https://doi.org/10.51408/issi2025_084

Examining the Cognitive Gap Between Authors and Peer Reviewers on Academic Paper Novelty

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Abstract

Novelty is a crucial metric for assessing the quality of academic papers. Scholars strive to highlight the novel aspects of their work, particularly in the title, abstract, and introduction, where they often emphasize the novel contributions of their research. Peer review, serving as the gatekeeper of scientific rigor, rigorously evaluates the innovativeness of papers to ensure they meet the standards of scientific publication. However, there may be a cognitive gap between the self-promotion by authors and the evaluation of novelty by peer reviewers. To investigate whether such a gap exists, we analyzed 15,328 academic papers published in Nature Communications from 2016 to 2021, along with their peer review comments. We extracted promotional statements from the introduction of these papers and evaluative statements on novelty from the review comments, categorizing them into theoretical innovation, methodological innovation, and result innovation. The findings reveal that both reviewers and authors place greater emphasis on result innovation, with reviewers adopting a more comprehensive approach when evaluating novelty. By examining the impact of promotional intensity on reviewers' evaluations in relation to the paper's inherent novelty, we found that highly innovative papers benefit from using more promotional language, receiving more positive evaluations from reviewers. In contrast, excessive promotional language in less innovative papers leads to lower evaluations of their novelty. Based on these results, we suggest that highly innovative papers can enhance positive reviewer evaluations by moderately employing promotional language, while less innovative papers should exercise caution to avoid being perceived as overstating their contributions. Additionally, the study underscores the need for clearer review standards to help reviewers evaluate the innovativeness of papers more objectively, minimizing the influence of promotional language.

Introduction

In recent years, the number of academic papers has grown exponentially. To ensure that high-quality research is published promptly and accurately in appropriate journals or conferences, the pressure on peer reviewers, who serve as gatekeepers of scientific publishing, has intensified. However, peer review is not without its challenges, including inefficiencies and potential biases(Parker et al., 2018; Stelmakh et al., 2019; Wicherts, 2016). Novelty, as a critical component of academic paper quality, is a key criterion reviewers use to make recommendations for acceptance or rejection.

The ability to communicate novel ideas and research findings effectively is an indispensable part of academic research and is crucial across many scientific domains, such as grant applications, patent writing, and academic paper writing (Peng et al., 2024). Academic papers are the primary medium for disseminating research outcomes, enabling researchers to share their discoveries and insights. To accurately and efficiently convey the innovative aspects of their work, researchers often highlight their contributions in the title, abstract, and introduction of their papers. These promotional statements have been shown to correlate with the subsequent impact of the papers (Pearson, 2020; Wheeler et al., 2021).

Table 1. Examples of three promotion types.

Promotion Type	Author description	Reviewer Comments
Exaggeration	This groundbreaking study introduces a revolutionary method that will completely transform data privacy in machine learning.	The claim that this method will ‘revolutionize data privacy in machine learning’ appears overly ambitious. For instance, Smith et al. (2021) demonstrated that while advancements in data privacy are significant, they often come with trade-offs in model performance and complexity. I recommend that the authors provide a more balanced view that acknowledges these trade-offs and the context in which their method may be effective.
Insufficient promotion	This study presents a approach to enhance data privacy protection in machine learning. While the method has demonstrated some effectiveness on certain datasets, it has not yet undergone extensive empirical validation.	To avoid understatement, more information about the advantages of the research method, specific experimental results, and its potential impact should be included in the description.
Appropriate promotion	This study presents a novel approach that demonstrates notable improvements in data privacy within machine learning frameworks compared to existing methods. Our results indicate enhanced protection of sensitive information while maintaining model performance.	The authors successfully provide a balanced description of their contributions, clearly articulating the improvements over existing methods without relying on hyperbolic claims.

Note: The parts marked in red are the promotional language used by the author.

However, inappropriate promotion in academic papers can lead to adverse consequences. Some scholars, driven by utilitarian motives or insufficient research of prior studies, may exaggerate the novelty of their work. If the research findings are later proven to be less novel than claimed, not only can the authors' academic reputations suffer significant damage, but other researchers may also be misled, investing time and resources in misguided directions. This can hinder the progress of the entire field and stifle genuine innovation. Conversely, some scholars may insufficient promote or inaccurately describe the novelty of their research, leading to their findings being overlooked and limiting their dissemination within academia and related fields. To prevent such scenarios, peer reviewers, as gatekeepers of scientific quality, rigorously evaluate the merits of submitted papers. Inappropriate promotion can result in setbacks during the peer review process. As shown in Table 1, if exaggeration is detected, reviewers may point out the exaggerations in their comments, such as "*Smith et al. (2021) demonstrated that while advancements in data privacy are significant, they often come with trade-offs in model performance and complexity.*", and provide corresponding references as evidence for the authors to revise their papers. In severe cases, the paper may even be rejected for publication. For papers that insufficient promotion, reviewers may struggle to grasp the innovative aspects of the research, leading to the findings being undervalued. This can result in a lower overall evaluation of the paper's quality by reviewers, ultimately affecting its chances of publication.

Therefore, appropriate promotion is crucial for reviewers to make informed decisions regarding acceptance or rejection. Specifically, we address the following three questions:

Firstly, to investigate in greater detail how authors and reviewers evaluate the novelty of academic papers, we adopted the classification framework proposed by Leahey et al.(2023). This framework categorizes innovation in academic papers into theoretical innovation, methodological innovation, and result innovation. Correspondingly, we classify the evaluations of authors and reviewers into theoretical innovation evaluation, methodological innovation evaluation, and result innovation evaluation. Based on this, we propose RQ1:

RQ1: Which aspects of innovation do paper authors and reviewers prioritize more?

Based on RQ1, we can statistically analyze which aspects of innovation authors and reviewers emphasize more when promoting or evaluating the novelty of academic papers. Building on this, we aim to explore the cognitive differences between authors and reviewers regarding the perceived innovative contributions of papers.

Specifically, we seek to identify which innovative points, after being promoted by authors, are also endorsed by reviewers. This leads us to propose RQ2:

RQ2: What are the differences in focus between paper authors and peer reviewers regarding the innovation of a paper?

Both RQ1 and RQ2 investigate the innovative aspects of papers, but what is the relationship between the intensity of promotion and the evaluation by reviewers? Could it be that the more promotional language authors use, the more positive feedback they receive from reviewers? To study the intensity of promotional language and to prevent both over-promotion and insufficient promotion, we have integrated the novelty indicator Novelty_U proposed by Uzzi et al.(2013), leading us to propose RQ3:

RQ3: What is the relationship between the intensity of promotion and the reviewers' evaluation of novelty?

The primary contributions of this paper are manifested in the following three aspects: Firstly, we have developed a novel methodology for extracting innovation evaluation sentences from academic papers and peer review comments. As an increasing number of journals opt to open their peer review comments, the importance of batch extracting information from a vast amount of peer review data has become more pronounced. Unlike academic papers, peer review comments lack a unified writing standard, making it challenging to extract innovation-related evaluations from them. This study has devised a "rule-based + machine learning" approach that can accurately extract reviewers' evaluations regarding the innovation of papers from peer review comments, thereby contributing to the comprehension of peer review feedback.

