

# 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 transforming the way messages are constructed, disseminated, and interpreted, with large language models (LLMs) like ChatGPT, Claude, and Gemini increasingly being integrated into various facets of writing, including academic and scientific contexts. While AI-MC has the potential to enhance writing efficiency, overcome language barriers, and foster diversity in text creation, it also raises concerns about bias, information loss, and the overall impact on communication accuracy and integrity.**

**Previous research has highlighted the complex role of AI in mediated communication, its influence on language use, interpersonal dynamics, and the ethical implications of AI integration. However, there is a notable gap in research specifically addressing AI-MC's role in non-academic and academic writing contexts, despite the widespread recognition and application of AI-MC in these domains.**

**Here, we present a dual-study approach to investigate the impact of AI-MC, specifically through LLMs, on positivity bias and information loss in non-academic and academic writing contexts. Our findings reveal that LLMs exhibit varied effects on bias perception, with ChatGPT 4.0 significantly reducing perceived bias in non-academic texts, while Claude 3 Opus and Gemini Advanced show no significant impact or slight enhancement of bias, respectively. Surprisingly, ChatGPT demonstrated the ability to convey emotional intensity more accurately than the original authors. In terms of information loss, no significant differences were found between original and AI-refined texts across both studies.**

**These results contribute to the ongoing discourse on the ethical, cultural, and technological considerations of AI-MC in scholarly communication. They provide empirical support for the policies of mainstream publishers permitting the use of AI for language polishing in academic articles. However, the study also highlights the need for further research to address limitations such as the exclusive focus on Chinese texts and participants, and to explore the implications across different languages and cultural contexts.**

**As AI continues to evolve and integrate into various aspects of communication, understanding its nuanced effects on bias and information loss will be crucial for harnessing its potential while mitigating unintended consequences. This study lays the groundwork for future research to delve deeper into the complex interplay between language, technology, and culture in shaping text comprehension and perception in the era of AI-mediated communication.**

## Introduction

In an era where the digital landscape is constantly evolving, the fusion of artificial intelligence (AI) with communication processes has given rise to a novel paradigm known as Artificial Intelligence Mediated Communication (AI-MC). This emergent field stands at the nexus of technological advancement and human discourse, transforming the ways in which messages are constructed, disseminated, and interpreted. The significance of AI-MC extends beyond mere technological innovation; it heralds a profound shift in the dynamics of interpersonal interactions and the fabric of communicative practices. As AI technologies, particularly large language models (LLMs) like ChatGPT, Claude, and Gemini, become increasingly integrated into various facets of writing—including academic and scientific writing—the implications of such integration warrant meticulous scrutiny.

The literature on AI-MC, notably contributions from Hancock et al. (2020), Hohenstein & Jung (2018), and subsequent studies, underscores the intricate role of AI in enhancing, altering, or generating messages to achieve specific communicative objectives. These studies collectively highlight the depth of AI's integration into communication and its dual impact on efficiency and the reshaping of linguistic norms and social dynamics. Moreover, the exploration of AI-MC's influence on human cognition and interpersonal dynamics points to its capacity to both enrich and complicate human interactions, necessitating a nuanced understanding of its ethical, cultural, and policy implications.

However, despite the expansive discourse on AI-MC's broader implications, there exists a notable gap in research specifically addressing its role in the realm of non-academic and academic/scientific writing. This omission is peculiar, given the widespread recognition and application of AI-MC in these domains, even amidst ethical dilemmas concerning authenticity and academic integrity. The potential of AI to transform scholarly communication—by enhancing writing efficiency, overcoming language barriers, and fostering diversity in text creation—brings to light ethical concerns, accuracy doubts, and plagiarism risks. These concerns underscore the need for a cautious yet open approach to the integration of AI in scholarly endeavors.

This paper seeks to bridge this gap by positing that the employment of LLMs for tasks such as refining, rewriting, or directly composing articles or academic papers should be recognized as instances of AI-MC. It argues that utilizing LLMs for writing assistance not only epitomizes an AI-mediated stage in the communication process (writing to reading) between humans but also engages with the core issues of concern within AI-MC research, such as technology design, effectiveness, and accompanying ethical and societal impacts.

Given the transformative potential of AI-MC in academic settings, this introduction sets the stage for a detailed examination of the role of LLMs like ChatGPT, Claude, and Gemini in scholarly communication. It raises critical research questions regarding the presence of positivity bias in LLM-generated texts and the challenge of information loss in text-based communication. These research questions aim to elucidate the impact of advanced AI technologies on writing and academic writing, thereby contributing to the ongoing discourse on 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 challenges 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; Babel, 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 literature 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, exhibit a significant bias 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 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

### *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

##### 1. Step 1: Content Creation

- Part 1 involved six participants 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.

##### 2. 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.

## ***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**

1. Step 1: Content Creation
  - Part 1 involved six authors of published academic papers in Chinese, spanning various fields, selecting excerpts from their works and rating them on six academic aspects using a 5-point scale.
  - Part 2 involved three authors of published academic papers in Chinese, from different fields, extracting sections (Introduction, Literature Review, and Conclusion) from their works and collaboratively creating five multiple-choice questions for each section.
2. 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.
3. Step 3: AI Enhancement

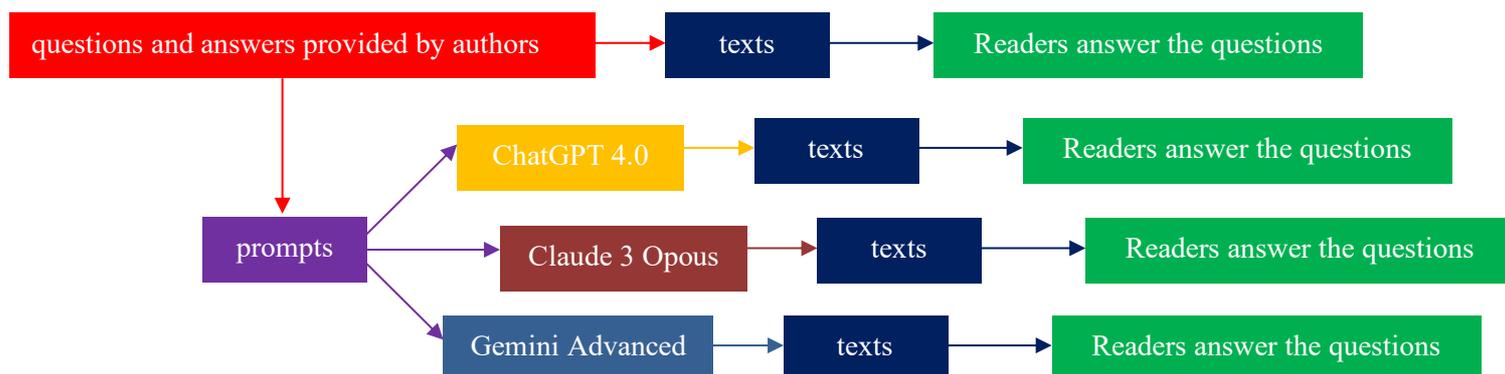
The same with Study 1 but Gemini Advanced was excluded due to its inability to interpret the required instructions.

