

Accepted with Minor Revisions: Value of AI-Assisted Scientific Writing

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Large Language Models have seen expanding application across domains, yet their effectiveness as assistive tools for scientific writing—an endeavor requiring precision, multimodal synthesis, and domain expertise—remains insufficiently understood. We examine the potential of LLMs to support domain experts in scientific writing, with a focus on abstract composition. We design an incentivized randomized controlled trial with a hypothetical conference setup where participants with relevant expertise are split into an author and reviewer pool. Inspired by methods in behavioral science, our novel incentive structure encourages authors to edit the provided abstracts to an acceptable quality for a peer-reviewed submission. Our 2×2 between-subject design expands into two dimensions: the implicit source of the provided abstract and the disclosure of it. We find authors make most edits when editing human-written abstracts compared to AI-generated abstracts *without* source attribution, often guided by higher perceived readability in AI generation. Upon disclosure of source information, the volume of edits converges in both source treatments. Reviewer decisions remain unaffected by the source of the abstract, but bear a significant correlation with the number of edits made. Careful stylistic edits, especially in the case of AI-generated abstracts, in the presence of source information, improve the chance of acceptance. We find that AI-generated abstracts hold potential to reach comparable levels of acceptability to human-written ones with minimal revision, and that perceptions of AI authorship, rather than objective quality, drive much of the observed editing behavior. Our findings reverberate the significance of source disclosure in collaborative scientific writing.

CCS Concepts: • Human-centered computing → Empirical studies in HCI.

Additional Key Words and Phrases: Generative AI, Human-AI Writing Assistance, Large Language Models, Scientific Writing, Text Editing and Evaluation, Alignment, Behavioral Science, Incentivized Random Trial

1 Introduction

Telling people about research is as important as doing it. Scientific publishing is an integral part of science, meant to disseminate research findings, foster collaboration, encourage reproducibility, and ensure that scientific knowledge is accessible and built upon over time [59]. Bad writing can and often does prevent or delay the publication of good science [28]. Researchers and scientists today, however, are often not formally trained to write, and generally learn by imitating the styles of their advisors and other authors [61]. Large language models (LLMs), with their writing abilities, offer a promising venue to assist researchers in both conducting and writing about research. However, a thorough assessment of their capabilities in scientific writing is lacking.

Even so, the use of language models continues to grow in this area. Many tools and platforms termed “AI co-scientist” have emerged in the past year [7, 32]. They are marketed to be capable of generating, executing, and writing papers, with some of them getting accepted in academic workshops organized by peer-reviewed conferences [97]. Popular scientific writing platforms such as Overleaf now offer writing assistant plugins.¹ However, anecdotal examples of

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¹https://www.overleaf.com/learn/how-to/Writefull_integration

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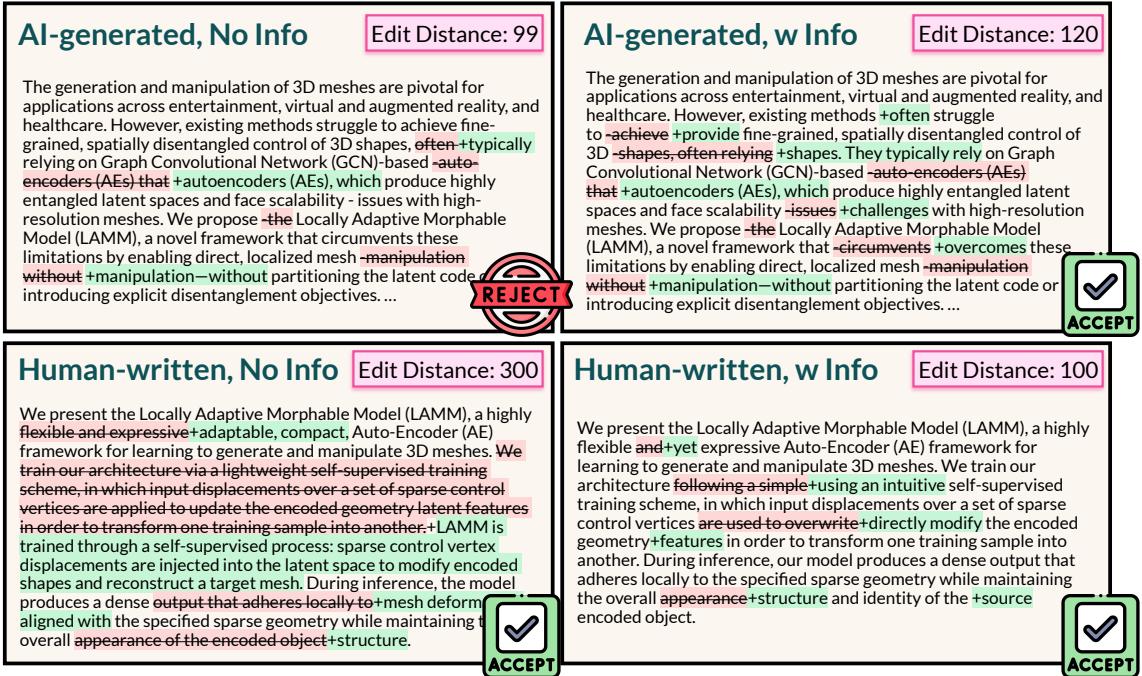


Fig. 1. Curious case of scientific writing: We find that *expert* authors (e.g., with PhD) make most edits when provided with human-written counterparts of AI-generated abstracts, especially so when the source of abstracts remains unattributed. With attribution, we see an opposite trend: authors made careful stylistic edits when the abstract was known to be AI-generated, which often raises the chance of getting the abstract accepted.

both seemingly AI-generated papers [18, 19] and peer reviews [75] have inspired criticisms [59]. In addition, across disciplines, recent studies have raised concerns over the declining quality of writing in scientific publications in several disciplines, attributing it to the rise of LLM-generated content [29, 54, 69]. These studies, however, have largely focused on corpus-level trends on unreviewed manuscripts and are conducted without consulting or involving writers such as the authors of said publications.

To raise awareness and prevent misuse by bad actors or unintentional use by over-reliant writers, there is an urgent need to conduct a systematic evaluation of the writing abilities of the current state-of-the-art models in specialized domains. Furthermore, despite current limitations, AI assistance holds tremendous potential in accelerating future scientific progress [64, 73, 84]. Towards understanding scientific writing capabilities, we seek to answer the following research question in this work: **maintaining the standard for scientific writing quality, to what extent do researchers rely on model-generated content for academic publishing?**

To answer this question, we simulate a realistic writing environment where authors (domain experts), the intended users of an AI assistant, use and edit model-generated text to create scientific prose with the goal of getting it accepted by reviewers (also domain experts) for publication. To scope this work, we focus on the task of writing abstracts. An abstract is meant to summarize research findings, highlight key results, and pique the readers' interest. Given selected research findings, we evaluate how existing state-of-the-art LLMs perform at generating abstract drafts.

We simulate an abstract editing and reviewing process mimicking the process of scientific publication in a laboratory setting using the methodology of *incentivized behavioral experiments* [5] to encourage participants to perform the task to the best of their ability. Authors edit the abstracts, and we quantify author reliance based on the extent of their modifications to make them submission-ready for a hypothetical conference publication. The task is conducted under two information conditions: (1) authors are informed that the original abstract provided to them was AI-generated, and (2) authors are not informed that the abstract was assembled by generative AI. To contextualize this behavior with a more realistic workflow, we also provide the authors with human-written abstracts under the same information conditions. By considering abstracts from different sources (human experts and LLMs), we assess the reception of LLM-generated abstracts by evaluating correlations between acceptance rates, edit frequency, and edit types.

The edited abstracts are then evaluated by a group of (incentivized) reviewers in a double-blind fashion, who vote to accept or reject the submitted abstract. This design allows us to examine how authors' reliance varies across source types and information conditions, and how expert reviewers perceive the quality and credibility of abstracts produced through generative AI workflows. These experiments result in a collection of model-generated and human-edited texts, where we capture keystroke-level edits. From this rich data of inputs, abstracts, and edits, we conduct several evaluations and analyses. Our main evaluation is based on the correlation between the rate of editing and the final rating an abstract receives, contrasting the controls and different treatments. We consider and measure the impact of variables like writer expertise (undergraduate students, graduate students, experienced researchers), and demographics and social factors (gender, perception of AI). In addition, we quantitatively (using linguistic tools) and qualitatively (via interviews with participants) characterize different kinds of edits authors make to understand the differences between edits made to AI- and human-authored abstracts.

Across our experiments, we find that both the implicit origin of abstract and the disclosure of it systematically shape editing behavior and outcomes. Without source disclosure, authors make fewer edits to AI-generated abstracts, perceiving them as more readable, though PhD-level authors edited AI text more extensively. Despite these differences, reviewer evaluations showed no differences in accepting abstracts edited under no disclosure conditions. Disclosure of source primarily triggers social adjustments: authors reduced edits for human-written text when the source was revealed, whereas disclosure had only minor effects on AI-generated abstracts, with small impacts on perceived readability and confidence. Our quantitative analysis of stylistic metrics reveals that edits to AI-generated abstracts are to improve cohesion, reduce nominalizations, and produce informative sentences. On the contrary, authors tend to lengthen the openings of the human-written abstracts. Similarly, disclosure of source information alone has a minimal direct effect on the writing style. Finally, thematic analysis of our interviews with authors confirms that authors adopt different strategies depending on the origin of the abstracts: they simplify AI-generated text, restructure human-authored abstracts for emphasis, and disclosure promotes the sense of accountability equally for human and AI. Together, through comprehensive large-scale experiments, we first highlight² the varying cognitive editorial strategies emerging from writing sessions that involve both human and AI-generated scientific writing.

2 Related Works

2.1 AI Systems for Automating Scientific Research

Early works on AI-assistance in scientific research largely focused on surface-level corrections and sentence-level improvements in writing [8, 43] with some attempts at drafting entire paper structure [92]. Recent work has started

²Our experimental data and instructions are provided as supplementary.

to apply LLMs to the entire research cycle, including hypothesis discovery [1, 65, 99, 100], experiment planning and execution [10, 35, 56], scientific writing [47, 52, 60], and writing reviews [81]. Within the writing stage, some works have focused on specific subtasks like metaphor generation [49], figure caption generation [48], citation generation [23, 46, 96], and related work generation [27, 57]. Such tasks are, typically, accompanied by reference answers, making evaluation relatively straightforward. More recent work has started focusing on generating entire papers without any human intervention [62]. In this work, we adopt a more realistic setup of humans relying on an AI-assistant to generate drafts, which they then edit [47]. We also use a principled method of human evaluation in the form peer review conducted via incentivized experiments.