Secondly, we have investigated the cognitive biases between paper authors and reviewers regarding the innovative aspects of papers. We began by analyzing which aspects of innovation are prioritized by authors and reviewers during the writing and reviewing processes, respectively. We then observed whether reviewers acknowledged the innovative contributions as described by the authors in each paper, thereby providing a preliminary exploration into the current state of cognitive biases between authors and reviewers.

Lastly, we have examined the relationship between the intensity of promotional language in the introduction of a paper and the level of agreement it receives during the review process. The consequences of using different degrees of promotional language in the introductions of academic papers, and whether more promotional language is invariably better, remain largely unexplored in current research. This study contributes to the understanding of these dynamics, thereby advancing the cause of reasonable promotion in the writing of academic papers.

Related work

Current research on promotional language in academic papers predominantly focuses on the titles and abstracts, while studies on peer review seldom address the extraction of innovation evaluation sentences. The related work section of this study encompasses two parts: research on promotional language in academic papers and research on innovation evaluation in peer reviews.

Innovative promotional language

Promotional language refers to the linguistic expressions and stylistic choices designed to market or advocate research findings. This type of language is often characterized by exaggeration, subjectivity, or emotional appeal, which may influence the reader's objective understanding of the research. Previous studies on promotional sentences have primarily concentrated on grant or project proposals. For instance, Millar et al.(2022) analyzed 717 NIH grant applications and found that applicants increasingly describe their work subjectively, relying on promotional language and emotional appeals. Peng et al.(2024) examined the promotional language in funding applications from NIH, NSF, and the Nord Foundation, investigating its relationship with the likelihood of funding and the future impact of the projects. It is evident that the dissemination of research not only depends on the output of research results but is also closely related to the manner in which it is promoted.

Current research on promotional language in academic papers delves into the titles, abstracts, and main text content, aiming to uncover phenomena present in scientific research and to provide recommendations for academic writing, thereby enhancing the quality of scholarly articles. Citation counts are often used as a proxy for the influence of a paper to study the effects of promotional language. Titles and abstracts, serving as summaries of the entire paper, are common corpora for research on promotional language in papers. Metrics such as length, vocabulary usage, and semantic complexity have been extensively studied by many researchers(Jiang & Jiang, 2023; Li, 2022; Pearson, 2020; Sagi & Yechiam, 2008; Wheeler et al., 2021), as detailed in Table 2. However, the main text of academic papers remains under-researched due to the challenges in data acquisition and processing. In recent years, the open access to large-scale paper datasets and the development of large language models have propelled research in the semantic understanding of full-text academic papers. Such research often correlates writing style with other metrics. For example, Lu et al.(2019) found that cultural background influences sentence structure and word choice. Costello et al.(2023) discovered a relationship between gender and writing style, as well as the crucial role of editors in mitigating these differences, by examining the use of uncertain language in papers written by male and female authors. Wu et al.(2025) found that the introduction part of the paper is more suitable for measuring its novelty.

Moreover, there is relatively scant research utilizing large-scale corpora to investigate the use of promotional language in academic papers. Thanks to the advancements in large language models, we are now better equipped to process the vast corpora that are currently available, extracting more information from them. This study draws on research related to promotional language in grant applications, employing large language models to automatically extract and classify promotional language from the introductions of academic papers. Based on this, we assess the intensity of promotional language in academic papers and examine the relationship between the intensity of promotion and the level of endorsement by reviewers.

Table 2. Related works of promotion language in academic article.

Source	Authors	Contribution
Title	Pearson(2020)	The study found that the structure and characteristics of titles may influence a paper's academic impact.
	Sagi & Yechiam(2008)	The study provides empirical evidence that humorous titles in scientific articles are associated with fewer citations.
	Jiang & Jiang, (2023)	Reveal significant trends in title length, complexity, and syntactic structures.
Abstract	Wheeler et al.(2021)	Reveal a significant increase in the use of personal pronouns and expressive confidence (referred to as "clout") in psychology journal abstracts.
	Li(2022)	It explores the relationship between passive voice usage and active voice initiated by personal pronouns, contributing to a better understanding of the evolving style of academic writing.
	Song et al.(2023)	The findings suggest that papers published in higher quartile journals tend to exhibit greater lexical density and sophistication, implying a connection between writing quality and scientific impact.

Innovation Evaluation in peer review

Peer review stands as the cornerstone of academic exchange and the bedrock of scientific publishing(Ghosal et al., 2022). Peer experts, with their profound domain knowledge and professional experience, are capable of evaluating the overall quality of academic papers. The innovativeness of a paper, being a decisive factor of its quality, has always been highly regarded by reviewers(Teplitskiy et al., 2022).

However, the peer review process has been subject to controversy due to its lengthy review cycles, lack of transparency, and potential biases (Parker et al., 2018; Stelmakh et al., 2019; Wicherts, 2016). To address these issues, several journals, including Nature Communications and Plos One, have begun to make peer review comments publicly available ("Transparent Peer Review for All," 2022). The disclosure of peer review comments has promoted transparency in the review process and enhanced the efficiency of communication between paper authors and reviewers. Reviewers are expected to make rational judgments about the quality of papers and provide revision suggestions to authors based on these judgments, without being influenced by other factors. For instance, Sun et al.(2024) analyzed peer review comments from Nature Communications and found that authors who used the second person in their communications with reviewers received more positive evaluations.

To enhance researchers' understanding of innovation evaluation during the review process, we employed rule-based and machine learning methods to extract innovation evaluation sentences from peer review comments. We studied the current methods and focus points of innovation evaluation in the review processes across different disciplines and, in conjunction with the promotional language in the introductions of papers, provided recommendations for authors on the use of promotional sentences in academic writing.

Data and Methodology

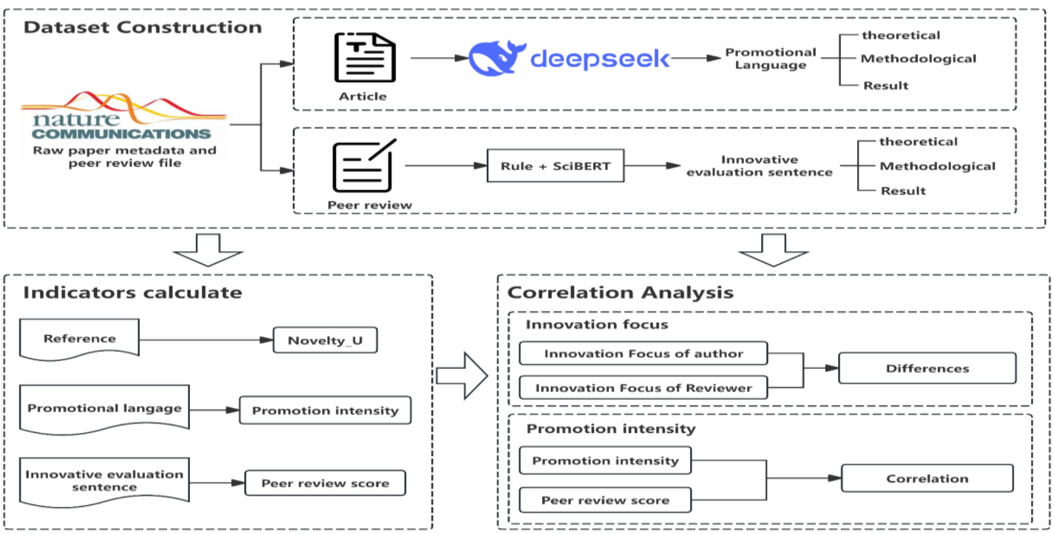

Figure 1. Framework of this study.