### **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.

**Figure 1. Exemplified Experiment Procedures**

\*For detailed experiment procedures, please refer to the Supplementary Information.

### 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.

**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.

### Data Analysis

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

### 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**

The AI modifications were made using publicly available versions of ChatGPT 4.0, Claude 3 Opus, and Gemini Advanced, without any custom code.

## **Results**

The results are separated as Study 1 and Study 2.

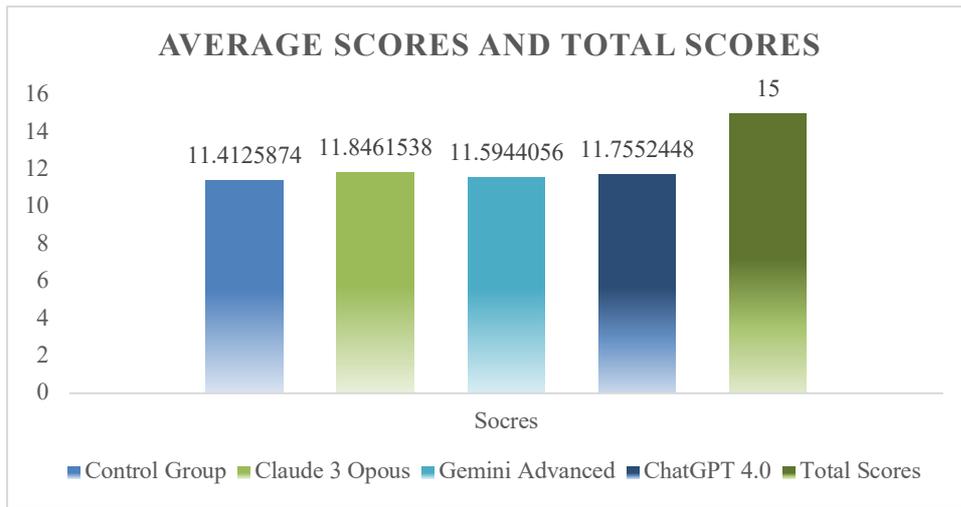
### ***Study 1***

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 Opus, 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.

## **Figure 2. Average and Total Scores for Information Loss in Non-Academic Texts**

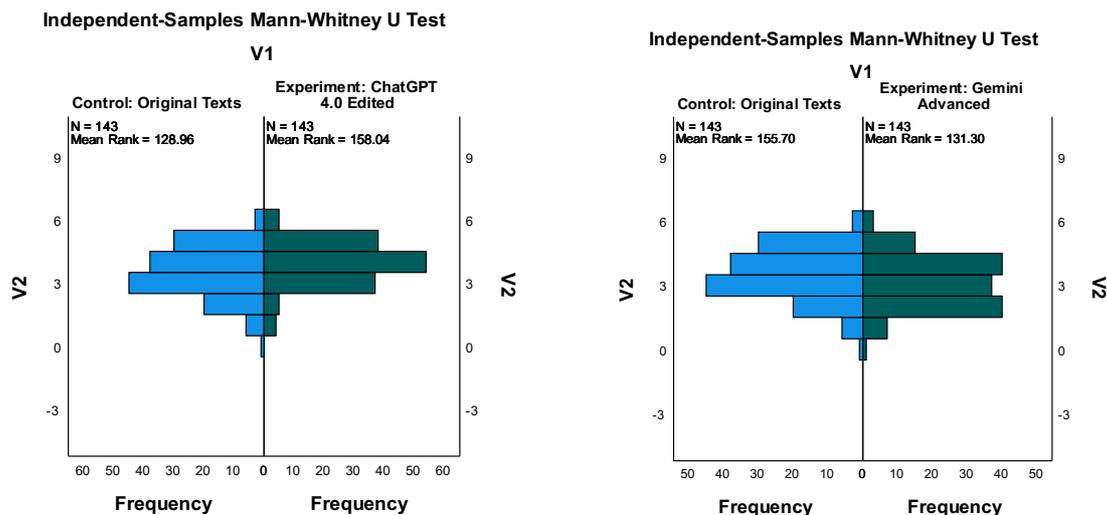


**Bias Perception**

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.