A wide range of commercial³ as well as open-source tools now offer services for every stage of the writing process, from literature review and synthesis to full manuscript drafting, editing, and refinement [80]. Specific features, such as automated abstract and title generators, are also becoming commonplace⁴. The widespread availability and marketing of these tools signify a de facto adoption that necessitates rigorous empirical evaluation of their effectiveness, their impact on the quality of scientific output, and the human behaviors they engender, which our study addresses.

2.2 Human AI Collaboration and Co-writing

The majority of prior research on Human-AI co-writing has focused on creative writing [82]. Using LLMs, researchers have developed and evaluated systems supporting story writing [98], playwriting [34], and character development [77]. Some works also explore higher-level writing tasks such as prewriting [91], and generating perspective-specific feedback [78]. Specialized creative applications have emerged for tasks including metaphor generation [90], collaborative storytelling [94], and personal diary writing [50]. User studies reveal complex dynamics in how writers interact with and perceive AI writing assistance. At a system interaction level, the design of AI suggestions significantly impacts user behavior and output: sentence-level suggestions promote original content creation, while paragraph-level suggestions improve efficiency [20, 26]. Writers' engagement with AI assistance is also influenced by their personal values and goals [9, 36]. Writers show varying receptivity to AI support based on their confidence levels, demonstrating higher acceptance in areas where they lack expertise [4, 93], and their desires for support are closely tied to their perception of support actors and personal values [37, 41]. Professional writers note persistent challenges with AI systems' ability to maintain consistent style and voice [14].

Moreover, this Human-AI writing relationship raises important concerns. Studies reveal that biased AI models can influence not only the resulting text but also users' own opinions [44]. Prior research has identified biases, quality issues, lack of structure, and superficiality in AI-generated text, especially in domains like fiction and satire [14, 15, 42, 67, 70, 71]. Researchers have also found LLM-generated content to be overly positive and lacking in nuance and have highlighted the need for more diverse and representative training data to mitigate these shortcomings [88]. Our work adapts evaluation practices from prior studies in co-writing by focusing on the quality of AI-generated text using the amount of edits made to it by a human co-writer.

2.3 Cognitive Biases in Human-AI interaction

The inability of humans to reliably detect AI-generated text makes their beliefs about a text's origin a powerful psychological variable, opening the door for cognitive biases to influence their judgment and behavior [22, 39, 45]. A rich literature in HCI and psychology documents two opposing, context-dependent human tendencies when interacting

³<https://www.gatsby.com/>, <https://anara.com/blog/ai-research-tools>

⁴<https://www.writefull.com/>

with automated systems [21, 53, 76]. On one hand, **automation bias** describes the tendency to over-rely on or excessively trust automated outputs, often using them as a cognitive shortcut to reduce mental effort [63, 72]. This can lead to errors of commission (accepting incorrect AI-generated information) and errors of omission (failing to notice problems that the AI missed) [2].

On the other hand, **algorithm aversion** describes a tendency to prefer human judgment over algorithmic judgment, even in cases where the algorithm is demonstrably better or equivalent [86]. This aversion is often heightened in high-stakes, subjective, or ethically charged tasks, such as medical diagnosis [24]. It can be driven by a fundamental desire for human agency, a negative emotional reaction to being judged by a machine, and a belief that human experts possess unique, ineffable knowledge that algorithms cannot capture.

Our study's finding—that authors edit AI-attributed abstracts significantly more heavily—can be interpreted as a manifestation of algorithm aversion. The explicit knowledge of the AI source appears to trigger heightened scrutiny and a greater perceived need for human intervention. Furthermore, our study advances the literature by shifting the focus from perceptual measures of AI-generated text such as self-reported “credibility” or “trust” [33, 55] to concrete, measurable behavior in terms of amount of edits made to the text. The finding that attribution significantly impacts the number of edits demonstrates that this cognitive bias translates into tangible, effortful action on the part of the expert.

2.4 Peer Review and Scholarly Evaluation

Our experimental design is situated within the broader field of science of peer review, which treats scholarly evaluation not as a purely objective process, but as a human endeavor subject to cognitive and social biases. A significant body of literature has used experimental methods to uncover these biases. For instance, landmark studies have shown that reviewer recommendations are significantly influenced by the prestige of an author's institution, a bias that double-blinding is intended to mitigate [13, 89]. Relatedly, we study the perceived origin of the text itself as a bias. The attribution of an abstract to either a human or an AI serves as an analogue to author identity, allowing us to investigate whether a “source identity bias” influences the authorial and review process in a similar manner to established forms of author bias.

In this work, following the methodology of behavioral scientists, we conduct incentivized randomized controlled trials of increasing complexity for this evaluation. Randomized controlled trials are widely regarded as the gold standard for establishing causal relationships in behavioral interventions [6]. Incentivizing participants in studies ensures higher engagement and more reliable data following a cost-benefit analysis from taking part in the study, thereby yielding results that better reflect real-world usage [30]. Recent studies have employed RCTs to assess the effectiveness of AI tools in various domains, including writing and education [51]. These trials provide empirical evidence on how AI interventions influence user outcomes, supporting their utility in scientific research.

3 Experiment Design

Writing scientific prose is a challenging task. It is intended to communicate complex ideas to the academic community or to the public, focusing on precision, clarity, and brevity [61]. It requires the synthesis of diverse specialized knowledge and information sources, including non-textual elements like tables, statistics, and figures, alongside long contexts with strict formatting requirements. Performed by domain experts such as researchers with varying expertise, it is an inherently iterative process [16, 66]. It is often collaborative, involving people with different experiences contributing, editing, and commenting on each other's written work.

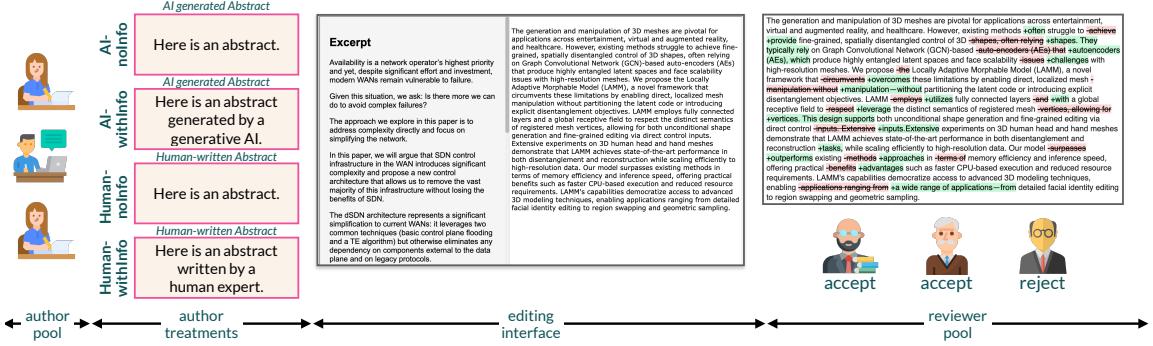


Fig. 2. Experimental workflow: Authors from a shared pool were randomly assigned to one of four treatments varying abstract source (AI-generated vs. human-written) and information disclosure (with vs. without source information). Authors revised abstracts in the editing interface. Each edited abstract was randomly assigned to three reviewers for their individual verdict. Reviewers see the final edited version of abstracts without knowing what edits were made. A majority vote decides the final verdict.

We aim to create a test-bed to evaluate how humans perceive and evaluate scientific writing. In this work, we focus on the domain of Computer Science. We follow a 4-step approach: (1) We select original research publications from peer-reviewed conference publication venues and curate AI-generated abstracts from the content of these papers using state-of-the-art LLMs; (2) We engineer an incentivized hypothetical conference set-up where we recruit human participants online to form an Author and a Reviewer pool. This allows us to emulate a real-world writing setting for both parties to play their part in the study; (3) We develop a web platform based on FirePad⁵ to capture fine-grained character-level edits such as insertion, deletion, or substitution with timestamps. Each abstract is shown to the authors on this platform to generate edited abstracts. (4) We show each edited abstract to three independent reviewers to obtain the final accept/reject decision by majority voting.

3.1 Collecting and Curating Abstracts

For the scope of this study, we focus on the computer science (CS) domain for several reasons. First, CS is a fast-paced field with high publication volume [17], rapid turnaround cycles, and a high impact factor, particularly in conferences [25, 79]. This makes it a relevant and timely setting to study the integration of AI in scientific writing. Second, the widespread adoption of AI tools by researchers in CS provides ecological validity for examining human-AI collaboration in this context. Finally, as CS researchers ourselves, we are well-positioned to assess the accuracy and relevance of domain-specific content. While our study centers on CS, the design is generalizable and can be extended to other scientific domains. A typical research process involves identifying a research problem, reviewing existing literature, formulating a hypothesis, collecting data, analyzing the

Table 1. Abstracts from papers across venues

Venue	Count	Average Citation	Year
NeurIPS	6	18.83	2024
CVPR	6	24.17	2024
ACL	6	30.33	2024
SIGCOMM	6	5.83	2024
VLDB	5	2.60	2024
IEEE S&P	6	19.83	2024
ICSE	5	10.80	2024
ASPLOS	5	15.40	2024

⁵The editing platform codebase is available at: <https://github.com/skai-research/scientific-writing-assistance>

data, and potentially modifying the hypothesis and repeating the process. At the end, the researchers draw conclusions and present the findings. We evaluate the role of AI-assistance in the final stage, where, given research findings, *an LLM generates a coherent abstract summarizing the results of the study in a factual, coherent, and appealing way.*

The most realistic setting to conduct our experiment is to involve different researchers who are at the end of their studies and wish to write up their findings. This setting, however, is expensive and prohibitively slow to emulate. Instead, we choose already published recent papers and convert them into a format of “research excerpts” that could be fed to an LLM to generate abstracts. We deliberately choose already published papers to isolate the effect of the quality of writing from the quality of the research itself; we only aim to evaluate the latter.

We select 45 published papers from top-tier conference venues in various subfields of CS.⁶ For each venue’s latest publication, we randomly sample papers as shown in Table 1. Using GPT-4o, we create research **excerpts**, i.e., extract all relevant text from the paper that is necessary to write an abstract. We provide the exact prompt we use in Figure 13 (Appendix F). Note, we focus on extraction rather than generation to make sure no facts in the original paper are misrepresented in the generated plan. We also manually verify each model output for factual correctness. We provide a sample output in Figure 14 (Appendix F).

Using these excerpts, we also generate versions of AI-generated abstracts with respect to their original counterpart, also using GPT-4o. We chose this model due to its immense popularity. We provide the prompt to generate the abstract and a sample abstract in Figure 15 and Figure 16, respectively (Appendix F). Corresponding original abstracts is provided in Figure 17 (Appendix F).

