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The Ethics of Generative AI in Social-Scientific Research: A Qualitative Approach for Community-Based AI Ethics

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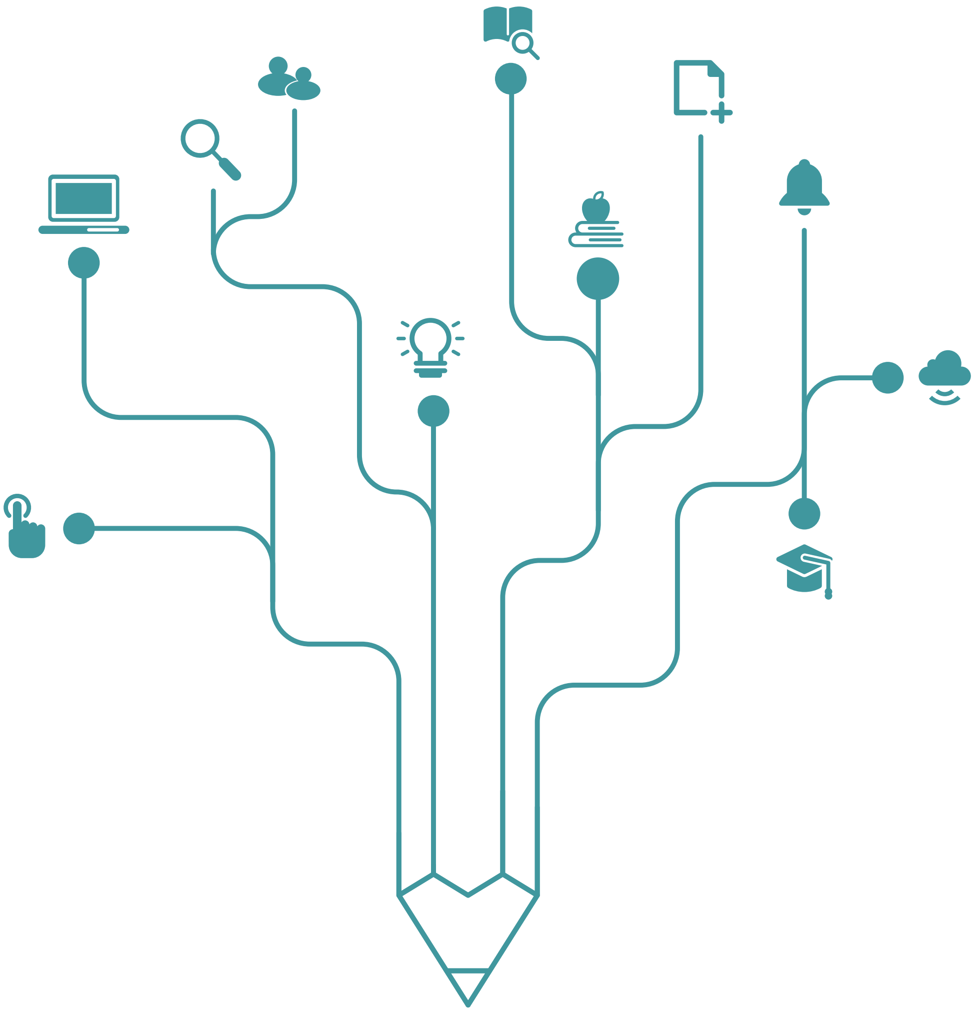

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Abstract
Despite growing attention to the ethics of Generative AI, there has been little discussion about how research ethics should be updated for the social sciences. This paper fills this gap at the intersection of AI ethics and social science research ethics. Based on 17 semi-structured interviews, we present three narratives about generative AI and research ethics: 1) the equalizer narrative, 2) the meritocracy narrative, and 3) the community narrative. We argue that the ethics of AI-assisted social-scientific research cannot be reduced to universal checklists. Instead, the community-based approach is necessary to organize "ethics-in-practice." In all narratives, technical functions of Generative AI were merely necessary conditions of unethical practices, while ethical dilemmas started to arise when such functions were situated in the institutional arrangements of academia. Our findings suggest that the ethics of AI-assisted research should encompass not only the specific ethical rules concerning AI functionalities but also community engagement, educational imperatives, institutional governance, and the societal impact of such technologies. It signifies democratic deliberations to address the complex, emergent interactions between AI systems and societal structures.

Keywords: Artificial intelligence, Research ethics, (several more!)

1. Introduction

As generative AI fundamentally shifts the nature of work and production in countless industrial sectors, scholars have widely debated various impacts of Generative AI on the labor market, the national economy, social inequality, mass communication, and security and privacy, to mention a few[1–4]. The academic industry is not an exception. Generative AI is already exerting a substantial influence across a range of academic activities, including teaching, experimental execution, manuscript composition, editorial practices, and illustrative techniques[5–7]. Scholars are rapidly inventing new ways to make use of Generative AI in their research, not only to enhance productivity but also to conduct substantially new research, utilizing third-party-generated prompts and figures in their experimental settings[8].

While there is growing attention to both general ethical concerns about Generative AI and specific practical strategies for the use of Generative AI in scientific research, discussion of the research ethics of Generative AI-assisted academic research has remained restricted in the realm of what we call *ethical checklists*—a list of principles scholars have agreed to allow or prohibit[9]. This principle-based approach is, in fact, in line with a longstanding bureaucratic codification of research ethics in science, which originated from the Belmont report of 1978 that established major principles of human-subject research. Despite their apparent utility for setting the moral foundation for research conducts, one limitation is that these principles are minimal *practical* guidelines at best, rather than *ethical* guidelines that consider the morality of research in complex situations of researchers, research subjects, and institutional settings. In this context, now it is evermore imperative to re-contemplate meanings and boundaries of research ethics because Generative AIs are immensely changing the nature of academic practices.

