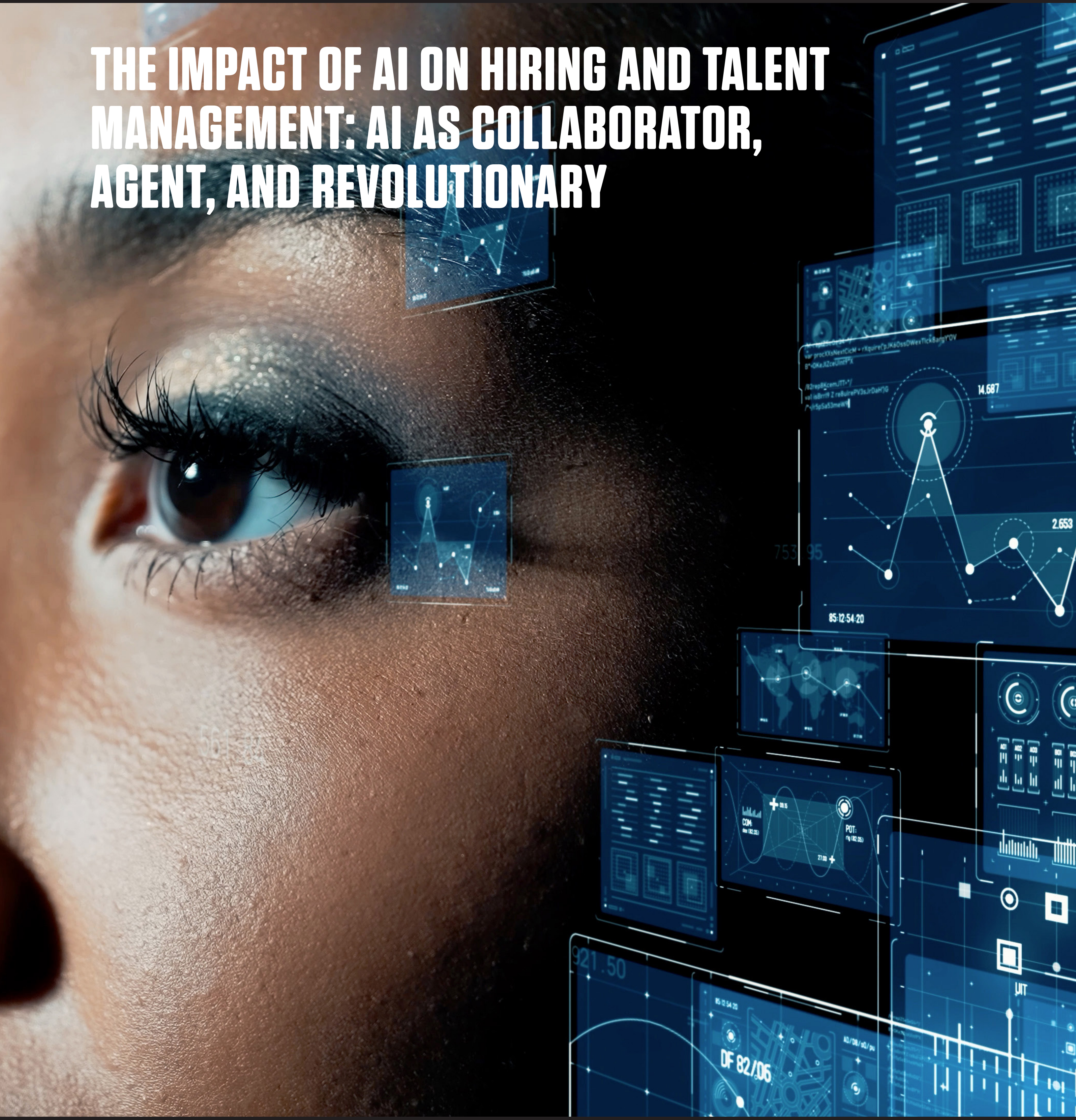
THE IMPACT OF AI ON HIRING AND TALENT MANAGEMENT: AI AS COLLABORATOR, AGENT, AND REVOLUTIONARY



Northeastern University
Center for the Future of Higher Education and Talent Strategy

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EXECUTIVE SUMMARY

The integration of Artificial Intelligence (AI) into Human Resources (HR) is revolutionizing talent management and acquisition. AI's impact is complex, offering both opportunities and challenges.

Informed by interviews with 20 HR leaders and technology developers, this report explores the current and potential implications of AI in HR practices. We gathered insights on how AI is being used, the excitement and concerns surrounding it, and the innovative use cases being imagined. The interviews revealed three types of AI uses in HR: as a collaborator, agent or revolutionary.

Most of the HR leaders we spoke to were actively experimenting with AI to help as a collaborator assisting with tasks like summarizing meetings or drafting offer letters. Some interviewees described this shift as gaining a new junior employee. This is productive but raises the question of how first-time job seekers might gain experience if AI was doing the sorts of tasks that provided real-world training to junior workers in the past. The embrace of AI as a collaborator may require new kinds of education strategies.

Some HR leaders were using AI as an agent to automate routine processes, notably around candidate screening and employee onboarding. They were also beginning to anticipate the introduction of an AI agent as a member of a business unit team. In addition to thinking about building, buying, or borrowing (i.e. hiring a consultant) talent, HR leaders can now consider introducing a bot. Overseeing work teams composed of both human and bot contributors will emphasize the need to be clearer about what humans contribute and how this is assessed. Historically, evaluating durable skills, the most human of skills, has been challenging for companies and will require new focus.

Finally, HR tech vendors are excited about using AI to revolutionize hiring and talent management. The current narrow model of defining a role and filtering people to find someone to fill it may be replaced by a more three-dimensional model in which individuals are mapped to an ideal fit within a landscape of opportunities. Changing how we match people to jobs will require creating and managing an expanded, more holistic view of each individual and of the work that has to be done. This translates to demand for much more and much better data. We are seeing an increased number of solutions that source and compile behavioral observation data by tapping into work systems, such as email, instant messaging, and phone calls, as well as work product repositories, such as GitHub.

Collectively, the opportunities created by AI point to a few clear next steps for HR leaders, educators, tech developers, and policymakers.

1 HR practitioners will need to get comfortable understanding the details of AI technology.

While experimenting with AI as a collaborator is helpful for HR leaders to understand the new GenAI tools, the really impactful use cases will likely occur when using GenAI and a broad range of other AI techniques for the agent or revolutionizing use cases. To help their companies more effectively navigate a changing landscape, HR leaders need to go beyond playing with GenAI tools and invest in learning enough about the technology to evaluate its potential and assure strong protection against its liabilities. As one example, being familiar with the basics of modeling techniques and data analysis is necessary to safeguard against bias as well as to identify areas for prioritization of AI application.