The aim of our study is to examine the differences in focus between paper authors and reviewers regarding the novelty of papers during the publication process, as well as the relationship between the use of promotional language by authors and the evaluations by reviewers. To achieve this, we utilized original academic papers and peer review comments from various fields in *Nature Communications*, extracting sentences related to innovation evaluation for analysis. We also assessed the promotional intensity of the original papers using the novelty metric proposed by Uzzi et al.(2013). The framework of our study is illustrated in Figure 1. Specifically, we conducted our research in three steps. The first step involved the construction of the dataset, where we collected all academic papers published in *Nature Communications* from 2016 to 2021 along with their publicly available peer review comments. We parsed their contents to extract authors' promotional language about their own research from the introduction of original papers and reviewers' innovation evaluation sentences from the review comments. The second step was the comparison of innovation focus points across different disciplinary fields. Based on the five disciplinary categories provided by the *Nature Communications* website, we observed how researchers' focus on innovation varies across fields and how the focus points of paper authors and reviewers differ regarding the novelty of papers. The third step combined a reference-based method for calculating paper novelty to investigate the relationship between the use of promotional language in papers with different levels of novelty and reviewer comments.

Dataset and Data Preprocessing

This section outlines the process of dataset construction and preprocessing for our study. Initially, we collected the original papers and peer review comment files from the *Nature Communications*[1] website. Subsequently, we employed large language models to extract promotional language from the original papers and utilized a "rule-based + machine learning" approach to extract innovation evaluation sentences from the peer review comments. This groundwork lays the foundation for our subsequent analysis of the authors' and reviewers' evaluations of the papers' innovativeness.

Raw article and peer review corpus collection: The data source for this study is Nature Communications, a subsidiary journal of Nature. This journal encompasses the latest research findings across various fields of natural sciences and has been committed to the transparency of peer review to enhance the quality of the review process, being one of the earliest journals to make peer review comments publicly available. Since 2016, authors have had the option to disclose the exchanges between

[1] https://www.nature.com/ncomms/

themselves and the reviewers. Papers with disclosed review comments can be found with corresponding peer review PDF files on their content pages, which include the reviewers' comments and the authors' responses from each round of review.

We collected the publication dates, titles, abstracts, main texts, and publicly available peer review PDF files of all papers published from 2016 to 2021 from the *Nature Communications* website. Based on the journal's disciplinary classification, we categorized the papers into five fields: biological science, health science, earth and environmental science, physical science, and scientific community and society. A single paper could belong to multiple disciplinary fields. We identified the structure of the papers using HTML tags within the main text and extracted the introduction sections as the corpus for subsequent promotional language extraction. We required that the collected papers have complete titles, authors, abstracts, and introduction content, along with publicly available peer review comments. Ultimately, we gathered 15,328 academic papers along with their peer review comments. Since the reviewers' comments and authors' responses in the publicly available peer review comments for each paper were contained within the same PDF file, we used the Python package PyMuPDF [2] to parse the text and segmented the reviewers' comments from the authors' responses based on linguistic features and font size characteristics.

Extract promotional language from academic papers: To investigate the promotional intensity of authors regarding the innovative aspects of their work, we need to extract contribution-promoting sentences from the papers. Here, we define contribution-promoting sentences in academic papers as "sentences used to explicitly highlight the main contributions and innovative points of the research work." Although authors tend to emphasize the key points of their research in the title and abstract, they may still lack descriptions of innovative aspects in some detailed parts. In the introduction of a paper, authors clarify the research background while explicitly stating the specific problems to be solved or the core themes of the research, and they articulate the purpose and significance of the study, promoting the main innovative points of the research. Therefore, we selected the introduction of the paper as the corpus for extracting contribution-promoting sentences, extracting these sentences from the title, abstract, and introduction of the paper. Additionally, referencing the classification method of academic paper innovation by Leahey et al.(2023), we categorized the innovation in academic papers into theoretical innovation, methodological innovation, and result innovation, with specific definitions of each type of innovation as shown in Table 3.

[2] https://pymupdf.readthedocs.io/en/latest/

Table 3. Definition of three Innovation types.

Innovation Type	Definition
Theoretical Innovation	Refers to breakthroughs in theoretical frameworks, models, or concepts. This can involve new theoretical perspectives, redefinitions of concepts, or extensions of existing theories, which advance the understanding and development of the discipline.
Methodological Innovation	Involves improvements or innovations in research methods, techniques, or tools. This can include new experimental designs, data collection methods, and analytical techniques, making research more efficient and reliable, or enabling the resolution of previously unsolvable problems.
Result Innovation	Refers to new findings or conclusions obtained from the research. This type of innovation emphasizes the new knowledge or data gained from the research and its potential applications, which can have a significant impact on theory, practice, or policy.

When extracting contribution-promoting sentences from academic papers, we opted to utilize a large language model for this task. We employed DeepSeek-V3[3] as our extraction model. DeepSeek-V3 is an exceptional Mixture of Experts (MoE) language model with an overall parameter scale of 671B, where each token activates 37B parameters, and it has surpassed other open-source models in performance across multiple test datasets (DeepSeek-AI et al., 2024). We referenced the prompt templates provided by DeepSeek's official documentation to craft corresponding prompts that define innovative contribution sentences, instructing the large model to extract the original text of innovative contribution sentences from the titles, abstracts, and introductions of papers. To investigate the innovative points that academic paper authors focus on, we directed the large model to extract contribution-promoting sentences and categorize them into theoretical innovation, methodological innovation, and research outcome innovation, with each contribution-promoting sentence belonging to only one category. After completing the prompt, we tested its extraction performance, randomly selecting 10 papers after each extraction test to observe the results, ensuring that all contribution-promoting sentences in the papers were extracted and assigned to the correct category, and that these sentences were sourced from the original text rather than generated by the model. Once the extraction performance met our expectations, we used the refined prompt to extract

[3] https://www.deepseek.com/

and classify contribution-promoting sentences from the introductions of papers across the entire dataset. The final prompt we used is shown in Table 4.

