An MIT Exploration of Generative AI • From Novel Chemicals to Opera

# The Impact of Generative AI on Labor Market Matching

**Justin Kaashoek**[1] **Manish Raghavan**[1] **John J. Horton**[2]

[1]MIT, [2]MIT & NBER

**MIT**

**Published on:** Mar 27, 2024

**DOI:** https://doi.org/10.21428/e4baedd9.d562223c

# 1. Introduction

Imagine applying for jobs by simply asking your artificial intelligence (AI) assistant to “please put together a resume and cover letter based on my experiences and submit the application to senior management positions at clean-energy start-ups with fewer than 100 employees.” The release of ChatGPT and subsequent large language model (LLM)–powered services have already enabled the first part of this prompt: applicants can ask ChatGPT to write a cover letter and format a resume in a matter of seconds, even if the results are not always stellar. It is not hard to envision a future where a bot can also submit applications to firms that meet a set of criteria. An analogous AI-powered process exists for firms. LLMs can write job posts and, in the future, could power agents that solicit and evaluate materials from applicants. These examples illustrate that generative AI not only makes it easier for both applicants and firms to find and process existing information, but, as suggested by the name, it can also generate written materials (job posts, resumes, cover letters, and interview questions) that factor into their decisions. This dual ability to process and create information promises to have a large impact on labor market matching (the process of matching applicants and employers).

0:00 / 38:03

Listen to this article

A defining feature of labor markets is that it can simultaneously be true that job seekers have a hard time finding a job and that hiring managers struggle to fill positions. Part of what makes the matching problem difficult can be attributed to information processing costs: it takes time for both applicants to search and apply for jobs and for employers to find, interview, and recruit applicants—referred to as “search and recruiting friction” in the economic literature (Mortensen and Pissarides 1999; Rogerson et al. 2005). Another challenge is the quality of the information applicants and firms receive. The labor market relies heavily on signaling: neither firms nor applicants can directly observe the productivity or fit of their counterparts and must rely on signals to determine whether to hire or even apply in the first place (Spence 1973). A strong signal on both sides of the market will lead to better matches, and a tool such as generative AI will either improve or worsen the quality of matches depending on whether it improves or worsens the quality of the signal applicants and firms receive.

The proliferation of generative AI promises to impact these factors while also adding a new dimension to the labor market matching process. Like any tool, LLMs make certain actions easier. For example, writing a recipe for tomato soup in iambic pentameter is difficult for most people; appropriately tuned LLMs can do so fairly easily. Labor market matching generally requires **text generation** (resumes, job descriptions, etc.), and we would expect LLMs to substitute for human effort in these tasks. At first glance, it might appear that this will positively impact labor market matching. For example, a small employer who has never hired a marketing team might write a better job description given access to an LLM that has been trained on hundreds of such job descriptions. However, there are potential negative consequences as well. For example, an overreliance on LLMs might lead candidates to submit near-identical cover letters, reducing their signaling value.

Despite the name, language models are not limited to text processing and generation. Researchers have already started to explore the capabilities of LLM-powered **AI agents** (Wang et al. 2023). It is likely that such agents will become capable of some degree of autonomous task execution not too far in the future (Metz and Weise 2023). For the labor market, this might look like an AI agent monitoring job listings for those suitable for a user and automatically applying on the user's behalf, as suggested by our opening example. The widespread use of these agents on both sides of the market could also result in a scenario where applicants and firms rely solely on AI to make decisions for them.

Generative AI is a novel technology that enables these new behaviors, but it is not the first technological advancement that has promised to impact the labor market. With the rise of the internet, job boards and newspapers were replaced with online job search. This transition allowed job seekers to expand their search and gather more information about positions, behaviors that, as we will discuss, are further enabled by generative AI (Autor 2001). While these and other parallels might appear to be informative, generative AI possesses the additional capability of creating signals that makes reasoning about downstream consequences unique and challenging.

In what follows, we will expand on the areas where generative AI might appear in the labor market, considering both text generation and potential future agent-based use cases. We build on these scenarios to illustrate how the evolution of AI in the labor market could have positive or negative impacts on market efficiency and access to opportunity. Crucially, reasoning about the direct effects of AI-based interventions may fail to predict their impacts in the long run. We conclude with a list of recommendations to mitigate risks while promoting the benefits of AI.

## 2. Use Cases for Generative AI in the Labor Market

Generative AI can be incorporated into the labor market in various ways for both applicants and firms. In this section, we describe how job seekers and firms might use generative AI. We will discuss the positives and negatives of these use cases in section 3.

### 2.1. Generative AI and Job Seekers

A clear use case of generative AI for job seekers is the low-effort creation of personalized text-based materials, namely resumes and cover letters. We asked ChatGPT to provide us with a cover letter for a Data Analyst position with the marketing team at a large tech company.