2 Educators have an opportunity to rethink training for entry-level workers as well as their participation in the hiring information ecosystem.

AI models require more data and better data to drive the desired outcomes. It was notable in our interviews that data on the contribution of education to a skills profile was largely absent. To better communicate information about education activity, especially in a world where learning is expected to continue beyond a single early investment, educators will need to rethink how they connect to data flow in the hiring tech ecosystem. Digital profiles of education activity, such as Learning and Employment Records (LERs), offer one example of a tool that educators may want to adopt. In addition, educators have an opportunity to offer new methods for assessment of durable skills as well as training options designed specifically to develop and accentuate skills that junior employees used to learn in the entry-level activity that is now being offloaded to AI.

3 Technology companies and policymakers should seek to address issues of data ownership and portability.

Data consumption by AI models also provides a good opportunity for policy makers. Data ownership and privacy is a paramount concern if behavioral observation becomes a prominent source of worker data. Similarly, assuring portability of data acquires new urgency if presenting a holistic view of yourself becomes a more important part of getting a job and a key part of your profile remains with your prior employer. For policymakers who feel that they missed addressing privacy in the early days of the Internet and are now trying to claw it back, the time is ripe to think about data governance, particularly ownership and portability, for use in AI-driven HR decision-making.

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INTRODUCTION

The integration of Artificial Intelligence (AI) into Human Resources (HR) is a dynamic and emerging field, with the potential to fundamentally alter the landscape of talent management and acquisition. AI's impact on equity, in particular, is multifaceted, presenting both opportunities and challenges.

On one hand, AI can enhance access to services, offer personalized solutions, and foster a skills-based hiring process, which can help underserved communities. On the other hand, there are significant risks, including the potential for perpetuating biases if AI systems are trained on flawed data, and exacerbating the digital divide if access to technology is uneven. A conscious consideration of how AI should best be used appears to be in order.

This report, informed by interviews with technology developers and HR practitioners, delves into the current and potential implications of AI in HR practices. We interviewed 20 executives and HR leaders from large and small HR technology providers. We asked the HR practitioners how they were using AI and what they were excited or concerned about. We discussed how AI was being built into tools and what new use cases were being imagined with the HR developers.

From the scenarios described in our interviews, we've organized the applications into three fundamentally different kinds of use cases:

COLLABORATOR – Generative AI (GenAI) as a collaborator supports HR professionals by assisting with tasks such as content creation, summarization, and analysis.

AGENT – While the collaborator role enhances human capabilities, the agent role can lead to more independent functioning of the AI. Here, the AI model automates routine processes or handles specific operational functions and makes decisions with minimal human intervention.

REVOLUTIONARY – Tech developers painted a picture of how AI would begin to alter our current way of considering the work of hiring and talent management in a more profound way. In this use case, AI is genuinely revolutionary.

What the examples provided in the interviews made clear was that the growing adoption of AI will require creating and managing an expanded view of each employee or applicant and of the work that has to be done. This almost certainly means that data collection is going to increase dramatically. We also learned that the embrace of some uses of AI suggests a need for new methods of candidate and employee evaluation, as well as new kinds of education strategies for entry-level workers.

To navigate these changes, HR practitioners will need to get comfortable understanding the details of AI technology, educators will need to rethink training for entry-level workers as well as their participation in the hiring information ecosystem, and technology companies and policymakers should seek to address issues of data ownership and portability.

What do we mean when we say "AI"?

Artificial Intelligence (AI) is a broad field of computer science focused on creating systems capable of performing tasks that typically require human intelligence. This encompasses everything from understanding natural language to recognizing patterns and making decisions. The defining characteristic of AI algorithms is that they get better at their tasks by learning from data rather than following fixed instructions. This helps AI systems make predictions and adapt to new information over time.

At the heart of AI is machine learning, a subset of available methods in which algorithms identify patterns in existing data and use that learning to evaluate new data that is presented to them. Machine learning is often used to categorize things or identify anomalies. Generative AI (GenAI) is a more specific branch of machine learning that focuses on creating new content such as text, images, or music by mimicking the patterns distilled from existing data. In working with either GenAI or machine learning more generally, it is important to understand four concepts: vectorization, probability, training, and foundational models.

VECTORIZATION

For information about something to be processed in an AI model, it must be turned into a vector of numbers. In language models, notably those used in GenAI models, a fundamental concept called embedding is used to translate words or pieces of text into vectors of real numbers, capturing semantic meaning and relationships between them. Words with similar meanings or contextual uses will have similar vector representations. This numerical approach allows machine learning models to perform tasks like text classification, sentiment analysis, or translation more effectively.

What elements are encoded in the vector can often impact the nature of the output. For example, a model that predicts whether someone should be given a mortgage that chooses to include a representation of race in the numerical vector may inadvertently be encoding a certain bias. The act of reducing characteristics that we find meaningful as humans to an abstract series of numbers means that it can sometimes be difficult to understand what pieces of input information are driving the most impact in defining output results. This, along with the black-box nature of how AI models form interim internal patterns that connect ultimately to the output, is part of why bias can be a challenging concept to monitor in AI models.

PROBABILITY

Probability plays a crucial role in AI models by providing a framework for making predictions and handling uncertainty. AI systems, particularly those based on machine learning, often rely on probabilistic methods to estimate the likelihood of various outcomes based on input data. For example, classification models use probabilities to determine the likelihood that a given data point belongs to a particular category. By integrating probability into their algorithms, AI systems can better manage incomplete or noisy data and adapt their responses based on the confidence of their predictions.

The use of probabilistic algorithms also means that there is inherent variability in output. Results may not always be consistent or predictable. A GenAI model might generate different text responses to the same query, or a ranking of candidates may not produce the same results on the same set of candidates twice in a row.

TRAINING

Models are typically trained on data to create an initial state that reflects the relationships in the training data. There are a variety of training techniques but most generally include some notion of feeding a model input information that is either explicitly or implicitly connected to some desired "correct" output information. By virtue of being told the patterns, models can settle into an ability to recognize them. When they are presented with a large number of patterns, models create internal representations that include enough abstraction of one pattern that it can also recognize a second, different one as well. This creates a slightly lower probability a model will correctly recognize the first pattern but adds the ability to recognize the additional pattern.

