# From Human-Centered to Social-Centered Artificial Intelligence: Assessing ChatGPT's Impact through Disruptive Events

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#### Abstract

Large language models (LLMs) and dialogue agents have existed for years, but the release of recent GPT models has been a watershed moment for artificial intelligence (AI) research and society at large. Immediately recognized for its generative capabilities and versatility, ChatGPT's impressive proficiency across technical and creative domains led to its widespread adoption. While society grapples with the emerging cultural impacts of ChatGPT, critiques of ChatGPT's impact within the machine learning community have coalesced around its performance or other conventional Responsible AI evaluations relating to bias, toxicity, and 'hallucination.' We argue that these critiques draw heavily on a particular conceptualization of the 'human-centered' framework, which tends to cast atomized individuals as the key recipients of both the benefits and detriments of technology. In this article, we direct attention to another dimension of LLMs and dialogue agents' impact: their effect on social groups, institutions, and accompanying norms and practices. By illustrating ChatGPT's social impact through three disruptive events, we challenge individualistic approaches in AI development and contribute to ongoing debates around the ethical and responsible implementation of AI systems. We hope this effort will call attention to more comprehensive and longitudinal evaluation tools and compel technologists to go beyond human-centered thinking and ground their efforts through social-centered AI.

#### Keywords

human-centered, social-centered, artificial intelligence, ChatGPT, dialogue agents, large language models

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# Introduction

ChatGPT, a generative dialogue agent created by OpenAI, launched in November 2022. By January 2023, it had reached 100 million monthly active users, quickly becoming "the fastest-growing consumer application in history" (Hu, 2023). Since then, journalists and social scientists have spilled much ink on ChatGPT's widespread adoption and the social impact it has engendered. Schools and teachers rushed to adapt their classroom policies and practices to prevent students from using the dialogue agent to cheat on their assignments (Castillo, 2023; Roose, 2023). *Science* Journals released a public statement stating that the rise of submissions listing ChatGPT as a co-author urged an update to their license and editorial policies to dissuade further entries of a similar nature (Thorp, 2023). As corporations find their employees increasingly rely on ChatGPT to perform critical business tasks (Nolan, 2023), many are scrambling to rewrite their workplace policies to ensure that sensitive, confidential, or proprietary data do not enter the system. The rapid growth in the reach of ChatGPT is unparalleled—with hundreds of downstream applications incorporating the ChatGPT API (application programming interface), the system's powerful functionalities will soon be in everything and everywhere (Eadicicco, 2023; Kelly, 2023).

While society grapples with the emerging cultural impacts of ChatGPT, the machine learning community is bogged down by a different set of metrics. Invocations of 'impact' for AI developers tend to focus on the risk of harm inflicted on individual users from a performance and safety standpoint (for example, see Borji, 2023). Generally, high-performance LLM (large language model) outputs reflect user intentions, are factually accurate, and are low on 'hallucination' (i.e., the tendency to generate inaccurate outputs unfaithful to the training data). On the other hand, safety is broken down into two central tenets: 1) that the system is evaluated for fairness, bias, and toxicity, and 2) there are sufficient system guardrails to prevent misuse (Bai et al., 2022; OpenAI, 2022; Ouyang et al., 2022; Thoppilan et al., 2022). We argue that the focus on individual users and their psyches, which draws on a particular view of human-centered AI, is a double-edged sword—while it prioritizes a user's capacities and needs during system development and evaluation, human-machine alignment under such a configuration atomizes and dislodges users from their social contexts (Selbst et al., 2019). As a natural extension of this logic, the 'impact' of an AI system could, thus, be tempered by way of continuous model refinement. Feedback mechanisms in the ChatGPT web interface, which give individual users the ability to thumbs up, thumbs down, and leave qualitative comments, exemplify this tendency.

The machine learning community's propensity for individual-level assessments assumes that taking care of the individual takes care of society, and obscures the urgent need to examine and respond to higher levels of impact (Joyce et al., 2021; Nolan, 2023). To address this, we argue that the implementation and evaluation of societal-scale technologies (i.e., artifacts or systems that impact people across political, economic, geographical, and cultural boundaries; Cooper, 2023) such as ChatGPT need to take into account their effects on *social groups, institutions, and their norms and practices*. In other words, we urge AI practitioners to go beyond individual-level thinking in current deployments of human-centeredness to prioritize methods and techniques that take AI into a social-centered era.

In this article, we define *social-centered AI* as an approach that prioritizes the needs of groups and institutions across multiple domains of society in the development and implementation of AI systems. The concept is a rejoinder to existing individualistic practices in machine learning and advocates for evaluations of AI's broader effects on society. More importantly, we hope that socially-conscious forecasts and assessments can guide and alter how AI practitioners work on a fundamental level. Using three 'disruptive events' engendered by ChatGPT as points of discussion, we demonstrate how group and institutional-level evaluations related to law, teaching and learning in higher education, and workplace practices can benefit the machine learning community in the long run. We then propose concrete suggestions on how to integrate social-centered thinking into technical development. In addition, we reflect on policy recommendations that can propel structural changes, all while being mindful of the institutional barriers different actors face. Although this article is by no means a blueprint for navigating how to better align AI with societal needs, we hope that it offers pragmatic directions that spur AI development towards more social-centered ends.