In a matter of seconds, ChatGPT outputs a page-long document expressing our interest in the position, detailing our "strong analytical skills" that include "visualization tools such as Tableau and Power BI" (which is more flattering than true) and our "marketing acumen" that allows us "to connect data-driven insights to marketing goals effectively." A similar query, this time asking for the outline of a resume for the same position, gives perhaps an equally workable result. We are given the important resume sections (professional experience, technical skills, and education) and a list of skills to include if applicable: data analysis tools, marketing analytics software, A/B testing, and machine learning. The power in generative AI is not just that LLMs can save us time on this one application but that they are able to personalize materials at a massive scale. Today, we can use ChatGPT to create a template that we can programmatically fill with different company names, but in the future, LLM-powered services will likely be able to personalize and customize to an even greater extent with even less human supervision.

While the ChatGPT-generated materials, specifically the cover letter, do not 'sound' exactly like us in the style they are written, it is unlikely that this will be a concern in the future. Massive investments in training LLMs have led to improvements across a wide range of benchmarks between models such as GPT-3.5 and GPT-4 (OpenAI 2023). We can already ask ChatGPT to write in a certain style (Shakespearean iambic pentameter if we really wanted). It would be surprising if we cannot eventually have LLMs write material in *our* specific style.

After submitting their ChatGPT-generated materials, applicants can also use generative AI at the interview stage. Various start-ups already boast the ability to help prepare applicants for interviews using generative AI (i.e., Yoodli and Interview Prep AI). Since the pandemic, many interviews are asynchronous (consider tech companies giving candidates a coding task to work on for a few days), which allows applicants to ask generative AI for help in answering these questions. Although typically frowned upon, applicants can even use generative AI to help answer questions during real-time virtual interviews (i.e., Soutar 2023).

Applicants can also use AI agents to automatically perform tasks for them at different stages. During the search stage, AI-powered agents could pick out a list of jobs for an applicant to apply to based on their resume and background. Assuming employers have deployed a bot of their own, applicants could use their bot to ask questions of employers to help further filter where they will apply. Is there a remote option? What kind of benefits come with the job? Applicants might prefer to have a bot ask questions that they do not know how to ask or believe might be viewed more favorably coming from a bot. How much parental leave does the company provide? Some applicants might feel more comfortable with an agent discussing salary rather than having the conversation directly with a hiring manager. Based on a prospective employer's responses, the agent could choose to apply for the position on behalf of the applicant. Additionally, if firms deploy bots to screen applicants, job seekers could provide their bot with responses to standard interview questions. These capabilities, in addition to the text-generation abilities of generative AI, could provide a layer of automation to every step of the search and apply process.

## 2.2. Generative AI and Employers

The text-based capabilities of generative AI enable employers to easily create and ‘workshop’ job postings. We asked ChatGPT to write a job post for a senior project manager at a clean-energy start-up. The output is a complete post giving a company overview, a position description, and a list of responsibilities and qualifications such as stakeholder management, risk management, and a bachelor’s degree. Not only is this job description ready to post with minor edits, but a company could generate and publish multiple versions of a job post to see which ones elicit candidates who are a better match for the position. Companies could even post jobs to test the strength of the application pool. These use cases are not just theoretical: Pennsylvania’s governor, Josh Shapiro, recently announced that state employees will use generative AI to draft job descriptions (Zeff 2024).

Just as applicants could use AI-powered agents, firms could use such bots to execute tasks. A firm could use a bot to scan online professional networks and solicit applications. They might deploy a chatbot to screen candidates and answer basic questions about the job opening. They could also use an LLM-based agent to determine whether an applicant possesses the required skills, such as a particular programming language. (This, of course, presumes that the candidate cannot simply deploy their own chatbot in response.) Whether or not AI-based agents can more reliably evaluate candidates remains an open question and will no doubt be explored by employers in the coming months and years.

# 3. Risks and Benefits

The vast array of use cases raises a key question: what will be the impacts of widespread AI adoption on labor market matching? The starting point of our analysis is that LLMs reduce the cost of certain behaviors. We focus our analysis on three behaviors: generation of text-based materials, search and solicitation, and evaluation and information elicitation. These three behaviors are not an exhaustive list, rather they are examples that highlight the important considerations when thinking about the impact of generative AI on labor market matching. For each of these behaviors, we envision a positive and negative outlook for applicants and firms (see Figure 1 for a summary) and discuss both the factors that could lead to each and market responses that might prevent a scenario from occurring. The eventual equilibrium of the labor market could certainly include elements of both outlooks. We introduce them separately to highlight the range of potential outcomes and to highlight the factors at play.

Much of our following discussion is speculative. Predicting the impacts of changes in behavior throughout the market is difficult, and impacts might not be uniform across industries. Moreover, the rapid progress of technological development brings additional challenges, as generative models progress across modalities like audio and video. We do not aim to provide an authoritative forecast on the future of labor market matching. Instead, we seek to demonstrate how a careful analysis of the interaction between technological growth and economic self-interest can raise important questions and provide recommendations to guide the integration of generative models in labor market matching.