**Figure 3. Control VS ChatGPT 4.0 and Gemini Advanced**



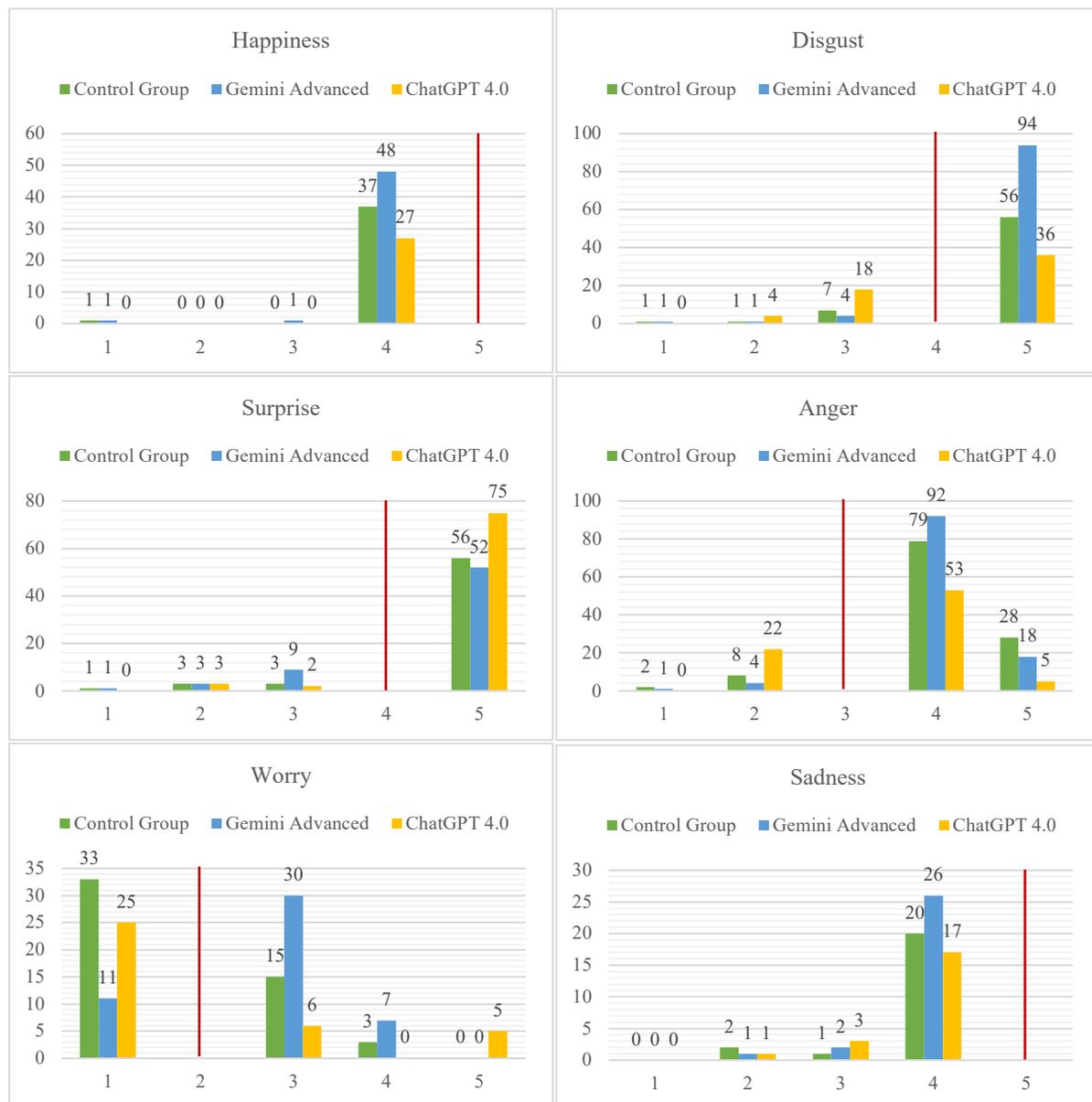
**Emotional Bias Influence**

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.
- 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.

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.

**Figure 4. Distribution of Bias Error Answers in Non-Academic Texts (Red Lines Indicate Correct Answers)**



**Demographics, Responding Time and Reading Habbits**

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.

## ***Study 2***

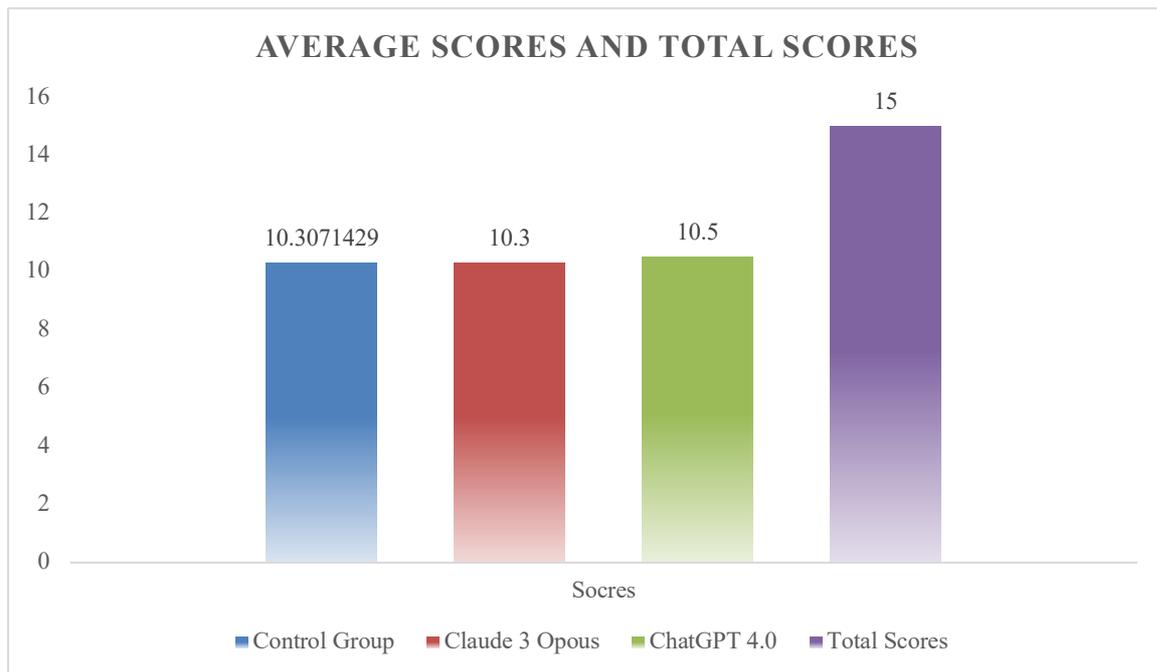
Study 2 ( $n=420$ ) explored the influence of AI-MC on bias perception and information loss within academic texts, focusing specifically on the text refinement effects of LLMs: ChatGPT 4.0 and Claude 3 Opus. Given that Gemini Advanced was unable to interpret the prompts, it was not included as part of 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 Opus, 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 Opus Edited Texts:** Similarly, the comparison between control texts and those edited by Claude 3 Opus demonstrated no significant difference in information loss, with a significance level of .573.

**Figure 5. Average and Total Scores for Information Loss in Academic Texts**



### 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.

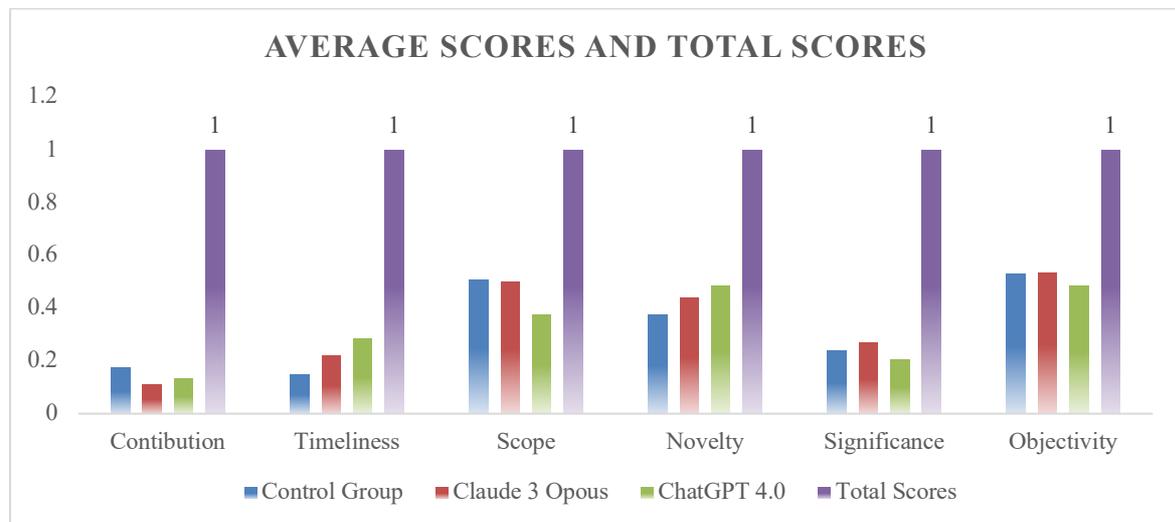
The distribution of bias error answers for each aspect provides additional insights, with the correct answer level indicated by red lines. In the case of the contribution aspect (correct answer level 2), the majority of responses across all three groups fall within levels 3 and 4, suggesting the presence 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.