In this paper, we develop and articulate Generative AI-assisted research ethics with several strategies. First, we approach this problem at the intersection between technology ethics and research ethics. Scholars in Science and Technology Studies (STS) have argued that the ethics of technology overarches the processes for designing technological artifacts, the distribution of benefits and harms of technology, and the conflicts of science and technology with existing ethical systems, such as bioethics and law[10,11]. It encompasses social, institutional, and moral aspects of technological design and application [10–12], and such insights are useful in reconsidering research ethics with new technological tools. Second, we strategically focus on social science research ethics because social science fields are particularly relevant to new utilities of Generative AIs that assist data gathering, analysis, and writing processes [13]. In fact, social scientists are rapidly developing new Large Language Model-augmented research methods in predicting unanswered survey responses [14], annotating textual data [15,16], and calculating causality between textual data [17,18], to mention a few. In these regards, revealing new research ethics in AI-assisted social science would be useful in inspiring ongoing ethical dialogue among researchers in various fields. Finally, to transcend the principle-based approach, we use the narrative approach—an empirical method to analyze people's experience-based cultural and moral narratives behind the veil of standardized written protocols [19]. In this way, we aim to articulate *research ethics-in-practice* that social scientists start to imagine and experience. With these strategies, we ask how contemporary social scientists define research ethics, and how such views are impacted by Generative AIs.

We argue that the research ethics of Generative AI should be discussed and developed by community-based democratic deliberation, as AI-related ethical problems are deeply connected with existing social and moral problems of academic communities, as narrative by contemporary social scientists. To accomplish this goal, we interviewed 17 junior-level social scientists and analyzed the interviews to find common narratives. We designed the study to collect qualitative discourses strategically from technologically advanced computational social scientists. Particularly, we hypothesized that junior social scientists under the rites of the institution [20] would be better positioned to become extremely sensitive to the ethics of Generative AI and their own relationship with such a double-edged sword because they are not only beginning to utilize Generative AIs but also institutionalizing themselves in accordance with those new tools and related disciplinary changes. They were varied by discipline, gender, first language, and country of primary affiliation. In so doing, we analyzed heterogeneous experiences, narratives, and discourses from strategically chosen samples [21]. None of the ethics narratives in the interviews we conducted were exclusively focused on the technical functionalities of Generative AI per se; instead, Generative AI acquired ethical meanings only when it was situated within the matrix of institutional practices. For instance, AI was perceived as unethical when it undermined researchers' collective capability to write and code, while it was regarded as ethical when it empowered scholars at the margin to get writing advice from AI. In other words, interview data signal that ethical issues regarding Generative AI are relevant beyond AI itself; therefore, it is crucial to approach the ethics of AI as an ethics-in-practice, rather than as an ethics-of-artifacts that is static, isolated, and universal.

There are two practical implications of this research. First, democratic deliberation is key for developing AI ethics. It becomes evident that the ethics of AI, beyond the research ethics of social science, should be discussed and articulated among a wide range of AI users, not only by engineering experts. Considering that ethics is an emergent phenomenon, contingent upon various contexts of human-computer interaction, it is imperative to collect, and thus connect, real-life ethical dilemmas people face in their own institutional (meso-level) settings. Second, this study ultimately implies that regulations and rules to deal with the ethical problems of AI should be broader than technology regulation. These problems will not be resolved simply by regulating particular functions or services. Future codes of ethics surrounding Generative AI should include social policies, beyond technology policies, to be fully operative in the real world where technology enacts itself in collaboration with various users.

2. Literature Review

2.1. Research ethics in social science research and recent challenges

Numerous studies have developed ethical codes of social science research, and such works originate from research ethics of biomedical and behavioral research. These rules established guidelines for experimentation on human subjects, as seen in the Nuremberg Code or the Belmont Report, which mainly discusses that scholars should treat human subjects with respect and beneficence [22]. In the social sciences, the famous Stanford Prison Experiment fostered similar ethical discussions and raised researchers' awareness of how to treat human subjects [23,24]. As history tells us, the meanings and boundaries of ethical research have been changed in conjunction with social changes, and now research ethics even emphasize the inclusive design of research that does not harass and demean any human participants, including researchers themselves.

Aside from fairly treating and respecting vulnerable populations in the research process, researchers also discuss research ethics to make scientific findings rigorous, reproducible, and accountable. One of the most serious issues is intentional research misconduct, such as data fabrication, fake peer reviews, or self-plagiarism. Data fabrication and self-plagiarism are common reasons for paper retraction in social science [25,26]. While not as serious as research misconduct, there is growing concern about questionable research practices, such as p-hacking or hypothesizing after results are known, that require researchers' attention [27,28]. Finally, the academic community strives to increase scientific rigor by holding authors more accountable. For example, instead of listing authors according to their contributions, many journals have begun to adopt the Contributor Roles Taxonomy to specify each author's contribution to the published works [29].

The research ethics used in the social sciences in the past are facing new challenges as social interactions have become increasingly digital. The large-scale online experiments through social media platforms make it difficult to receive proper consent from participants [30,31]. The granular nature of big data may reveal an individual's identity even after being anonymized [32]. The shift in the form of journal publishing from offline to online unleashes the number of articles that can be published, which increases the emergence of predatory journals that publish articles without rejection and the proper peer review process [33,34].

Faced with a rapidly changing social and academic environment, researchers are constantly challenged to navigate the right research ethics while maximizing their research efficacy [35].

2.2. Generative AI and research ethics

Sociologists and historians have long discussed the ethical design of sociotechnical systems[10,11,36,37]. Particularly, scholars writing within the SCOT (Social Construction of Technology) paradigm have widely argued that the design and function of technological artifacts and systems represent the existing social structure; therefore, technology reinforces the social structure that brought about the very design component itself [11]. This tradition makes clear that social studies of technical artifacts require analyzing "not just the history of the artifact itself, but also economic history, demographic history, and industrial history"[36].

Despite the complexity of the problem, thus far, the rise of Generative AI and research ethics have been related in narrow ways. Outside of social science, there have been a few discussions about the ethical concerns of Generative AI in the academic community; however, controversies are organized around issues of data generation or fabrication, plagiarism, originality, and authorship. First, data analysts have pointed out that machine-generated data and real data are often inter-mixed in analyses, and AI can even be utilized in problematic predictive research. Among the few previous articles on the ethics of AI-assisted social-scientific research, a few scholars have warned that machine-generated data might become a cheap and fast alternative for social survey research, while AI is capable of generating preferable social datasets for privileged social groups [38,39].