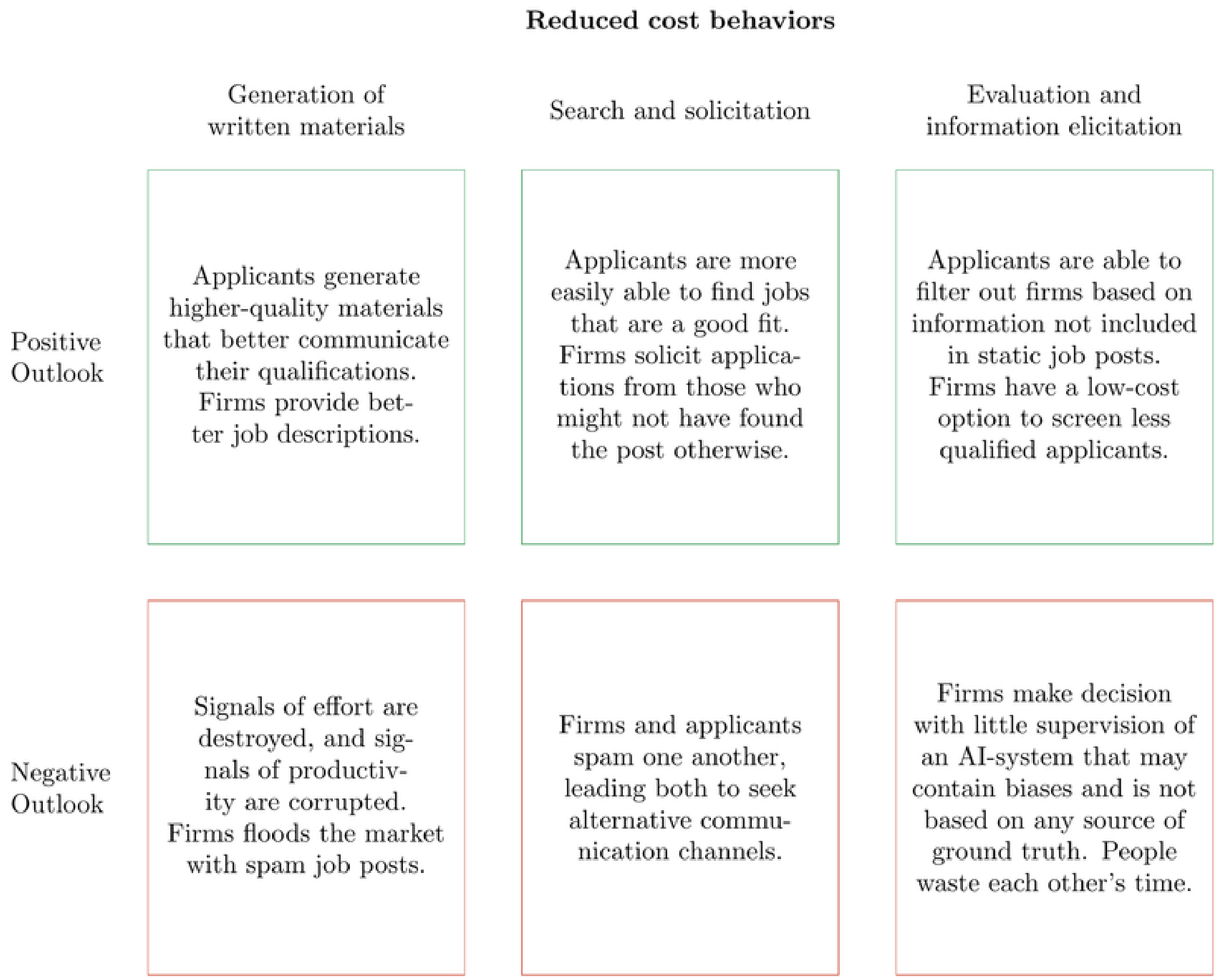


**Figure 1**
A summary of our risks and benefits analysis.

## 3.1. Generation of Text-Based Materials

As it becomes cheaper for both applicants and firms to put together written materials, more people and organizations will turn to generative AI. This could have the benefit of creating higher-quality applications and job posts. On the other hand, applicants could become indistinguishable as everyone turns to generative AI to create their materials, while firms flood the market with job posts.

**The positive outlook: Applicants generate higher-quality materials and face reduced barriers to expressing qualifications. Employers generate better job descriptions.**

On the applicants' side, generative AI could increase the quality of the signal of an applicant's productivity. A better signal would make companies and applicants better off, at least on average, because companies are able to hire the 'best' applicant for the job. More concretely, generative AI could give applicants who struggle with writing the tools to provide a more accurate representation of themselves. For example, non-native speakers who struggle to express themselves as effectively in English (or whatever language the job requires) and those who are not as strong writers could see the quality of their signal improve because generative AI can help write a cover letter or resume that more clearly and concisely expresses their talents, relevant experiences, and why they are a strong candidate. LLMs can also tailor the materials to a conventional, readable format. As LLMs improve, they might even be able to surpass the quality of the strongest writers' application materials, increasing the signal quality of all applicants. The more accurately an applicant can signal their inherent productivity for that job, the better decision a company can make.