In this paper, we refer to three versions of abstracts which we use accordingly henceforth. (1) We refer to the authentic human-written abstracts of the published research papers from the peer-reviewed conference publication venues that we used in our study as **original abstracts**; (2) We refer to the populated AI-generated versions of original abstracts of the respective published papers as **AI-generated abstracts**; (3) We use the term **provided abstracts** to indicate those abstracts that we provide the authors to edit. Provided abstracts could be either original abstracts (in Human-noInfo or Human-withInfo treatments) or AI-generated abstracts (in AI-noInfo or AI-withInfo treatments). (4) We use the term **edited abstracts** to indicate the edited versions of the provided abstracts. To clarify, these edits have been made by the recruited authors. Our investigation includes two participant pools: Authors and Reviewers. We discuss the tasks, incentives, and recruitment procedures of each pool in the respective sections.

3.2 Authors

3.2.1 Task. The main task of the authors is to make edits to the provided abstracts. Authors complete three tasks. In Task 1, we elicit authors’ perceptions about their LLM use. The authors answer four questions. In the first question, we ask if authors use generative AI systems (e.g., ChatGPT) for any writing tasks. Participants choose between four options: they use generative AI to solely generate content, they use generative AI to only edit existing content, they use generative AI to both generate and edit content, or they do not use generative AI for any writing tasks at all. In the second question, we use an incentive-compatible method to elicit authors’ second-order beliefs about the overall use of GPT in writing tasks. We ask what percentage of other authors they believe use GPT to generate new content or edit existing content. Authors are informed that if their selected percentage bracket matches the actual percentage (as calculated by the experimenter), they will receive a bonus of \$0.50. In the third and fourth questions, we ask authors to rate the performance of AI systems in generating and editing content, respectively.

⁶To ensure that our selected research papers were not a part of the training dataset of the state-of-art LLMs, we use only very recent papers published in the top conferences of the domain. For more details, please Table 3.

Task 2 entails the main editing task. Every author is presented with three independent research excerpts and their respective provided abstracts. The editing task appears to the authors as illustrated in Figure 9 (Appendix A). Figures 3 and 4 provide the detailed illustration provided to the authors to help them understand the instructions. Authors are instructed to first review the excerpts in the left panel of the screen. A scroll bar is provided to the authors to completely review the excerpt, which may extend beyond the scope of the current screen space. Simultaneously, the right panel entails the editing interface that shows the provided abstract. We explicitly instruct the authors to make all edits in the editing interface only. We disabled copy-pasting from the editing interface so that the participants cannot copy and paste to edit on a platform other than the one provided to them. Additionally, this will also limit authors from generating or making edits using existing AI models. The main goal of the authors is to receive **at least two Accept decisions** by the reviewers on their edited abstracts. Before starting with Task 2, the authors answer two screening questions (Appendix B). These questions were designed to assess the authors' understanding of task instructions. Correctly answering these questions was a prerequisite for moving forward with the main editing task.

After the screening questions, the authors go through each excerpt-provided abstract combination and make relevant edits. After the authors have made their edits, we elicit two confidence metrics from the authors in an incentive-compatible method. First, we ask the authors to evaluate the provided abstract and indicate how likely they believe it is to receive at least two Accept decisions by the reviewers. In the next question, authors are asked to evaluate the edited abstract, which now includes their own revisions, and indicate how likely they believe it is to receive at least two Accept decisions from reviewers. Responses for both questions are recorded on a slider scale ranging from 0 (not likely at all) to 50 (highly likely). An author edits **three** instances of provided abstracts and submits respective confidence questions for the three edited abstracts. We also ask authors to rate the quality of the provided abstracts (excellent to poor), describe their frequency of edits, mark the kind of edits authors have made (e.g., addition, deletion, correction, substitution, and reordering), and finally rate the readability of the provided abstracts, using a slider scale where 0 indicates no readability and 100 indicates complete readability.

Authors proceed to Task 3 after they have made their edits and submitted the final versions of edited abstracts. Task 3 involves completing an exit questionnaire that gathers demographic information (such as gender, age, education, current profession), details on how author's self reported thoughts about the quality and readability of the unedited abstracts, frequency of their edits, kind of edits (such as addition, deletion, correction, substitution or reordering), their familiarity AI-generated text versus human-written text, experience with AI tools in daily life, trust in AI tools, and frequency of AI tool usage for writing tasks.

3.2.2 Incentives. Authors earn a fixed participation fee of \$15 for participating in this study and completing all the tasks. Note, authors receive this payment irrespective of their abstracts being accepted by the reviewers or not. Using the methodology of economics experiments, we additionally incentivize the participants to receive a bonus pay of \$15 if a randomly selected abstract out of the three edited abstracts receives at least two Accept decisions from the reviewers. Authors also receive a bonus for their answers in the confidence questions, respectively, according to their submitted confidence levels. For example, if an author marks 20 on the slider for the edited abstract and it receives at least two Accept decisions from the reviewers, the authors earn a bonus of \$0.20. An author can receive a maximum of \$0.50 from each of the confidence questions.

To encourage genuine effort and careful editing, our incentive structure followed conventions from experimental economics, where performance-contingent rewards are known to elicit higher attention and task quality [12, 83]. The fixed participation fee ensured baseline engagement, while performance-based bonuses motivated authors to

produce edits that improved clarity and persuasiveness rather than completing the task superficially [3]. A small confidence-based bonus further encouraged accurate self-assessment, helping us interpret reported confidence as a meaningful behavioral signal [74]. Together, these mechanisms help maintain data quality and internal validity while aligning with best practices in incentive-aligned experimental and crowd-sourcing studies [40, 68].

In total, an author could earn a guaranteed amount of \$15, with the possibility of an additional maximum bonus reward of \$16.50 (i.e., a maximum total of \$31.50). The authors were paid after the completion of the study. After completing all three tasks, the participation fee was immediately transferred to the authors. For the bonus, the computer randomly selected one edited abstract out of the three that the authors submitted for the hypothetical conference set-up, and the authors were informed that they would be paid their bonus based on the reviewer's decisions for the selected abstract. The average and median time taken for this task were both 1 hour and 8 minutes; our payments justify the stipulated hourly rates on Prolific.

3.2.3 Procedures and Author Recruitment. We recruit 300 authors via the online crowd-sourcing platform Prolific⁷. We use the Qualtrics interface to set up our study, which was then linked to Prolific for every author. Participation in the study was voluntary. At the onset of the experiment, each author was shown information about the study, followed by an informed consent form.

For our analysis, we exclude 3 authors owing to malformed responses, resulting in 297 authors. Limiting our study to only the CS domain limits us to restricting authors based on their total number of study approvals on Prolific. The median total approval number for our authors is 336.0 approvals, with a minimum of 0 and a maximum of 5560 approvals. 88.51% of authors have their registered first language as English. The average age bracket for the authors' pool falls in the range of 25–40, and 42.42% of the authors are female (as self-reported).

Since all our source material for creating the abstracts is strictly limited to the CS domain, we restrict authors to belonging to the CS domain by prescreening them based on their reported *Subjects*, as recorded on Prolific. It is a general norm in the highly competitive field of CS that students are engaged in scientific writing since their undergraduate years. To optimize for authors to have some experience with formal writing in CS, we also filter authors by their *Highest education level completed*. Authors include individuals who have an undergraduate degree (BA/BSc/other), a graduate degree (MA/MSc/MPhil/other), and/or a doctorate (PhD/other). 80.00% of authors are currently maintaining their student status, with 55.56% of authors having at least an undergraduate degree with a major/minor in CS.

3.3 Editing Interface

Our primary evaluation and analyses are based on recording edits made by the authors. To store these edits, we explored multiple popular text editing tools that provide versioning history, such as Google Docs and Microsoft Word. Having faced several challenges with these tools, we were encouraged to build our own interface. For example, these platforms do not store every keystroke. Instead, they record versions at a fixed time interval, which cannot be modified by the user. This results in us losing many edits that were valuable for our analysis. Furthermore, these platforms do not allow finer-grained control over how the edits can be made. For example, to prevent authors from using AI-assistance to make edits, we needed to disable copying, which none of the existing platforms allow. We also explored Revision History, a Google Docs Extension that offers full document composition record at character-level. This tool offers the magnitude of editing details we sought. However, it operates entirely within Google Docs, is handled online, and therefore does not

⁷This research has been IRB approved by the Office of Responsible Research Practices at Ohio State University under study number 2024E1034. We also pre-registered for our trial at AEA RCT Registry: <https://doi.org/10.1257/rct.16740-1.0>

Task 2.1

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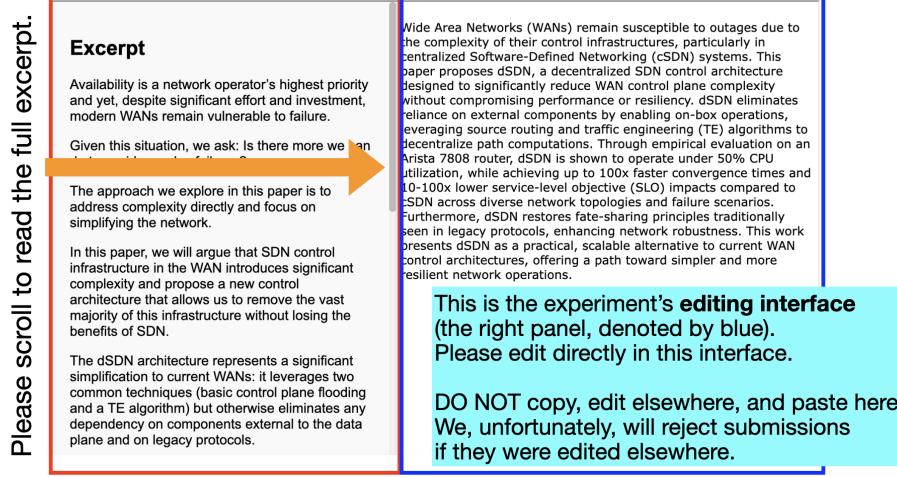
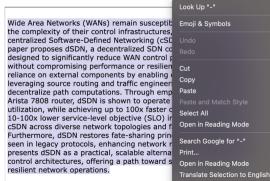


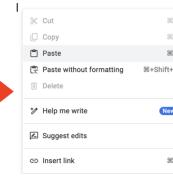
Fig. 3. An example of the first detailed pictorial representation where experimenters show the authors the author panel and provide them explicit information that edits need to be made directly in the interface. We conducted several pilot studies where we found that the recruited authors were copy-pasting the provided abstract and making edits elsewhere. Providing these graphic instructions and additional screening questions helped mitigate this problem and enabled capturing keystroke-level edits for every abstract.