# The Multiple Levels of AI Impact

## Human-Centeredness: Impact on Individuals

Human-centered technology arrived in the 1980s as a response to the foundering of technology-centered thinking. As technologists sought to prioritize the 'human factor' (Vicente, 2006), the move towards human-centeredness positioned human operators as an asset and saw human-computer interaction as complementary rather than adversarial (Henning and Ochterbeck, 1988). The emergence of value-sensitive design from the 1990s (Friedman, 1996), a widely adopted design principle that takes into account human values and behaviors, coincided with the bend towards human-centeredness.

As a guiding principle, human-centeredness gives AI developers an accessible vocabulary to articulate how their work is responsibly built. The term "human-centered" is found not only in the publications of LLMs, but also across the websites of prominent organizations such as Google (Croak, 2023), IBM (Geyer et al., 2022), and AI4GOOD (Lamoutte, 2022). Furthermore, as evidenced by the volume of papers and workshops, interest in human-centered research has proliferated within prominent machine learning and computing conferences such as NeurIPS (Conference and Workshop on Neural Information Processing Systems) and CHI (Conference on Human Factors in Computing Systems) in recent years.

The appeal of human-centered AI is, in part, due to its conceptual looseness. Without a unifying framework, researchers adapt the concept to suit their research agendas (Shneiderman, 2020). For example, in his paper "Toward human-centered AI: A perspective from human-computer interaction," Xu (2019) decomposes human-centered AI into three main components:

1) ethically aligned design, which creates AI solutions that avoid discrimination, maintain fairness and justice, and do not replace humans

2) technology that fully reflects human intelligence, which further enhances AI technology to reflect the depth characterized by human intelligence (more like human intelligence)

3) human factors design to ensure that AI solutions are explainable, comprehensible, useful, and usable.

Proposing another triptych, Landay (2023) argues that true human-centered AI development must be "user-centered, community-centered, and societally-centered." Beyond these definitions, human-centered AI is also at once the use of "machines to enhance the human experience" (Appen, 2021), something that is "collaborative, augmentative, and enhancing to human productivity and quality of life" (Stanford Institute for Human-Centered Artificial Intelligence, 2020), and a principle that "preserve(s) human control in a way that ensures artificial intelligence meets our needs while also operating transparently, delivering equitable outcomes, and respecting privacy" (Geyer et al., 2022). The polysemic nature of the concept turns human-centered AI into a grab-bag—deployment is largely contingent on a researcher's training, interest, and embedded networks. Such dispersions further stymie the creation of shared goals and visions.

The methods of achieving human-centered AI are equally in flux, though they have coalesced around the gathering of individual user feedback. In *Human-Centered AI*, Schneiderman (2022: 9) argues that what sets 'regular' AI apart from human-centered AI is that the latter relies on an array of "user experience design methods," such as "user observation" and "usability testing," to build products that "amplify, augment, empower, and enhance human performance." Soliciting individual feedback through user experience research is a common practice in AI development and oftentimes relies on the problematic assumption that the utterances and behaviors of a user are generalizable to the larger collectives to which they belong. But such methods can bring about many challenges (Kliman-Silver et al., 2020). For one, user experience studies often offer a partial view of how people use technology in the wild (Takatalo et al., 2011). Frequently conducted in highly orchestrated, laboratory-like settings, individual testers are atomized and removed from the social contexts where they would be found using the technology at hand (Dourish, 2006). Without such contexts, technology design often fails to meet the needs of real-world deployment. Moreover, as Auernhammer (2020) argues, involving people in the design process does not necessarily mean they are "centered."

#### How Evaluations of ChatGPT Reflect Human-Centered AI

The way GPT models are evaluated for their impact reflects this individualistic orientation in human-centered AI. For background, the initial version of ChatGPT ran on GPT3.5 and was fine-tuned for conversational dialogue (see Figure 1). GPT3.5, the backbone of ChatGPT, was trained with human feedback to help align model outputs with user intent (OpenAI, 2022). More specifically, GPT3.5 was initially evaluated against three criteria: helpfulness (following user instructions), truthfulness (the tendency for 'hallucinations'), and harmlessness (toxicity and bias of outputs) (Ouyang et al., 2022). To build a tool that detected harmful content produced by ChatGPT, OpenAI relied in part on labeled examples of toxic language produced by outsourced Kenyan laborers (Perrigo, 2023).

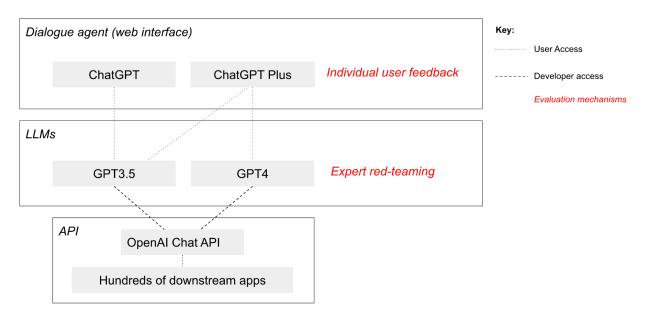


Figure 1: Simplified overview of ChatGPT and related LLMs and API

Following initial training and evaluation, OpenAI focused on 'red teaming' ChatGPT before public release—a form of evaluation in which users prompt a dialogue agent to elicit undesirable model behaviors. Red teaming was done by OpenAI staff in conjunction with external collaborators, though it is unclear how ChatGPT was updated based on their feedback prior to the initial release (Heaven, 2023). OpenAl continued to use expert red teaming before the release of GPT4 (Sanderson, 2023), recruiting more than 50 external experts to "qualitatively probe, adversarially test, and generally provide feedback on the GPT4 models" over a period of six months before its release (OpenAI, 2023a: 4). Despite the interdisciplinary nature of this expert congregation, comprising those trained in "alignment research, industry trust and safety, dis/misinformation, chemistry, biorisk, cybersecurity, nuclear risks, economics, human-computer interaction, law, education, and healthcare" (OpenAl, 2023a: 5). considerations of societal impact in GPT4's System Card pale in comparison to the documentation of engineering-centric mitigation efforts directed at improving performance for individual users.