Second, the writing capability of Generative AI has elevated general concerns about plagiarism. Scholars have pointed out that Generative AI might innovate scholars' writing process, as it can drastically reduce the amount of time and energy needed to tailor sophisticated writing for an academic audience [6,9]. In terms of the style and quality of the writing produced by Generative AI, which is not far from academic standards, Generative AIs are even capable of replicating personal writing styles [5]. Overall, worries about plagiarism mostly center around relatively obvious misbehaviors in academic products.

Finally, controversies about AI's eligibility for authorship have led academic communities to develop AI-related rules for their journals and conferences. For instance, Nature Machine Intelligence, NeurIPS, NAACL, and EMNLP announced that they will not allow AI to be listed as an author [40], because human authors are deemed to be more responsible for the final product than "machine authors." To ensure the ethical conduct of research, some have suggested that a rigorous checklist for academic researchers should be provided by journals and conferences [9].

In summary, the discussion around research ethics using Generative AI simplifies issues into rules that we can binary judge as right or wrong. In reality, ethical problems in academia are rather blurry than discrete. Depending on the institutional context where researchers are located or the stage of the researcher's career, researchers may have different criteria for research ethics [41]. Generative AI introduces more grey areas in research ethics than researchers had before as it begins to actively replace skills deemed to be unique to human beings, such as data exploration or reasoning. For example, when a graduate student advisee does the entire explorative analysis with Generative AI, should it be considered ethical or not? The answers to this question may differ by career stage or the level of expertise in the field, which is the reason why we need a more narrative-based approach to deepen our understanding of the nature of AI ethics in various organizational, occupational, and institutional settings.

3. Methods

As stated earlier, this research is based on qualitative interviews with social scientists to collect their ethical narratives related to AI-assisted social science research. A qualitative interview is a systematic study to understand narratives and discourses of variously positioned social actors [42,43], and is most useful in discovering unfixed identities, fluid categories, and non-standardized rationales behind standardized stories [44]. This is a highly promising method to study people's ethical considerations because neither survey responses nor experimental studies can adequately capture people's conceptions, imaginations, and vocabulary of motives behind one's moral actions. Therefore, social studies of moralities have often utilized in-depth interviews to analyze people's taken-for-granted worldviews and moral values [45,46]. Regarding the data analysis process, theoretical interpretation and empirical discovery were inseparably dialectical throughout the entire process [47]. For instance, we initially hypothesized to listen to a solid code of ethics from interview participants; however, we unexpectedly (and surprisingly) faced more nuanced and convoluted ethical dilemmas, which led us to rethink research ethics not as a universal guideline but as a practice.

We conducted semi-structured interviews with 17 junior-level social scientists. We strategically chose to interview junior social scientists to target the most 'tech-savvy' population and to understand how the process of being socialized and institutionalized as a member of the scholarly community interacts with emerging technologies, such as Generative AI. They were recruited via various seminar series for computational social scientists in Korea, and this setting was helpful in ensuring interviewees' interests and experiences with Generative AI in their research and education.

All interviewees were fluent in English; however, we conducted interviews in the language with which they felt most comfortable. We let interviewees choose between an individual interview or a group interview in case they felt uncomfortable talking about their AI usage in front of other interviewees. Interviewees' information is summarized as follows:

Label	Career stage	Nationality	Place of education	Discipline	Gender
R1	Doctoral student	United States	United States	Political Science	Male
R2	Doctoral student	United States	United States	Political Science	Male
R3	Doctoral student	India	Non-US	Informatics	Female
R4	Master completed	Korea	United States	Communication	Male
R5	Master student	Korea	Non-US	Political Science	Female

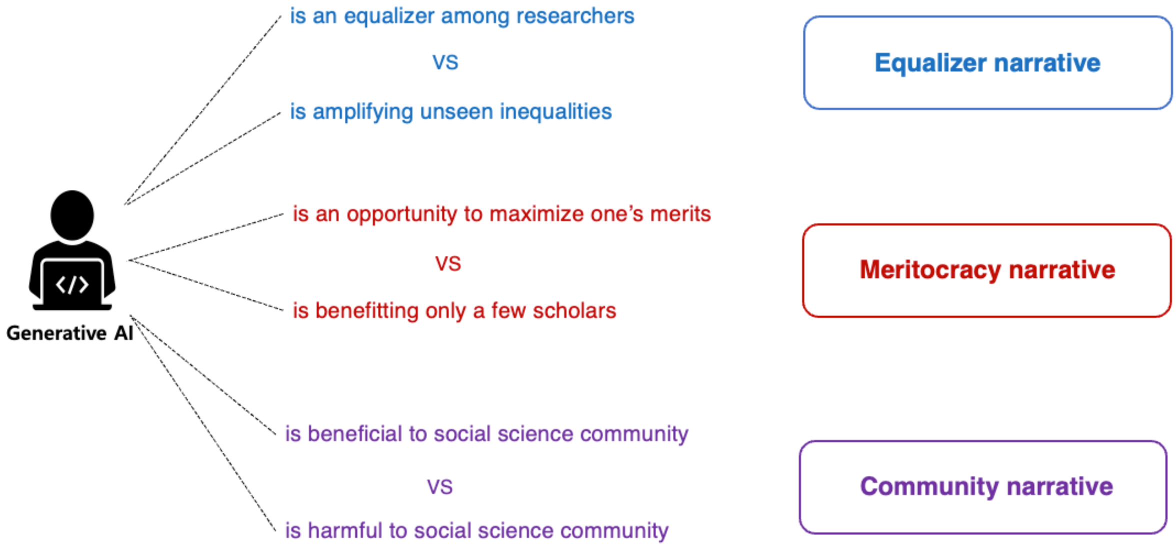
R6	Doctoral student	Korea	United States	Communication	Male
R7	Doctoral student	Korea	United States	Sociology	Male
R8	Doctoral student	Korea	United States	Social Work	Male
R9	Doctoral student	Korea	United States	Sociology	Female
R10	Doctoral student	Korea	United States	Management	Female
R11	Doctoral student	Korea	Non-US	Political Science	Male
R12	Doctoral student	Korea	Non-US	Policy Studies	Male
R13	Doctoral student	Korea	United States	Policy Studies	Female
R14	Master student	Korea	Non-US	Sociology	Female
R15	Doctoral student	Korea	United States	Informatics	Male
R16	Master completed	Korea	Non-US	Political Science	Male
R17	Master completed	Korea	Non-US	Management	Male