On the firms' side, generative AI could give job seekers a more accurate representation of both the job and skills required to succeed in a particular position, thus allowing them to make a more informed decision. Job posts frequently contain a long list of requirements that the firm believes would make an applicant successful in the role, but which of these requirements are strictly necessary, and which ones are missing? Generative AI can incorporate the job postings of other, similar positions at firms in the same industry and make recommendations based on this vast set of data. As a result, job posts would contain only the strictly necessary traits to make a candidate successful and draw a pool of applications that is better suited for the job.

**The negative outlook: Signals of effort are destroyed, and signals of productivity are corrupted. Firms flood the market with spam job postings.**

Enticed by the generative AI's ability to create materials almost instantaneously, all applicants could turn to LLMs. Cover letters, which previously served as a signal of effort and interest if nothing else, could now become useless to employers as that signal is destroyed. Employers could institute other 'ordeals,' tasks that require effort on the part of the applicant, to filter the pool to a set of applicants who are highly interested in the position (Nichols and Zeckhauser 1982; Alatas et al. 2013). Applicants might perceive these ordeals as unnecessary, however, and decide to not apply, especially if they become used to investing minimal effort in their applications.

A widespread adoption of generative AI could also corrupt an applicant's signal of their productivity. In this negative view, generative AI could make applicants look better or worse than they are, meaning that firms are unable to make accurate decisions. One specific and concerning type of corruption is if generative AI causes most written materials to look the same, creating a problem of indistinguishability. Given that a relatively small number of LLMs can put together seemingly strong application materials, applications could all be generated by similar algorithms operating on the same underlying dataset. Rather than helping applicants emphasize the traits that make them unique, generative AI could start to wash out important differences in application materials.[1] If written materials possess no signal of effort and do not effectively reflect an applicant's productivity, companies will refuse to make decisions based on these materials. Instead, they may only hire based on referrals, legacy hires, or other offline channels. These practices have diversity implications depending on how companies implement them (Rubineau and Fernandez 2015; Castilla and Poskanzer 2022; Carmichael 2023; Frank 2018).

A similar problem of indistinguishability could develop in firms' job posts: homogeneity in posts could reduce the signal an applicant receives on how strong of a fit the job and company are for their skill set and professional goals. Applicants might now struggle to filter out which jobs they should apply to, prompting a flood of applications as job seekers apply to a wide range of positions (Wiles and Horton 2023).

The problem is exacerbated by the potential for a flood of spam postings. Firms can generate more job posts to test the strength of the applicant pool even when they are not sure they want to make a hire. Job seekers, as a result, become faced with countless, indistinguishable job postings. This could lead to frustration on the job seeker's side and make it more difficult to determine where to apply. As a result, qualified applicants might refrain from applying to jobs or, if the cost of putting together application materials is sufficiently low, apply to jobs they are not a strong match for.

## 3.2. Search and Solicitation

As LLMs enable AI agents to perform certain tasks, applicants can use such agents to find relevant jobs. Firms can use agents to find applicants who they believe would make a strong candidate for an open position. One potential consequence is that applicants and firms now face an expanded pool of strong, potential matches. Alternatively, both sides of the market face too large a pool and spam one another.

**The positive outlook: Applicants are more easily able to find jobs that are a good fit. Firms solicit applications from candidates who might have not found the post otherwise.**

For applicants, AI agents could filter through a larger set of job posts than a human would be able to on their own. The AI agent could automatically submit strong, accurate, and personalized application materials to each job. These jobs would include ones that the applicant is a strong fit for and would not have found on their own (or did not have the time to find on their own). Applicants who combine this search capability with the text-generation capabilities discussed before could always be on the job market by deploying a bot that continuously monitors the internet for relevant posts and, once it finds one, writes and submits a personalized application. As a result, applicants could more easily obtain and leverage offers to ensure they are receiving a competitive salary. Employers, if they want to ensure higher retention rates, could work to keep employees by improving other facets of work life, such as employee benefits and company culture. More likely is that employers include contract lengths into job offers and force employees to pay if they want to switch positions (Kaiser-Schatzlein 2023). Overall, however, this process creates better matches for the applicant with less effort.

Even if a strong applicant does not find a job posting with their agent, firms can now deploy their own AI agents to scan the internet for strong applicants. They could use these agents to solicit applications from these candidates, which gives the firm an even stronger pool of applicants with less human effort. This capability would be especially useful to find employees who are undervalued in their current position without realizing it or who are less quick or comfortable in adopting AI agents of their own.