ChatGPT's public release was also part of OpenAI's approach to align the system with human values "through an iterative process where [OpenAI] deploy[s], get[s] feedback, and refine[s]" (Heaven, 2023). Accordingly, the web interface includes a mechanism for users to provide feedback to OpenAI on the outputs of the model—by rating an answer to a prompt with a thumb up or down, indicating whether a regenerated response is 'better,' the 'same,' or 'worse' than the original, and giving additional open-ended feedback. OpenAI used feedback on non-factual responses acquired through this mechanism, with other labeled comparison data, to train reward models in order to reduce GPT4's tendency to 'hallucinate' relative to GPT3.5 (OpenAI, 2023a).

We regard this approach—combining expert red teaming and reinforcement learning from human feedback (RLHF)—to exemplify the 'human-centered' approach to AI development. This take on LLM alignment is reflected across the industry and in how evaluations are

managed (Bai et al., 2022; Glaese et al., 2022; Liang et al., 2022). We contend that this approach is emblematic of the machine learning community's limited understanding of the social and its prioritization of individualized mechanisms to assess and manage impact. Under this configuration, users, atomized and removed from their larger social contexts, are primarily farmed for their feedback—their ability to produce insights on generated outputs is instrumental for iterative development processes and AI practitioners' ability to control how their systems affect people. As users now use ChatGPT and downstream apps supported by its API to perform a wide range of tasks across social contexts, we need to expand our conceptualization of and evaluation strategies around 'impact' to include a more *social* dimension. This requires a shift away from interrogating individualized interactions between user and machine, and toward anticipating and understanding the effects of those interactions on human relations in complex and situated environments. Doing so, we believe, will help AI systems better meet the needs of larger societal entities.

## Social-Centeredness: Impact on Groups and Institutions

In this section, we differentiate impacts at the societal level from those at the level of individual users. Unlike narrower AI systems, where limits are more defined, the deployment of societal-scale technologies like ChatGPT impacts social groups and institutions across "political, economic, geographical, and cultural boundaries" (Cooper, 2023: 1). To comprehend this social impact, we encourage AI practitioners to closely monitor and analyze disruptions to the norms and practices of those groups and institutions—including intended and unintended effects, and cumulative impacts of interactions between users and agents in situated contexts over time (as opposed to concentrating on isolated interactions).

For definitional clarity, we define groups as collectives of persons characterized by shared place, common identity, collective culture, or social relations. Extant research shows that individuals are affected by group norms or scripts, and that people behave differently when embedded within different groups (Feldman, 1984; Postmes et al., 2000). Groups not only give individuals a sense of belonging, but they also help individuals figure out different courses of action in various domains of their lives.

Conversely, institutions are more abstract entities that encompass "systems of established and prevalent social rules that structure social interactions" (Hodgson, 2006: 2). The family, the state, religion, and law are all examples of institutions. While they emerge from "the thoughts and activities of individuals," they are "not reducible to them" (Hodgson, 2006: 2). Crucially, institutions are durable—they stabilize expectations and interactions between people, which in turn undergirds convention and culture (Haveman and Wetts, 2019). That said, during unsettled times (Swidler, 1986), where social norms are in flux due to the arrival of new sociopolitical ideas or technologies, institutions may undergo shifts. ChatGPT's arrival marks such a moment.

That groups and institutions originate from social interactions underscores the need to evaluate both the effects of user-system interactions *and* the impacts of such systems on social interactions outside the immediate user-system relationship. In other words, how is the use of ChatGPT changing the norms and practices of the law, higher education, or the workplace? So far, individual-centric methods favored by the machine learning community have largely ignored these questions. After all, machine learning aligns closely with fields such as cognitive science,

psychology, and neuroscience, all of which skew toward the individual as their primary unit of analysis (Hutchins, 1995). Tech spaces, known for their frequent anti-bias and sensitivity training, foster an equally individualized culture where "the evidence of bias in AI systems is often perceived as a vestige of the human bias coded into them by individual programmers who need better training" (Joyce et al., 2021: 5)

Incorporating groups and institutions into social impact considerations does not, however, mean we take a 'net benefits' approach and apply it to new units of analysis. Exemplified by the question "Is ChatGPT Good or Bad for Society?" (Kim, 2023), the 'net benefits' of an intervention or system is determined by weighing positive and negative outcomes against one another. When considering societal-scale technologies such as ChatGPT, weighing positive and negative outcomes for these entities is not only logistically challenging, but its products, often culminating in poorly theorized reflections or pros and cons lists, are ultimately questionable for the machine learning community.