You actions such as follows are NOT allowed, and it will lead to rejection of your submission

1. Copy the provided abstract



2. Paste elsewhere (e.g., text-editor, ChatGPT)



3. Paste elsewhere (e.g., text-editor, ChatGPT)

Wide Area Networks (WANs) remain susceptible to outages due to the complexity of their control infrastructures, particularly in centralized Software-Defined Networking (cSDN) systems. This paper proposes dSDN, a decentralized SDN control architecture designed to significantly reduce WAN control plane complexity without compromising performance or resiliency. dSDN eliminates reliance on external components by enabling on-box operations, leveraging source routing and traffic engineering (TE) algorithms to decentralize path computations. Through empirical evaluation on an Arista 7808 router, dSDN is shown to operate under 50% CPU utilization, while achieving up to 100x faster convergence times and 10-100x lower service-level objective (SLO) impacts compared to cSDN across diverse network topologies and failure scenarios. Furthermore, dSDN restores rate-sharing principles traditionally seen in legacy protocols, enhancing network robustness. This work presents dSDN as a practical, scalable alternative to current WAN control architectures, offering a path toward simpler and more resilient network operations.

5. Copy and paste it back to your experiment

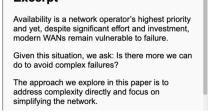
Do NOT make any edits outside the given space below.

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Task 2.1

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4. Edit elsewhere (e.g., text-editor, ChatGPT)

This paper proposes dSDN, a decentralized SDN control architecture designed to significantly reduce WAN control plane complexity without compromising performance or resiliency. dSDN eliminates reliance on external components by enabling on-box operations, leveraging source routing and traffic engineering (TE) algorithms to decentralize path computations. Furthermore, dSDN restores rate-sharing principles traditionally seen in legacy protocols, enhancing network robustness.

Fig. 4. Illustration of prohibited actions during the abstract editing task. Authors in the second schematic illustration are instructed not to copy the provided abstract into external tools (e.g., text authors, AI assistants), make edits outside the designated experimental interface, or paste modified content back into the system. We inform authors that such actions violate the experimental protocol and may lead to exclusion from the study.

support exporting the edit history. Google also prohibits automated web scraping of their data, and thus, this pipeline was not reproducible for mass edit log collection.

To build our own interface, we used Firepad, an open-source text editing tool that stores detailed edit history on Firebase Realtime Database and uses CodeMirror as the underlying text editor. While Firepad is no longer being hosted globally, we used its open-source code⁸ to host it ourselves through Firebase Web Hosting. Throughout this study, we used Firepad to record the time, the index, and the edited content per keystroke. We implemented our interface using Firepad 1.5.11, Firebase 5.5.4, and CodeMirror 5.17.0. We plan to open-source this interface for ease of reproduction and use by other researchers. For each author and abstract pair, we create unique Firepad pages. The combination and the index of each pair are used as URL parameters to dynamically populate the authors. Each Firepad page is structured as research findings or excerpts on the left and provided abstracts on the right (Appendix A). To allow authors to refer to the provided abstract when necessary, even though they made changes to the provided abstract, we include the provided abstract at the bottom of the excerpts section. Excerpts are in HTML and embedded in the page and made a non-editable part. Abstracts are located in the editing box. We embed the Firepad links into a Qualtrics⁹ survey form.

3.4 Reviewers

3.4.1 Task. Reviewers complete three tasks. Task 1 is identical to the Task 1 completed by the authors. Task 2 entails reviewing abstracts. Each reviewer is presented with a set of 20 abstract pairs—the original abstract that accompanied a selected research paper and the respective edited abstract by an author. We inform the reviewers that the edited abstracts encapsulate the same research idea, with the same research methodology and results as the original abstracts. However, it may or may not be expositionally different from the original abstract. Reviewers need to review the edited abstract in reference to the original abstract and answer the following question: *Does the edited abstract provide adequate justice to the research idea presented in the original abstract?* The reviewers answer using a slider that ranges from 0 (no justice, worse than the original abstract) to 100 (better than the original abstract), with the default set at 50 (i.e., both abstracts can be considered equally good and one is not better than the other). We also elicit the absolute confidence of the reviewer in each of their 20 decisions. Additionally, to get more insights into the decision-making process of the reviewers, we provide a text box where the reviewers can address this in free-form text. Reviewers proceed to Task 3 after completing Task 2. Task 3 is identical to task 3 as completed by the authors. We ask two additional questions about the publication record of the reviewers and their prior knowledge of the topics discussed in the abstracts.

3.4.2 Incentives. Reviewers earn a fixed participation fee of \$25 for participating in this study and completing all the tasks, irrespective of their decisions in the tasks. Leaning back onto the methodology of incentivized experiments, to increase data quality, we provide an additional bonus of \$8 to the reviewers whose evaluations align closely with those of their peers. One of the twenty abstracts is randomly selected, and two independent reviewers, alongside the reviewer-in-question, assess the same abstract pair using the slider scale described in Task 2. We then compute the median of the three ratings, and if a reviewer's score falls within 10 points above or below this median, they receive the \$8 bonus. This peer-alignment incentive helps ensure careful, calibrated judgments and reduces random or inattentive responding. Additionally, they can earn a bonus of \$2 from Task 1. The first quartile of time taken for the reviewing task is also 1 hour and 8 minutes. However, the reviewers were not required to complete the task during one continuous

⁸<https://github.com/FirebaseExtended/firepad>

⁹<https://www.qualtrics.com/>

sitting, and therefore, many took more than a day. Payments to reviewers were made through registered Amazon gift cards.

3.4.3 Procedures and Reviewer Recruitment. We have a total of 159 reviewers. We recruited the reviewers from the current student population at universities who are currently pursuing their graduate and doctoral studies to review 891 abstracts. 174 students signed up for reviewing using the distributed recruitment form. However, only 118 finally took part and completed the study¹⁰. 41 remaining reviewers were recruited on Prolific. On Prolific, we maintain the same restrictions for recruiting reviewers as authors; however, the reviewers are now restricted to having completed the highest education level of a graduate degree (MA/MSc/MPhil/other) and/or a doctorate (PhD/other). All reviewers were shown information about the study prior to starting the study, followed by an informed consent form.

32.70% of the reviewers are female (self-reported), 73.59% of reviewers hold at least a master's degree, 89.94% of reviewers either have a publication or are in progress, with 66.04% having prior knowledge regarding the topics discussed in the abstracts. We have 112 reviewers who provided a Google Scholar or Semantic Scholar link. The median number of publications is 6.5, with a minimum of 1 and a maximum of 61. The median number of citations is 32.5, with a minimum of 0 and a maximum of 4974. For reviewers recruited on Prolific, the median total approval number is 367, with a minimum of 2 and a maximum of 6795 approvals.

3.4.4 Reviewer Assignment. We adopted an automated pipeline to assign abstracts to recruited reviewers by mimicking the in-practice reviewer assignment mechanism in OpenReview, adopted by several CS conferences [85]. In addition to topical fit, we also try to ensure that no reviewer can review more than one version of an edited abstract originating from the same original abstract to avoid contamination. First, we collect each reviewer's scholarly profile using the Semantic Scholar APIs. Then we compute the semantic similarity between reviewer publications and base original abstracts using GPT-4o. We account for the reviewer's citation count to weigh the similarity between an individual paper and submitted abstracts, so that we assign related abstracts closer to the reviewer's most cited works. Finally, we solve the reviewer assignment as a constrained optimization problem by a minimum-cost flow, with constraints that each submitted abstract gets exactly three reviewers and each reviewer preferably does not review edit versions of the same original abstracts.

3.5 Computed Variables

We additionally compute the following variables for our analysis. For the Author pool, we collect every character-level edit that the author makes to the original abstract provided to them. From here, we compile **edit distance score** measures the character-level Levenshtein distance¹¹ between the original and edited abstract. This is the main variable of interest. For the reviewers, for each abstract, we collect a score between 0-100 indicating if the edited abstract does justice to the original abstract. If the score is > 50, then we binarize that decision to be "Accept" (else "Reject") since the original abstract is from a published work. For each edited abstract, three independent "Accept"/"Reject" decisions are collected, and we compute a **final decision** ("Accept"/"Reject") using the majority voting rule. The binarized final decision is the same variable that we use to determine the author bonus.

¹⁰The first set of 60 reviewers reviewed nine abstracts and received a flat payment of \$15, with a bonus of \$0.50 from Task 1. To maintain a high-quality of the reviewers, we maintained a restricted pool, which required us to increase per-reviewer assignment as well as hourly payment.

¹¹https://en.wikipedia.org/wiki/Levenshtein_distance

4 Study A: Human-written vs AI-generated Abstracts

Study A focuses on exploring how authors evaluate and make edits to scientific writing, irrespective of the source information of the script. In a between-subject experiment, we compare two treatments, **Human-noInfo** and **AI-noInfo**. Authors are uniformly randomly assigned to either of the two treatment groups. Authors in Human-noInfo treatment edit the original abstracts from the selected published research paper, whereas the authors in the AI-noInfo treatment edit the pre-populated AI-generated abstracts of the selected published research paper. Authors do not have any information about the source of the abstracts and are only provided the excerpts and the abstracts to make their edits. This comparison allows us to observe the natural editing behavior of authors free from disclosure-driven bias. By removing any source cues, we observe how individuals naturally engage with a piece of scientific writing, how they judge its clarity, coherence, and overall quality without being influenced by who (or what) produced it.

4.1 Results

4.1.1 Overall edit. When authors were unaware of whether an abstract was written by a human or an AI system, we found systematic yet heterogeneous differences in editing patterns. We use ordinary least squares (OLS) regression with heteroskedasticity-consistent standard errors to estimate that the authors made significantly smaller edits to AI-generated abstracts compared to human-written ones, on average, about 63 characters fewer (see Figure 5, Left). When the source of the text is unknown, authors perceived AI-written text as closer to a submittable form with lower intent to modify it.

4.1.2 Heterogeneity through education. To account for differences across individual authors, we consider demographic characteristics such as gender and education, along with their interactions with the treatments. Authors with doctoral degrees made substantially more edits to AI-generated abstracts ($p = 0.012$; joint Wald test), reversing the average effect. On the contrary, those with undergraduate or master's degrees made smaller changes (see Figure 5, Middle). This pattern hints that academic (writing) experience promotes the ability to identify idiosyncrasies of AI-generated text. In contrast, less experienced authors interpret the same fluency as high quality, leading to fewer definitive edits.