While many models include techniques to update themselves as new information is presented to them, incremental learning is often just that, incremental. For this reason, models need to be refreshed periodically with a new training dataset. The subset of GenAI focused on language uses Large Language Models (LLMs) that are trained on a diverse range of text from the internet. However, it's important to note that LLM models are trained at specific points in time. Any written content after the training date may not be reflected in the knowledge base the model can draw from.

FOUNDATIONAL MODELS

The release of ChatGPT, a chatbot user interface on top of a generative AI model, fundamentally changed how we approach AI modeling. The versions of GPT that fuel ChatGPT are known as foundational models, large, general-purpose machine learning models trained on extensive datasets to capture broad and deep representations of data. Foundational models provide a base that can be adapted to specific tasks with less data and computational effort than training models from scratch. The natural language interface that ChatGPT supports has also made using AI significantly easier. We now have access to an interface that allows anyone to interact with AI models simply by typing what they want. The requests can be a direct question or command, or it can be instructions to create an additional AI application. The greater ease in simply giving instructions to a chatbot to create what is essentially another chatbot with a specialized focus has opened up a set of opportunities, both big and small, for the application of AI in many areas.

AI AS COLLABORATOR

In our discussion with HR leaders about how they were using AI in their work, we heard a lot about experimentation with the "AI as collaborator" cases. Because one of the primary advantages of GenAI is its ability to create and refine content, almost all of the HR leaders we talked to were experimenting with its use in tasks such as drafting job descriptions, performance goals, and development objectives.

In addition to content creation, GenAI was also used to summarize information. This included synthesizing performance reviews, offering a cohesive overview of employee evaluations. It was similarly used in hiring to streamline the recruitment process by summarizing candidate profiles for hiring managers and suggesting interview questions. Another common use was to create summaries of meetings, including key themes and action items. And finally, a surprisingly large number of HR practitioners referenced their use of GenAI in keeping employee handbooks up to date, ensuring that these documents reflect the latest policies and practices. Indeed, the collaborative use of GenAI is so common in the HR community that several repositories for prompts, the instructions to the AI model, have been created by and shared among HR leaders.[1]

In many instances, the use cases that were described involved an individual accessing a generative AI model on their own, often using a version that was openly available to the public. In a few cases, HR leaders talked about using third-party tools that have been built on top of a foundational model and designed to address a particular, narrow use case. Tools like Inqqa.ai, for example, specifically enable HR teams to draft and analyze engagement surveys, offering insights into employee feedback and helping to create written reports for leadership.

For many of the HR leaders we spoke to, the value found in using AI was that it streamlined the time that needed to be invested in more mundane tasks. More than once, we heard reference to the idea that everyone has just gotten a "junior level assistant." This was deemed very positive by many interviewees who noted that using AI for these collaborator roles frees HR up for more strategic work. As Tricia Shields, CHRO of Naviant explained, "I feel like we're doing higher value things in the organization because we've allowed technology to do these other pieces."

In addition to fostering higher work productivity and more strategic focus, a few users also expressed enthusiasm for how GenAI can generate neutral language or refine content for any bias it may encode. Jonna Mooney, Principal of Affogato HR Consulting, imagined using GenAI to summarize candidate feedback from interview committees. She believes this could be a very useful, more neutral mechanism to allow each interviewer's observations to be considered and avoid the dynamic of having the conclusions of one senior or more passionate interviewer outweigh those of other committee members.

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1. A few examples: https://www.gptforhr.com/, https://www.aihr.com/blog/chatgpt-prompts-for-hr/, https://docs.google.com/document/d/1u0OQiirBtOtZhXJgay10oH4gjWQ7-iEdWWnt5YstBFw/edit

These use cases, while impactful, were not all that revolutionary for the HR space. There was nothing particularly strategic in how AI was being applied, as these sorts of uses for summarization or wordsmithing are being tried across many industries and roles.

AI AS AGENT

A more interesting use of AI was as an agent of some sort. Interviewees discussed using AI to do things like enhancing employee self-service. One recounted a company project that successfully implemented a chatbot to help onboard new employees. By automating responses to common employee questions, the chatbot not only streamlines getting information to employees, but evaluation surveys suggest that it also improves overall engagement with the company's various professional development and wellness programs.

The use of chatbots has also driven greater efficiency in the recruitment process. Allowing for variations in one-on-one communications to include content that is more personalized or applicable to a given candidate was deemed very successful in the face of reports of stunningly low candidate experience satisfaction.[2] One HR leader reported that the introduction of a chatbot to respond to candidate questions resulted in a significant increase in the click-through rate for job applications.

In talent assessment and interviewing, GenAI can also play an agentic role by acting as an extra evaluator. Some companies offer full-scale candidate interviews with GenAI-driven chatbots. Some, such as Zal.ai, simulate workplace scenarios that are specific to the employee's role and the company's unique proficiency standards to assess durable skills. Others walk candidates through assessment of specific skills such as coding. A benefit touted by companies offering these solutions is that there can be real loss of company productivity when mission critical employees, such as engineers, are pulled into interview situations. With an AI agent, this lost time is no longer necessary.

While having AI take over various functions within HR activity is gaining pace, the necessity for human oversight persists. Almost all HR leaders and tech developers we spoke with stressed the idea of assigning final decision-making authority to human beings–a practice often summarized by the term "human in the loop." Consider the case in which screening interviews are conducted by AI. As with any tech adoption, both parties in the interview, employer and candidate, are exploring using the new chatbot technology. Just as automatic filtering of resumes prompted the rise of tools that help job seekers tailor resumes to get through filtering, chatbot interviewers are faced with the challenge of determining if a candidate is presenting himself or has a surrogate chatbot actually

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2. Example studies include: https://www.indeed.com/lead/indeeds-ghosting-in-hiring-report, https://grnhse-marketing-site-assets.s3.amazonaws.com/production/Greenhouse-candidate-experience-report-October-2023.pdf, https://api.eremedia.com/wp-content/uploads/2024/02/2023-Global-CandE-Benchmark-Research-Report_FINAL.pdf, https://www.icims.com/wp-content/uploads/2022/11/iCIMS-2023TalentExperienceReport_US.pdf

providing responses. Agentic uses of AI, it would seem, need to build in awareness of the "bot-on-bot" potential. Humans can offer more contextually aware oversight to help identify when this is happening.