While the value of ChatGPT continues to be actively debated by different stakeholders, the evaluations of LLMs appear to have stabilized around a core set of concerns related to human-centered AI. We seek to disrupt this stabilization by steering attention away from a 'net benefits' metric to an equity-based framework that examines the distribution of benefits in situated contexts. Prioritizing groups and institutions compels us to confront how people, with their distinctive know-how and resources, use technologies in the wild. For instance, in the college setting, what kinds of students are more equipped to use ChatGPT for their homework assignments, and who is more likely to be caught for plagiarism? How might we better understand the responses of instructors who must adapt their pedagogical approaches to meet the demands of new learning environments? If the machine learning community continues to primarily rely on analyzing micro-level effects between users and dialogue agents, we will never get proper answers to these types of questions, and the tendency to mischaracterize the impacts of widespread AI use will persist.

# The Emerging Social Impacts of ChatGPT

In this section, we use ChatGPT as a case study to show how group and institutional-level impacts could be studied and used productively to benefit the machine learning community. We recognize that systems such as ChatGPT can bring about several kinds of impacts to different entities, but our critical approach underscores effects of the negative kind. Positive impacts are more likely to be anticipated and devised by AI practitioners, while negative impacts—those that are more costly and disruptive—tend to be ignored or downplayed (Ashurst et al., 2022; Liu et al., 2022).

Below, we showcase three disruptive events to delineate how ChatGPT's widespread adoption impacts three societal domains—law, education, and work. We draw on Aquino et al.'s (2022) definition of disruptive events as those that have "significant consequences for [those] who experience them, but [their] effects do not occur equally across the population." Importantly, these events do not just affect individuals at a micro-level—they implicate different groups and institutions, alongside their norms and practices, in disparate ways. The case studies we have chosen are broad in scope and continue to evolve, but our analysis demonstrates a productive form of social-centered thinking.

## Al Chatbot's First Defamation Lawsuit: Impact on Law

#### Case study

In November 2022, Brian Hood, an elected Mayor from Hepburn Shire Council, in Victoria, Australia, received news from concerned voters that ChatGPT claims he was involved in a foreign bribery scandal in the early 2000s involving a banknote printing business called 'Securency,' a subsidiary of the Reserve Bank of Australia (Reuters, 2023). When asked, "What role did Brian Hood have in the Securency bribery saga?", ChatGPT erroneously 'hallucinated' details, claiming that Hood was "charged with three counts of conspiracy to bribe foreign officials in Indonesia and Malaysia" and "one count of false accounting," pleaded guilty in 2012, and was "sentenced to two years and three months in prison" (Bonyhady, 2023).

Except none of it was true (Sands, 2023). In fact, Hood, an ex-employee of the subsidiary, was the whistleblower responsible for notifying authorities and exposing this international scandal in the first place. Hood was "shocked" and "angry" when he learned about this misinformation, and his lawyers sent a "concerns notice" to OpenAI on March 21, 2023, "the first formal step to commencing defamation proceedings."

This is the first time someone in the country has lodged a defamation suit against ChatGPT or, more generally, AI (Bonyhady, 2023). Ushering this case to trial means the judicial system has to decide whether the creators of a dialogue agent could be held legally responsible if the agent churns out defamatory statements about an individual. To win this case, Hood must also prove that enough people have seen the ChatGPT output to constitute "serious harm."

#### Societal impact analysis

When accessing ChatGPT's web interface, users are reminded that the system "may produce inaccurate information about people, places, or facts." When there are gaps in its training data, ChatGPT 'hallucinates' in order to be convincing; as a result, it frequently gets critical details wrong. Because ChatGPT's outputs do not come with confidence scores, those with lower levels of digital literacy may take false information at face value. 'Hallucination' is not unique to ChatGPT—many LLMs that emerged prior are capable of generating falsehoods that people can spread and weaponize. However, the massive, global adoption of ChatGPT in a short period inscribed it with a form of legitimacy few AI systems have enjoyed. This status, incidentally, also invites greater legal scrutiny.

Hood's case compels us to ask: what happens when ChatGPT's fabricated outputs—or misinformation—begin making inroads in society to impact different people's lives? And how might the way such trends intersect with the law offer a look into how a particular form of institutional disruption is underway?

Although defamation laws vary across different jurisdictions (Johnson, 2017), 'defamation' generally refers to written or verbal false statements that could damage a third party's reputation. When applying defamation laws, legal entities try to balance allowing individuals to speak freely without the fear of litigation arising from every mistake or insult and protecting the reputation of those who could be adversely affected by false allegations (Milo, 2008).

Historically, making damaging allegations against someone is costly to an accuser; the latter risks exposing themselves to threats, physical harm, lawsuits, and other potential social ramifications of making these allegations (see Hershkowitz et al., 2021 for an example). The

impersonal nature of ChatGPT challenges this condition; without embodiment and a way to ascribe "authorship" to the machine, ChatGPT's "accusations" could be perceived as more insidious given the low-cost nature of generating and making false allegations.

The primary legal conundrum boils down to one question: what exactly is OpenAl's role in ChatGPT's misstep? Whether OpenAl should be held accountable involves legally determining whether the company is the *publisher* of defamatory material. Similar legal cases launched against Google and YouTube in Australia suggest that making such an argument involves a complex legal maneuver. For instance, in a case involving Google search results, the High Court of Australia did not regard the company as a publisher of the websites it links (*High Court Judgments Database*, 2022). Similarly, in the case of ChatGPT, much of its training data are not produced by OpenAl, and the company could make a similar argument that ChatGPT is more like a distributor or "bookstore"—while it contains work that may be dangerous or false, it does not amount to being an "author." No matter the lawsuit's outcome, its impact on the legal perception of responsibility when it comes to Al-generated misinformation could be long-lasting.