To probe further, we estimate a mixed-effects model for both author and abstract, capturing unobserved heterogeneity in editing intensity. The model finds negligible between-abstract variance (intra-class correlation = 0), suggesting that most variation comes from idiosyncratic styles rather than intrinsic differences in abstract quality. In an auxiliary model using *perceived readability* as a moderator, higher perceived readability strongly predicts lighter editing ($p < 0.001$). This does not significantly interact with the AI treatment. We find that the baseline content features of AI-written text shape how authors edit, and that this behavior depends critically on authors' writing expertise rather than the inherent readability of the content.

Furthermore, authors' prior familiarity with AI tools, trust in AI, and expectations about AI performance show little influence on how extensively authors edit the abstracts. None of the interaction terms between experience with AI and AI-treatment are statistically significant, suggesting that even frequent AI users or authors who highly trust AI do not edit AI-generated text differently from those less experienced with AI. The main treatment effect remains robust and negative ($\beta = -64.9$, $p = 0.038$). Authors make substantially fewer edits to AI-generated abstracts, but the observed differences stem primarily from intrinsic properties of the text (e.g., readability), and not from authors' prior beliefs on AI.

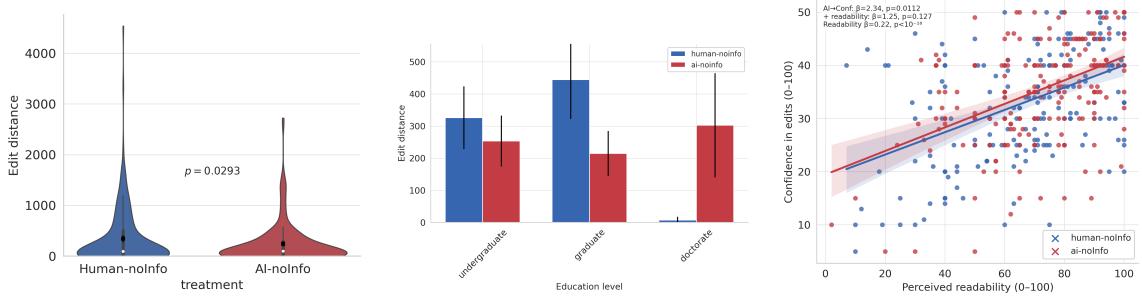


Fig. 5. Patterns of editing effort in Study 1 ($N = 495$ abstracts). **Left:** Distribution of Levenshtein edit distance in two conditions: Human-nolInfo (blue) and AI-nolInfo (red). Black squares mark the sample means $\pm 95\%$ CI; the Welch unequal-variance test indicates a statistically reliable reduction in edits for AI abstracts ($p = 0.0293$). **Middle:** Mean edit distance broken down by the authors' highest education level. Authors with undergraduate or graduate degrees make markedly larger edits to human text than to AI text, whereas doctorate-level editors show the opposite. **Right:** Scatter-plot of abstract's perceived readability (0–100) vs the author's confidence in their edits (0–100). The positive slopes show that authors feel more confident when an abstract reads more smoothly; readability, not AI, as the source explains authors' higher confidence in the AI-nolInfo condition.

4.1.3 Ability to distinguish AI-generated text partly explains edits. We next examine whether authors' self-reported ability to distinguish AI- from human-written text shapes their editing behavior. We focus exclusively on the *AI-nolInfo* condition, since we elicit authors' ability to distinguish AI vs human-written text in the AI treatment only. We compare the edits of authors who reported being able to distinguish AI from human text ("Yes/Quite often") with those who reported being unable or unsure ("Rarely/Never"). Authors who claim they could distinguish AI-generated writing made larger edits on average ($M = 257.03$, $SD = 316.38$, $N = 198$) than those who could not ($M = 157.56$, $SD = 204.57$, $N = 27$), the difference being statistically significant ($p = 0.033$; Welch's t -test). To account for potential confounds, we regress edit distance on self-reported ability to distinguish AI text along with original confidence, perceived readability, and demographic controls (gender and education). The effect of AI distinguishability remains positive but becomes statistically insignificant ($\beta = 97.15$, $p = 0.124$, $N = 135$), which indicates the initial difference is partly explained by correlated covariates. Authors with higher pre-edit confidence tend to make smaller edits ($\beta = -6.20$, $p = 0.074$), while perceived readability does not significantly predict edit distance ($p = 0.990$). This implies that authors who believe they can identify the difference between AI and human writing tend to edit AI-generated text more extensively, but this effect is not independently robust once we control for individual confidence and perceived readability.

4.1.4 Perceived readability mediates confidence. Authors express consistently higher confidence in their edits on AI-generated abstracts ($\beta = 2.34$, $p = 0.011$ from an OLS) compared to human-generated ones when they remain unaware of the source of the text. However, this effect reduces significantly once authors' *perceived readability* is included in the model. When we add perceived readability as a covariate, the coefficient on the AI indicator drops by nearly half and becomes statistically insignificant ($\beta = 1.25$, $p = 0.123$), while perceived readability itself emerges as a strong positive predictor of confidence ($\beta = 0.22$, $p < 10^{-18}$), as shown in Figure 5, Right. Authors rate AI-generated abstracts as more readable on average ($M = 73.01$, $SD = 19.91$) than those written by humans ($M = 67.94$, $SD = 22.80$), and perceived readability is moderately correlated with confidence ($r = 0.48$). Together, these patterns indicate that readability perceptions substantially moderate and explain the higher confidence associated with AI-generated text. Once we account for readability, the direct effect of the AI source largely disappears. Even after including demographic controls (gender and education), perceived readability remains a strong and stable predictor of confidence ($\beta = 0.19$,

$p < 10^{-9}$), whereas the AI effect remains modest and only marginally significant ($\beta = 2.24, p = 0.024$). The perception of how readable the abstract is mediates how the author gains confidence in their edits.

4.1.5 Reviewer decisions. Finally, we model final acceptance decisions for Human-noInfo and AI-noInfo conditions. We find no difference in acceptance probability (AI: $\beta = -0.198, p = 0.346$), indicating authors are able to bring the abstracts to an acceptable quality when starting from either AI- or human-authored versions when the source is undisclosed.

5 Study B: Source Information Disclosure

The source of text, in recent times, could be human-written or AI-generated. While detection is often challenging, disclosing the source of a scientific text could be fundamental in shaping individual evaluation and interaction patterns with the text. Individuals have often reported reading AI-generated text more critically, anticipating errors, and focusing on the factual accuracy to encounter model hallucinations. In contrast, knowing that a text is human-produced can either invoke trust, or a reluctance to make additional edits. Individuals often feel a stronger sense of oversight when working with AI, or greater deference when editing human work. [11, 58] provides evidence that transparent source information is crucial to altering calibration, confidence, and task performance.

By varying source disclosure, we can examine how people edit in light of source disclosure and why, whether their actions stem from intrinsic perceptions of quality or from social and cognitive biases linked to authorship cues. We have two disclosure treatments: Human-withInfo and AI-withInfo. In both treatment conditions, we inform authors of the source of the provided abstract. As outlined earlier, the provided abstract could either be the original abstract or the AI-generated abstract.

5.1 Results

5.1.1 Overall edit. To examine how disclosure of source information influences the authors' overall edit intensity, we compare the character-level edit distance pairwise across the final four treatments (Human-noInfo, Human-withInfo, AI-noInfo, and AI-withInfo). Authors make substantially larger edits when they were not told that the abstract was human-written ($M = 309.98, SD = 353.40, N = 225$). In contrast, than when source information is disclosed ($M = 247.87, SD = 294.86, N = 219$), there emerges a statistically significant difference, $t(431.96) = 2.01, p = .045$ (see Figure 6, Left). Disclosure appears to dampen authors' inclination to edit human-authored text. This proposes a restraint based on self-reputation once authorship is made known. A similar but nonsignificant pattern emerged for AI-generated abstracts. Edits were moderately higher ($p = .176$) in the no-information condition ($M = 245.09, SD = 306.50, N = 225$) than when AI origin was disclosed ($M = 210.50, SD = 228.27, N = 222$). As disclosure reduces the total edits, the smaller and nonsignificant effect suggests *less sensitivity to provenance cues* when participants knew the text was AI-generated. Comparing the two conditions where the source information was disclosed always, authors tend to make larger edits to human-authored original abstracts ($M = 247.87, SD = 294.86$) than to AI-authored ones ($M = 210.50, SD = 228.27$). This difference was, however, not significant, $t(410.46) = 1.49, p = .138$. Thus, knowing that a text originates from an AI model did not independently increase the extent of editing, once the source information was disclosed. Overall, disclosure mainly affects authors' effort when the abstract is human-authored. In contrast, knowing that the abstract is AI-generated does not elicit additional editing propensity. We conjecture disclosure primarily acts as a social rather than a purely evaluative signal.

5.1.2 Heterogeneity Effects: We probe whether the treatment effects on edits vary across *author characteristics* (gender, age, education, profession) and *AI perceptions/usage* (e.g., trust in AI, reported use of generative AI, willingness to use

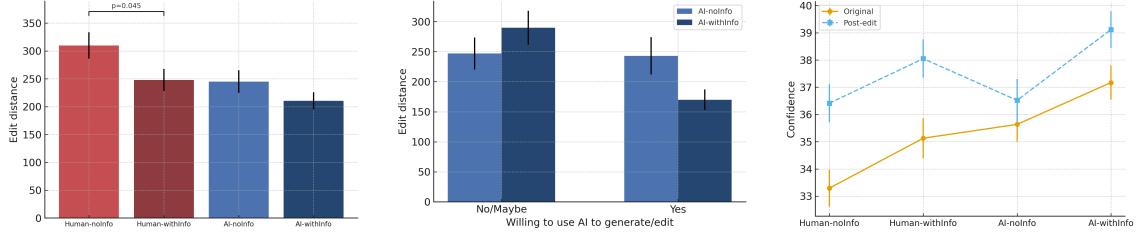


Fig. 6. Treatment effects on editing behavior, heterogeneity, and confidence in Study 2 (N = 495 abstracts). **Left:** Mean character-level edit distance (\pm SE) for each treatment condition. Disclosing human authorship (Human-withInfo) significantly reduced edits relative to the no-disclosure baseline (Human-noInfo; $p = .045$), whereas the analogous AI contrast was smaller and nonsignificant. **Middle:** For AI-generated abstracts, the disclosure effect depends on whether authors say they would personally use generative AI. Among those not willing to use AI, disclosure had little impact; among those willing to use AI, edit intensity fell markedly in the AI-withInfo condition, highlighting that individual AI adoption attitudes shape editing effort. **Right:** Disclosure of source as AI slightly lowers self-reported pre-edit confidence in acceptance but does not alter the post-edit confidence gains observed across all conditions.