The concept of having a "human in the loop" also came up frequently in terms of validating AI's interpretation of information. Alison Lands, Director of SkyHive by Cornerstone, discusses AI's role in workforce planning: "AI's predictive capabilities are incredibly valuable in workforce planning, but they must be guided by human strategic oversight to be truly effective. It's about balancing the data-driven insights AI provides with the nuanced understanding that only humans can bring to strategic decision-making."

Tim Whitley, Director of HR Technology for Oklahoma State University, also alluded to the "human in the loop" as both the necessary expertise upfront in designing the systems, as well as serving as an auditor regularly conducting due diligence on the back end. "It's similar to what manufacturing organizations do right now with quality. You take a sample, and you do a double check."

The prominence of the references to "human in the loop" makes it clear that trust in AI is still evolving. However, the use of AI in candidate interviewing and onboarding activity described by HR leaders certainly suggests that there is an embrace of using AI as an agent. This trend is particularly important because, as Adam Wood, Founder of Future State, explained, the possibility of AI agents allows HR leaders to rethink how work might be conceived. Having an "AI in the group," where an agent AI acts as an autonomous participant within a work team, is becoming an option. Now, as a new workforce needs in a company arises, HR leaders can source talent to meet that need by upskilling current employees (build), hiring someone new (buy), contracting with a consultant or temporary worker (borrow), or assigning the task to an AI agent (bot).

The option to "build, buy, borrow, bot" presents companies with an interesting strategic tool. It also introduces new talent management challenges. In a "build, buy, borrow, bot" world, managers and their HR partners will be confronted with novel questions about how to manage interactions between humans and bots effectively.[3] They may need to rethink what they prioritize in human candidates and how to better gauge those competencies. Historically, the evaluation of durable skills, which one might argue includes the kind of contextual awareness that a "human in the loop" might provide, has been challenging to assess.

And finally, HR leaders may be confronted with a more profound dilemma. The ability to offload tasks to a bot, particularly offloading tasks that might be given to junior employees, raises the question about how new human entrants to the workforce will be able to gain the experience they need to allow them to offer the value that humans bring in providing contextually aware oversight. Having access to AI collaborators and agents may change traditional development pathways for human employees and open up a need for new forms of education altogether. Collectively, new requirements for managing new types of teams and rethinking how to select and prepare humans to participate in them suggest greater urgency for new methods of candidate and employee evaluation, as well as new kinds of education strategies.

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3. For interesting developments along these lines: Zhang, Y., Robertson, P., Shu, T., Hong, S., & Williams, B. C. (2024). *Risk-Bounded Online Team Interventions via Theory of Mind*. IEEE. https://doi.org/10.1109/ICRA57147.2024.10609865

AI AS REVOLUTIONARY

The collaborative and agentic uses of GenAI that HR leaders described to us tended to be practical and immediate. The use is happening today and is likely increasing even from when we spoke with our interviewees. In addition to these developments, a number of HR technology developers painted a vision in which the application of AI could drive deeper change that would fundamentally alter how we approach hiring and talent management today.

In the past few decades, we have seen a rise in the use of technology both to expose opportunities to potential employees as well as to process applications from interested candidates. Among other innovations that facilitated more scaled information processing was the ability to reduce both job and candidate descriptions to a list of skills. Recruiters could source candidates more efficiently by searching on skill keywords; Applicant Tracking Systems (ATSs) could effectively winnow a large number of incoming applications to a manageable subset of potential interviewees with filters on skill keywords. However, for the positives that may have been accrued from the creation of job boards and ATSs, recent surveys suggest that it has also led to a significant decline in the candidate's experience. Many job seekers feel that they are no longer receiving the consideration they deserve.[4] One reason for the challenge is that searching and filtering only accesses short, acontextual skill keywords derived from incomplete information.

Issues with the quality of data sources for employee information are well known to HR tech developers and HR leaders. User-generated data, such as LinkedIn profiles, has limitations, including spotty accuracy and incompleteness. One study from ResumeLab estimates that about 45% of Americans have outdated information in their LinkedIn profile.[5] An HR leader from one large company offered a cautionary example of what this means in practice. This company launched a project to connect employee LinkedIn profiles with their HRIS system. After a considerable initial effort, the data became outdated within just six months due to the static nature of the information.

Similarly, attempts to improve the quality of information at the point an employee joins a company have enjoyed mixed results. The process of translating the unstructured data found on a resume into data structured into the fields used by a company's hiring tools often loses information. Skills that might be learned from education experiences, notably from online courses or certifications, are likely not to be captured.[6]

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4. Example studies include: https://www.indeed.com/lead/indeeds-ghosting-in-hiring-report, https://grnhse-marketing-site-assets.s3.amazonaws.com/production/Greenhouse-candidate-experience-report-October-2023.pdf, https://www.eremedia.com/reports/2023-global-candidate-experience-cande-benchmark-research-report, https://www.icims.com/wp-content/uploads/2022/11/iCIMS-2023 TalentExperienceReport_US.pdf
5. Turczynski, B. (2024). *Keeping Career Resources Up To Date.* ResumeLab. https://resumelab.com/resume/how-often-to-update
6. Welsh, A., Stoddard, E., Nanovic, A., Houston, C., Leuba, M., Soares, S. (2024). *Bringing Richer, Verifiable Candidate Data Into HR Systems: An Ecosystem Roadmap*. Northeastern University College of Professional Studies, Center for the Future of Higher Education and Talent Strategy. https://cps.northeastern.edu/wp-content/ uploads/2024/09/ecosystem_ roadmap.pdf

In addition, the searches conducted or the filters defined may be based upon an inaccurate understanding of what the ideal candidate really looks like. FutureState's Wood emphasizes that accurately matching candidates requires not only identifying their skills but also comprehensively understanding the job itself. Sandra Loughlin, Chief Learning Scientist from EPAM, further supports this view, asserting that describing both work and candidates in terms of specific skills is essential for making meaningful matches. Without this level of detail and precision, even the most advanced skills-focused systems may struggle to align candidates with the right opportunities effectively. Although a concerted effort to define job roles and skill sets accurately is fundamental to realizing the full potential of innovative hiring models, the HR leaders we spoke with almost universally acknowledged that this is not a strength of their organizations and represents a body of work that requires additional consideration.

In the end, it's difficult to realize a revolution in hiring and managing people if you have a limited view of each individual and of the work that has to be done.

MORE AND BETTER DATA

In response to problems with skills data, HR tech providers have been investing in improvements from traditional ML techniques to develop predictive models and increase our understanding of skills through imputation. Imputation in machine learning involves using a variety of clustering and categorization techniques to estimate and fill in missing or incomplete data based on patterns and relationships identified in the available data. This has been helpful, but, perhaps, not enough.