In light of these ongoing cultural and legal debates, it is imperative for us to consider which groups in society have the legal resources or know-how to act on false information generated about them. While ChatGPT is more equipped to answer biographical questions about prominent people, making this population particularly sensitive to inaccurate outputs, they are also more likely to have the legal resources to seek justice for themselves. In the near future, dialogue agents may become more intimately linked to search, and one could imagine the next generation of systems would encompass more information about laypeople. What happens when an employer uses ChatGPT to inquire about a prospective employee's personal background or history and fails to perform the due diligence of fact-checking? Those who belong to under-resourced groups with limited access to corrective or legal measures may bear the brunt of ChatGPT's fabrications.

## A Turn Away from Turnitin? Impact on Higher Ed Teaching & Learning

#### Case study

Ethan Mollick, an associate professor at the University of Pennsylvania's Wharton School, takes a radical approach to ChatGPT inclusion in the classroom (Wood and Kelly, 2023). Mollick's decision to include the dialogue agent as an assistive research tool in his syllabus just weeks after its launch stands in stark contrast to other educators' crackdowns on the use of the technology. Mollick's students are required to work with ChatGPT to write, including learning to refine their prompts and bouncing ideas off them. Although Mollick admits to approaching ChatGPT with a mix of enthusiasm and anxiety, he sees it as an unavoidable element of his students' futures in education. "The truth is, I probably couldn't have stopped them even if I didn't require it," Mollick said. A January 2023 survey by Study.com indicated that while 21% of educators had used ChatGPT to support their teaching in some capacity (by creating lesson plans, providing writing prompts, teaching writing styles, or operating as a digital tutor), more than 89% of students admitted to using ChatGPT to complete homework assignments and 48% had used it on a test, quiz, or essay (Study.com, 2023).

The rapid spread of ChatGPT use across educational systems necessitated development in not only classroom policy but also technical support. On January 13, 2023, less than two months after ChatGPT was made publicly available, the plagiarism detection program

Turnitin announced it was developing new tools to detect AI writing (Chechitelli, 2023). Calling such work "misconduct," it promised its own AI team was working hard to keep detection services at pace with generative models. A longstanding tool for educators to catch dishonest students, Turnitin is being forced onto new terrain as educators and their students struggle to control the tools for writing.

#### Societal impact analysis

Cheating and plagiarism in higher education is an industry of its own (Walker and Townley, 2012). From hiring essay writers online to lifting paragraphs verbatim from internet sources, students have continuously found ways to get academic writing done. Unfortunately, despite the pervasive nature of the problem, catching students who plagiarize is also notoriously complex; instructors either rely on manual techniques (e.g., by comparing work to a student's earlier writing) or use a plagiarism detection service like Turnitin to check students' submissions against a database of previously submitted work and other digital sources.

What does ChatGPT mean for this uneasy truce? Almost immediately after its release, educators began sounding the alarm about the threat ChatGPT posed to student assessment. OpenAI did not initially release any accompanying services to detect text ChatGPT generates or rely on watermarking techniques, leaving educators scrambling to find a solution for a new kind of plagiarism. Before the emergence of dialogue agents like ChatGPT, educators generally trusted Turnitin to catch students who were not writing their own work, and warning students that Turnitin would evaluate their work deterred many would-be plagiarizers (Heckler et al., 2013). Turnitin's long-term usefulness may hinge on its ability to incorporate new techniques to evolve along with dialogue agents (for example, to shift away from similarity checks to examine the "origin of content," as suggested by Khalil and Er, 2023).

Because OpenAI did not release plagiarism software alongside ChatGPT's release, AI-detection startups emerged to fill the gap in this space. For example, GPTZero—founded by Princeton senior Edward Tian—is a classification model that predicts whether a document was written by ChatGPT by comparing the variation and complexity of sentences. Although GPTZero has been cited by some outlets as a relatively reliable AI detector (Wiggers, 2023), its creators caution against using the system to punish indicated plagiarism: "We recommend educators to take approaches that give students the opportunity to demonstrate their understanding in a controlled environment" (Tian, 2022). When OpenAI released its own detection tool two months after ChatGPT debuted, it came with similar words of caution: "Our classifier is not fully reliable....[it] correctly identifies 26% of AI-written text (true positives) as "likely AI-written," while incorrectly labeling human-written text as AI-written 9% of the time (false positives)" (OpenAI, 2023b).

Research on plagiarism detection in the era of ChatGPT shows that the path forward remains uncertain. While Khalil and Er's (2023) study shows that only 20% of the essays generated by ChatGPT failed Ithenticate's (a Turnitin-like tool) plagiarism detection, Aydın and Karaarslan's (2022) study found the occurrence to be more frequent—40%. A variety of factors, including the style, length, or topic of the essays evaluated, play a role in mediating the chances of something being labeled unoriginal. While the education sector awaits more sophisticated tools, educators react by adapting how they evaluate their students' learning. For example,

many advocate for more in-class writing assignments or oral assessments, while some design entirely new kinds of projects that ChatGPT cannot handle (Rudolph et al., 2023).