AI). For Human-noInfo vs. Human-withInfo ($N=444$), none of the demographic or AI-perception covariates showed a reliable interaction with disclosure conditions. For AI-noInfo vs. AI-withInfo ($N=447$), we observe a significant moderation by *author's willingness to use AI*. Specifically, participants who reported *they would use AI to edit/generate* exhibited a lower editing tendency ($p = 0.030$) compared when authors who would not (see Figure 6, Middle). For Human-withInfo vs. AI-withInfo ($N=441$), two AI-perception moderators significantly differentiate the source effect. First, authors who believe *others would use GPT* show a larger human-versus-AI difference $\beta = +193.86$, $p=0.005$. Second, authors who reported *they would not use GPT* exhibit a smaller human-versus-AI difference $\beta = -189.80$, $p=0.028$. This implies that, when the source is always disclosed, these authors amplify their relative editing tendency on human-written abstracts versus AI-generated abstracts. On the other hand, individual reluctance toward AI is associated with a diminished human-vs.-AI gap in editing. Overall, heterogeneity emerges primarily along perceptions about AI, not along demographics. Authors' own willingness to use AI and their beliefs about others' AI usage reliably mediate (i) how much AI disclosure affects editing of AI abstracts, and (ii) how strongly authors differentiate between human and AI abstracts when disclosure is present.

5.1.3 Weak treatment effect in Confidence. We examine two measures of authors' self-reported confidence: (a) *original confidence*—the expected acceptance of the unedited abstract, and (b) *confidence change*—the difference between confidence in the edited and original abstract. For each of the three pairwise treatment comparisons, we compute Welch's unequal-variance t -tests and cluster-robust OLS (clustered by provided abstracts). We then run exploratory mediation analyses for any effect achieving significance $p < .10$. Authors' confidence does not differ significantly between the Human-noInfo and Human-withInfo conditions. Mean original confidence and post-edit confidence were statistically indistinguishable ($p > .10$), suggesting that disclosing human authorship does not influence how strongly authors believe the abstract would be accepted. For AI-authored abstracts, a modest disclosure effect emerges. Authors show slightly higher *original confidence* when AI authorship remains undisclosed ($\beta \approx -0.15$, $p = .08$), as well as confidence change did not differ significantly. Thus, disclosure of AI authorship marginally lowers authors' original confidence in the abstract's acceptability, though it did not change their post-editing confidence gain. With disclosure (Human-withInfo vs. AI-withInfo), neither original confidence nor confidence change differed significantly ($p > .10$), indicating that once source information is provided, perceived human or AI authorship alone does not affect confidence.

Given the marginal effect of AI-disclosure on original confidence, we examine whether perceived readability or beliefs on AI mediate the effect. We find disclosure of AI authorship slightly reduces perceived readability ($p = .06$), and readability positively predicts original confidence ($p = .02$). The Sobel test for the indirect effect remains marginal ($z = 1.72, p = .085$). Lower perceived readability may partially mediate the small decline in original confidence when AI authorship is disclosed (see Figure 6, Right). This reduction primarily manifests through *perceived readability*: when an abstract is identified as AI-written, authors perceive it as slightly less readable, which in turn lowers their confidence. Post-editing confidence gains, however, remain stable across treatments, indicating that authors regain confidence after their edits.

5.1.4 Reviewer decisions. We next examine whether the acceptance rate by the reviewers differs across treatment conditions. We model the final decision as a binary variable (1 =Accept, 0 =Reject) and compare acceptance rates across the three treatment contrasts, using both 2×2 proportion tests and cluster-robust linear probability models with standard errors clustered by the original abstract. The acceptance rates remain nearly identical, with no statistical significance, across edited abstracts from human treatments: 0.730 in Human-noInfo versus 0.736 in Human-withInfo ($\Delta = -.006$). For edited abstracts from AI treatments, acceptance rates are 0.706 in AI-noInfo versus 0.773 in AI-withInfo, indicating a modest increase under disclosure ($\Delta = -.068, p=0.081$). This suggests that edited versions of AI-generated abstracts, when authors know about the source, make definitive editing decisions that lead to higher acceptance, as shown in Figure 7. Keeping disclosure effect constant, comparing acceptance of edited abstracts from Human-withInfo (0.736) versus AI-withInfo (0.773) yields no significant difference. We further investigate how AI disclosure to authors may increase acceptance. Focusing on the marginal contrast in acceptance in edited abstracts from (AI-noInfo vs. AI-withInfo), we examine potential mediators reflecting editing effort, confidence, perceived readability, and AI beliefs. For each candidate mediator M , we estimate (i) $M \sim \text{Treatment}$ and (ii) $\text{FinalDecision} \sim \text{Treatment} + M$ using cluster-robust SEs by baseline abstract; the indirect effect was tested via Sobel's z . Among all mediators, editing magnitude through edit distance exhibits the strongest pattern. Disclosure of AI authorship slightly shifts the volume of edits ($p < .10$), and higher editing effort predicts a higher likelihood of acceptance ($p < .05$), producing a marginally significant indirect effect. Authors make slightly different editing decisions when aware of AI authorship, and these editorial behaviors modestly enhance the final review outcome.

6 Study C: Quantitative and Qualitative Analyses of Edits

Stylistic guidance for scientific writing is grounded in empirical work on how readers cognitively process text. Psycholinguistics research shows that comprehension improves when information arrives in a predictable fashion. Readability of scientific writing improves when the topic position for context is known to the readers or the stress position for new or important information is expected [31, 38]. Clarity in scientific prose improves when grammatical subjects mention real “characters” and verbs express actions, rather than nominalizing them [87, 95]. We perform post-hoc quantitative and qualitative analyses of the edits to elicit editing strategies emerging from different treatment conditions.

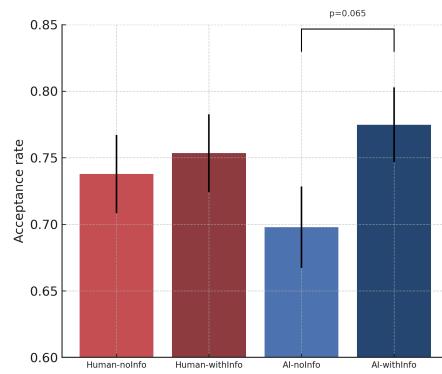


Fig. 7. Reviewer decisions differ in AI conditions

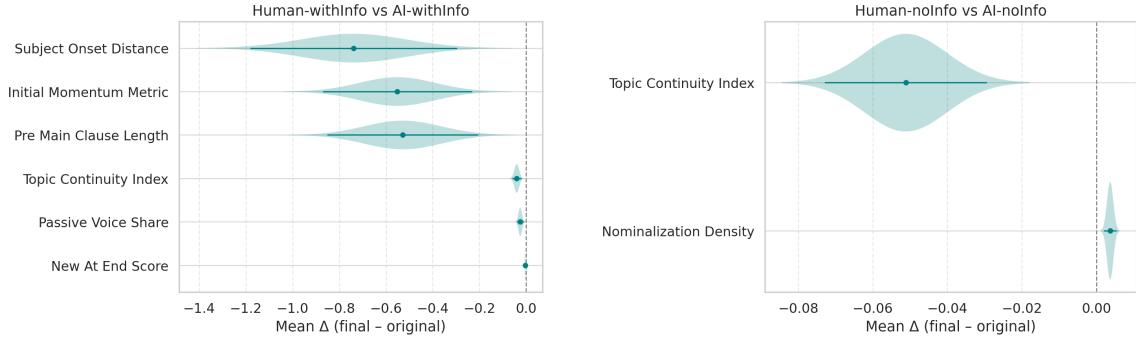


Fig. 8. Mean stylistic differences (Δ) between edited and original abstracts across conditions. Shaded bands denote uncertainty distributions around 95% CIs.

6.1 Quantitative Stylistic Metrics for Better Scientific Writing

Building on the reader-centric principles of clarity for scientific writing, we operationalize 36 computational linguistic metrics encompassing broad themes of writing: Action, Characters, Cohesion & Coherence, Emphasis, and Sentence Shape. Each metric can be computed with a part-of-speech tagger and first-order dependency labels (e.g., nsubj, ROOT, nsubjpass), making them tractable for post-hoc analysis. We use Spacy¹² to compute these linguistic features at scale for all provided and edited abstracts to understand how authors edit to improve clarity in their submissions. In subsequent analysis, we find seven of these features stand out that explain the most variance in the data and show significant trends across treatments. Each of these metrics quantify a cognitive signal through abstract's surface form: 1) *Nominalization Density* detects when actions are hidden in nouns; 2) *Passive-Voice Share* reveals disguised agency of the main sentence character; 3) *Topic-Continuity Index* represents cohesion & coherence by tracking whether successive sentences maintains the same topic; 4) *New-at-End Score* tests whether novel information is delivered in the stress position; and 5) *Subject-Onset Distance*, 6) *Initial-Momentum*, and 7) *Pre-Main-Clause Length* jointly estimates the sentence shape objective of reaching the subject and verb quickly. All metrics except Topic-Continuity and New-at-End Score trending high are a favorable sign of clear scientific writing.

6.1.1 Stylistic Shifts Across Treatments. We analyze how authors changed the linguistic structure of abstracts across four conditions. For each of 36 stylistic metrics, we computed the change from the original to the edited version ($\Delta = \text{edited} - \text{original}$) and compared conditions using Welch's unequal-variance *t*-tests. Within each comparison, we controlled for multiple testing.

Across all conditions, there was no reliable stylistic effect of disclosure alone. This indicates that simply knowing whether the text was AI- or Human-generated did not meaningfully change how participants edited its stylistic form.

By contrast, several stylistic differences emerged based on the source of the abstract being edited, as shown in Figure 8. When editing AI-generated versus Human-generated abstracts without disclosure (*Human-noInfo vs. AI-noInfo*), authors produced lower Topic-Continuity Index ($\Delta_{\text{AI}} - \Delta_{\text{Human}} = +0.051; p = 0.0002$) and higher Nominalization Density ($\Delta_{\text{AI}} - \Delta_{\text{Human}} = -0.0036; p = 0.0007$). These effects suggest that authors, when revising human-written texts without source information, tend to make them read heavier and slightly less cohesive, whereas edits to AI-generated abstracts achieve a smoother topical cohesion and fewer nominalizations.

¹²<https://spacy.io/>

Noteworthy stylistic changes appear when authors edited in disclosure conditions (*Human-withInfo* vs. *AI-withInfo*). All six metrics show significant changes: Topic-Continuity Index ($p = 0.0032$), New-at-End-Score ($p = 0.0032$), Passive-Voice Share ($p = 0.021$), Initial-Momentum ($p = 0.024$), Subject-Onset Distance ($p = 0.036$), and Pre-Main-Clause Length ($p = 0.044$). Across all six, edits to AI-generated abstracts were to make them structurally shorter, less passive, and more information-dense, while edits to human-written abstracts were to induce longer openings and delayed sentence subjects.