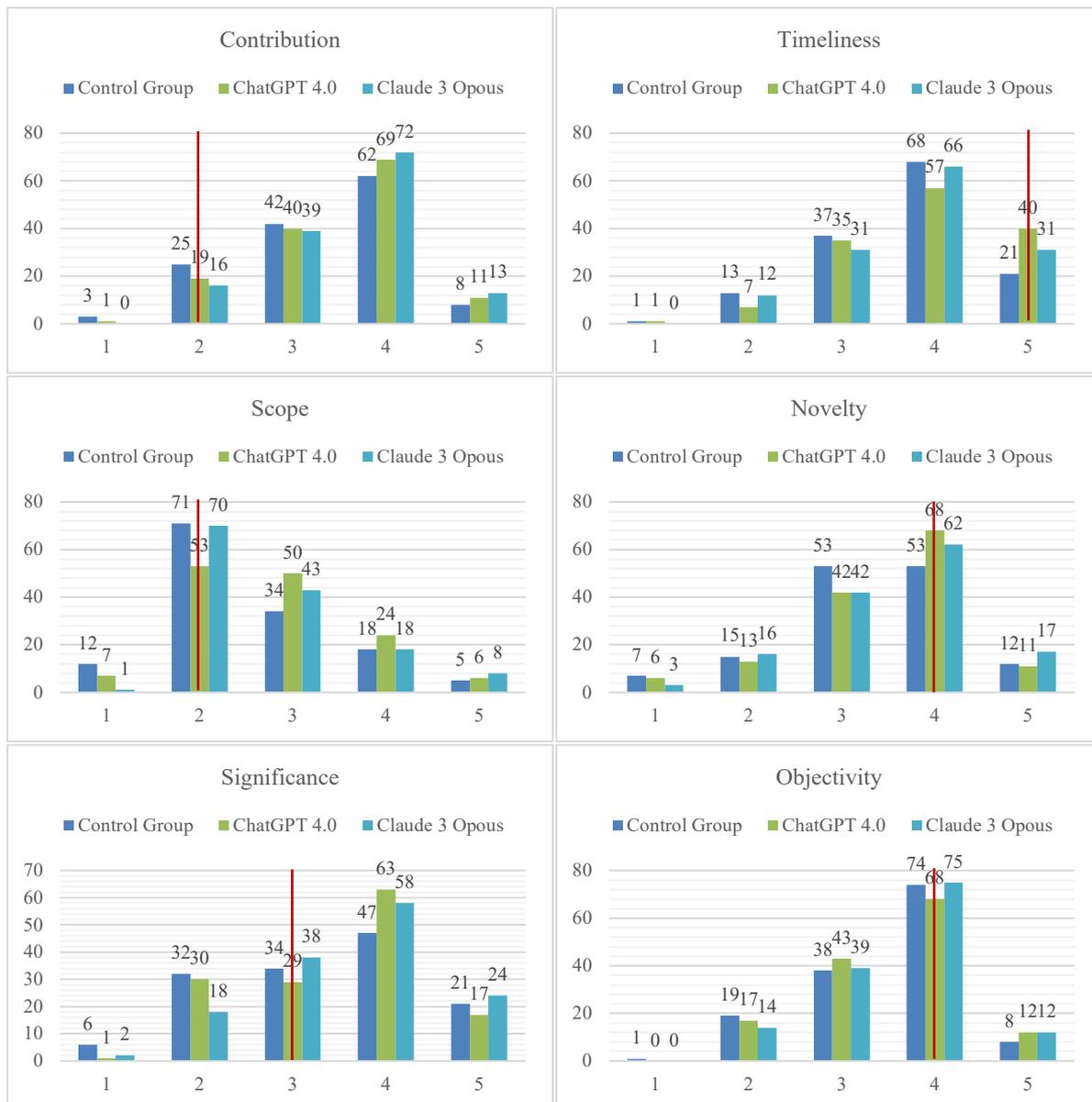
For novelty (correct answer level 4) and significance (correct answer level 3), the distribution of responses is more evenly spread across levels 2 to 4, with a slight positive bias observed in the AI-edited groups. Lastly, the objectivity aspect (correct answer level 4) demonstrates a relatively accurate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

**Figure 6. Average and Total Scores for Bias in Academic Texts**



**Figure 7. Distribution of Bias Error Answers in Academic Texts (Red Lines Indicate Correct Answers)**



### Demographics, Responding Time and Reading Habbits

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. Total scores (obtained) represents the accuracy of readers' 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 Opus, 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 contributes to the existing body of knowledge on text-based communication, particularly in the context of bias and information loss, through several novel approaches and findings.

### Methodological Innovation

A key methodological contribution of this work lies in the approach to studying bias and information loss in text-based communication. By objectively comparing readers' and authors' perspectives, this study establishes a framework for analyzing bias and information loss in text-based communication, which can be used as a tool for future research. Furthermore, this approach can be employed to evaluate the performance of AI systems in the context of communication.

### Empirical Contributions

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, future research should explicitly indicate the AI tools they use. Notably, the study not only investigates positivity bias but also examines negativity bias, providing a more comprehensive understanding 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.

### **Impact of LLMs on Academic and Non-Academic Texts**

This paper confirms that LLMs do not significantly influence either bias or information loss in academic texts. In the context of non-academic texts, the study finds that LLMs do not have a significant impact on information loss.

These findings provide empirical support for the policies of mainstream publishers like Nature, Science, Sage, and Elsevier, which permit the use of AI for language polishing 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 could explore the implications for English academic texts.

In summary, this paper not only underscores the nuanced role of LLMs in enhancing text-based communication by potentially reducing bias but also highlights the need for authorial diligence in employing AI for text editing. The methodological and theoretical contributions of this work provide a foundation for future research on the impact of AI on communication processes. As the integration of AI into communication continues to evolve, understanding its implications across different languages and cultural contexts will be crucial for harnessing its full potential while mitigating unintended consequences.

