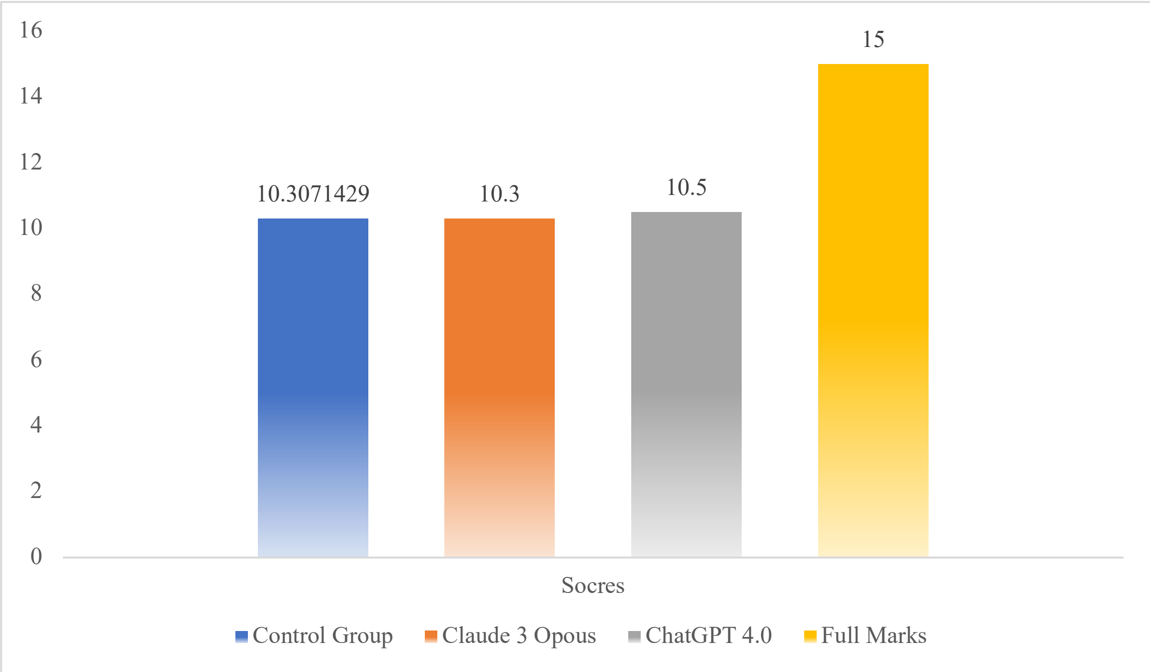


Figure 6

Mean and Total Scores for Bias in Academic Texts

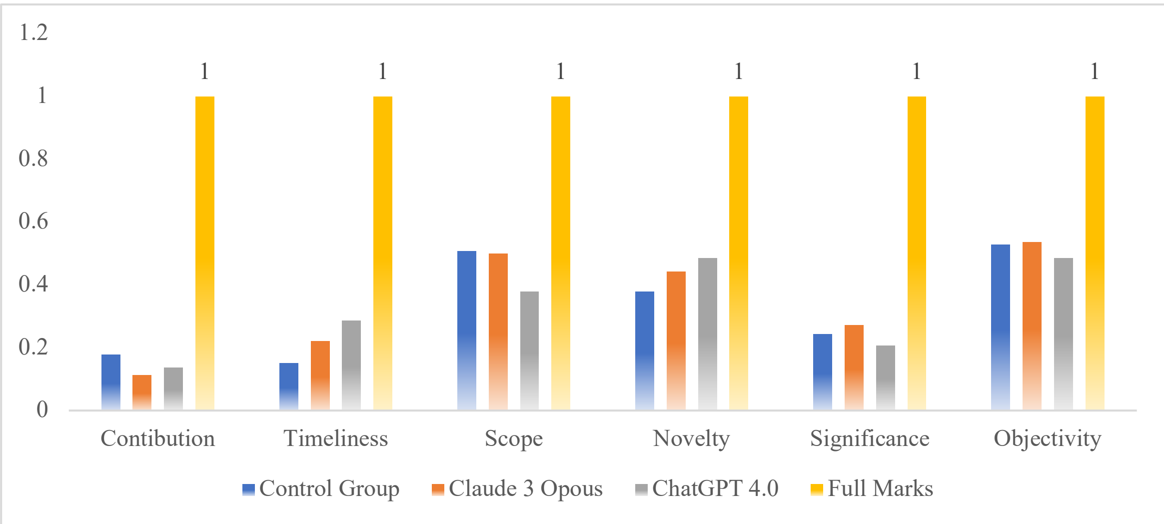
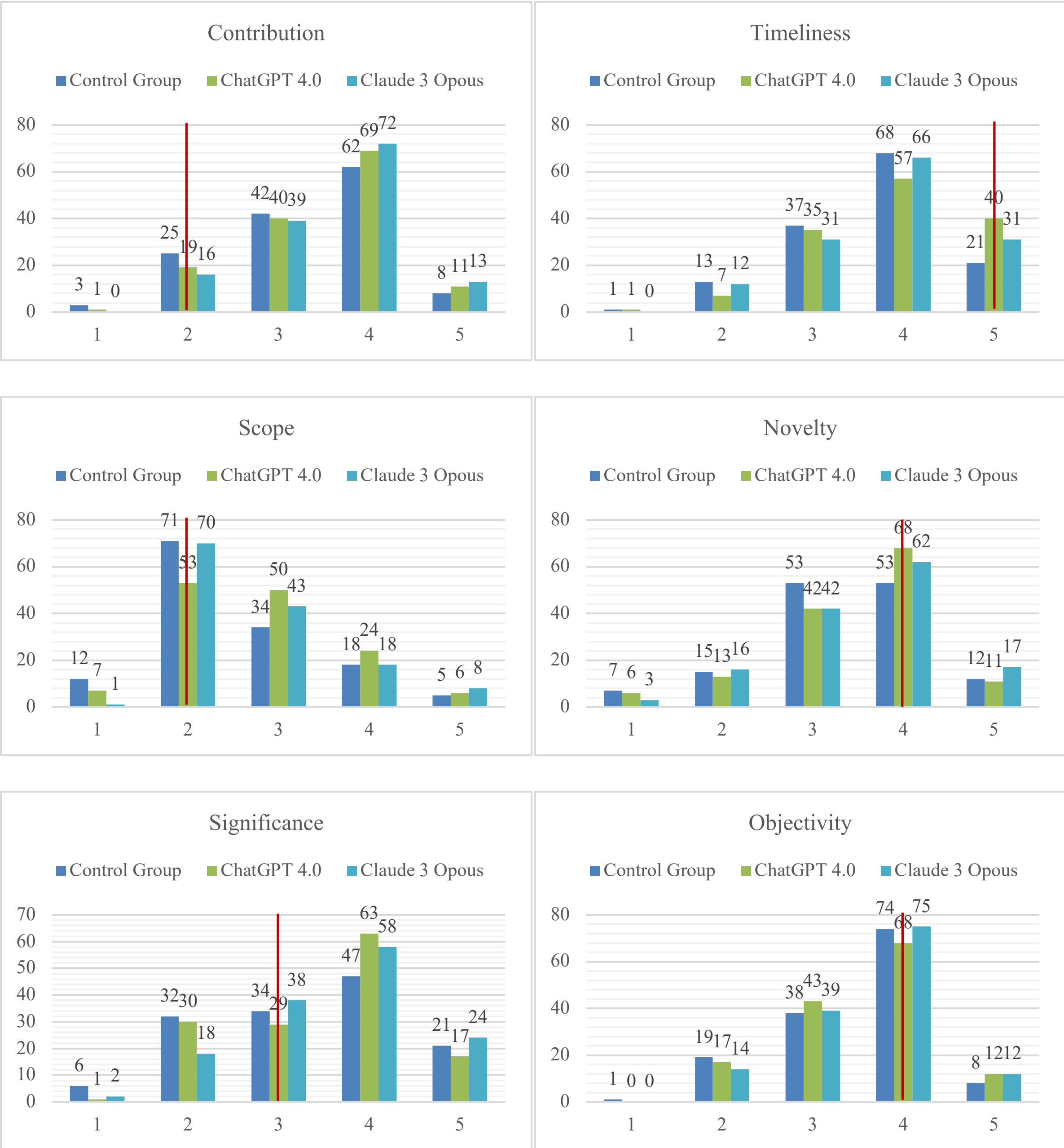


Figure 7

Distribution of Bias Error Answers in Academic Texts (Red Lines Indicate Correct Answers)



Note: The correct answers indicated by the red lines were set by the authors themselves.