6.2 Post-experiment Author Interviews

To align our quantitative understanding of how authors edit several treatment conditions, we conducted a series of semi-structured interviews following the main experiment. Studies 1 and 2 quantify how the implicit source and its disclosure moderate editing behavior, whereas these interviews attempt to elicit the reasoning behind such editing behavior. We interviewed 6 authors, randomly sampled across all four treatment conditions, who successfully completed the editing task. Each interview, conducted over Zoom, lasted for 15 minutes, for which they were compensated with a \$10 flat fee. Post-hoc thematic analysis of the transcripts reveals how authors adopted several editing strategies and their perception of AI-assistance in scientific writing.

Improving readability. Authors across all conditions described a common goal of “making the abstract easier to read.” However, their editing strategies were different depending on treatments. When editing AI-generated abstracts, authors simplified language and syntax, whereas when editing human-written abstracts, they reorganized structure and emphasis. One AI-NoInfo editor explained, “*I was just thinking how to make it easier for someone else to understand, but still having all the details*” (P3). In contrast, authors in Human conditions focused on structure rather than verbosity: “*I broke it into paragraphs to make it easier to read*” (P1).

Restructuring for emphasis. Beyond clarity, authors re-ordered information to highlight what they saw as the “core” contribution. Those in the Human-withInfo condition displayed the strongest reordering edits, often bringing the paper’s novelty to the beginning. P5 mentioned: “*Instead of giving the full background first, I wanted it to say what is being proposed right off the bat.*” AI-WithInfo editors, by contrast, focused on organization: “*It would be more legible if restructured into paragraphs that are logically organized*” (P4). No-information editors rarely altered structure, limiting their work to grammar or tense adjustments (P0). Disclosure of source thus encouraged rhetorical restructuring rather than surface-level edits.

Perception of authority. Knowing who (or what) authored the abstract reshaped editors’ stance toward authority. Healthy skepticism exists for both types of abstracts; “*Even if it’s written by experts, they can also make mistakes*” (P5) or “*I always have the habit of double-checking because LLMs hallucinate*” (P4). Human-WithInfo participants knew experts had written the originals, yet still intervened confidently: “*Even if it’s written by experts, they can also make mistakes*” (P5). By contrast, authors in no disclosure conditions edited at face value, relying only on textual cues (P0).

Accountability. Across treatments, authors assumed their role to uphold the scientific integrity of the abstracts. They exerted equal oversight to ensure accuracy and coherence, irrespective of human or AI-generated abstracts. As P1 noted, “*AI is like an employee—it needs to prove itself before I stop rechecking everything*”. Disclosure amplified the sense of accountability: “*I still double check anything from AI,*” (P4). The editing exercise reveals the author’s intrinsic nature of executing expertise and moral obligation to balance the efficacy and efficiency (by using AI) in the critical act of scientific communication.

7 Discussions and Conclusion

We offer a systematic evaluation of AI-assisted scientific writing through a randomized controlled trial simulating a peer review process. Our results show that authorial behavior is significantly influenced by both the implicit source of an abstract and the disclosure of it: authors made the most revisions to human-written texts when source information was withheld, whereas AI-generated abstracts received mildly more edits when attribution was not disclosed. However, reviewer decisions were not significantly affected by the abstract's source. Instead, acceptance outcomes were primarily driven by the degree of meaningful edits. Our analysis suggests that careful edits on the AI-generated abstract can yield higher, if not equal, acceptance as compared to abstracts that are human-authored.

This work establishes a foundation for evaluating AI-generated scientific writing in realistic incentivized authorial and review settings. Future research should extend this methodology to other domains beyond computer science to understand domain-specific interactions with AI. Investigating collaborative workflows such as co-writing between multiple authors with AI support would uncover both potential and pitfalls in the use of AI assistance. Additionally, scaling to full-paper evaluations and incorporating multimodal inputs (e.g., tables, figures) would provide a more comprehensive assessment of LLM utility in scientific communication. Finally, data created using such studies could also be used to train models to conduct edits to further improve text quality in the domain of science.

Looking beyond a standalone experiment, longitudinal studies could help us understand how repeated use of AI-assisted writing affects authors' skill development, stylistic habits, and confidence over time, as well as how it reshapes norms around peer review and scientific communication. Finally, we raise an important point: ethical considerations around transparency, attribution, and responsible use of AI in research are understudied and can have welfare-altering impacts. Our study highlights the importance of academic experiences for authors, which play an important role in understanding and effectively utilizing the benefits of AI assistance. At a large scale, we must expand training programs, which are lacking, to inform novice researchers about the socially beneficial use of AI in science. Community-driven investigations of responsible use of AI in science thus must uncover downstream effects on scientific rigor, reproducibility, and community norms to optimally reap the democratic benefits of AI.

GenAI Usage Disclosure

We used GPT-4o to generate AI-generated abstracts central to our experiments. Similarly, GPT-4o was used for assigning reviewers to relevant abstracts for review, again critical for our experiments.

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A Editing Interface

Task 2.1

Do NOT make any edits outside the experiment's editing interface (the right panel).

[Toggle for Instructions](#)

Excerpt

We believe that ensuring heterogeneous services perform well side-by-side is essential to a stable and inclusive Internet.

One of the Internet's core promises is to multiplex shared resources but this promise fails if a user has to pause their YouTube video every time their roommate needs to attend an online meeting.

Hence, in this paper, we study a simple question: Are there 'winners' and 'losers' when popular services compete for bandwidth on the Internet today?

While many researchers are concerned with this question, existing research studies focus primarily on how a single aspect of a service's design (typically the CCA) impacts winners and losers.

We argue that it is necessary to evaluate Internet services as a whole, as a wide range of design choices can impact a service's contentiousness (i.e. how much 'pressure' it puts on competing services) and its sensitivity (i.e., how much a service suffers under competition).

To evaluate deployed services in the wild, we present Prudentia, an independent 'watchdog' for Internet fairness.

Prudentia evaluates contending Internet services by simultaneously accessing two live, deployed services through a controlled testbed, configured to emulate different link conditions.

We believe that it is important for a public and independent watchdog that identifies winners and losers to exist.

Over the two years Prudentia has been running,

With the rise of heterogeneous congestion control algorithms and increasingly complex application control loops (e.g. adaptive bitrate algorithms), the Internet community has expressed growing concern that network bandwidth allocations are unfairly skewed, and that some Internet services are 'winners' at the expense of 'losing' services when competing over shared bottlenecks. In this paper, we provide the first study of fairness between live, end-to-end services with distinct workloads. Rather than focusing on individual components of an application stack (e.g., studying the fairness of an individual congestion control algorithm), we want to provide a direct study over real-world deployed applications. Among our findings, we observe that services typically achieve less-than-fair outcomes: on average, the 'losing' service achieves only 72% of its max-min fair share of link bandwidth. We also find that, some services are significantly more contentious than others: for example, one popular file distribution service causes competing applications to obtain as low as 16% of their max-min fair share of bandwidth when competing in a moderately-constrained setting.

FIREPAD

Fig. 9. The above image illustrates how the authors view the abstracts. The left non-editable, copy-paste disabled panel includes the excerpts from a selected research paper, and the right panel includes the embedded firepad author where the authors can make changes at the keystroke level.

B Screening Questions

Based on the task instructions and above visuals, please select what happens if you copy the first two sentences of the provided abstract, edit them in a separate text-editor (not the one provided in the experiment), and paste them back to the experiment's editor interface? You cannot move to the next step until you answer this question correctly.

We will accept your submission

We will reject your submission

Based on the task instructions and above visuals, please select what happens if you copy the first two sentences of the provided abstract, paste them in this experiment's editor interface, and edit in the experiment's editor interface? You cannot move to the next step until you answer this question correctly.

We will accept your submission

We will reject your submission

Fig. 10. Screening questions assess the authors' understanding of task.

C Comments

We analyze the sentiment of the comments received by the authors. 139 authors out of 297 left a comment, and 54 left a comment indicating “no comment”. Remaining 85 comments are divided into three topics: study (study design), abstract (experiences with the abstracts provided), and AI (opinions regarding the AI usage trend). Table 2 shows the sentiment analysis of each topic. Most reviewers are positive toward the study design, have a less positive opinion toward the abstracts, and are split about AI usage. Word cloud of authors’ comments is in Figure 11.

Table 2. Author comment sentiment analyzed.

Topic	Positive	Negative	Positive Rate
Study	62	9	0.873
Abstract	7	3	0.700
AI	2	2	0.500



Fig. 11. Word cloud for authors' comments.

D Distinguishing AI and Human Texts

We asked the same question to both authors and reviewers: “Can you describe some distinguishing features that help you differentiate between AI-generated and human-written texts?” Popular responses included differences in word choices, sentence structure, and tone of presentation. Some reported that they are barely distinguishable. Word cloud for this question is in Figure 12.



Fig. 12. Word cloud for distinguishing factors between AI and human texts, from both authors and reviewers.

E List of Papers

Table 3. List of papers we used and the venues where they were published.