More recently, there have been advances through adoption of the embedding technique used to understand natural language in GenAI models. Skill2Vec, for example, is an algorithm that helps understand and compare different skills in a way similar to how LLMs process language to comprehend words and their meanings.[7] It works by converting skills and the information about them stored in standardized formats, such as the W3C Verified Credential (VC) standard, into numerical representations (vectors), which allow for mathematical comparisons. For example, it can determine that "data analysis" and "statistics" are more related to each other than "graphic design" is to either of them. Essentially, Skill2Vec acts like a smart map for skills, showing the relationships between them, a capability useful both for filling in missing data as well as offering greater understanding of what skills cluster for a specific use case.

In addition to evolving the techniques for understanding skills data, skill extraction is also being layered on top of foundational models that can interpret unstructured data sources, i.e., natural language or video or audio files. This has opened up access to new kinds of data that facilitates moving beyond traditional reliance on job titles and keyword lists as the primary data sources for skills.

Mike Evers, Chief Strategy Officer of Nebula.io, offers an example of how this is changing where data can be gathered on a candidate. Nebula.io employs a comprehensive approach to creating user profiles by aggregating and processing data from a wide array of sources, including social media

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7. Van-Duyet, L., Quan, V. M., & An, D. Q. (2017). *Skill2vec: Machine learning approach for determining the relevant skills from job description*. arXiv preprint arXiv:1707.09751.

platforms like Facebook, Instagram, and TikTok, as well as personal information such as Amazon wish lists and published articles or papers. By collecting and analyzing data from these diverse outlets, Nebula.io can follow data "breadcrumbs" across various platforms and piece together a detailed professional profile for each individual. This integrative approach ensures that the profiles are both comprehensive and reflective of the individual's multifaceted online presence.

To help companies create a richer notion of the work that applicants should be matched to, companies such as hrflow.ai process a range of HR objects into AI-friendly vectors. These objects could include project management documents, team summaries, and job descriptions. Vectors of similar HR objects will cluster together, making it easier for HR tech developers to offer their clients tools to better understand the activity that is happening in their companies. This approach addresses a common problem with many current solutions, that they often fail to reflect the real work being done.

The shift in the data elements that can now be processed for information about work also includes a growing use of behavior data repositories collected by work tools. For example, platforms such as Gong.io record and analyze sales calls to provide real-time coaching and performance insights to salespeople. This enables detailed monitoring of employee interactions and behaviors, offering valuable feedback and optimization opportunities. The normalization of recording Zoom meetings further supports this trend. Other workplace tools that HR tech developers are tapping into include Jira, GitHub, Slack, and email.

The impact of this new ability, as Evers from Nebula described, is that we can now think of mapping both people and roles in a three-dimensional skills space. Realizing this promise flips the current model: rather than identifying a role and then filtering data to find a person to match it, we can now have a broader view of an opportunity landscape and match a role to a person. Bryce Winkelman, CRO from SeekOut, explained this shift as embracing the challenge: "How do we hire everyone in the world?"

FROM HIRING TO MATCHMAKING

The concept of the flipped model re-imagines the recruitment process to match candidates with the most suitable job opportunities, rather than simply filling a position. Karat, an interviewing platform, for example, maps candidates' skills and experiences to potential roles across various employers, rather than just focusing on a single vacancy. If a candidate interviews for a role at one company but their skills and experience align well with another position at a different company, Karat's system will identify and recommend these alternative opportunities. This notion of third-party talent marketplaces that emphasize finding the best fit for both the candidate and the employer would optimize the job seeking process we know today.

On a deeper level, the embrace of hiring as matchmaking feels very aligned with a broader cultural shift recognized by a few of our interviewees. Jeff Schwartz, VP of Insights and Impact at Gloat, in particular, emphasized the shift from a traditional employer-centric dynamic to a mutual selection process reminiscent of a dating relationship, where both parties assess compatibility. He suggests we need to acknowledge a shift in power dynamics. When we do this, groups that have historically felt somewhat left out of the mainstream conversation are more open to participating. Schwartz noted how women and underrepresented minorities were more inclined to be on Gloat's own internal marketplace platform. "It's a different way of accessing opportunity, and it has demonstrated itself to do a better job than the traditional ways that people find projects and mentors and jobs and organizations."

FROM MANAGEMENT TO CAREER CONSULTING

While flipping the hiring model may be a revolutionary notion, the underlying capability that allows it is the use of AI to deliver more specific evaluation of more information. Expanding data collection and interpretation has implications that extend beyond hiring to internal mobility and management.

For ongoing management of employees, GenAI can significantly enhance how companies gauge and respond to employee sentiment. Traditional methods such as periodic employee satisfaction surveys often fall short in capturing the real-time emotional climate of a team. By processing recordings of video conferences, Spiky.ai analyzes meeting metrics and communication patterns to detect signs of dissatisfaction or issues among employees, such as increased complaints or negative sentiment during meetings. This approach allows managers to identify and address problems proactively, fostering a more responsive and supportive work environment.

The use of AI to understand and enhance employee performance is also exemplified by the "democratization of executive coaching," a concept explained by Neha Monga from Lattice. By leveraging AI to analyze and summarize data from various platforms like Jira, GitHub, and Slack, Lattice is working to provide a comprehensive view of team activities and progress. This approach allows AI to generate insightful weekly status reports for managers, drawing from key sources of data relevant to different roles–such as software engineering metrics from Jira and GitHub, sales performance from Salesforce, and project updates from Basecamp for design teams. This capability helps managers understand where their employees stand, identify areas for improvement, and provide targeted support, effectively offering a form of executive coaching that was previously available only to senior leaders. By making these insights accessible across the organization, AI facilitates more personalized and actionable feedback, driving overall employee development and performance.

In addition to insights gleaned from tapping into real-time behavioral information, AI's power also lies in its ability to sift through data and identify talent within an organization that might otherwise go unnoticed. As Nancy Hauge, CHRO of Automation Anywhere explains, "About 50% of our operations are fully automated and AI enhanced." This represents a turbo-charged example of opportunity for behavioral monitoring that, Hauge points out, makes each employee's talents more visible more quickly. Automation Anywhere is using this data for more efficient and accurate identification of internal candidates for leadership roles. AI can effectively identify individuals who are ready for new challenges, thus supporting succession planning and talent development in a way that was previously not possible.