**The negative outlook: Firms and applicants spam one another, leading both to seek alternative communication channels like referrals.**

Now that both firms and applicants deploy AI agents to find and submit or solicit applications with nearly zero effort, online channels become flooded. Firms are overwhelmed with applications. They could either waste time sifting through the applications, or more likely, they could ignore these channels in favor of another communication channel that gives fewer applicants, such as referrals. To discourage this behavior, online job platforms (or firms themselves) might adopt policies that limit the number of firms an applicant can reach out to (or vice versa). Such a “preference signaling” policy can increase the quality of matches (Coles and Niederle 2013; Horton et al. 2021).

## 3.3. Evaluation and Information Elicitation

AI agents would also lower the cost of applicants and firms evaluating each other early on in application process. The positive outlook suggests that generative-AI–powered agents allow firms to more quickly and accurately filter through applicants, while applicants can easily determine if they are a good fit for a company, saving time for both sides of the market. The negative outlook argues that firms rely on inaccurate AI to make decisions on applicants without any supervision of the decision.

**The positive outlook: Applicants are able to filter out firms based on information not included in static job posts. Firms have a low-cost option to screen less-qualified applicants.**

When applicants apply, firms could use LLM-powered chatbots to filter out applicants who are clearly not qualified or overqualified. On the other side of the market, applicants can ask more specific, pointed questions of the firm to decide if they even want to apply to the firm in the first place. This saves both the applicant and firm time and increases the quality of matches because hiring managers within a firm now select from a pool of applicants who are pre-filtered to be a better fit for the job. It also helps to mitigate against any concerns around spam.

**The negative outlook: Firms make decisions with little supervision of an AI system that may contain biases and is not based on any source of ground truth. People waste each other’s time.**

If both sides of the market can interact with each other through AI agents, there is little preventing either applicants or firms from eliciting information from all prospects. Both sides can now waste each other’s time by communicating with all potential candidates, neglecting to put in any up-front effort to filter the pool of potential matches.

Another negative outlook of the lower cost of evaluation is tied closely to the quality of the technology that replaces human decision-making. Firms already use various machine learning (ML) algorithms that, given an applicant, are trained to accurately predict a quantifiable, observable metric such as tenure, sales, or performance reviews (Raghavan et al. 2020). ML algorithms generally have well-known issues: they can encode demographic biases (Barocas and Selbst 2016), give unexplainable predictions (Lipton 2018), and are often trained to optimize the wrong metric (Jacobs and Wallach 2021). LLMs are distinct from existing ML screening technologies in that they are not trained on a source of a ground truth; rather, they are trained to output the most likely next word or phrase. As a result, beyond the existing problems with ML-based screening tools, LLMs raise new concerns in that their objectives are inscrutable. We do not have a full picture of how LLMs might encode either the existing issues of traditional ML or the yet unknown issues of generative models in the labor market (initial results from Tamkin et al. (2023) suggest that out-of-the-box LLM decisions are discriminatory).

Especially early on in their adoption, then, it is crucial that firms closely supervise their systems, but currently, they have few external incentives to do so. A firm would use AI chatbots precisely because they want to limit human involvement. Furthermore, as long as a hiring manager is happy with one of the candidates the technology does not screen out, they have little reason to return to transcripts or interrogate why the bot made the decisions it did. We might hope that the law would provide some direction here; however, in most of the United States, incentives to validate and supervise employment screening tools are only as strong as the enforcement of discrimination law, which can be especially hard in the context of AI where candidates and regulators have very little information about proprietary systems (Kim 2019; Raghavan and Kim 2023). Given the lack of a clear incentive, we currently rely heavily on the benevolence and bandwidth of firms to uniformly and diligently monitor their internal systems.

## 3.4. Parallels to Online Job Search

Various threads discussed in these risks and benefits have connections to literature around the transition to online job search that took place from the 1990s to the early 2000s. As the internet grew in popularity, applicants turned to online platforms to find jobs, a practice that is commonplace now. Relative to in-person search, online search reduced the cost of information processing: applicants were able to expand their search and gain more information about jobs, both of which have been enabled to an even greater extent by generative AI (Autor 2001). Empirical work on this transition found that, while online search crowded out traditional avenues of search and had large impacts in other markets (such as the home rental market), online search did not impact unemployment rates and did not decrease unemployment time (Kroft and Pope 2014; Kuhn and Skuterud 2004). In fact, Kuhn and Skuterud (2004) hypothesized that unemployment time increased for certain online applicants, because applying online became a negative signal: the applications were so low cost to put together that they reflected a lack of interest in the position or signaled a less-robust social network. These echo the concerns we raised in our negative outlook of low-cost text generation. Because there are strong parallels to the transition to online job search, should we expect a similarly minimal impact of generative AI? Given that generative AI does not only make information processing easier, but it also creates signals for both sides of the market to incorporate into their decisions, it is likely that generative AI will have a greater impact on the labor market than did online job search.