Extract innovative evaluation sentences from peer review: To investigate reviewers' opinions on academic papers, we developed a "rule-based + machine learning" method to extract innovation evaluation sentences from review comments. Initially, we referenced the work of Leahey et al.(2023) on extracting innovation evaluation sentences from academic papers, using a large language model to generate common templates for innovation evaluation in peer review comments. We also conducted a survey of language patterns in existing peer review corpora to develop and refine a lexicon for the preliminary extraction of innovation evaluation sentences, as detailed in Table A1 in the Appendix. However, due to the polysemous nature of innovation indicator words in peer review comments—for example, 'original' can mean innovative or refer to the reviewer's initial opinion when placed before 'review'—we established corresponding rules. For instance, if 'new' is followed by words such as 'version', 'fig', or 'review', it is not recognized as a candidate for an innovation sentence. Based on this lexicon and these rules, we used regular expressions to extract candidate innovation sentences from peer review comments, initially extracting 108,033 sentences containing innovation indicators from 15,328 peer review comments.

To address the issue of low recall in the rule-based extraction method, we employed a machine learning approach to further classify the initially extracted innovation evaluation sentences. Specifically, we utilized SciBERT as our classification model to determine whether the preliminarily extracted innovation evaluation sentences were genuinely related to innovation. SciBERT is a pre-trained model based on the BERT architecture, optimized specifically for scientific texts and currently applicable to various natural language processing tasks such as text classification, named entity recognition, and question-answering systems, particularly in scientific applications (Beltagy et al., 2019). We randomly selected 1,500 candidate innovation evaluation sentences for manual annotation, distinguishing between innovation evaluation sentences and non-innovation evaluation sentences. The annotation was performed by two graduate students in library and information science, with a unified definition of innovation evaluation sentences in peer review comments as "sentences in which reviewers make positive or negative evaluations about the innovation of the paper's theory, methods, results, etc." The Kappa coefficient calculated after annotation was 0.92. We then divided all 1,500 sentences into training, validation, and test sets in an 8:1:1 ratio to evaluate the model's performance on this task. Ultimately, our extraction model achieved an accuracy of 0.88, a recall of 0.94, and an F_1 score of 0.92 on the test set.

We employed SciBERT to classify the pre-extracted candidate sentences into two categories: innovation evaluation sentences and non-innovation evaluation sentences. Ultimately, we extracted 38,561 innovation evaluation sentences from all peer review comments and categorized them into three types: theoretical innovation, methodological innovation, and result innovation. The classification rules are detailed in Tables A2, A3, and A4 in the Appendix, and the extraction results are illustrated in Figure 2. Not every innovation evaluation sentence falls into one of these three categories, as some sentences provide an overall assessment of the paper's innovativeness. For example, the sentence "*In my opinion, the novelty of this work is enough to guarantee a publication in Nature Communications.*" expresses a positive evaluation of the paper's overall innovativeness without specifying any particular aspect of innovation.

Table 4. Prompt used in promotion language extraction.

Instruction	**The persona pattern:** You are a proficient linguist skilled in reading academic articles. **Introduce the target of our task:** You will be given a paragraph in the Introduction section of a publication. Please follow the instructions to label the paragraph in the Introduction section provided by user. In the introduction of a paper, the author mentions the innovations of the entire work, which we define as contribution statements. **Definition of contribution statement:** Contribution statements are sentences or paragraphs in academic papers that clearly highlight the main contributions and innovations of the research work. **Definition of three types of innovation:** These contributions can be categorized into three types: **(See Table 3.)** **Introduce the details in our task:** Each paper's introduction may contain one or more of these three types of innovations, and each sentence belongs to only one type of innovation. Please read the provided research paper's introduction carefully and extract the original sentences representing these contribution statements, categorizing them into theoretical innovation, methodological innovation, and result innovation. No explanations are needed for the extracted results.
Input	Introduction of an article.
Output	**theoretical innovation**: [extracted theoretical innovation statement](if none, leave blank); **methodological innovation**: [extracted methodological innovation statement](if none, leave blank); **result innovation**: [extracted result innovation statement](if none, leave blank)"

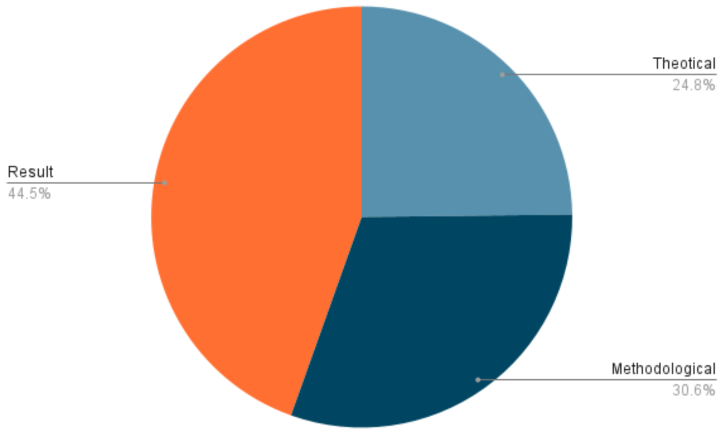

Figure 2. The proportion of three types of innovation evaluation sentences.

After completing the extraction and classification of peer review comments, we calculated the innovation evaluation scores given by peer reviewers to the papers using the extracted innovation evaluations. Specifically, we conducted a survey of common linguistic forms of innovation evaluations in peer review comments and constructed a lexicon of positive evaluations and a lexicon of negative innovation evaluations, as detailed in Tables A5 and A6 in the Appendix. The positive innovation lexicon includes sentiment words such as 'highly' and 'important', indicating that reviewers highly affirm the paper's innovativeness; whereas the negative innovation evaluation lexicon includes negative sentiment words such as 'lack' and 'insufficient', suggesting that reviewers find some aspect of the paper lacking in innovation. If an innovation evaluation sentence contains a positive innovation word, it is scored as 2 points; if it contains a negative innovation evaluation, it is scored as -1 point; all other ordinary innovation evaluation sentences are scored as 1 point. We accumulated the scores of each type of innovation evaluation sentence for each paper to obtain the innovation evaluation score for each paper's peer review, and then normalized it by dividing by the number of reviewers for each paper.

Calculating the novelty of academic papers

Novelty evaluation is vital for the promotion and management of innovation(Zhao & Zhang, 2025). To assist authors of academic papers in better promoting the innovative contributions of their research, we integrated existing metrics for measuring the innovativeness of academic papers to provide recommendations for authors on how to write about their innovative contributions. This study employed the Novelty_U metric proposed by Uzzi et al., (2013) to measure the innovativeness of academic papers. This method is based on Schumpeter's (Chen et al., 2024) theory of combinatorial innovation, interpreting the innovation of a paper as a new combination of knowledge units and using the references of academic papers as a proxy for their knowledge sources to calculate the paper's novelty. The combination of knowledge, especially the combination of different types of knowledge, often produces novel knowledge(Chen et al., 2024). The advantage of this calculation method is that it can immediately determine the innovativeness of a paper after its completion, allowing authors to have a preliminary estimate of their research's novelty.