Similarly, a pilot program at Fenton, using AI technology from Zal.ai, is testing the application of AI in helping employees envision career pathways within the organization. Fenton's Chief People Officer Karla Wagner explains, "We are intrigued by the use of AI as it relates to career pathing and helping our employees achieve their ultimate career goals. Although we are still early in our journey, we believe that this technology, in understanding the competencies in our organization, can help individuals chart out their path."

The vision, and beginning use cases, for the new generation of AI in hiring and talent management paint a picture that is an enticing expansion beyond the current over-automated and reductionist models of how we represent individuals and jobs. With an understanding of the possibilities presented by our interviewees, the important next question is what are the practical next steps to realize this and assure that it actually is a better state?

WHAT NEXT?

When we think about the opportunities created by thinking about how work might change as well as how human resource management might change, we return to two observations: first, that embrace of agentic uses of AI suggests a need for new methods of human candidate and employee evaluation, as well as new kinds of education strategies; and second, that flipping the current hiring and talent management model requires creating and managing an expanded view of each individual and of the work that has to be done.

To navigate these changes, HR practitioners will need to get increasingly comfortable understanding the details of AI, educators have an opportunity to rethink training for entry level workers as well as their participation in the hiring information ecosystem, and technology companies and policy makers should seek to address issues of data ownership and portability.

"JUST START USING IT" IS NOT ENOUGH

The most common advice to leaders unsure about how or whether to prioritize a use of GenAI, in particular, is to simply begin playing around with it. The easy user interface makes this practical for the first time and the impact of how access has opened up cannot be overstated. However, we are rapidly moving to the use of AI in business decisions that is beyond what casual trial and error can comfortably inform. Contrary to the optimistic notion that AI will handle mundane tasks and free up HR professionals for strategic people work, the reality may require HR leaders to become more technically proficient.

Consider how the influx of new data, as well as the use of new techniques, in HR has prompted reasonable concern about how we manage bias in HR practices. It is important for HR professionals to be aware of bias but, as one interviewee recounted, questions about bias are being raised in projects simply because they use AI in some way, even if that use represents very low to no risk. The lack of understanding about AI this example highlighted can pose a significant barrier to implementing more complex AI use cases in HR.

Indeed, understanding the underlying technology of how AI learns can help HR leaders rethink how we've been framing the issue of addressing bias more profoundly. Retraining bias out of a model with new data is often more feasible than altering human biases due to the fundamental differences in how models and humans process information. AI models base their outcomes on patterns learned directly from the data they are trained on, making it relatively straightforward to adjust their behavior by updating or diversifying the data they receive. In contrast, humans interpret data through a complex lens of personal experiences, social reinforcement, and pre-existing worldviews, which can significantly influence their judgments. These layers of interpretation allow humans to fit new information into their existing beliefs, potentially reinforcing rather than challenging biases. Consequently, while retraining a model involves recalibrating algorithms and data inputs, changing entrenched human biases requires deeper shifts in individual perspectives and societal norms, which are inherently more challenging to achieve. A clearer understanding of how models work can help HR leaders engage with technology vendors more actively to refine model bias reduction strategies more effectively.

This can be especially important because, although the concept of a "human in the loop" is frequently cited as essential for vetting AI outcomes and mitigating bias, there is a fundamental problem with relying on human feedback. The burden on human beings to monitor and manage bias in LLM outputs is a significant challenge, often underestimated in practice. As Kyle Lagunas of Aptitude Research points out, many systems lack effective prompts or mechanisms to ensure that managers actually review or edit AI-generated content. This gap means that managers might bypass their responsibilities, leading to biased outputs that are not effectively addressed. For instance, if job descriptions generated by LLMs contain an extensive list of skills that are not genuinely required, this could lead to discriminatory practices if the description was used without being carefully reviewed. Furthermore, the added responsibility of

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Methods to Identify Bias

Experiments to uncover bias in Large Language Models (LLMs) are crucial for understanding and mitigating the potential negative impacts of these AI systems. Most of these techniques are being adopted by developers. HR leaders should be aware of these techniques and actively engage with vendors to identify what they are doing.

DATA PRE-PROCESSING AUDITS: Since bias can arise from data imbalances, examining the training data for bias is crucial. This includes checking for sampling bias, ensuring that different groups are adequately represented in the training data and labeling bias, ensuring that labels aren't skewed due to human bias, as in biased performance reviews or historical biases in crime data.

SUBGROUP ANALYSIS: Researchers often conduct tests using benchmark datasets designed to evaluate various types of biases, such as gender, race, or age biases. For instance, experiments may involve prompting LLMs with queries related to different demographic groups to see if the model generates biased or stereotypical responses. Specific measures include parity, whether positive outcomes are equally distributed across different groups, and calibration, whether predictions are equally reliable across groups. Game theory or analysis of statistical residuals (differences between predicted and true values) can also be used to measure how much individual features (e.g., gender, race) contribute to the final prediction.

ADVERSARIAL PROMPTS: Adversarial prompts involve crafting specific input scenarios that are designed to expose biases in the model's responses. These prompts might include questions or statements that are likely to trigger biased outputs, thereby revealing how the model's training data and algorithms might be perpetuating harmful stereotypes or unfair assumptions.

COUNTERFACTUALS: Counterfactual data augmentation involves examining model output using alternative versions of data where one or more attributes have been changed while keeping everything else the same. This technique is used to assess model bias by comparing how the model's predictions change when attributes related to sensitive variables are modified. If the model behaves differently when these attributes are altered, it may indicate bias.

FAIRNESS THROUGH UNAWARENESS: This principle involves intentionally excluding sensitive attributes (like race or gender) from the training data. However, this is not always sufficient because other correlated features (like zip code as a proxy for race) can still introduce bias.

being the "grownup" to oversee and correct AI outputs may in fact be an unfair and burdensome expectation on managers. Without a clear framework for how to implement and monitor human-in-the-loop processes, there is a risk that these critical oversight roles are inadequately fulfilled.

In addition to better navigating concerns about bias, HR leaders need a deeper understanding of AI tech to make them a strategic partner to their leadership. A common question we heard in our HR leader interviews was how to prioritize the embrace of AI. This is challenging to answer because there are a lot of possible applications that can all be quite meaningful to a company. There was no single area of focus that appeared to hold most promise. Aside from somewhat anodyne observations that apply to all change management–start small, secure fast wins–the most interesting counsel we heard was that enabling HR leaders to have a true understanding of the tools being put at their disposal is necessary and important to allow them to work with company leaders to effectively navigate the right prescription for their company's situation.