Meanwhile, ad-hoc implementations of plagiarism detection strategies across classrooms in different locales may lead to unequal outcomes for different groups of students. Those more skilled at tinkering with ChatGPT's prompts and outputs could benefit more from using the technology than those less adept. Running on GPT4, the latest version of ChatGPT (i.e., ChatGPT Plus) is only available to those paying for a premium subscription at 20 USD per month. As usage increases, this might create an access divide among students. Moreover, the widespread use of imperfect detection services means that more students risk being accused of using ChatGPT even when they have not. Early research suggests students who are non-native English speakers are more likely to be misclassified by GPT detectors as plagiarizers (Liang et al., 2023). The deciding factors in whether or not the accusations stick will likely depend on a student's social and cultural capital (Strangfeld, 2019).

## To Use or Not to Use: Impact on Workplace Practices

#### Case study

ChatGPT is now a common workplace tool for workers across different industries. A February 2023 survey by FishBowl found that "70% of workers using ChatGPT at work are not telling" their employers (Graham, 2023). As a result, a new wave of data privacy issues has risen from workers inputting personal and sensitive data to ChatGPT. Some examples include doctors inserting patients' names and conditions into medical report prompts to enterprise workers using ChatGPT to draft business proposals containing proprietary information. Companies are now rushing to take action against such violations (Lemos, 2023), with JP Morgan restricting its employees' use of ChatGPT, and Microsoft and Walmart advising caution and banning the sharing of "sensitive information" on such platforms.

Many companies that allowed employee access to ChatGPT are actively grappling with the consequences of such decisions. For example, while Amazon initially told workers that they could use ChatGPT if they were careful about sharing sensitive material, a company attorney later warned employees against sharing code with the dialogue agent after the enterprise reportedly witnessed ChatGPT responses reproducing internal Amazon data (Hurler, 2023). Similarly, after lifting an initial ban on ChatGPT, Samsung caught three engineers from the company's semiconductor division inputting sensitive organizational information into ChatGPT. The incidents include an employee sharing source code from a semiconductor database, one attempting to identify defects in equipment by asking ChatGPT to diagnose its code, and another asking ChatGPT to generate minutes of an internal meeting (Dreibelbis, 2023).

#### Societal impact analysis

ChatGPT's comprehensive set of capabilities has turned it into a one-stop-shop for many work-related tasks (Chen et al., 2023). Today, workers use ChatGPT to code, summarize, and draft all sorts of documents, from thank-you emails to legal documents. Because of its generative capabilities, ChatGPT produces outputs that outperform traditional templates, and much collective digital attention has been directed toward ways to refine results through prompt tinkering (see u/bdaddykane, 2023 for an example). The convenience of using one tool for multiple tasks makes ChatGPT particularly enticing, and its global popularity, alongside the

widespread commentary on the potential of ChatGPT as a 'copilot' (Philps and Tillman, 2023), places considerable pressure on employees to incorporate the tool into their workflows.

Such a workplace trend elevates information security risks for many organizations and corporations worldwide. For one, ChatGPT's free-to-use platform cultivates a reciprocal relationship with its users (Fourcade and Kluttz, 2020). Without monetary payment, what OpenAI gets in return is the copious amount of data individuals contribute to the system. Sharing sensitive and confidential information with publicly-accessible systems like ChatGPT poses a significant risk to corporations such as Samsung (Newman, 2023). These sources of information could be used by OpenAI to train subsequent systems and potentially appear in responses to other users in future iterations of the dialogue agent and other downstream applications. Ultimately, this exact risk led Samsung to ban employee access to ChatGPT outright (Gurman, 2023).

This worrying phenomenon may also disrupt protocols around data management. Facing disruptions to institutional norms around how proprietary data is used, employers must create policy on the fly as they determine, on the one hand, how to facilitate access to the tools that increase the productivity of their workforce and, on the other, how to retain sensitive information. Even companies that bar ChatGPT may face issues with compliance. Already, some employees are finding workarounds (such as using a VPN) to continue using ChatGPT to complete work-related tasks (u/The-Doodle-Dude, 2023). Evidently, preventing the use of ChatGPT in a climate where dependency has been cultivated is a profoundly challenging endeavor.

OpenAl could offer a paid version of ChatGPT that does not retain any of the data users feed to the system, but such economic alternatives do not work well for data-hungry models in the long run. Companies will thus have to find ways to balance the need to exploit the benefits of systems like ChatGPT while preventing information leakage. Such a balancing act, we believe, will predominantly come down to an organization's resources. For example, more resourceful companies like Samsung plan to create their own private dialogue agent for employees (Gurman, 2023). In contrast, less resourceful organizations may not have access to these privacy-preserving dialogue agents due to hardware, software, or other organizational barriers. As ChatGPT usage becomes more and more prevalent in the workplace, uneven access to privacy-preserving systems could reinforce inequalities between groups and organizations in the long run.

## **Discussion & Conclusion**

#### From Human-Centered to Social-Centered AI

The idea that the recent proliferation of LLMs and dialogue agents can have long-standing impacts on society has been articulated ad nauseam by journalists and social scientists alike (Abdullah et al., 2022; Sanders and Schneier, 2023). We use the three disruptive events above to show that beyond individual-level impact brought about by these systems, implementing societal-scale technologies like ChatGPT can profoundly impact groups and institutions, alongside their norms and practices, across multiple domains of society. While some of these disruptions could lead to positive outcomes and further human-machine collaboration, the fruits they bear are generally unevenly distributed. Because the social cost of responding to

ChatGPT's proliferation is placed on groups and institutions, those with more resources will be better equipped to tackle shifting needs. That ChatGPT further widens the gap between the haves and have-nots flies in the face of its creator OpenAI's mission, which is to "ensure that artificial general intelligence benefits all of humanity."