<Table 1. Summary of interview respondents>

These interviewees had unique career contexts that could not be summarized in the table above. First, most of them had experience with academic institutions in the United States, even those who were currently studying in Korea. For instance, R16 and R17 had just finished their Master's degrees in Korea but recently got admitted to graduate schools in the U.S. R5, R11, and R14 were studying at a graduate school in Korea; however, they had a strong desire to go to the U.S. during their careers. The only noticeable exception who was not under the influence of U.S.-based academic culture was R3. Second, most participants had cross-cultural experiences in academic institutions. For instance, R4, R7, R12, and R13 had changed their majors, and R1 and R2 were second-generation immigrants in the U.S. Also, it is worth emphasizing that except R1, R2, and R3, most participants were non-native English users who would be highly incentivized to use Generative AI for language supports. The diversity of participants' academic and cultural experiences was beneficial for this research.

4. Results

Based on the interviews, we identified three major categories of research ethics concerns. They are i) an equalizer narrative, ii) a meritocracy narrative, and iii) a community narrative. First, the equalizer narrative includes various responses regarding whether Generative AI can resolve present inequalities in the social sciences. Second, the meritocracy narrative involves discourses on AI usage as an individual capability. Third, the community narrative encompasses various worries and opportunities regarding the effect of Generative AI on the growth of the academic community. These categories are not mutually exclusive, and they are interconnected discourses. For instance, the equalizer narrative often functions as evidence of the community narrative, and vice versa. We manually coded transcripts and systematically sorted key themes to reveal emergent categories of seemingly disordered conversations. Participants mostly had conflated views of the research ethics of AI-assisted social-scientific research; therefore, none of the participants' views were reducible to any particular discourse. Instead, our discourse categories reveal possible descriptions of debates that are often inconsistent and incoherent.



<Figure 1. Categories of AI-ethics discourses>

4.1 The equalizer narrative

Most noticeably, all interviewees primarily equated the meaning of ethics in social science with the matter of inequality within academia. In other words, in discussing ethics in social science, they all immediately contemplated whether generative AIs can be a good tool that might mitigate existing inequalities within social science. There are two contrasting views within the equalizer narrative: whether AI mitigates or amplifies existing inequalities.

4.1.1 Discourse: AI is a great equalizer among social scientists

First, some argued that AI would be a helpful "equalizer" among social scientists. The underlying consensus among all interview participants was that social science is currently operating on the basis of multiple inequalities. R3 mentioned that the most significant inequality in social science starts with advisors and mentors:

> "The reason I started to use ChatGPT is that in my institute, no one does machine learning and artificial intelligence research. So, it was very new to me and there was no one to guide me, even my advisor. She will help me with the conceptual part, not the coding part. and I was just wondering what I should do, and I got to know about ChatGPT, so it helped me a lot [with my coding]" (R3).

R3 was a doctoral candidate at an Indian university and was generally satisfied with her training experience in India. Still, this does not mean that R3 never felt the global inequality of social science. For instance, she mentioned that her advisor had too many students, and it was impossible to get careful mentorship from the advisor. The inequality was attributable to the lack of resources that prevents junior social scientists from being properly trained and mentored. R5, a graduate student at a Korean university, confessed to a similar experience. She has often been told that "you should take care of your own research by yourself," not only from faculty members but also from senior graduate students. It was institutional wisdom that students needed to figure out a survival strategy. Advisors were not fully available for research consultation:

> "Even before I came to graduate school, I knew that professors would minimally help me during the thesis writing process. I saw other senior students who met their professors with bright ideas, and then were rejected by advisors, over and over again. But I never saw a single senior student who complained about their advisors. It was so natural to me that I should bring a great idea to my advisor, and I tried to use generative AI tools to navigate the topic" (R5).

Other graduate students in non-US-based universities echoed R5's view. R5 used Generative AI to assist with her literature review, while R16 used Generative AI to assist with his English writing for either academic manuscripts or informal emails. He was shocked to see that ChatGPT generated "so much White male English as if I am working in the Silicon Valley," but he slowly accepted that it would be helpful to overcome the linguistic and cultural barriers to participation in global social science. R1 agreed that generative AI is helpful, especially because most Korean students have to get help from someone to polish their English anyhow. Tools like ChatGPT are a helpful equalizer because they are cheap, fast, and can remain secretive:

> "When Korean students apply to graduate schools in the US, I think 70-80% of them would use editing services. (...) In the department, students are mostly open to AI, and the director of graduate studies even openly told students that she uses ChatGPT for her research. (...) But I was like; I was a bit afraid of how others would judge me if I said I used ChatGPT for my research. I guess ChatGPT is most helpful if you use it stealthily" (R1).

According to R1 (and to R9 and R16), being transparent about whether one uses Generative AI is an academic privilege. For them, Generative AI becomes a useful equalizer when they can secretly use it to assist their work, often to overcome hidden hurdles in academia, such as required English fluency, programming skills, and culturally proper communication. We asked them if they felt ethical enough about using ChatGPT-assisted sentences in their academic works or emails, and they asked us back about the meaning of ethics. R9 said, "I am not 100% proud of it, but if someone criticizes me for being unethical, I will ask them back, what do you mean by being ethical." Here, we can observe a cleft between conventional ethical codes and ethics that are practiced by Generative AI users. This confirms that research ethics is a highly contextualized concept, and it is more important to figure out broader and situated ethical guidelines rather than "do or don't" type of universalized checklists. In sum, many junior social scientists perceive Generative AI as a useful equalizer, particularly because of the lack of resources in non-U.S. universities and the subtle racism inside of academia.