The consensus of both our developer and HR practitioner interviews was that, just as AI has the potential to evolve our notion of work, it is also bringing along with it a need to evolve the conception of the HR function and is increasing demands on HR practitioners. As Lagunas put it, "With AI, we should be evolving the function more so than simply automating work." HR leaders need to expand their toolkits. Simply playing around with a GenAI model is not enough.

ATTENDING TO EDUCATION INFORMATION, THE MISSING PIECE OF THE PUZZLE

To make the flipped model of hiring–in which we find roles for people, rather than candidates for roles–work, more data needs to be collected. The most impactful visions for the use of AI leaned upon curating a holistic understanding of an individual or a role. This holistic model implies that the data that is curated is not just the data that is easily available today. Amidst considerable dialogue about changing workplaces, evolving skill gaps, and the need for lifelong learning, it was particularly striking that none of the discussions we had with technology providers touched upon how education was represented in hiring or talent management. The reality is that it is dramatically under-represented most of the time.

In most hiring today, a job seeker submits an online application that includes filling in some contact information and uploading a resume. The resume is then translated into structured data where pre-defined database fields are populated with the appropriate information. While translating the resume, parsing algorithms also extract the skills suggested by the resume content. An average resume may yield anywhere from 10-30 skills. As noted earlier, these skills can be very important for the earlier stages of hiring. A job posting may yield 300 or so applications. Identifying the 5 candidates that will likely be interviewed for a role from among the hundreds of applicants is often a function of filtering candidates by their skills, among other data items. Unfortunately, recent research[8] suggests that parsing algorithms relying on resumes extract almost all of the skills associated with the applicant from work experience alone, and not

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8. Welsh, A., Houston, C., Leuba, M., Nanovic, A., Soares, S., Stoddard, E. (2024). *Bringing Richer, Verifiable Candidate Data Into HR Systems: An Ecosystem Roadmap*. Northeastern University College of Professional Studies, Center for the Future of Higher Education and Talent Strategy. https://cps.northeastern.edu/wp-content/uploads/2024/09/ecosystem_roadmap.pdf

from education. This is a natural consequence of the fact that most resumes indicate education only with the name of the program or credential, the issuing organization, and the date it was earned. This representation of education activity is not very rich, and at best, one or two skills might be eked out of the program name.

The systems for resume parsing and the traditions of how education is presented on a resume create a large gap in how individuals communicate the full spectrum of their capability. This can be particularly challenging for new entrants to the workforce, those who have invested in education as a step in making a career transition, and those who have embraced education as part of meeting the demands for upskilling. The latter group is estimated to include half the U.S. workforce.[9]

The inability to capture skill development that occurs from non-traditional forms of education is also quite important for a segment of the population that may not be well represented in professional profile forums. Workers in factories are less inclined to have a LinkedIn profile. They are, however, just as susceptible to behavioral monitoring by their employer. Without conscious investment in representing the other sides of these workers' identities, there is a danger that they will be represented in the AI-facilitated three-dimensional space with a very mono-dimensional view of their possible contribution. The potentially negative implications of this differential treatment could be worrying.

The paucity of education-related information in a resume was less of a problem when most viable candidates were granted an interview and given the opportunity to present their capabilities in a give-and-take conversation. However, in a model where interviews are a bit of a luxury or where matchmaking offers a less linear path that requires more complete knowledge of a candidate earlier in the process than has been typical in the past, we might imagine that the imagination and activity for AI as a revolution constitutes a bit of a call to arms to education providers.

One response to that call to arms can be found in the development of Learning and Employment Records (LERs) and digital identity documents, most obviously Digital Driver's Licenses. A growing awareness of these tools, which store information in digital wallets, suggest that we are evolving to a world in which we will begin to have digital profiles that we connect and share as we need to. However, while a driver's license as a credential is enough to prove your identity at the airport, your education record ideally contains more information that speaks not only to credential validation but also to the content of the learning. Data standards for LERs address this by defining standardized fields for credential metadata as well as what skills were taught. The uptake of digital credential information in wallets, however, has been modest to date.

One reason could be the lack of attention from higher education about the dire need to connect more deeply to the platforms that are used in hiring or talent management. It could also be that higher education is more comfortable working through intermediaries that consolidate learning information, such as the National Student Clearinghouse. Either way, greater emphasis on including information about education content—both traditional learning and new models that are adapting to address upskilling needs—feels like ripe territory for a focused application of AI capabilities.

In one AI-based experiment, OpenSyllabus.org, a non-profit with information from 20M+ syllabi, is working with a George Washington University project called LAiSER to catalog skills from the OpenSyllabus repository. The LAiSER project uses embedding techniques to combine information

9. Rothwell, J. (2021). *The American Upskilling Study Shows Workers Want Skills Training*. About Amazon. https://www.aboutamazon.com/news/workplace/the-american-upskilling-study-shows-workers-want-skills-training

across a number of skill taxonomies and reports high accuracy in defining the nature of learning more precisely. Allowing this kind of information to be collected along with other data elements in the imagined three-dimensional talent maps can address a key gap that currently exists.

In addition to greater attention from education providers to assure that learning experiences are included in the richer datasets used to connect workers to opportunities, there is also a need to imagine new models of teaching to help entry-level workers quickly gain experience that prepares them to offer contextual human-in-the-loop decision-making. Similarly, there may be benefits in experimenting with how to teach and evaluate the human skills necessary in a workplace with an "AI in the group." Unfortunately, aside from Spiky.ai and one reference to scenario-based role-playing, we did not encounter anything in our interviews that pointed to a clear solution to address this opportunity.

GETTING AHEAD OF DATA PRIVACY, OWNERSHIP, AND PORTABILITY

In addition to the new needs in education that AI might seem to trigger, the hunger for data inherent in effective applications of AI also increases the need for attention to data ownership and governance of use. It would be ideal to avoid turning employee behavioral observation into an unbearable panopticon. Additionally, the implications of increased information collection need to be considered for workers seeking to change employers, not just those looking for work for the first time or progressing inside their current company.

The move toward leveraging comprehensive behavioral data to enhance productivity and performance will almost certainly challenge traditional notions of workplace privacy. To date, most regulation that has been enacted or is under consideration has focused on reducing any hidden bias in hiring. The Equal Employment Opportunity Commission (EEOC), for example, has provided some guidance on using AI and other automated tools in video hiring interviews. Algorithmic analysis of face or body language can inadvertently reinforce biases related to race, gender, age, or other protected characteristics, as these non-verbal cues can be interpreted subjectively and may not accurately reflect a candidate's qualifications or capabilities. Beyond the focus on mitigating bias, however, as EQ Community CEO and Founder Marcus Sawyerr put it, "Outside of the New York law, there is currently no regulation, there is only discussion that there might be regulation." Clearly, there is room for work to be done.