### 3.5. Synthesis

Throughout our analysis, certain common trends have emerged in our discussion of positive and negative outlooks. The positive outlooks propose that generative AI improves signals on both sides of the market and reduces friction in search and recruitment all while requiring less human effort. The negative outlooks warn against three major concerns. First is **signal corruption**, where written materials become a worse signal for both applicants and firms. One specific case of signal corruption we discussed was homogenization; when applicants and firms become impossible to distinguish. Second is that, in jargon, both sides of the market **fail to internalize their externalities**. In other words, before generative AI, the costs of participating in the labor market were sufficiently high to prevent the two sides of the market from spamming each other. Now that the costs have dropped, applicants and firms have less incentive to limit their participation, forcing an increase in evaluation effort on one another. Last is the **inscrutability of AI systems**, where we rely on generative AI technologies to make decisions without fully understanding the decision they make. Notably, signal quality appears in our discussion of both the positives and negatives of generative AI. Whether generative AI improves or corrupts signals remains to be seen and is tied to both the technical quality of LLMs and how people use them.

## 4. Recommendations

The recommendations we make are for applicants, firms, and policy makers in the hopes of steering the labor market toward the positive themes we laid out in section 3.

### 4.1. Balancing Quality and Quantity

Both sides of the market (applicants and firms) must be wary of where the costs have lowered and find a balance between casting a wide enough net and spamming the internet with fake interest and fake job posts. As discussed, generative AI is highly effective in reducing the cost of different behaviors, such as writing cover letters and finding jobs or creating job posts. Both candidates and firms run the risk of casting a wider net in favor of spending more time on the companies or people of high interest.

### 4.2. Creating or Adapting Informative Signals

As applicants use generative AI to write cover letters, workshop resumes, or respond to interview questions, companies will have to respond to ensure that they are still receiving accurate signals of an applicant's productivity. This could be done by keeping track of manager satisfaction with applicants who were hired using online methods versus word of mouth or by measuring tenure differences among employees. If these traditional applicant materials are losing their signal, firms must adapt their hiring process in a way that is still fair for applicants, which will likely be an industry-specific initiative.

## 4.3. Internal Monitoring of Hiring Channels

Firms run the risk of hiring solely based on referrals. Applicants from the general public might be at a disadvantage if their application is not given the same consideration as someone who has a connection within the firm. By monitoring which channels they favor (online posts vs. word of mouth), a company can ensure they do not only hire talent that is already connected within the industry.

## 4.4. Close Monitoring and Supervision of AI-Based Decisions

Companies must diligently monitor the use of generative AI, especially early on in their adoption. Firms run the risk of becoming highly reliant on these systems to screen and filter applicants before ever interacting with a human without fully understanding the biases baked into generative AI. To mitigate against this scenario, firms can collect and monitor data tracking who applies, who is screened out, and who is interviewed. Demographic shifts in these numbers from before incorporating generative AI suggest that there are some biases encoded in the algorithms. We additionally recommend random readings of the transcript of conversations applicants have with chatbots. This could help catch intrusive, invasive, or illegal questions without relying on the candidate to report such behavior.

## 4.5. Procedures for Reporting and Policies for Recourse

Algorithms, like people, are not perfect, and firms must have policies and procedures in place when AI makes mistakes. We cannot expect algorithms to be perfect, and there will be errors, especially while firms and academics develop a deeper understanding of both the theoretical underpinnings and how they will be used in the real world. Companies that incorporate these algorithms should have free and clear methods for candidates to report problems they experience with the technology. Companies should have procedures to respond to such reports in a timely manner and implement policies for recourse in situations where the algorithm caused harm to an applicant.

## 4.6. Development of a Consistent Legal Framework

There is a need for a consistent legal framework that applies to using generative AI technologies in the labor market. Clearly, generative AI should adhere to existing laws around fair hiring practices, but as it becomes clear how the current legal framework falls short of regulating these new technologies, we must respond and adapt our legislation promptly. The EU Artificial Intelligence Act, a law regulating the use of aritifical intellgience in the Eurpean Union that was recently approved by the EU's Parliament, can offer guidance. The act imposes additional requirements around data governance, monitoring, documentation, and more for high risk AI systems, which explicitly includes systems that place targeted job ads, screen applications, and evaluate candidates (European Commission 2021a, 2021b). One clear existing shortcoming in the United States is that discrimination law is mainly concerned with binary decisions and does not generalize well to (say) free-form text interactions or summaries (Raghavan and Kim 2023).