## References

1. AlAfnan, M. A., Dishari, S., Jovic, M., & Lomidze, K. (2023). Chatgpt as an educational tool: Opportunities, challenges, and recommendations for communication, business writing, and composition courses. *Journal of Artificial Intelligence and Technology*, 3(2), 60-68.
2. Aune, T., Juul, E., Beidel, et al. (2021). Mitigating adolescent social anxiety symptoms: The effects of social support and social self-efficacy in findings from the young-HUNT 3 study. *European Child & Adolescent Psychiatry*, 30, 441-449.
3. Balel, Y. (2023). The Role of Artificial Intelligence in Academic Paper Writing and Its Potential as a Co-Author: Letter to the Editor. *European Journal of Therapeutics*, 29(4), 984-985.
4. Bolin, J. H., & Hayes, A. F. (2014). Introduction to mediation, moderation, and conditional process analysis: A regression-based approach. *Journal of Educational Measurement*, 51(3), 335-337. <https://doi.org/10.1111/JEDM.12050>.
5. Cai, S. Q. (1992). A comparative study on physical education curricula and extracurricular physical activities in Chinese and Japanese universities [中日高校体育课程、课余体育活动的比较研究]. *Sichuan Sports Science [四川体育科学]*, (01), 54-57+53. <https://doi.org/10.13932/j.cnki.sctyx.1992.01.014>.
6. Cao, T., Liu, Z., Zeng, J. M., & Wang, J. (2012). Pathways and insights into the professionalization of adapted physical education teachers in the United States [美国适应体育教师专业化的路径及启示]. *Chinese Journal of Special Education [中国特殊教育]*, (07), 30-35.
7. Chang, J., & Cui, C. Y. (2023). Urban agglomeration expansion and county economic development: Empirical evidence from the Wuhan urban circle [城市圈扩容与县域经济发展——基于武汉城市圈的实证]. *Statistics and Decision [统计与决策]*, (7), 133-137.
8. Chen, J. J., & Ren, Y. J. (2021). The impact of parenting style on the academic achievement of left-behind children: The mediating role of future orientation [父母教养方式对留守儿童学业成就的影响: 未来取向的中介作用]. *Chinese Journal of Health Psychology [中国健康心理学杂志]*, 29(5), 721-726.
9. Chen, Q. H. (2005). Theory and practice of competence-based physical education talent training [能力本位体育人才培养理论与实践]. *Bulletin of Sport Science & Technology [体育科技文献通报]*, (07), 7-8.
10. Chen, T.-J. (2023). ChatGPT and other artificial intelligence applications speed up scientific writing. *Journal of Chinese Medical Association*, 86(4), 351-353. <https://doi.org/10.1097/JCMA.0000000000000900>
11. Chua, T. H. H., & Chang, L. (2016). Follow me and like my beautiful selfies: Singapore teenage girls' engagement in self-presentation and peer comparison on social media. *Computers in human behavior*, 55, 190-197.
12. Cingel, D. P., Carter, M. C., & Krause, H. V. (2022). Social media and self-esteem. *Current Opinion in Psychology*, 45, 101304.
13. Cohen, S., & Wils, T. A. (1985). Stress, social support, and the buffering hypothesis. *Psychological Bulletin*, 98(2), 310-357.
14. Cui, L. J., & Xiao, Y. M. (2022). Improving the social support system based on the rural revitalization strategy: Strategies to promote social adaptation of left-behind children [依托乡村振兴战略改善社会支持系统: 留守儿童社会适应促进对策]. *Journal of Soochow University (Educational Science Edition) [苏州大学学报(教育科学版)]*, 10(1), 20-30.
15. Diamond, N. (2024). AI Does Not Alter Perceptions of Text Messages. arXiv:2402.01726v2.
16. Ding, Z. X. (2018). On socioeconomic status, lifestyle, and health inequalities [论社会经济地位、生活方式与健康不平等]. *Modern Business [现代商业]*, (35), 186-187. <https://doi.org/10.3969/j.issn.1673-5889.2018.35.095>.
17. Dwivedi, Y. K., Kshetri, N., Hughes, L., Slade, E. L., Jeyaraj, A., Kar, A. K., ... & Wright, R. (2023). "So what if ChatGPT wrote it?" Multidisciplinary perspectives on opportunities,

- challenges and implications of generative conversational AI for research, practice and policy. *International Journal of Information Management*, 71, 102642.
18. Elsevier. (n.d.). The use of generative AI and AI-assisted technologies in writing for Elsevier. Retrieved from <https://www.elsevier.com/about/policies-and-standards/the-use-of-generative-ai-and-ai-assisted-technologies-in-writing-for-elsevier>
  19. Fales, J. L., Schmaling, K. B., & Culbertson, M. A. (2021). Acute pain sensitivity in individuals with borderline personality disorder: A systematic review and meta-analysis. *Clinical Psychology: Science and Practice*, 28(4), 341.
  20. Fan, Z. Y., & Wu, Y. (2020). Parent-child relationship and loneliness, depression among rural left-behind children: The mediating and moderating role of gratitude [亲子关系与农村留守儿童孤独感, 抑郁: 感恩的中介与调节作用]. *Psychological Development and Education [心理发展与教育]*, 36(6), 734-742.
  21. Fergus, S., & Zimmerman, M. A. (2005). Adolescent resilience: A framework for understanding healthy development in the face of risk. *Annual Review of Public Health*, 26, 399-419.
  22. Fitria, T. N. (2023, March). Artificial intelligence (AI) technology in OpenAI ChatGPT application: A review of ChatGPT in writing English essay. In *ELT Forum: Journal of English Language Teaching* (Vol. 12, No. 1, pp. 44-58).
  23. Fleary, S. A., Joseph, P., & Pappagianopoulos, J. E. (2018). Adolescent health literacy and health behaviors: A systematic review. *Journal of Adolescence*, 62, 116-127. <https://doi.org/10.1016/j.adolescence.2017.11.010>.
  24. Floridi, L. (2016). *The Fourth Revolution: How Artificial Intelligence is Reshaping Human Reality* [第四次革命: 人工智能如何重塑人类现实] (W. W. G., Trans.). Hangzhou: Zhejiang People's Publishing House [杭州: 浙江人民出版社].
  25. Floridi, L. (2016). 第四次革命: 人工智能如何重塑人类现实 [The Fourth Revolution: How Artificial Intelligence is Reshaping Human Reality] (W. W. G., Trans.). 杭州: 浙江人民出版社 [Hangzhou: Zhejiang People's Publishing House].
  26. Gan, Y. Q. (2011). The two-stage sequential model of future-oriented coping and its time perspective mechanism [未来取向应对的双阶段序列模型及其时间透视机制]. *Advances in Psychological Science [心理科学进展]*, 19(11), 1583-1587.
  27. Gibbs, R. (2001). Authorial Intentions in Text Understanding. *Discourse Processes*, 32(73-80).
  28. Glikson, E., & Asscher, O. (2023). AI-mediated apology in a multilingual work context: Implications for perceived authenticity and willingness to forgive. *Computers in Human Behavior*, 140, 107592.
  29. Goldenthal, E., Park, J., Liu, S. X., Mieczkowski, H., & Hancock, J. T. (2021). Not all AI are equal: Exploring the accessibility of AI-mediated communication technology. *Computers in Human Behavior*, 125, 106975.
  30. Grossberg, A., & Rice, T. (2023). Depression and suicidal behavior in adolescents. *Medical Clinics of North America*, 107(1), 169-182. <https://doi.org/10.1016/j.mcna.2022.04.005>.
  31. Guo, W., Lu, J. Y., & Liu, L. P. (2022). Healthy China in the era of mobility: Socioeconomic status, health literacy, and health outcomes [流动时代的健康中国: 社会经济地位、健康素养与健康结果]. *Journal of Population [人口学刊]*, 44(2), 1-18. <https://doi.org/10.16405/j.cnki.1004-129X.2022.02.001>.
  32. H. Holden Thorp, ChatGPT is fun, but not an author. *Science* 379,313-313(2023).
  33. Han, C. L. (2006). A theoretical study on the integration of physical education teacher training and education [体育教师培养培训一体化理论研究]. *Bulletin of Sport Science & Technology [体育科技文献通报]*, (02), 36-37.
  34. Hancock, J. T., Naaman, M., & Levy, K. (2020). AI-mediated communication: Definition, research agenda, and ethical considerations. *Journal of Computer-Mediated Communication*, 25(1), 89-100.
  35. Hao, Y., Huang, G. P., & Qiao, H. F. (2023). Upward social comparison on social networks and nonsuicidal self-injury among high school students: The three-way moderating mediating