4.1.2 Discourse: AI will worsen hidden inequalities among social scientists

While Generative AI can help junior social scientists to become equal competitors, many of them equally worry about hidden, indeed deep, inequalities that might be triggered by Generative AI. The most frequent worry was the divide between thoroughly trained social scientists versus social scientists who are overly dependent upon Generative AI. The divide might be invisible in the short term; however, according to interviewees, social scientists worried that it would become evident as they enter the job market and become independent researchers. R6 and R17 worried that new graduate students tend to rely on Generative AI as if they do not have to hassle with programming languages:

> "People just imagine that GPT will do everything, but, I guess, the divide between computer scientists and scientists who just use codes as tools will become broader. The latter can barely 'use' it, but cannot apply it for their research. You should know how to apply it if you want to become a researcher anyway" (R6).

> "New cohorts these days… I mean, if I see anyone who can't write a single line of code, but just asking to ChatGPT for coding… I feel confused. The problem is it works so well. It works well, so they have zero motivation to study coding…" (R17).

They agreed that ChatGPT might train new social scientists to remain ignorant. R16 argued that politicians make silly mistakes when they simply rely too much on their policy advisors. Such side effects are going to be crucial for social scientists' writing skills as well. R11 thought that language assistance from Generative AI would worsen the gap because native English speakers would be better able to distinguish useful editing suggestions from nonsense. In other words, from social scientists' perspective, those who use Generative AI as an extra resource are much better positioned compared to those who have nothing but Generative AI as their toolkits:

> "Native English speakers can immediately know when GPT makes weird suggestions. But non-natives might simply rely upon GPT, and it will be a death spiral. We (Korean social scientists) cannot really know how accurate editing suggestions by GPT is" (R11).

Such inequality is connected to the technical limitations of Generative AI. Existing Generative AIs function much better when users interact with them in English. This means that language-wide help from the AI will be more significant for native English speakers. R9 found that her fellow native-English-speaking social scientists use Generative AI to make their English even better, and she thought that the quality difference between native and non-native speakers might become even larger:

> "I am not sure if GPT is truly helpful for non-native-English-speaking social scientists. Because, I think it works much better if you ask questions in good English. What I felt was that you can get good help only if you are already good at English" (R9).

Such editorial suggestions from Generative AI also contribute to amplifying the cultural hegemony of English-speaking scholars. R10 said, "When I see sentences that are edited by ChatGPT, I feel like they are not mine anymore." However, as R16 agreed, such feelings of being distanced from ChatGPT-edited sentences are evidence that the AI is really helping their English in a way that they themselves could never achieve. As much as they feel the power of ChatGPT, they also reflect upon the meaning of practicing "White English":

> "Sometimes, when GPT writes super-stylish sentences, for me, I feel like, 'Oh, I can recognize that this is not mine.' (...) [The] more I use it, the more I feel like I am wearing the wrong suit. It symbolizes

> that I am not really one of them, and I am just using a trick to be seen as one of them. If I use it, I can't even imagine vetoing the existing rule. I am just reinforcing power inequality, I guess" (R10).

In summary, interview data reveal various worries about hidden (and unintended) inequalities that might be induced by Generative AI. There are two takeaways. First, social scientists perceive Generative AI as unethical when it magnifies preexisting problematic (which they often narrate as 'wrong') features of social science academia. While social scientists are relatively generous to the ethics of technology usage itself (such as text editing by ChatGPT), they were much less tolerant of systematic intervention of such tools in worsening the ecology of their enterprise. Second, notably, such 'unethical' inequalities are not simply created by the technical functions of AI—instead, they arise when the technical (in)capability of AI works in tandem with existing problems of social science, such as language gaps, cultural-capital divides, and productivity-oriented training processes.

4.2 The meritocracy narrative

Another dominant narrative was about the deservingness of social scientists who can use Generative AI better than others. This narrative consists of mixed voices considering whether Generative AI is one of many social-scientific research tools, such as Stata, SPSS, or R, or whether it is a game changer that social scientists should worry about. We coded this narrative on meritocracy as a repertoire of ethical considerations because interviewees often legitimated or non-problematized Generative AI-assisted academic works with the name of meritocracy, while some of them starkly opposed such an approach because it distorts the hidden privilege of a few social scientists.

4.2.1 Discourse: It is to a researcher's merit if (s)he can use AI effectively

Some respondents suggested that Generative AI is not fundamentally special compared to other research-assistive tools. They mentioned R and SPSS, statistical computing tools that social scientists have widely used for decades, as well as more generic tools, such as Google search or EndNote, which have proliferated in recent decades. These tools are powerful and have changed the way social scientists work. In this sense, some suggested that Generative AI is no more than an additional skill set that social scientists might want to actively develop:

> "It is another tool. If you use it properly, that is good for you. I won't be surprised if my future competitors in the job market write ChatGPT as their software technique. I won't do that (laugh), but, I agree that it must be a very important skill set if you can use it well. Not everyone can 'dissolve' ChatGPT [from] their works" (R17).

A notable pattern was that many respondents justified the meritocratic argument since it is actually very difficult to use Generative AI well. R7, R10, R13, and R17 agreed that if someone uses ChatGPT for their research, (s)he deserves credit, because not every social scientist can achieve it, just as not all people can find they want on Google. They shared an understanding that most Generative AIs look easy to use, mostly because service providers focus on the interface between users and AIs. In truth, they are very difficult to use effectively, especially if a researcher wants to use them for a particular research purpose:

> "I'll respect it if someone uses ChatGPT for their programming. I really mean it. Of course, many of us can use ChatGPT for minor stuff, but I can't imagine any social scientist who achieves a grandiose research project simply due to ChatGPT. I think research is something much more than GPT" (R17).

> "I have been a very active user of ChatGPT. I've never seen other colleagues who use it deeper than I do. Look, I have almost a year-length conversation query with GPT, and in this window, it is a totally different one compared to GPT in a new window. I have trained this monster! I think this should be appreciated as a skill set. Not every social scientist can do this, I swear" (R13).