Specifically, this novelty calculation method quantifies the degree of innovation of an article by using the atypicality of the journal combinations to which the references of the academic paper belong. Firstly, the journals to which the references in each paper belong are paired two by two, and the frequency of occurrence of each journal pair is counted. Then, the references from the same year are recombined, ensuring that the length and temporal distribution of the references for each paper remain unchanged. This step is repeated multiple times to obtain the frequency of occurrence of each reference pair under random conditions. Finally, the atypicality z-score is calculated based on the actual occurrence and the frequency of occurrence under random conditions for each journal pair.

$$z\text{-}score = (obs_{ij} - rand_{ij})/std_{ij} \tag{1}$$

$$Novelty\_U = -P_{10}\,(z\text{-}score) \tag{2}$$

In this context, obs_{ij} represents the actual frequency of occurrence of two journals in a paper, $rand_{ij}$ is the expected frequency of occurrence of the two journals in a paper, and std_{ij} is the standard deviation of the occurrence of the two journals in a paper. Following the approach of Uzzi et al.(2013), we define the innovation of a paper as the negative value of the 10th percentile (P_{10}) of the z-scores of the reference journal pairs in the paper, sorted from smallest to largest. This means that the larger the value of Novelty_U, the more innovative the paper is considered to be.

Assessment of the intensity of promotional language

To promote transparency in academic communication and ensure that research findings are presented in a truthful and reasonable manner, we evaluated the intensity of promotional language extracted from the introductions of academic papers. For the intensity of promotional language in the introduction, we referred to the work of Sun et al.(2024) and designed two metrics. The first metric is the proportion of promotional language in the introduction of the paper (PL), which represents the amount of effort the authors have spent on promotion in the introduction. The second metric is the proportion of promotional words in the introduction of the paper (PW). Promotional words refer to those with strong emotional connotations or exaggerated effects, typically used to attract attention, stimulate interest, or enhance the perceived value of something.

$$PL = Num(words\ of\ promotional\ language) / Num(words\ of\ Introduction) \times 100\% \quad (3)$$

$$PW = Num(promotional\ words) / Num(words\ of\ Introduction) \times 100\% \quad (4)$$

In this study, we focused on innovation-related promotional words such as 'new', 'unique', 'revolutionary', etc., which emphasize the innovative value of research findings. When constructing the promotional word lexicon, we referred to the lexicon proposed by Millar et al., (2022) based on promotional language in NIH grant applications, which includes 139 scientific promotional words. We further constrained the lexicon by stipulating that words are only recognized as promotional if they appear in the promotional language we extracted, thereby reducing bias from the different meanings of words. Although the research corpus we used consists of the introduction sections of academic papers, the purpose of the promotional language is similar to that of grant applications, both aiming to promote their research to reviewers or readers. Therefore, based on Millar's lexicon, we manually surveyed the promotional language extracted using a large language model and added some commonly used promotional words in academic papers.

We used these two metrics as proxies for promotional intensity and, in conjunction with the reference-based innovation metric for academic papers, investigated what level of promotional intensity could garner more positive evaluations from reviewers at the same level of innovativeness. Combining the reviewers' innovation scores calculated in section 3.1, we compared the top 5% and bottom 5% of papers based on their Novelty_U scores to observe how the use of promotional language in papers with different levels of novelty affects innovation evaluations in peer reviews.

Result

In this section, we present the differences in innovation focus between paper authors and reviewers, and analyze the impact of promotional language in academic papers on the peer review process in conjunction with innovation metrics.

Innovation Focus

Here, we utilize the contribution description sentences extracted from academic papers and the innovation evaluations extracted from peer review comments to investigate *RQ1*, which is whether paper authors and reviewers place more emphasis on theoretical innovation, methodological innovation, or result innovation in scientific research within the field.

Innovation Focus of author In this section, we conduct a statistical analysis to determine which aspects of innovation paper authors are more focused on. We perform a statistical analysis on the various types of contribution-promoting sentences extracted using the large model. The statistical results are shown in Table 5, with the proportion of papers containing result innovation being the highest at 87.19%. This indicates that paper authors place greater emphasis on the innovation of results and are more likely to directly promote the innovation of their research findings in the introduction section of their papers.

Table 5. Total number and proportion of three promotion types.

Promotion Type	Number	Proportion
Theoretical innovation	5817	37.80%
Methodological innovation	4619	30.01%
Result innovation	13418	87.19%

From the proportion of various types of innovation, we can see that in some papers, authors claim that their research encompasses multiple types of innovation. We have counted the number of such papers and found that 33.4% of the papers contain at least two or more types of innovation-related contribution promotions. Among these, the proportion of papers that include all three types of innovation is the highest, at 26.46%. This allows us to explain why result innovation accounts for the largest proportion, namely that when paper authors make theoretical or methodological innovations, they often accompany these with innovative results. Authors of these papers believe that when declaring their contributions, they are comprehensively promoting the contributions of their research in all aspects. However, the majority of authors only promote the innovative results of their research in the introduction section, considering rseult innovation to be the core value of their study.

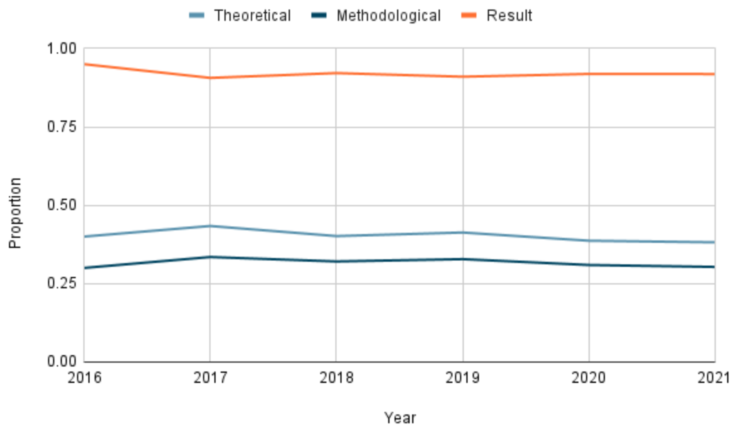

Figure 3. The changing innovation focus of authors over time.

We have examined the trend in the emphasis paper authors place on promoting various aspects of innovation by incorporating the publication dates of the papers. As shown in Figure 3, we can observe that the proportion of these three types of contribution promotions has remained relatively stable in recent academic writing. Most authors declare the innovative results of their research in the introduction section.

Next, we investigated which aspects of innovation are more emphasized by authors in different fields based on the domain of the papers. The results, as shown in Figure 4, reveal that authors across all five fields in Nature Communications place greater emphasis on the innovation of results, and their focus on theoretical innovation is also slightly higher than that on methodological innovation.