- effect [社交网络上行社会比较与高中生非自杀性自伤:三阶调节中介效应]. *Chinese Journal of Clinical Psychology* [中国临床心理学杂志], 31(5), 1085-1091. <https://doi.org/10.16128/j.cnki.1005-3611.2023.05.012>
36. Herbold, S., Hautli-Janisz, A., Heuer, U., Kikteva, Z., & Trautsch, A. (2023). A large-scale comparison of human-written versus ChatGPT-generated essays. *Scientific Reports*, 13(18617).
  37. Hohenstein, J., & Jung, M. (2018, April). AI-supported messaging: An investigation of human-human text conversation with AI support. In *Extended abstracts of the 2018 CHI conference on human factors in computing systems* (pp. 1-6).
  38. Hong, Y. B., & Hua, J. (2020). Socioeconomic status differences in the intergenerational transmission model of health behaviors: An empirical study based on CHNS2015 [健康行为代际传递模式的社会经济地位差异 ——基于 CHNS2015 的实证研究]. *Journal of Huazhong University of Science and Technology (Social Science Edition)* [华中科技大学学报(社会科学版)], 34(6), 39-48. <https://doi.org/10.19648/j.cnki.jhustss1980.2020.06.05>.
  39. Hooley, J. M., & Franklin, J. C. (2018). Why do people hurt themselves? A new conceptual model of nonsuicidal self-injury. *Clinical psychological science*, 6(3), 428-451.
  40. Hooley, J. M., & St. Germain, S. A. (2014). Nonsuicidal self-injury, pain, and self-criticism: Does changing self-worth change pain endurance in people who engage in self-injury?. *Clinical Psychological Science*, 2(3), 297-305.
  41. Hooley, J. M., Fox, K. R., & Boccagno, C. (2020). Nonsuicidal self-injury: diagnostic challenges and current perspectives. *Neuropsychiatric disease and treatment*, 101-112.
  42. Horváth, M. (2015). Authorial intention and global coherence in fictional text comprehension: A cognitive approach. *Semiotica*, 2015(39-51).
  43. Hu, Y. L. (2019). *A Strong Program in Media History: Philosophical Interpretations of Media Ecology* [媒介史强纲领: 媒介环境学的哲学解读]. Beijing: The Commercial Press [北京: 商务印书馆].
  44. Huang, A. F., Wu, H., & Gu, Y. Y. (2005). Perspectives on physical education teacher education issues under the new curriculum reform [新课改下的体育教师教育问题透视]. *Journal of Beijing Sport University* [北京体育大学学报], (02), 222-224. <https://doi.org/10.19582/j.cnki.11-3785/g8.2005.02.029>.
  45. Huang, H., Chen, J., & Wang, Q. F. (2022). The relationship between social support and social adaptation of rural left-behind children: The mediating role of self-esteem [农村留守儿童社会支持与社会适应的关系: 自尊的中介作用]. *Chinese Journal of Health Psychology* [中国健康心理学杂志], 30(5), 713-717.
  46. Hyun, C. P. M. H. (2022). Moderating effect of psychological flexibility in the relationship between neuroticism and self-harm. *Korean Journal of Clinical Psychology*, 41(1), 24-31.
  47. Jin, C. C., Zou, H., & Li, X. W. (2011). Adolescents' social adaptation: Protective and risk factors and their cumulative effects [青少年的社会适应: 保护性和危险性因素及其累积效应]. *Journal of Beijing Normal University (Social Sciences)* [北京师范大学学报(社会科学版)], (1), 12-20.
  48. Jordan, L. P., & Graham, E. (2012). Resilience and well-being among children of migrant parents in South-East Asia. *Child Development*, 83(5), 1672-1688.
  49. Kacena, M. A., Plotkin, L. I., & Fehrenbacher, J. C. (2024). The Use of Artificial Intelligence in Writing Scientific Review Articles. *Current Osteoporosis Reports*, 22(115-121).
  50. Kang, C., Zheng, Y., Yang, L., et al. (2021). Prevalence, risk factors and clinical correlates of suicidal ideation in adolescent patients with depression in a large sample of Chinese. *Journal of Affective Disorders*, 290, 272-278. <https://doi.org/10.1016/j.jad.2021.04.073>.
  51. Katz, A., & Lee, C. J. (1993). The Role of Authorial Intent in Determining Verbal Irony and Metaphor. *Metaphor and Symbol*, 8(257-279).
  52. Kirtley, O. J., O'Carroll, R. E., & O'Connor, R. C. (2016). Pain and self-harm: A systematic review. *Journal of affective disorders*, 203, 347-363.