Title	Venue	Citation	Year
An Analysis of Robustness of Non-Lipschitz Networks	NeurIPS	16	2024
RedCode: Risky Code Execution and Generation Benchmark for Code Agents	NeurIPS	37	2024
InstructVideo: Instructing Video Diffusion Models with Human Feedback	CVPR	62	2024
Locally Adaptive Neural 3D Morphable Models	CVPR	3	2024
ToolSword: Unveiling Safety Issues of Large Language Models in Tool Learning Across Three Stages	ACL	41	2024
To be Continuous, or to be Discrete, Those are Bits of Questions	ACL	4	2024
Prudentia: Findings of an Internet Fairness Watchdog	SIGCOMM	5	2024
Rodeo: Making Refinements for Diverse Top-k Queries	VLDB	2	2024
Titan: Efficient Multi-target Directed Greybox Fuzzing	IEEE S&P	20	2024
C-FRAME: Characterizing and measuring in-the-wild CAPTCHA attacks	IEEE S&P	3	2024
An Architecture For Edge Networking Services	SIGCOMM	5	2024
ModsNet: Performance-aware Top-k Model Search using Exemplar Datasets	VLDB	2	2024
Learning-based Widget Matching for Migrating GUI Test Cases	ICSE	29	2024
Harp: Leveraging Quasi-Sequential Characteristics to Accelerate Sequence-to-Graph Mapping of Long Reads	ASPLOS	4	2024
GraphTrail: Translating GNN Predictions into Human-Interpretable Logical Rules	NeurIPS	7	2024
RainbowCake: Mitigating Cold-starts in Serverless with Layer-wise Container Caching and Sharing	ASPLOS	50	2024
Mining Pull Requests to Detect Process Anomalies in Open Source Software Development	ICSE	1	2024
Uncertainty-aware Action Decoupling Transformer for Action Anticipation	CVPR	17	2024
DocLLM: A Layout-Aware Generative Language Model for Multimodal Document Understanding	ACL	91	2024
More is Merrier: Relax the Non-Collusion Assumption in Multi-Server PIR	IEEE S&P	8	2024
An exabyte a day: throughput-oriented, large scale, managed data transfers with Effingo	SIGCOMM	3	2024
FedSQ: A Secure System for Federated Vector Similarity Queries	VLDB	5	2024

Title	Venue	Citation	Year
Formal Mechanised Semantics of CHERI C: Capabilities, Undefined Behaviour, and Provenance	ASPLOS	11	2024
Code Impact Beyond Disciplinary Boundaries: Constructing A Multidisciplinary Dependency Graph and Analyzing Cross-Boundary Impact	ICSE	3	2024
Optimistic Critic Reconstruction and Constrained Fine-Tuning for General Offline-to-Online RL	NeurIPS	1	2024
DREAM: Diffusion Rectification and Estimation-Adaptive Models	CVPR	8	2024
Pareto Optimal Learning for Estimating Large Language Model Errors	ACL	5	2024
Distribution Preserving Backdoor Attack in Self-supervised Learning	IEEE S&P	37	2024
NegotiaToR: Towards A Simple Yet Effective On-demand Reconfigurable Datacenter Network	SIGCOMM	13	2024
Composable Data Management: An Execution Overview	VLDB	3	2024
WASP: Workload-Aware Self-Replicating Page-Tables for NUMA Servers	ASPLOS	8	2024
Predicting Performance and Accuracy of Mixed-Precision Programs for Precision Tuning	ICSE	11	2024
DiffuserLite: Towards Real-time Diffusion Planning	NeurIPS	28	2024
DeCoTR: Enhancing Depth Completion with 2D and 3D Atten-tions	CVPR	7	2024
Hard Prompts Made Interpretable: Sparse Entropy Regulariza-tion for Prompt Tuning with RL	ACL	4	2024
eAUDIT: A Fast, Scalable and Deployable Audit Data Collection System	IEEE S&P	31	2024
Fast, Scalable, and Accurate Rate Limiter for RDMA NICs	SIGCOMM	6	2024
SpannerLib: Embedding Declarative Information Extraction in an Imperative Workflow	VLDB	1	2024
ACES: Accelerating Sparse Matrix Multiplication with Adaptive Execution Flow and Concurrency-Aware Cache Optimizations	ASPLOS	4	2024
ACAV: A Framework for Automatic Causality Analysis in Au-tonomous Vehicle Accident Recordings	ICSE	10	2024
ChaosBench: A Multi-Channel, Physics-Based Benchmark for Subseasonal-to-Seasonal Climate Prediction	NeurIPS	24	2024
ViLa-MIL: Dual-scale Vision-Language Multiple Instance Learn-ing for Whole Slide Image Classification	CVPR	48	2024

Title	Venue	Citation	Year
Generative Cross-Modal Retrieval: Memorizing Images in Multimodal Language Models for Retrieval and Beyond	ACL	37	2024
SoK: The Long Journey of Exploiting and Defending the Legacy of King Harald Bluetooth	IEEE S&P	20	2024
OptimusPrime: Unleash Dataplane Programmability through a Transformable Architecture	SIGCOMM	3	2024

F Prompts and Output

GPT-4o prompt for extracting research plan and findings from published papers

Given this research paper, please extract content that will be useful for understanding the concept, background, findings, and result of the paper. For EVERY sentence extracted, please provide the page number from the information is taken in a square bracket as [page number].

DO NOT PRODUCE ANYTHING THAT IS NOT WRITTEN IN THE PAPER.

DO NOT LEAVE OUT ANY RELEVANT INFORMATION.

EXTRACT THE EXACT SENTENCE FROM THE PAPER.

EXCLUDE ANY CONTENTS FROM THE ABSTRACT OR CONTENT BEFORE INTRODUCTION.

DO NOT INCLUDE ANY EQUATIONS.

THE LENGTH OF THE CONTENT SHOULD BE AROUND 1000 WORDS.

DO NOT INCLUDE ANY REFERENCE TO FIGURES OR TABLES.

Give exact sentences without any formatting or dividing sections.

Use linebreaks. The extracted content should be sufficient to write the abstract.

Fig. 13. GPT-4o Prompt we used to extract research findings from papers. The output of the model (after verification) is used as the excerpt to generate abstract.

An Example of extracted research plan and findings from published papers

The capacity to generate and manipulate digital 3D objects lies at the core of a multitude of applications related to the entertainment and media industries, virtual and augmented reality and healthcare [1].

However, achieving fine control in mesh manipulation necessitates the learning of a disentangled representation of 3D shapes which is still an open research problem [1].

Recently proposed methods based on Graph Convolutional Network (GCN)-based Auto-Encoders (AEs) have demonstrated impressive performance in dimensionality reduction but typically learn a highly entangled latent space making them unsuitable for detailed shape manipulation [1].

Additionally, despite having a low parameter count, these methods struggle to handle high-resolution meshes, limiting their applicability [1].

Few works have dealt with the disentanglement of local identity attributes, however these methods still rely on GCNs and opt for controlling manipulations through the state of the latent code which is partitioned and assigned to predefined object regions [1].

Using the latent code to drive shape manipulation requires the use of explicit optimization objectives to learn a disentangled latent space [1].

Moreover, partitioning its state is critically suboptimal for learning compressed representations of 3D objects [1].

We propose a different paradigm which does not involve partitioning the latent code or relying on its state to drive changes in shape, resulting in state-of-the-art (SOTA) disentanglement and reconstruction capabilities in a unified architecture [1].

Instead, we use a global latent code for 3D object unconditional generation and utilise additional inputs to jointly train our generative model to locally overwrite the latent encoded geometry [1].

We present the Locally Adaptive Morphable Model (LAMM), a general framework for manipulating the geometry of registered meshes [1].

To the best of our knowledge, this is the first method that allows direct shape control with a single forward pass [1].

Applied on human 3D heads, LAMM exhibits SOTA disentanglement properties and allows for very fine geometric control over both facial identities and expressions [1].

Our models, trained for manipulation, concurrently exhibit SOTA performance in mesh dimensionality reduction compared against methods trained exclusively on this task [1].

As a result, a single model can be used to generate entirely new shapes and apply both localized and global modifications to their geometry [1].

We show how our framework can leverage direct control as a primitive to achieve higher level editing operations such as region swapping and sampling [1].

...

Fig. 14. An example of research findings fed as input to LLMs to generate abstracts. It is generated using the paper “Locally Adaptive Neural 3D Morphable Models” published at CVPR.

GPT-4o prompt for generating abstracts from extracted research plan and findings

You will be presented with an excerpt from research papers in Computer Science. I have curated these excerpts from research papers which have been published in top-tier peer-reviewed articles. Your goal is to write an abstract.

What is an abstract?

An abstract is a short summary of completed research. It is intended to describe the work without going into great detail. Abstracts should be self-contained and concise, explaining your work as briefly and clearly as possible. An abstract should be able to stand independently from the research paper and still tell the reader something significant. The most important function of an abstract is to help a reader decide if he or she is interested in reading your entire publication.

An effective abstract will contain several key features:

Motivation or problem statement: Why is the research/argument important? What practical, scientific, theoretical or artistic gap is the project filling?

Methods/procedure/approach: What did the researcher actually do to get your results? (e.g. analyzed 3 novels, completed a series of 5 oil paintings, interviewed 17 students)

Results/findings/product: After completing the above procedure, what did the researcher learn/invent/create?

Conclusion/implications: What are the larger implications of the findings, especially for the problem/gap identified previously? Why is this research valuable?

Keep the abstract short: A general rule of abstract length is 150-200 words.

Do not add any new information: If something doesn't appear in the input excerpt, then don't put it in the abstract. An abstract is supposed to convey scientific findings, so they have to be precise and factual. Please don't embellish any results or findings.

Except for writing the abstract: [Excerpt]

Fig. 15. GPT-4o Prompt we used to generate abstract given research findings (excerpts).

An example of generated abstract from extracted research plan and findings

The generation and manipulation of 3D meshes are pivotal for applications across entertainment, virtual and augmented reality, and healthcare. However, existing methods struggle to achieve fine-grained, spatially disentangled control of 3D shapes, often relying on Graph Convolutional Network (GCN)-based auto-encoders (AEs) that produce highly entangled latent spaces and face scalability issues with high-resolution meshes. We propose the Locally Adaptive Morphable Model (LAMM), a novel framework that circumvents these limitations by enabling direct, localized mesh manipulation without partitioning the latent code or introducing explicit disentanglement objectives. LAMM employs fully connected layers and a global receptive field to respect the distinct semantics of registered mesh vertices, allowing for both unconditional shape generation and fine-grained editing via direct control inputs. Extensive experiments on 3D human head and hand meshes demonstrate that LAMM achieves state-of-the-art performance in both disentanglement and reconstruction while scaling efficiently to high-resolution data. Our model surpasses existing methods in terms of memory efficiency and inference speed, offering practical benefits such as faster CPU-based execution and reduced resource requirements. LAMM's capabilities democratize access to advanced 3D modeling techniques, enabling applications ranging from detailed facial identity editing to region swapping and geometric sampling.

Fig. 16. An example of AI-generated abstract.

An example of human written abstract

We present the Locally Adaptive Morphable Model (LAMM), a highly flexible Auto-Encoder (AE) framework for learning to generate and manipulate 3D meshes. We train our architecture following a simple self supervised training scheme in which input displacements over a set of sparse control vertices are used to overwrite the encoded geometry in order to transform one training sample into another. During inference, our model produces a dense output that adheres locally to the specified sparse geometry while maintaining the overall appearance of the encoded object. This approach results in state-of-the-art performance in both disentangling manipulated geometry and 3D mesh reconstruction. To the best of our knowledge LAMM is the first end-to-end framework that enables direct local control of 3D vertex geometry in a single forward pass. A very efficient computational graph allows our network to train with only a fraction of the memory required by previous methods and run faster during inference, generating 12k vertex meshes at >60fps on a single CPU thread. We further leverage local geometry control as a primitive for higher level editing operations and present a set of derivative capabilities such as swapping and sampling object parts. Code and pretrained models can be found at <https://github.com/michaeltrs/LAMM>.

Fig. 17. An example of human-written abstract from the published papers.