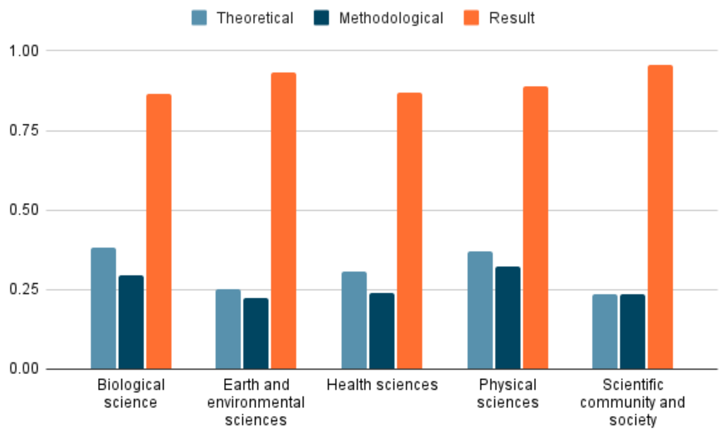

Figure 4. The innovation focus of authors in five different fields.

After extracting and statistically analyzing the contribution-promoting sentences in academic papers and the innovation evaluation sentences in peer review comments, we found that both reviewers and authors of academic papers are more inclined to evaluate and promote the innovative results of the papers. Analyzing the publication dates of the papers, we observed that the focus on innovation in the writing and review process of academic papers has remained relatively stable in recent years. When dividing the papers into different disciplinary fields for study, we discovered that authors from various disciplines have similar perspectives on the angles of contribution promotion, while reviewers' focuses differ significantly. For example, in the fields of scientific community and society and physical science, reviewers pay more attention to methodological innovation than in other fields.

Innovation Focus of reviewer We observed the focus of reviewers during the peer review process. From the peer review comments of 15,328 academic papers, we extracted 38,561 innovation evaluation sentences. After excluding sentences that evaluated the overall innovation of the papers, we categorized these sentences into theoretical innovation, methodological innovation, and result innovation. As shown in Figure 2, among all the extracted innovation evaluation sentences, result innovation accounted for the largest proportion at 50%, while theoretical innovation and methodological innovation evaluation sentences accounted for 22.4% and 27.6%, respectively. This indicates that reviewers place greater emphasis on the innovation of experimental results, such as new discoveries and conclusions in the research, when evaluating papers.

Analyzing the overlap in the evaluation of review comments, we found that 36.21% of the peer review comments for papers contained two or more types of innovation evaluations. Among these, 1,611 papers had all three types of innovation mentioned—theoretical, methodological, and result; 1,573 papers had both theoretical and result innovations mentioned; another 1,573 papers had both methodological and result innovations mentioned; and 686 papers had both theoretical and result innovations mentioned. This shows that the innovations in a paper often do not exist in isolation; for example, a paper may develop a new method and use it to discover new results. Reviewers tend to consider all aspects comprehensively when evaluating the innovation of a paper, which also explains why result innovation accounts for the largest proportion in innovation evaluations. This is because result innovation is more closely related to theoretical and methodological innovations, and when reviewers identify theoretical or methodological innovations, they are inclined to simultaneously evaluate the innovativeness of the results.

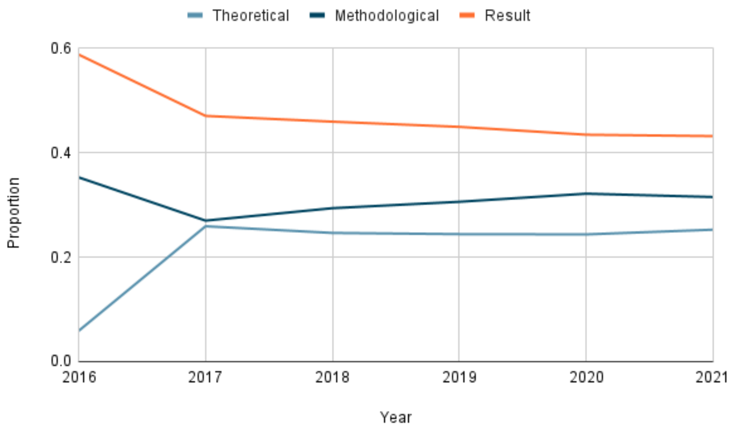

Figure 5. The changing innovation focus of reviewers over time.

We examined the proportion changes of different types of innovation evaluation sentences over time by incorporating the publication dates of the papers. Figure 5 illustrates the proportion changes of various types of innovation evaluation sentences from 2016 to 2021. Overall, the proportions of the three types of innovation evaluation sentences have remained relatively stable, with the proportion of methodological innovation evaluations showing an upward trend, while the proportion of result innovation evaluations has been declining. This indicates that in recent years, reviewers have been placing increasing emphasis on the innovation of research methods.

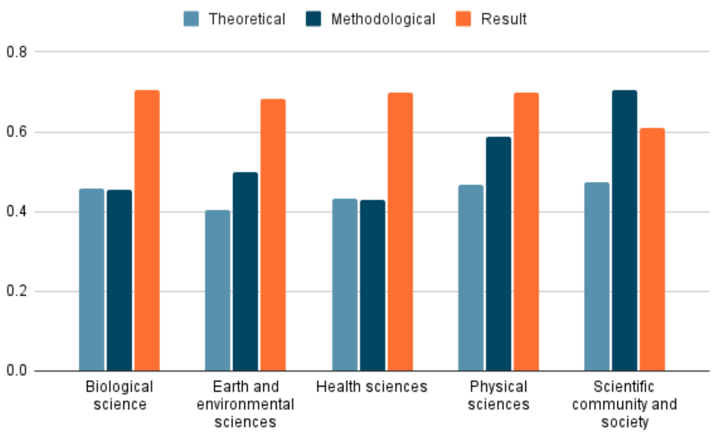

Figure 6. The innovation focus of reviewers in five different fields.

Next, we divided the study into five different disciplinary fields to examine the focus of reviewers on innovation in peer review comments. The results, as shown in Figure 6, indicate that all disciplinary fields comprehensively review various aspects of innovation in papers, especially the innovation of results. In the field of scientific community and society, reviewers' attention to methodological innovation is particularly prominent, with 70.52% of the innovation evaluation sentences in the peer review comments for papers in this field being assessments of methodological innovation. This is because this field is interdisciplinary, requiring timely follow-up and integration of new methods from various disciplines to address current social issues; whereas the other four fields mostly rely more on the specialized knowledge and techniques of their respective fields to drive the production of more innovative research outcomes.

Differences in Innovation Focus Between Authors and Reviewers

In section 4.1, we analyzed which aspects of innovation are focused on in academic papers and peer review comments, respectively. It can be observed that although both paper authors and reviewers pay considerable attention to the innovation of paper results, their focuses still differ. For instance, reviewers tend to be more comprehensive when examining papers, also paying attention to the theoretical and methodological innovations of the papers. Therefore, in this section, we address *RQ2*, which is what differences exist between authors and reviewers when evaluating the innovative points of a paper, and which innovations mentioned by authors in the introduction are recognized by reviewers?