They disagreed about whether Generative-AI users will receive undeserving credit, not only because it is difficult to use, but also because of comprehensive evaluative criteria in the social sciences. In short, if someone who uses Generative AI in their research becomes a 'superstar' in their field, that would not be simply due to AI—it must be due to that person's inherent talent that deserves to be appreciated. R10 even emphasized that faculty members are already training their mentors to be prepared for non-AI-related skills, such as speaking and presentation, which Generative AI cannot replace:

> "It is obvious that people will evaluate you based on something [for which] you cannot rely on Generative AI. Like, presentation skills and communication skills. (...) My advisor emphasized so many times to his students that you need to train yourself thoroughly, thorough[ly] enough to impress others that you are a great presenter. Why presentation? I guess, that is something you cannot use AI [for]—you are just yourself at the podium." (R10)

Therefore, Generative AI was often perceived as one more piece of homework for junior social scientists because, without using Generative AI, they felt anxious about quickly becoming obsolete. However, they thought that it was the social scientists' (especially junior social scientists') responsibility to train themselves to use the new tools instead of being critical about the tools themselves. In other words, some junior social scientists perceived Generative AI as just another useful tool, as R15 summarized: "It is another useful tool. All we need is institutional preparation to embrace it, including the educational curriculum to embrace it."

4.2.2 Discourse: The benefits of AI in social-scientific research cannot be fairly distributed

A considerable number of counter-arguments were also conveyed by respondents, including by those who expressed optimistic views on Generative AI. First, many worried that benefits would not be evenly distributed, because not all subfields can equally be benefitted by Generative AI. R7 and R11 insisted that Generative AI will benefit only a few subdisciplines, and it is likely that the relatively few scholars in such subfields will dominate precious opportunities in academia. R11 is a political scientist, and enjoys ChatGPT 4.0's code interpreter (currently renamed "Advanced Data Analysis") tool. He confessed that colleagues in political science who work on qualitative methods and theoretical topics are not eligible for getting help from AI as much as he is, because Generative AI has such a narrow range of application that cannot help those researchers. He said, “It is not a meaningful tool except for a rare experiment-based political scientist like me.”

R5 predicted a continuous decline of qualitative methods compared to quantitative and computational methods that can receive more direct help from Generative AI. As a political scientist, she had already witnessed the unequal distribution of her school's resources among qualitative and quantitative researchers in her department, legitimated by the logic of merit. These inequalities do not end inside of the department—they continue in the publication, conference, job market, and tenure processes. In particular, in the context of precarious labor market conditions for social scientists, R5 said that qualitative research, such as ethnography and in-depth interviewing, is likely to be more deeply marginalized than it already is:

> “I have a hunch that ethnography and qualitative studies will be even more neglected. Generative AI even generates survey responses, and then researchers are increasingly finding real person’s voice [sic] useless or not efficient enough to bet their career. If these trends continue, I mean, there will be a lack of demand for qualitative analyses that collect real people’s real experience. Academically, it will be praised, but, I mean, demand from a job market” (R5).

R5’s concern suggests that academic demands and job-market demands might not align, which implies that the advantages of Generative AI are likely to be unfairly distributed among scholars. She insisted that qualitative research is extremely meaningful, especially in the context of an LLM-based research paradigm, because qualitative research adds a new corpus of textual data for the models to draw on. However, this does not necessarily mean that qualitative or theoretical research will be appreciated by the job market, because productivity is the golden rule in the social sciences. Furthermore, researchers who provide underlying resources (e.g., a qualitative corpus) for Generative AI are not going to be rewarded, while resource users (e.g., quantitative social scientists) are likely to be immensely rewarded.

Being able to access Generative AI is another issue that hinders merit-based reward systems. R7 and R9 raised concerns that large global firms are likely to launch expensive premium services that only a select few will be able to utilize. They thought that free or cheap Generative-AI services are no more than samples that lure users to more powerful tools. In this case, the divide among social scientists will be correlated with economic power gaps:

> “Those companies are unethical. Period. It is so obvious because they are already running their business based on internet resources that they did not build by themselves. In a proverb, people say, it is difficult to start, but it is easy to continue. Clearly, they will continue this business strategy until they finally launch extremely expensive premium service for, like, marketing firms or research organizations. Then, social scientists would either be forced to spend their money or lag behind competitors” (R9).

If others purchase expensive resources, it is difficult to refrain from using them and still remain competitive. This resembles drug-taking in sports, according to R7. The difference is that drug-taking in sports is (and can be) prohibited, while this is not the case in academia. R7 said, “It might be inappropriate, but academia right now is like mixed martial arts without rules.” This means that researchers are incentivized to maximize their own survival strategies, and Generative AI is at the borderline between fair and unfair tools for survival. This unhealthy aspect of Generative AI in survival-oriented social science is connected to the next narrative, which concerns the pros and cons of Generative AI in the scholarly community at large.

4.3 The community narrative

The final narrative involved discourses on community-wide implications of Generative AI. Interviewees often interchangeably used the term “community” to denote either their academic community or their general social community. Still, we found that “research ethics in science” involves a lot more than just writing the paper—instead, it is inevitably connected to potential consequences in social scientists’ communities and the entire society. This narrative also reaffirms that the ethics of Generative AI-assisted research is related not only to the ethics of technology itself but also to the ethical and moral responsibility of academia overall.

4.3.1 Discourse: AI-assisted research is good for the social science researcher community

Some junior social scientists argued that Generative AI might be confusing and uncomfortable during the transition stage; however, it will ultimately boost scientific rigor, productivity, and efficiency. Notably, their notions of rigor, productivity, and efficiency were rooted in their experiences as junior trainees in the social sciences:

> “This is not only the case in political science. I have seen many friends in social work and sociology who mechanically test associations between variables, like trial and error. They simply pray until stars pop up, meaning that they find variable sets with [a] low enough p-value. I feel like, is this science? (...) Rather, I would say Generative AI is more scientific. Just put all of your data into the AI, and let it test thousands of models!” (R11)

For R11, humans’ step-by-step problem-solving processes have no reason to be preserved, because such processes have no scientific grounding at all. If Generative AI can reduce time and energy and test thousands of previously untested combinations of models, it is inevitably better science. Such an evaluation is based on an understanding of a generic research process by mundane social scientists, and it implies that unguided data-centered social science by human hands has no more legitimacy than AI-based automated social science.

Another criticism that arose was about the writing style of academic articles. R13, who reported that she had trained her ChatGPT page for her research, was concerned about inefficient and (almost) ceremonial aspects of academic manuscripts that should be expelled. For R13, Generative AI is a new tool that would likely innovate the way scholars write their manuscripts:

> “At the beginning of the manuscript, [we] all have to write mundane and meaningless paragraphs to simply make their manuscript fancy. That part is full of trivial stories, like the global environmental crisis is a severe problem, or anything that is too obvious. I think machines can write better. If so, I think there will be a change in styles of

> academic writing—journals will increasingly prefer concise manuscripts without such decorative components" (R13).