## 5. Conclusion

It remains to be seen how generative AI will impact the labor market, but there is no doubt that it will. At every step in the hiring process, candidates and employers have the potential to incorporate generative AI to increase efficiency and provide better matches, at the high risk of losing informative signals of candidate productivity, causing direct or indirect harm to candidates in initial chatbot screenings, and generating large amounts of spam. We provided a set of recommendations that will mitigate against the potential problems of generative AI while promoting the benefits. While we remain in the dark on exactly how applicants and firms will use this new technology—and the technology continues to develop at a high pace—we must be disciplined in our use of generative AI while we develop a greater understanding of the downstream consequences.

## Footnotes

1. If applicants realize that all the materials generated by LLMs sound the same or are reducing the quality of their signal, why would they ever use generative AI? First, the reduced cost of producing materials with generative AI could offset a reduction in signal quality. Second, applicants may not realize how their LLM-generated materials read to a firm. A hiring manager who reads 20 cover letters would quickly realize which are AI-generated, but an applicant likely only sees their own application. ↩

## References

1. Mortensen, Dale T. and Christopher A. Pissarides. 1999. "New Developments in Models of Search in the Labor Market." In *Handbook of Labor Economics* 3B, edited by Orley Ashenfelter and David Card, 2567–627. Amsterdam: Elsevier. https://doi.org/10.1016/S1573-4463(99)30025-0 ↩
2. Rogerson, Richard, Robert Shimer, and Randall Wright. 2005. "Search-Theoretic Models of the Labor Market: A Survey." *Journal of Economic Literature* 43, no. 4 (December): 959–88. https://www.aeaweb.org/articles?id=10.1257/002205105775362014 ↩
3. Spence, Michael. 1973. "Job Market Signaling." *The Quarterly Journal of Economics* 87, no. 3 (August): 355–74. https://doi.org/10.2307/1882010 ↩
4. Wang, Guanzhi, Yuqi Xie, Yunfan Jiang, Ajay Mandlekar, Chaowei Xiao, Yuke Zhu, Linxi Fan, and Anima Anandkumar. 2023. "Voyager: An Open-Ended Embodied Agent with Large Language Models." Preprint, submitted May 25. https://arxiv.org/abs/2305.16291. ↩

5. Metz, Cade, and Karen Weise. 2023. “How ‘A.I. Agents’ that Roam the Internet Could One Day Replace Workers.” *The New York Times*, October 16, https://www.nytimes.com/2023/10/16/technology/ai-agents-workers-replace.html. ↩
6. Autor, David H. 2001. “Wiring the Labor Market.” *Journal of Economic Perspectives* 15, no. 1 (Winter): 25–40. https://www.aeaweb.org/articles?id=10.1257/jep.15.1.25 ↩
7. OpenAI. 2023. “GPT-4 Technical Report.” Preprint, submitted March 15. https://arxiv.org/abs/2303.08774. ↩
8. Soutar, Liam. 2023. “Candidate Seen Using AI during Job Interview - and New Research Shows They’re Not Alone.” *HR Grapevine*, October 6, https://www.hrgrapevine.com/content/article/2023-10-06-candidate-seen-using-ai-during-job-interview-new-research-shows-theyre-not-alone. ↩
9. Zeff, Maxwell. 2024. “PennsylvaniaGPT Is Here to Hallucinate over Cheesesteaks.” *Gizmodo*, January 9, https://gizmodo.com/ pennsylvaniagpt-chatgpt-open-ai-governor-shapiro-1851153510. ↩
10. Nichols, Albert L., and Richard J. Zeckhauser. 1982. “Targeting Transfers through Restrictions on Recipients.” *The American Economic Review* 72, no. 2 (May): 372–7. http://www.jstor.org/stable/1802361 ↩
11. Alatas, Vivi, Abhijit Banerjee, Rema Hanna, Benjamin A. Olken, Ririn Purnamasari, and Matthew Wai-Poi. 2013. “Ordeal Mechanisms in Targeting: Theory and Evidence from a Field Experiment in Indonesia.” NBER Working Paper Series 19127, National Bureau of Economic Research, Cambridge, MA, June. http://dx.doi.org/10.3386/w19127 and http://www.nber.org/papers/w19127 ↩
12. Rubineau, Brian, and Roberto M. Fernandez. 2015. “Tipping Points: The Gender Segregating and Desegregating Effects of Network Recruitment.” *Organization Science* 26, no. 6 (October): 1646–64. https://doi.org/10.1287/orsc.2015.1015 ↩
13. Castilla, Emilio J., and Ethan J. Poskanzer. 2022. “Through the Front Door: Why Do Organizations (Still) Prefer Legacy Applicants?” *American Sociological Review* 87, no. 5 (October): 782–826. https://doi.org/10.1177/00031224221122889 ↩
14. Carmichael, Sarah Green. 2023. “Employee Referrals Fill Jobs But Hurt Diversity.” *The Washington Post*, August 26, https://www.washingtonpost.com/business/2023/08/26/employee-referral-programs-for-job-openings-hurt-diversity-efforts/fb21136e-440a-11ee-9677-53cc50eb3f77_story.html. ↩
15. Frank, Lydia. 2018. “How to Use Employee Referrals without Giving Up Workplace Diversity.” *Harvard Business Review*, March 15, https://hbr.org/2018/03/how-to-use-employee-referrals-without-giving-up-workplace-diversity. ↩