Although some proponents of human-centered AI have suggested that the field of machine learning research needs to consider humans at three 'levels' or 'spheres' (i.e., users, communities, and society at large; Landay, 2023), there is a lack of guidance on *how* to take social impact into account. Without clear directions, the machine learning community predominantly draws on individualistic approaches stemming from human-centered principles to tackle the issues they are technically equipped to handle—mitigating bias, toxicity, and 'hallucination.' These are important problems to solve, but the assumption that reducing individual-level harms translates directly to societal well-being results in poorly theorized conceptualizations of social impact.

## What does Social-Centered AI look like in Practice?

While social-centered impact assessment may be new to the machine learning community, there are well-established processes for conducting anticipatory and concurrent assessments of social impact in other disciplines. For example, health (World Health Organization, 2023), environmental (Glasson and Therivel, 2013), and human rights impact assessments (Kemp and Vanclay, 2013) all mandate a process for identifying, predicting, monitoring, and responding to the impacts of policies, programs, or projects on a population or environment. Each of these assessments—involving quantitative, qualitative, and participatory techniques to predict impact—is conducted prior to undertaking an intervention. In addition, these assessments include long-term monitoring to understand to what extent and how an intervention addresses the issues it is intended to confront. Drawing on this logic, we present concrete recommendations for achieving social-centered AI across different stages of AI development and flesh out necessary organizational conditions to enable social-centered AI. While social-centered AI should be a general goal all AI practitioners work towards, we target our interventions at large AI labs, often couched within big tech firms, as their privileged position makes them central to the development of societal-scale AI.

#### Phase 1: Conceptualization & development

To counterbalance the tendency within the machine learning community to prioritize technically interesting problems (Morozov, 2013), it is vital to collaborate with social scientists (i.e., sociologists, linguists, political scientists, human-computer interaction scholars, etc.) during the early phases of project conceptualization to theorize and empirically examine the real-world problems AI systems could attenuate (Dinan et al., 2021; Ovadya and Whittlestone, 2019). Furthermore, for societal-scale technologies that impact groups and institutions across various domains, it is vital to involve community stakeholders and identify key informants early to align goals through participatory research.

Distinct from performative user-experience research (Pervall, 2021) or 'scenic fieldwork' (Button, 2000), both of which describe social problems in vague terms, a productive effort involving social-centered thinking features sincere engagements with theory and rigorous empirical work (whether it's interviews, surveys, ethnographies, quantitative analyses, or

population-level natural experiments). The outcome of this collaboration may extend project timelines and even lead to existential questions. For example, instead of multifunctional dialogue agents, would narrow Al—systems that are limited in scope, well-defined in their capabilities, and potentially less disruptive—better tackle the social problem at hand?

In our analysis of ChatGPT, we show that from a technical and design perspective, displaying confidence scores on outputs, implementing watermarks and a plagiarism-detection application in synchrony with ChatGPT, and developing a privacy-preserving corporate version of the dialogue agent could all be ways to better equip the dialogue agent for societal deployment. In addition, participatory research, such as focus groups with educators, could have elicited important insights and mitigation strategies to help OpenAI identify interest areas for a particular group of stakeholders. With such data in hand, machine learning researchers can better direct engineering efforts and instigate measures that help society more adequately prepare for the deployment of high-impact technology.

#### Phase 2: Short-term societal impact evaluation

Before a novel medical drug is approved for the general public, trials are performed on smaller groups of people to determine its safety and allow scientists to make any necessary changes to ensure responsible scaling. In such contexts, researchers are particularly sensitive to the needs of high-risk and vulnerable populations. We believe that societal-scale AI deployment should adopt a variation of this strategy—beta testing with specific populations that are likely to be heavily impacted rather than facilitating wide-scale access. Staggered releases give room for careful documentation and impact analysis, which could then be taken to developers for further iteration. Beyond individual user feedback sourced from platform interfaces, understanding how people use a particular system in different real-world contexts are important data points that companies who release such products should collect (and not leave only to university researchers) to allow for quicker internal adjustments.

After wide release, societal-scale AI systems will likely impact various groups and institutions at disparate rates. During this critical period, where norms and practices are actively being negotiated, AI practitioners must triage problems and prioritize areas of focus. Here, relationships forged with community partners in the previous stage are vital. Infrastructure that allows the two sides to communicate frictionlessly would facilitate efficient feedback gathering from the most impacted communities and stakeholders. In the short run, platform features could be tweaked, altered, or added to allow for safer and less socially disruptive adoption. It is important to acknowledge that predicting every possible short-term outcome is impossible, but prioritizing communicative channels that transcend individual-level feedback on a platform interface could help alleviate more immediate issues.

#### Phase 3: Longitudinal adaptations

Conducting social impact evaluations of LLMs and dialogue agents prior to and at the time of release will provide a cross-sectional view of shifts in norms and practice at a point in time. However, longitudinal studies are necessary for researchers to detect shifts or developments in groups and institutions over time and compare predictions before release with actual impacts at different time scales (Menard, 2002). Longitudinal studies also afford a more precise window into how different groups and institutions adapt to emerging technologies at different rates. Such

studies are costly, requiring ongoing ethnographic fieldwork with affected entities and quantitative analysis across different societal contexts, which may only sometimes produce insights for the design of technical features of interactive systems (Dourish, 2006). Nonetheless, insights from such approaches will be critical for shaping (or adapting) approaches to the deployment of future dialogue agents to maximize benefit and minimize harm for affected groups and institutions.