53. Lai, X. R. (2018). Adolescent health literacy: Theory, research, and school practice [青少年健康素养: 理论、研究与学校实务]. Taipei: National Taiwan Normal University Press [台北: 国立台湾师范大学出版中心].
54. Lear, M. K., Wilkowsky, B. M., & Pepper, C. M. (2019). A daily diary investigation of the defective self model among college students with recent self-injury. *Behavior therapy*, 50(5), 1002-1012.
55. Lew, B., Chistopolskaya, K., Liu, Y., et al. (2020). Testing the strain theory of suicide - the moderating role of social support. *Journal of Contingencies and Crisis Management*, 41(2), 82-88.
56. Li, J., Chu, Y., & Xu, J. (2023). Impression transference from AI to human: The impact of AI's fairness on interpersonal perception in AI-Mediated communication. *International Journal of Human-Computer Studies*, 179, 103119.
57. Ling, H., Zhang, J. R., & Zhong, N., et al. (2012). The relationship between loneliness, friendship quality, and social status among left-behind children [留守儿童的孤独感与友谊质量及社交地位的关系]. *Chinese Journal of Clinical Psychology* [中国临床心理学杂志], 20(6), 826-830.
58. Liu, X., Fan, X. H., & Shen, J. L. (2007). The relationship between social support and problem behavior among junior high school left-behind children [初中留守儿童社会支持与问题行为的关系]. *Psychological Development and Education* [心理发展与教育], (3), 98-102.
59. Liu, X., Huang, X. T., & Bi, C. H. (2011). Development of the Adolescent Future Orientation Questionnaire [青少年未来取向问卷的编制]. *Journal of Southwest University (Social Science Edition)* [西南大学学报(社会科学版)], 37(6), 7-12.
60. Liu, Z. (1993). A comparison of teacher guidance methods in physical education teaching in Chinese and American primary and secondary schools [中美两国中小学体育教学中教师指导方式之比较]. *Sport Science* [体育科学], (02), 21-23+93.
61. Liu, Z. F. (2013). A study on social support and loneliness among rural primary school left-behind children [农村小学留守儿童社会支持与孤独感研究]. *Education Review* [教育评论], (2), 33-35.
62. Luo, Z., & Qi, B. C. (2021). The effect of industrial transfer and upgrading and the synergistic development of banks due to environmental regulation: Evidence from water pollution control in the Yangtze River Basin [环境规制的产业转移升级效应与银行协同发展效应——来自长江流域水污染治理的证据]. *Economic Research Journal* [经济研究], 56(2).
63. McCabe, K. M., & Barnett, D. (2000). The relation between familial factors and the future orientation of urban, African American sixth graders. *Journal of Child and Family Studies*, 9(4), 491-508.
64. McLuhan, M. (2011). *Understanding Media: The Extensions of Man* [理解媒介: 论人的延伸] (H. D. K., Trans.). Nanjing: Yilin Press [南京: 译林出版社].
65. Miao, H. L., Guo, C., & Wang, T. Y., et al. (2021). Reliability and validity evaluation and application of the Social Adaptation Questionnaire for children and adolescents [儿童青少年社会适应问卷的信效度评价及应用]. *Journal of Southwest Normal University (Natural Science Edition)* [西南师范大学学报(自然科学版)], 46(10), 106-113.
66. Miao, J., Thongprayoon, C., Suppadungsuk, S., Garcia Valencia, O. A., Qureshi, F., & Cheungpasitporn, W. (2024). Ethical Dilemmas in Using AI for Academic Writing and an Example Framework for Peer Review in Nephrology Academia: A Narrative Review. *Clin. Pract.*, 14(1), 89-105.
67. Miglani, M., Chavan, B. S., & Gupta, N. (2021). Pain threshold and pain tolerance as a predictor of deliberate self-harm among adolescents and young adults. *Indian journal of psychiatry*, 63(2), 142-145.
68. Ministry of Education of the People's Republic of China. (2023). Seventeen departments including the Ministry of Education issued the Special Action Plan for Comprehensively Strengthening and Improving the Mental Health of Students in the New Era (2023 - 2025)

- [教育部等十七部门印发《全面加强和改进新时代学生心理健康工作专项行动计划(2023—2025年)》]. *Moral Education in Primary and Secondary Schools [中小学德育]*, (5), 79.
69. Nature Portfolio. (n.d.). Artificial Intelligence (AI). Nature. Retrieved from <https://www.nature.com/nature-portfolio/editorial-policies/ai>
70. Pan, H. X. (2020). Deficiencies and Positive Reconstruction of Intelligent Information Recommendation Algorithms in the Smart Media Era [智媒时代智能信息推荐算法的缺陷及正向重构]. *Future Communication [未来传播]*, 27(5), 36-41.
71. Peng, W. Y., Deng, J. P., Liu, W. Q., et al. (2023). 青少年抑郁症住院患者自杀行为发生率及其相关风险因素分析 [Study on the incidence and related risk factors of suicidal behavior in adolescents with depression]. *中华精神科杂志 [Chin J Psychiatry]*, 57(1), 33-40. <https://doi.org/10.3760/cma.j.cn113661-20230818-00038>.
72. Peplau, L. A., & Perlman, D. (1983). *Loneliness: A source book of current theory, research, and therapy*. New York: Wiley.
73. Pickering, M. J., & Garrod, S. (2013). An integrated theory of language production and comprehension. *Behavioral and brain sciences*, 36(4), 329-347.
74. Pisanty, V. (2015). From the model reader to the limits of interpretation. *Semiotica*, 2015(37-61).
75. Prenas, R. S. (2001). Mothering from a distance: Emotions, gender, and intergenerational relations in Filipino transnational families. *Feminist Studies*, 27(2), 361-390.
76. Robbins, R., & Bryan, A. (2004). Relationships between future orientation, impulsive sensation seeking, and risk behavior among adjudicated adolescents. *Journal of Adolescent Research*, 19(4), 428-445.
77. Rosebury, B. (1997). Irrecoverable intentions and literary interpretation. *British Journal of Aesthetics*, 37(15-30).
78. Sage Publications. (n.d.). ChatGPT and Generative AI. Retrieved from <https://uk.sagepub.com/en-gb/asi/chatgpt-and-generative-ai>
79. Shao, M. L., & Zhang, Q. (2021). The impact of parental migration patterns on problem behaviors of rural left-behind children [父母迁移模式对农村留守儿童问题行为的影响]. *Chinese Journal of Child Health Care [中国儿童保健杂志]*, 29(1), 52-55.
80. Sun, X. F., Hu, H., Gao, Q., et al. (2007). An introduction to peer-driven sampling method [同伴推动抽样法的简介]. *Chinese Journal of Health Statistics [中国卫生统计]*, 24(6), 662, 664. <https://doi.org/10.3969/j.issn.1002-3674.2007.06.038>.
81. Tang, H. G. (1992). Exploration of educational internship implementation strategies for students at the Kiev Institute of Physical Education [基辅体育学院学生教育实习实施策略探溪]. *Journal of Wuhan Institute of Physical Education [武汉体育学院学报]*, (02), 26-30. <https://doi.org/10.15930/j.cnki.wtxb.1992.02.006>.
82. Thorp, H. H. (2023). ChatGPT is fun but not an author. *Science*, 379(6630), 313.
83. Thorp, H. H., & Vinson, V. (2023, November 16). Change to policy on the use of generative AI and large language models. *Science Blog*. Retrieved from <https://www.science.org/content/blog-post/change-policy-use-generative-ai-and-large-language-models>
84. Turecki, G., & Brent, D. A. (2016). Suicide and suicidal behaviour. *The Lancet*, 387(10024), 1227-1239. [https://doi.org/10.1016/S0140-6736\(15\)00234-2](https://doi.org/10.1016/S0140-6736(15)00234-2).
85. van der Venne, P., Balint, A., Drews, E., et al. (2021). Pain sensitivity and plasma beta-endorphin in adolescent non-suicidal self-injury. *Journal of Affective Disorders*, 278, 199-208.
86. Wamahiu, S. P., Mannathoko, C., & Ojoo, A. (2002). *Life Skills Education With A Focus On HIV/AIDS: Eastern And Southern Africa Region*. Unicef Eastern And Southern Africa Region.
87. Wang, F. Q. (2011). Does social mobility help to reduce health inequalities? [社会流动有助于降低健康不平等吗?]. *Sociological Studies [社会学研究]*, (2), 78-101.