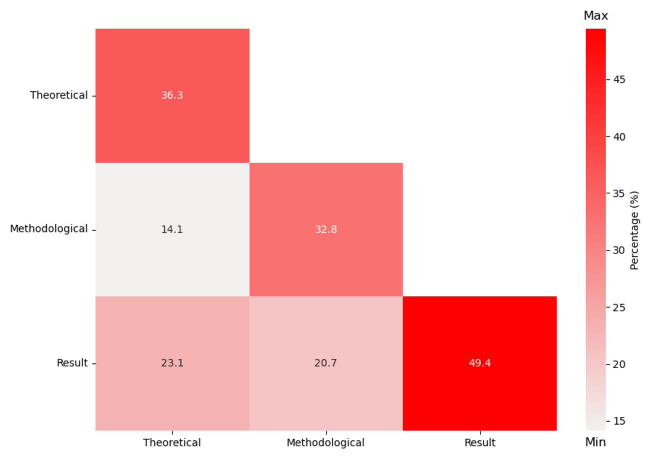

Figure 7. Heatmap of overlap ratio between reviewers' positive evaluations and authors' promotional language.

We investigated the relationship between the contribution-promoting sentences provided by authors and the innovation evaluations given by reviewers in the same academic paper, and used this to create a heat map. As shown in Figure 7, the horizontal axis represents the types of innovation described by the paper authors, and the vertical axis represents the types of positive innovation evaluations given by peer review experts. The content of each cell indicates the proportion of papers that received corresponding positive evaluations from review experts when authors provided that type of contribution-promoting sentence. For example, 49.4% of the papers that promoted their research result innovations were recognized by peer review experts; 20.7% of the papers that promoted their research methodological innovations also received positive evaluations for theoretical innovation from the review experts. From the figure, we can see that when describing research result innovations in a paper, it is more likely to receive positive evaluations from review experts compared to the other two types of innovation. Considering that a paper may contain multiple innovations and that review experts may also make innovation evaluations on various aspects of the paper, we can observe that theoretical innovation is closely linked with result innovation, with 23.1% of the papers proposing theoretical innovation and receiving positive evaluations from reviewers for their result innovations.

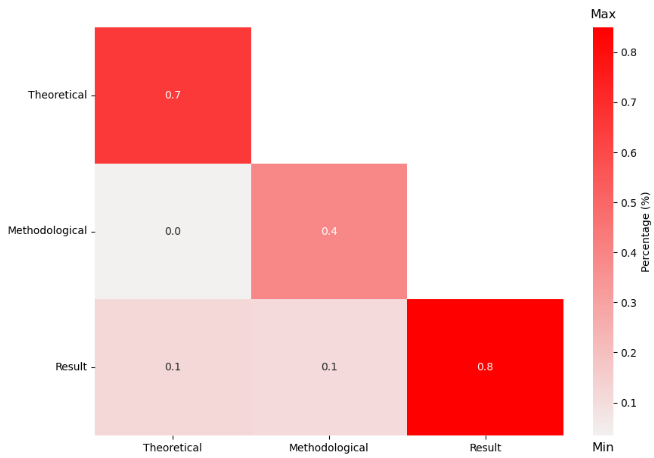

Figure 8. Heatmap of overlap ratio between reviewers' negative evaluations and author promotional language.

However, during the review process, reviewers may also provide negative evaluations, such as considering that the paper is not as novel as claimed, or that similar topics have been studied before but the authors did not mention them. We have also conducted statistics on these papers, and the results are shown in Figure 8. Since the data we used only includes the original texts of accepted papers and peer review corpora, the quality is generally high, and there are fewer negative evaluations in the peer review comments. Among them, negative evaluations mostly appear in the innovation points claimed by the authors themselves. For example, 0.8% of the authors promoted the innovativeness of their results, but the reviewers considered their results not to be innovative.

Through the above research, we can find that the innovation promotion in the introduction of a paper does indeed draw the attention of reviewers to that type of innovation. However, if the contribution is misrepresented or improperly promoted, it is more likely to be refuted by review experts. As for innovations not declared in the introduction, review experts rarely give negative opinions.

The Relationship Between Promotional Intensity and Peer Review

To delve deeper into the impact of promotional language in the introduction of papers on the review process, we address *RQ3* in this section: Does promotional language influence review comments, and what level of promotional intensity is appropriate in a paper? To tackle this issue, we incorporated the novelty calculation metric Novelty_U based on references proposed by Uzzi et al.(2013). The advantage of this metric is that it can be calculated immediately upon completion of the writing, allowing for an assessment of its novelty. To measure the intensity of promotional language in the introduction of papers, we use the proportion of promotional language in the introduction to gauge the effort authors spend on promoting innovation, and the proportion of promotional words in the introduction to assess the degree of promotion.

Since the inherent innovativeness of a paper is a key factor influencing the scores given by peer review experts, we controlled for the paper's own innovativeness to study how the promotional language in a paper affects reviewers' comments when the paper's innovativeness is the same or similar. We identified the top 5% most innovative papers and the least innovative 5% of papers based on Novelty_U from all the papers to investigate the relationship between the promotional language in their introductions and the innovation evaluations provided by peer review.

Table 6. Correlation between the proportion of promotional language in the introduction and peer review score in top 5% Novelty_U.

Variable	promotional language	promotional word	promotional language square	promotional word square	peer review score
promotional language	1.000	.608***	1.000***	.608***	0.044
promotional word	.608***	1.000	.608***	1.000***	.089*
promotional language square	1.000***	.608***	1.000	.608***	0.044
promotional word square	.608***	1.000***	.608**	1.000	.089*
peer review score	0.044*	.089**	0.044*	.089**	1.000

Note: *: p <0.05, **: p < 0.01, ***: p < 0.001.

Table 7. Correlation between the proportion of promotional language in the introduction and peer review score in bottom 5% Novelty_U.

Variable	promotional language	promotional word	promotional language square	promotional word square	peer review score
promotional language	1.000	.850***	.483***	.850***	0.019
promotional word	.850***	1.000	.518***	1.000***	-0.021
promotional language square	.483***	.518***	1.000	.518***	-0.001
promotional word square	.850***	1.000***	.518***	1.000	-0.021
peer review score	0.019	-0.021*	-0.001	-0.021*	1.000

Note: *: p <0.05, ***: p < 0.001.

We first conducted a study on the most innovative portion of the papers. Table 6 shows the relationship between the proportion of promotional sentences in the introduction, the proportion of promotional words, and the peer review scores. We can see that both the proportion of promotional language and the proportion of promotional words are positively correlated with peer review scores, with the correlation for promotional words being significant. This indicates that for the most innovative introductions, the more promotional words used, the more likely it is to receive positive evaluations from review experts.