The collective feeling of the uncanny that much of society is experiencing in the present moment vis-à-vis ChatGPT, where fascination and fear intermingle (Gunning, 2008), is partly the result of a lack of shared knowledge or foresight on the future impact of this system on our social lives. This uncertainty has been further fuelled by the rapid proliferation of other LLMs and dialogue agents throughout society in recent months. To this end, the implementation of longitudinal studies investigating the impact of dialogue agents already deployed could prove instrumental. Such research would underscore the importance of social-centredness within the machine learning community, promoting it as a key research domain. Furthermore, this culture of social-centredness will be essential to support broader initiatives to establish institutions and enforce regulations designed to oversee the deployment of future LLMs and dialogue agents.

# Organizational and Regulatory Considerations for Social-Centered AI

We acknowledge that implementing the steps above may require a sea-change in organizational and regulatory conditions. First, AI labs, notoriously insular from a disciplinary standpoint, should **prioritize an interdisciplinary work environment.** While technical workers like research scientists and engineers are well-equipped to handle human feedback provided by individual users, social evaluations on a larger scale demand investments by those with different skill sets (Kusters et al., 2020). Creating opportunities for machine learning researchers and social scientists to work together may require hiring more from the latter group or establishing sustainable collaboration channels between university and industry researchers.

In contrast to a multidisciplinary approach, whereby individuals in a group each draw on their disparate disciplinary and methodological toolkits, *interdisciplinarity* represents an earnest attempt at integrating knowledge and methods from different disciplines to engender a *synthesis* of labor (as opposed to a division of labor; Van den Besselaar et al., 2001). To this end, social scientists must feel empowered in their capacity to contribute. Accordingly, the machine learning community must redistribute some of its power to allow researchers with diverse training to inform everyday decision-making and treat their presence as more than ceremonial.

Secondly, realizing social-centered AI requires **incentive alignment**. Right now, priorities like profit motives, rapid deployment to edge out competition, and protecting intellectual property are all factors that could impede the implementation of social-centered AI, which calls for a slower and more measured approach. As individual workers rarely have the power to nudge obstinate corporate cultures in new directions, establishing social-centered incentives demands industry-wide regulations (a point we get to below). Relatedly, boosting requirements that compel researchers to reflect more comprehensively and critically about social impacts in professional conferences and journal submissions will be an important step toward a culture where social-centered approaches become the norm rather than the exception.

This leads us to the third and most important dimension of realizing social-centered AI—governance (Dafoe, 2018). More specifically, **building institutions and governmental** 

**agencies that create policies and regulatory standards**—mechanisms that structurally enforce behavior—remain imperative. New initiatives in Europe and the United States show that governments are increasingly recognizing the societal impacts of AI and the inadequacy of existing legal and policy arrangements to deal with those impacts. For instance, the EU Parliament recently adopted a draft negotiating mandate for the EU AI Act, including provisions that would put obligations on builders of 'foundation models' (like GPT models) to ensure downstream users comply with fundamental rights and EU law (Benifei and Tudorache, 2023).

Work by some US government agencies to develop frameworks to protect citizens is also underway, such as the Blueprint for an Al Bill of Rights (The White House Office of Science and Technology Policy, 2022). The Blueprint suggests an array of implications for Al application, regulation, and design, marking promising new strategies that reckon with potential risks. However, beyond pegging individuals as the primary unit of measurement, it exists only as a guiding document with no teeth to enforce its proposed reforms. We encourage policymakers to think in a more social-centered manner and potentially explore the possibilities of creating regulatory structures the likes of Institutional Review Boards (IRB) to help Al labs better understand how to navigate complex ethical questions around the social (and environmental) costs of building evergrowing LLMs.

While some may argue that regulating AI research and deployment could hinder commercial progress, the situation we find ourselves in today (alongside calls for regulatory oversight) is not without precedent in the United States. The 1929 stock market crash precipitated one of the most significant financial reforms in the country's history—the founding of the Security and Exchange Commission (SEC). When President Franklin Roosevelt signed the Securities Exchange Act into law in 1934, he and his appointees to the new agency faced an uphill battle to convince Wall Street that more regulation would be good for business (Durr and Kinnane, 2005). But with faith in the free market at a new low following the Great Depression, the SEC would ultimately succeed in convincing investors to return and businesses to regain confidence in the American economy. Meaningful external regulation like the SEC was possible because of the massive damage that failure to regulate had caused, not only to industry but to societal norms and institutions. While regulatory institutions have historically come about in response to cataclysmic events, we believe that deliberative AI governance has the potential to shape future impacts in a measured and systematic way.

If ChatGPT's rise to fame has sparked an AI arms race, we suspect that more powerful, multi-purpose chatbots will soon emerge. As future iterations of these AI systems include an increasing number of modalities and languages, the impact they have on society at large will be more widely felt. In a recent op-ed titled "This Changes Everything," columnist Ezra Klein (2023) argues that "One of two things must happen. Humanity needs to accelerate its adaptation to these technologies or a collective, enforceable decision must be made to slow the development of these technologies." By proposing social-centered AI, we chart a path toward the latter objective. We acknowledge that building a culture around the concept will incontrovertibly slow down the developmental progress of AI, but we believe that it is a necessary trade-off to ensure the responsible and ethical integration of its systems into society in the long run.

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