88. Wang, F. Q. (2012). Socioeconomic status, lifestyle, and health inequalities [社会经济地位、生活方式与健康不平等]. *Society [社会]*, 32(2), 125-143.
89. Wang, F., Zhao, S. Y., & Chen, W. (2017). The relationship between parent-child harmony and loneliness among rural left-behind junior high school students: The mediating role of emotional regulation self-efficacy [农村留守初中生亲子亲和与孤独感的关系: 情绪调节自我效能感的中介作用]. *Chinese Journal of Special Education [中国特殊教育]*, (10), 76-80+87.
90. Wang, T. Y., Guo, C., Miao, H. L., et al. (2021). Social adaptation of left-behind children under the COVID-19 pandemic and its relationship with emotion regulation strategies [新冠肺炎疫情下留守儿童的社会适应及其与情绪调节策略的关系]. *Journal of Southwest University (Natural Science Edition) [西南大学学报(自然科学版)]*, 43(8), 1-9.
91. Wang, X. Y., & Shao, G. S. (2023). Continuation and reconstruction: Multiple perspectives on the ethics of artificial intelligence [延续和重构: 人工智能伦理研究的多重视角]. *Future Communication [未来传播]*, 30(1), 70-77.
92. Wen, L. G. (2019). *Media Ecology: Evolution of Thought and Multidimensional Perspectives [媒介环境学: 思想沿革与多维视野]* (H. D. K., Trans.). Beijing: Encyclopedia of China Publishing House [北京: 中国大百科全书出版社].
93. Wen, L. G. (2019). 媒介环境学: 思想沿革与多维视野 [Media Ecology: Evolution of Thought and Multidimensional Perspectives] (H. D. K., Trans.). 北京: 中国大百科全书出版社 [Beijing: Encyclopedia of China Publishing House].
94. Wen, Z. L., & Ye, B. J. (2014). Mediating effects analysis: Methods and model development [中介效应分析: 方法和模型发展]. *Advances in Psychological Science [心理科学进展]*, 22(5), 731-745. <https://doi.org/10.3724/SP.J.1042.2014.00731>.
95. World Health Organization. (2019). Suicide worldwide in 2019 [Data set]. <https://www.who.int/publications-detail-redirect/9789240026643>.
96. Xiao, Y. M., Yang, Y., & Feng, N. N., et al. (2022). The relationship between future orientation types and maladaptation in left-behind children: Based on a latent profile analysis [留守儿童未来取向类型与适应不良的关系: 基于潜在剖面分析]. *Journal of Southwest University (Natural Science Edition) [西南大学学报(自然科学版)]*, 44(8), 13-19.
97. Xie, C. Y., Yang, C., & Li, Y. Q., et al. (2023). The relationship between types of social support and specific areas of social adaptation of left-behind children: A multiple mediation model [社会支持类型与留守儿童具体领域社会适应的关系: 一个多重中介模型]. *Chinese Journal of Health Psychology [中国健康心理学杂志]*, 31(10), 1582-1588. <https://doi.org/10.13342/j.cnki.cjhp.2023.10.027>.
98. Yao, R. S., Guo, M. S., & Ye, H. S. (2018). The mechanism of social support on the social well-being of the elderly: The mediating role of hope and loneliness [社会支持对老年人社会幸福感的影响机制: 希望与孤独感的中介作用]. *Acta Psychologica Sinica [心理学报]*, 50(10), 1151-1158.
99. Yin, Z. H., Deng, S. Y., Wang, X. Z., & Ji, L. (2010). A comparative study on the new professional standards for physical education teachers at different levels in the United States NCATE [美国 NCATE 不同级别新体育教师专业标准的比较研究]. *Journal of Beijing Sport University [北京体育大学学报]*, 33(07), 95-98. <https://doi.org/10.19582/j.cnki.11-3785/g8.2010.07.027>.
100. Zhang, A. J., & Wang, F. (2021). The Political Security Risks of "Big Data Profiling" [“大数据杀熟”的政治安全风险]. *Future Communication [未来传播]*, 28(2), 46-51+124-125.
101. Zhang, G. L. (2017). The relationship between loneliness and social adaptation among rural left-behind children: The mediating role of gratitude [农村留守儿童孤独感与社会适应的关系: 感恩的中介作用]. *Education Research and Experiment [教育研究与实验]*, (3), 25-30.

102. Zhang, J., Zhao, G., Li, X., et al. (2009). Positive future orientation as a mediator between traumatic events and mental health among children affected by HIV/AIDS in rural China. *AIDS Care*, 21(12), 1508-1516.
103. Zhang, L. L., & Zhang, W. X. (2008). Personal planning in middle and late adolescence and its relationship with parent-child and peer communication [中晚期青少年的个人规划及其与亲子、朋友沟通的关系]. *Acta Psychologica Sinica* [心理学报], 40(5), 583-592.
104. Zhang, Q. H., Zhang, L., & Li, S. Z., et al. (2019). The impact of parent-child cohesion on loneliness and depression among rural left-behind children: A longitudinal study [亲子亲合对农村留守儿童孤独感与抑郁的影响: 一项追踪研究]. *Chinese Journal of Special Education* [中国特殊教育], 3(7), 69-75.
105. Zhang, Y. H., Li, G., Wang, J. C., et al. (2022). The current situation and frontier evolution of physical education teacher training research in China in the past two decades: A visualization analysis based on CiteSpace knowledge map [近二十年我国体育教师培养研究现状与前沿演进——基于 CiteSpace 知识图谱的可视化分析]. *Bulletin of Sport Science & Technology* [体育科技文献通报], 30(9), 143-146. <https://doi.org/10.19379/j.cnki.issn.1005-0256.2022.09.039>.
106. Zhang, Z., Cheng, B. H., Jiang, Z. Q., et al. (2024). Building a multidisciplinary and multi-agent collaboration model for monitoring and preventing the risk of depression and suicide in adolescents [构建青少年抑郁自杀风险监测与防治的多学科多主体协作模式]. *Chinese Journal of Psychiatry* [中华精神科杂志], 57(1), 12-17. <https://doi.org/10.3760/cma.j.cn113661-20231026-00157>.
107. Zhao, Y., Zhang, W., Abou-Elwafa, S. F., Shabala, S., & Xu, L. (2021). Understanding a mechanistic basis of ABA involvement in plant adaptation to soil flooding: The current standing. *Plants*, 10(10), 1982.
108. Zhao, Z. Y., & Li, W. D. (2023). The impact of family socioeconomic status on condom use among male college students engaging in male-to-male sexual behavior: The mediating effect of health literacy [家庭社会经济地位对男男性行为大学生安全套使用的影响: 健康素养的中介效应]. *Chinese Journal of AIDS & STDs* [中国艾滋病性病], 29(6), 668-671. <https://doi.org/10.13419/j.cnki.aids.2023.06.11>.
109. Zheng, L., Fang, K., & Wang, Y. Y. (2024). The relationship between inconsistent dual performance feedback and corporate ESG information disclosure quality [双重绩效反馈不一致与企业 ESG 信息披露质量的关系研究]. *Research and Development Management* [研究与发展管理], 36(1), 53-65. <https://doi.org/10.13581/j.cnki.rdm.20230692>.
110. Zou, H., Liu, Y., & Zhang, W. J., et al. (2015). Assessment of protective and risk factors for adolescents' social adaptation [青少年社会适应的保护性因素与危险性因素的评估]. *Psychological Development and Education* [心理发展与教育], 31(1), 29-36.