R13 further insisted that Generative AI is not going to simply boost the efficiency of social scientists but improve the routines and academic tastes of social scientists. Other than articles being concise, she predicted that AI-assisted peer review will likely happen sooner rather than later. AI will not completely replace peer reviewers; however, it can assist reviewers. She said, "In [the] near future, journal editors will attach AI-Generative [sic] peer review drafts to peer reviewers [sic]. Perhaps editors themselves will rely on Generative AI to select papers to be desk-rejected." Again, such changes could be beneficial to social scientists because the community of social scientists is already too weak to realize the moral economy peer review, which is a system of egalitarian and voluntary labor for the community. Given that editors' workloads have skyrocketed and finding peer reviewers is getting difficult, junior social scientists already perceive that Generative AI seems to be a feasible (and realistic) alternative to voluntary labor from the academic community.

Finally, R12 predicted that Generative AI-based translation tools and bibliographic services are going to increase the readership of social-scientific articles, overcoming language and expertise barriers. For a long time, academic journals have failed to diversify their readership, and academic publishers have built their business model almost exclusively around a small group of experts, not for the general public in different countries. But such a bar is likely to be lowered, according to R12, because the quality of translation by Generative AI is undoubtedly high, and summarized versions of academic papers are already attracting readers on social media outlets such as Twitter (X) and YouTube:

> "As more people are going to read our papers, our responsibility is increasing. To make an analogy, humanities and social sciences scholars should do their research as if they are physicists in the Manhattan project. In the good old days, we all wrote papers only for our closest peers, but now… Imagine that your paper becomes viral on Twitter or YouTube. Once it is picked up by their algorithm, it is not yours anymore. Furthermore, language cannot stop it, because automated translation is just fantastic. Our job is becoming more complicated" (R12).

In this context, R12 is conceptualizing Generative AI as an ethical tool because it can make the social-scientific community more reflexive and impactful—two crucial traits that the academic community has not demonstrated well. In sum, much of the narrative around the positive impact of Generative AI on the social-scientific community is deeply rooted in junior social scientists' reflexive perspective as intermediate participants of the community.

4.3.2 Discourse: AI-assisted research may be harmful to the community of social-scientific researchers

Lots of counter-narratives about the ways in which Generative AI may impact the social-scientific community were also collected. Most notably, the majority of interviewees worried that the overall quality of the academic community's collective intellectual output will be harmed by Generative AI. These worries are particularly aligned to ongoing crises in academia, such as the productivity-oriented job market and the fragile solidarity among scholars.

First, many interviewees insisted that the methodological paradigm of social-scientific research is likely to be compromised by Generative AI. R16 argued that social scientists devalue the literature review section of papers too much, treating it as if reviewing existing literature is a non-creative and useless task that Generative AI can easily accomplish. This is, however, not true, according to R16:

> "Literature review parts of all papers on similar topics are going to mimic each other, if Generative AI takes a part. It is not constructive for the whole academic community, because I think literature review is equally creative as result and discussion parts. We get trained to tailor literature review to specify our contribution to the field. It is not merely a summary of previous works. If it is written on a conveyor belt, I don't think we will learn anything" (R16).

There are also quality concerns about the fundamental design and approach of social-scientific research. R11 thought that ideal social-scientific research maintains a dialectical relationship between empirical data and theoretical hypotheses. If one determines the other, it is not science anymore, according to R11. R15 agreed with this point, saying that "data analysis should maintain a tension with a hypothesis-driven framework." In R15's view, however, Generative-AI-assisted social-scientific researchers are largely concentrated in subfields that rely on quantitative and big-data analyses that start the research design from data. This "data centrism" is a double-edged sword—powerful in inductive inquiry; however, its description easily lacks theorization:

> "I think the ultimate goal of social science training is to make researchers raise their own questions. Research methodologies [exist] to answer such questions. But with Generative AI, such a process is under the crisis [sic], because we are literally outsourcing the data analysis part to AI. Maybe we are witnessing a sort of paradigm shift in social science—being data-driven can become a new normal science" (R11).

It is difficult to decide whether data-driven social science is a worse model than question-driven social science. The point is that, as both R11 and R15 contend, the shift is happening unintentionally and almost seamlessly. "We don't have a chance to resist this shift, because we are just learning the social science method in such a new way," R15 said.

A second issue that interviewees discussed is the concern that with Generative AI, an unknown mechanism behind the scenes generates experimental questions and even missing values in survey data. Even if researchers try their best to be reflexive about their research designs, some interviewees worried that their processes would not be reproducible if AI takes part in generating experimental questions and fills in data. Interviewees repeatedly described their experience dealing with inconsistent AI responses. Even if each independent usage produces quality output, AI may not be consistent across interactions:

> "Generative AI is simply a black box. When researchers divide tasks among humans and AI, AI's parts will be simply fancy but non-reproducible. It will generate different things every single time you ask the task. This can be ethically problematic, because reproducibility is a core virtue of scientific research" (R15).

Note that R15 used the term "black box" to denote characteristics of Generative AI. A black box is a sophisticated machine that generates outputs from inputs; however, users cannot know how the task is done. When a black box is normalized, users do not even ask about the mechanism inside of it. R15 worried that researchers tend to be accustomed to automated parts of their research, as quantitative researchers do not bother hand-calculating p-values when they run multivariate regressions. Generative AI provides incomparably more powerful tools than other computational software, and it is possible that an unimaginable crisis in social-scientific research might be forthcoming, according to R15.