For the least innovative 5% of papers, as shown in Table 7, we find that the promotional words in their introductions are negatively correlated with peer review scores. This means that for papers lacking in innovation, it is not advisable to excessively promote their innovativeness in the introduction, as it may cause dissatisfaction among reviewers.

In summary, we have found that the use of promotional words in papers is related to their own innovativeness. When a paper possesses strong innovativeness, more promotional words and language can be used in the introduction to better convey the novelty of the research to review experts, garnering more positive evaluations and facilitating the publication of the paper. However, when a paper lacks innovativeness, it should avoid exaggerate in the introduction to prevent causing aversion among reviewers.

Discussion

Implications

We will elaborate on the implications of this study from both theoretical and practical perspectives.

Theoretical implications: This study explores the cognitive gap between authors and peer reviewers regarding the perception of novelty in academic papers, specifically using *Nature Communications* as a case study. Despite the availability of open peer review datasets, these resources often lack standardized writing conventions, which complicates the extraction of meaningful insights.

We developed a novel "rules + machine learning" approach to effectively extract novelty assessment sentences from peer review comments, demonstrating improved accuracy in identifying relevant evaluations. Furthermore, we utilized the large language model DeepSeek to automatically extract and categorize contribution statements from the introductions of academic papers. This innovative method transcends traditional rule-based information extraction, enabling a more nuanced understanding of how novelty is communicated in academic writing.

Our findings reveal significant discrepancies in how authors and reviewers perceive the novelty of research contributions, as evidenced by our analysis of the extracted data. By integrating literature-based novelty measurement indicators, this study not only provides a new framework for examining peer review comments but also highlights the potential for further research into the communication of innovation in various academic contexts.

Overall, this research contributes to the theoretical discourse on peer review practices by offering a systematic approach to assess and understand the dynamics of novelty evaluation, paving the way for future studies to explore other dimensions of author-reviewer interactions.

Practical implications: The experimental conclusions of this study can provide recommendations for researchers in academic paper writing. To better enable review experts to understand the innovative aspects of the paper, authors should articulate the corresponding points of innovation in the introduction section, but also avoid over-promotion. This is because while promotional language in the introduction can benefit genuinely innovative parts, improper promotion may also raise doubts among review experts.

After completing the writing of their papers, authors can refer to existing academic paper innovation metrics to estimate the novelty of their own research. If the research is highly novel, more promotional language and words can be used in the introduction to make reviewers more aware of the innovative aspects of the research; if the novelty is low, the use of aggressive promotional words should be avoided to prevent exaggerate from raising doubts among reviewers.

Limitations

Indeed, this study has certain limitations. Firstly, the effectiveness of extracting contribution-promoting sentences from the original academic papers and innovation evaluation sentences from peer review comments needs improvement. The accuracy of the extraction results may affect the validity of subsequent conclusions. Particularly, the lack of uniform standards in peer review comments, the varying language styles of reviewers, and some implicit evaluations of paper innovation have impacted our extraction accuracy to some extent. Secondly, the corpus we used is limited to papers published in *Nature Communications*. Although this journal covers multiple disciplines within the natural sciences, the findings of this study have not been fully validated in some disciplinary fields. Moreover, different journals may have different review requirements, and the focus of reviewers on innovation may change with alterations in review criteria. However, currently, only a minority of scientific publications choose to open peer review comments, so this study has only made a preliminary exploration of the research question using papers published in *Nature Communications*. Lastly, the dataset used in this study consists solely of accepted papers and their peer review comments, and does not include data from rejected papers, which may also affect the generalizability of the study's results.

Conclusion and future works

In this paper, we investigated the cognitive differences between paper authors and reviewers regarding the innovation of papers during the writing and review process, provided recommendations for academic paper writing, promoted appropriate promotion in the academic paper writing process, and reduced the cognitive gap between paper authors and review experts.

In future work, firstly, we aim to improve the accuracy of extracting contribution-promoting sentences from the original academic papers and innovation evaluation sentences from peer review comments. Currently, large models have shown superior performance in natural language processing tasks, and we can attempt to use different large models to optimize this extraction task. Optimizing this extraction task can not only enhance the understanding of innovation-related writing in academic papers but also extend to various aspects of knowledge in academic papers, such as the extraction and analysis of future work sentences, thereby advancing the development of information extraction in academic papers. Secondly, the dataset for this study can be expanded to analyze the original texts and peer review comments of rejected papers, investigating whether the reasons for rejection are related to over-promotion or insufficient promotion, to supplement and extend the conclusions of this study. Finally, we can incorporate disciplinary fields into the study of this issue to observe whether the focus of paper authors and review experts varies across different disciplinary fields.

Acknowledgments

This paper was supported by the National Natural Science Foundation of China (Grant No.72074113).

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Appendix: Dictionaries and Rules for Coding

Table A1. Innovation Signifying Terms Dictionary.

New			
novel	new	innovative	creative
novelty	uncover	fill the knowledge gap	methodological step
breakthrough	groundbreaking	pioneering	trailblazing
disruptive	revolutionary	unprecedented	advancement
introduce	propose	unique	originaL

When these words appear after the word "new" or 'original', the word "new" or 'original' is not tagged as NEW: 'figure', 'we', 'our', 'table', 'version', 'fig', 'review', 'paragraph', 'claim', 'manuscript', 'comment', ' added', 'new text', 'sample', 'avoid', 'supp'.

We exclude mentions of "first" as NEW, unless one of these words appears immediately afterward: principle', 'result', 'observation', 'attempt', 'experiment', 'synthesis', 'study', 'comprehensive', 'application', 'description', 'describe', 'evidence', 'design', 'time'.

Table A2. Theoretical Innovation Terms Dictionary.

Theoretical			
concept	generalize	mechanism	synthesize
theoretical	explanation	hypothesis	model
term	theory	insight	point
idea	hypotheses	thesis	explain

Table A3. Methodological Innovation Terms Dictionary.

Methodological			
method	analysis	classification	experiment
methodology	strategy	analyze	criteria
formula	procedure	technique	apparatus
criterion	index	process	technology
design	means	protocol	tool
equipment	measure	quantify	calculate
test	examine	experimental	approach

Table A4. Result Innovation Terms Dictionary.

Result			
structure	confirm	finding	observation
response	correlation	found	outcome
result	effect	discovery	prove
support	evidence	identify	rate
show	observation	data	report

If a sentence contains two or more different terms from the innovation aspect dictionaries, we conduct a syntactic analysis to observe which terms from Table A1 modify the terms from Table A2 to A4, thereby determining the innovation type of the sentence.

Table A5. Positive Innovation Terms Dictionary.

Positive			
highly	interest	completely	important
strong	indeed	surprise	extensive
sound	timely	extremly	incredibly
remarkably	exceptionally	significantly	thorough
thoughtful	clever	unquestionably	robust

Table A6. Negative Innovation Terms Dictionary.

Negative			
lack	insufficient	inaccurate	ineffective
unconvincing	inappeoriate	slight	

When the word "not, "no," or "lack" appears near the word "new," it is tagged as negative.