16. Wiles, Emma, and John J. Horton. 2023. "The Impact of AI Writing Assistance on Job Posts and the Supply of Jobs on an Online Labor Market." (working paper, October). https://emmawiles.github.io/storage/jobot.pdf ↩
17. Kaiser-Schatzlein, Robin. 2023. "Pay Thousands to Quit Your Job? Some Employers Say So." *The New York Times Magazine*, November 20, https://www.nytimes.com/2023/11/20/magazine/stay-pay-employer-contract.html. ↩
18. Coles, Peter, and Muriel Niederle. 2013. "Preference Signaling in Matching Markets." *American Economic Journal: Microeconomics* 5, no. 2 (May): 99–134. https://www.aeaweb.org/articles?id=10.1257/mic.5.2.99 ↩
19. Horton, John J., Ramesh Johari, and Philipp Kircher. 2021. "Sorting Through Cheap Talk: Theory and Evidence from a Labor Market." NBER Working Paper Series 29445, National Bureau of Economic Research, Cambridge, MA, November. http://www.nber.org/papers/w29445 ↩
20. Raghavan, Manish, Solon Barocas, Jon Kleinberg, and Karen Levy. 2020. "Mitigating Bias in Algorithmic Hiring: Evaluating Claims and Practices." In *FAT* '20: Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency*, 469–81. New York: Association for Computing Machinery. https://doi.org/10.1145/3351095.3372828 ↩
21. Barocas, Solon, and Andrew D. Selbst. 2016. "Big Data's Disparate Impact." *California Law Review* 104, no. 3 (June): 671–732. https://doi.org/10.15779/Z38BG31 ↩
22. Lipton, Zachary C. 2018. "The Mythos of Model Interpretability: In Machine Learning, the Concept of Interpretability Is Both Important and Slippery." ACM *Queue* 16, no. 3 (June): 31–57. https://doi.org/10.1145/3236386.3241340 ↩
23. Jacobs, Abigail Z., and Hanna Wallach. 2021. "Measurement and Fairness." In *FAccT '21: Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency*, 375–385. New York: Association for Computing Machinery. https://doi.org/10.1145/3442188.3445901 ↩
24. Tamkin, Alex, Amanda Askell, Liane Lovitt, Esin Durmus, Nicholas Joseph, Shauna Kravec, Karina Nguyen, Jared Kaplan, and Deep Ganguli. 2023. "Evaluating and Mitigating Discrimination in Language Model Decisions." Preprint, submitted December 6. https://arxiv.org/abs/2312.03689. ↩
25. Kim, Pauline. 2019. "Big Data and Artificial Intelligence: New Challenges for Workplace Equality." *University of Louisville Law Review* 57, no. 2 (Spring): 313–28. https://img1.wsimg.com/blobby/go/05e8fd6b-a5de-4f26-b65a-ac38591fe866/downloads/57ULouisvilleLRev313.pdf?ver=1711505635069 ↩

26. Raghavan, Manish, and Pauline Kim. 2023. “Limitations of the ‘Four-Fifths Rule’ and Statistical Parity Tests for Measuring Fairness.” Presented at the *Workshop on Regulatable Machine Learning: Towards Bridging the Gaps between Machine Learning Research and Regulations at the 37th Conference on Neural Information Processing Systems (RegML @ NeurIPS 2023)*, New Orleans, LA, December. https://georgetownlawtechreview.org/limitations-of-the-four-fifths-rule-and-statistical-parity-tests-for-measuring-fairness/GLTR-01-2024/ ↩

27. Kroft, Kory, and Devin G Pope. 2014. “Does Online Search Crowd Out Traditional Search and Improve Matching Efficiency? Evidence from Craigslist.” *Journal of Labor Economics* 32, no. 2 (April): 259–303. https://doi.org/10.1086/673374 ↩

28. Kuhn, Peter, and Mikal Skuterud. 2004. “Internet Job Search and Unemployment Durations.” *The American Economic Review* 94, no. 1 (March): 218–32. https://www.aeaweb.org/articles?id=10.1257/000282804322970779 ↩

29. European Commission, 2021. "Artificial Intelligence Act." Retreived from: https://eur-lex.europa.eu/resource.html?uri=cellar:e0649735-a372-11eb-9585-01aa75ed71a1.0001.02/DOC_1&format=PDF ↩

30. European Commission, 2021. "Annexes to the Artificial Intelligence Act." Retreived from: https://eur-lex.europa.eu/resource.html?uri=cellar:e0649735-a372-11eb-9585-01aa75ed71a1.0001.02/DOC_2&format=PDF ↩