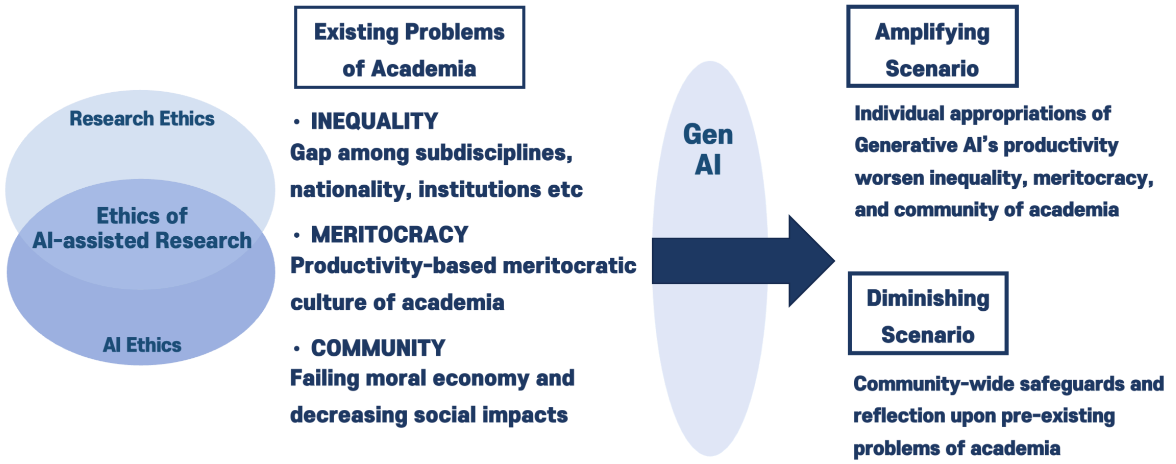
Finally, asymmetric usage of Generative AI in different stages of research was discussed as a potential threat to the social-scientific community. R12 pointed out that Generative AI is much more helpful during the production process than the review process of social-scientific research. As a result, he suggested a scenario where inflated productivity far exceeds the review capacity of the social-scientific community. In other words, AI being problematic for the social-scientific community depends upon the capacity of the social-scientific community to embrace output changes:

> "If the GPT is given, it might provide a productivity boost to researchers. Then they will start pouring papers into journals, and the question is, who is going to review all of them? It is a serious problem because of both technical limitations of GPT and community capacity of social scientists. Technically, Generative AI cannot help the review process as much as the writing process. Socially, the current social science community, I think, cannot 'digest' what AI is pouring" (R12).

In summary, interviewees worried that Generative AI could amplify preexisting (but hidden and ignored) problems in the social-scientific community. None of the problems are simply due to the technical functions of Generative AI—instead, they are co-constructed by community-wide problems and the functional limitations of AI.

5. Conclusion and Discussion

What do we mean by the 'ethical' use of Generative AI in social science research? While universal checklists would easily (and quickly) become obsolete or unrealistic, a narrative-based approach to this question reveals several fertile insights into this problem. Junior social scientists in this study narrated three broad types of ethical issues related to Generative AI: the equalizer narrative, the meritocracy narrative, and the community narrative. In the equalizer narrative, interviewees described Generative AI as potentially making social science more equal. On the other hand, some contested hidden inequalities (such as technical, language, and cultural inequalities) are going to be amplified by Generative AI. In the meritocracy narrative, interviewees argued that using Generative AI well demonstrates merit and should be rewarded, while others predicted that merits are going to be unevenly distributed. In the community narrative, some argued that Generative AI would benefit the social-scientific community by innovating academic style and methods, while others disagreed, arguing that Generative AI might worsen the reproducibility crisis and peer-review jam in the social sciences. Taking these insights into account, overall, this paper argues that the research ethics of Generative AI in social science is an area beyond the realm of technology regulatory ethics. Ethical problems arise when Generative AI resonates with preexisting inequalities and injustice, and our data reveal that current academic institutions might incentivize such resonance. The fact that junior tech-savvy social scientists, who are concurrently institutionalizing themselves vis-à-vis new tools, are perceiving the research ethics of Generative AI as a comprehensive question beyond the “do or don’t” rule implies that the scholarly community should take the rise of Generative AI as an opportunity to reflect upon their current problems rather than simply decrying the “harmfulness” of technical functions of Generative AI, because harmfulness is a socially achieved consequence. All ethical discourses point out that different institutions and disciplines should start discussing their community-wide ethics of Generative AI to reach a consensus regarding their common goals and resource allocation strategies to prevent amplifying resonance between pre-existing problems of academia and Generative AI.



<Figure 2. Existing problems, amplifying scenario, and diminishing scenario>

This study is theoretically guided by STS and the philosophy of technology and empirically grounded in strategically recruited samples and narratives. There are two broader implications. First, the ethics of artificial intelligence should encompass technological functionalities and social susceptibilities; therefore, democratic deliberations by various social groups are necessary to achieve these goals. As demonstrated in our case study, the ethics-in-practice in academia becomes evident via a narrative approach, and community-wide reflexivity turned out to be a key to alleviating sociotechnical problems by Generative AI. Similarly, our protocol would be replicable in other social realms, such as different industrial sectors, governmental policy sectors, and media and communication sectors. It is worth noting that socially decontextualized ethical codes of artifacts themselves are susceptible to oversimplification and may fail to address the complex, emergent interactions between AI systems and societal structures. Second, the dynamic and pervasive nature of AI technology necessitates ongoing ethical scrutiny that adapts to technological advancements and societal changes. This means establishing a continuous, iterative process of ethical evaluation that engages various stakeholders, including technologists, ethicists, policymakers, and the public at large. Such an inclusive approach ensures that the ethics of AI are not static but evolve with our growing understanding of AI's impact on different aspects of human life. Therefore, integrating ethics into the lifecycle of AI development and deployment is imperative for responsible innovation and the fostering of trust in AI applications.

Our study has several limitations. First, our community-based approach prioritizes the social “process” of designing AI ethics, not the formal rules themselves. Therefore, it is completely possible that community-based deliberation opens contradictory and contrasting viewpoints among members rather than forming a consensus. Indeed, science communication scholars have pointed out that scientific and technological debates in social communities often face antagonistic divides because members have heterogeneous views and understandings of technoscientific objects[48,49]. Still, we contend that such long-term debate is necessary to deal with ever-evolving AI technology and AI ethics. Future studies are required to collect a variety of ethics narratives by variously positioned agents in diverse types of organizations and occupations not only to deepen our understanding of general AI ethics but also to develop practical strategies to facilitate community-based deliberation about Generative AI.

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