Similarly, if presenting a holistic view of yourself becomes a more important part of getting a job, there is also more urgency for workers to be able to take their work profile info–including non-proprietary behavioral measures–with them when they leave a role. Think about the act of building up your credit history. If you had to start that process over each time you got a new credit card, it would be quite exhausting and potentially unfair. With AI, the problem is even worse. Instead of reporting a gap in the data, an AI model will simply make something up, typically called a "hallucination." Mark Hanson, VP of Strategy at Lightcast, emphasizes the importance of robust data, stating, "AI models, in general, are not flawed… but with limited data, they fail miserably." This underscores the need for ample, high-quality data to support AI models, ensuring that they can make accurate and reliable inferences. Imagine the plight of the middle-aged worker looking to transition careers in a world of three-dimensional ATS's if some notion of worker profile information portability doesn't exist.

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Regulation Enacted or Under Consideration

NEW YORK CITY'S LOCAL LAW 144: This law became effective July 2023 and requires employers using Automated Employment Decision Tools (AEDTs), such as AI-driven software, to conduct annual bias audits to ensure tools do not disproportionately affect candidates based on race, ethnicity, or sex. Employers must publicly post audit results and notify candidates at least 10 days in advance, allowing them to opt for alternative evaluation methods.

ALGORITHMIC ACCOUNTABILITY ACT: This proposed legislation aims to address concerns about algorithmic bias and transparency. If enacted, it would require companies to conduct impact assessments of their AI systems, including those used in HR functions, to ensure they do not perpetuate bias or unfair practices.

AI ACT (EUROPEAN UNION): The EU is in the process of enacting the Artificial Intelligence Act, which will regulate high-risk AI applications, including those used in HR. This act aims to ensure that AI systems are used responsibly and ethically, imposing requirements for transparency, risk management, and human oversight in high-risk applications.

EQUAL EMPLOYMENT OPPORTUNITY COMMISSION (EEOC) GUIDELINES: In the U.S., the EEOC provides guidance on the use of AI in employment practices to ensure compliance with anti-discrimination laws. AI tools used in recruitment, performance evaluation, and other HR functions must comply with the Equal Employment Opportunity laws to prevent discrimination based on race, gender, age, disability, or other protected characteristics.

GENERAL DATA PROTECTION REGULATION (GDPR): In the European Union, GDPR imposes strict requirements on the processing of personal data, including data used by AI systems. It mandates transparency, fairness, and accountability in data handling, which impacts how AI is used in HR functions such as recruitment and employee monitoring. For instance, GDPR's principles of data minimization and purpose limitation restrict how personal data can be collected and used by AI systems.

CALIFORNIA CONSUMER PRIVACY ACT (CCPA): In the United States, the CCPA provides similar protections to GDPR for California residents. It gives individuals the right to know what personal data is being collected and how it is used, and includes provisions that can affect AI in HR, such as the right to access and delete personal data.

Embracing data portability also implicitly raises the issue of data ownership. Data ownership issues with LLMs are a significant concern due to the complexities involved in managing and protecting sensitive information. For instance, if an organization uses an LLM to analyze proprietary or confidential data, questions arise about who owns the processed data, how it is stored, and how it might be used by the model provider. This can complicate compliance with data protection regulations and raise concerns about intellectual property and data leakage.

A promising approach to address some of these data ownership issues is the use of Retrieval-Augmented Generation (RAG). In a RAG setup, an LLM generates responses based on information retrieved from a company's database or knowledge source rather than relying solely on its internal training data. This means that sensitive data can be kept separate from the model's core training process and only accessed on-demand. By querying a company's secure repositories for specific information and integrating it into the generated responses, RAG helps maintain data privacy and clarity of ownership. The next evolution of the RAG model could allow LLMs to access training data from the model developer, proprietary information from the company to understand the business needs, and user profiles from a third-party agency to provide sharable individual information on a selective, as-needed basis. Models could tap into these third-party profile brokers to gather information about an individual that predates their time at their current company to inform HR decisions, such as identifying matches for roles or surfacing promotion opportunities. This implies a complex system of data flow between a number of parties, not unlike the way the online advertising ecosystem ultimately organized itself. For policymakers who feel that they missed addressing privacy in the early days of the Internet and are now trying to claw it back, the time is ripe to think about data governance, particularly ownership and portability, for use in AI-driven HR decision-making.

CONCLUSION

This report, informed by interviews with technology developers and HR practitioners, delves into the current and potential implications of AI in HR practices.

Our conversations suggest that HR practitioners will need to get increasingly comfortable understanding the details of AI, that data collection about current and prospective employees is going to increase dramatically, and that the evolution of AI as a more capable agent is going to reshape how we consider training and evaluation of durable skills. To adapt to these changes, HR professionals will need to become more familiar with the intricacies of AI. Educators have a chance to redefine entry-level training and engagement within the hiring information ecosystem to ensure better propagation of what is learned. Meanwhile, technology companies and policymakers should focus on resolving challenges related to data ownership and portability. There is a balance between bringing caution to new capabilities, and taking action to implement quality controls that foster equitable data coverage of individuals as well as ensure that data use and management are fair. These issues have long been identified for HR, but with the additional capabilities and speed of transactions possible with AI, they have become more pressing.

1

HR practitioners will need to get comfortable understanding the details of AI technology.

2

Educators have an opportunity to rethink training for entry-level workers as well as their participation in the hiring information ecosystem.

3

Technology companies and policymakers should seek to address issues of data ownership and portability.

APPENDIX

Interview Participants

- Burak Aksar, Spiky.ai
- Mike Evers, Nebula
- Lisha Gray, Affogato HR Consulting
- Mark Hanson, Lightcast
- Nancy Hauge, Automation Anywhere
- Kyle Lagunas, Aptitude Research
- Alison Lands, SkyHive by Cornerstone
- David Ludlow, SAP
- Darryl Louisaire, Karat
- Neha Monga, Lattice
- Jonna Mooney, Affogato HR Consulting
- Marcus Sawyerr, EQ.app
- Danny Seto, KPMG
- Tricia Shields, Naviant
- Jeff Schwartz, Gloat
- Kayvon Touran, Zal.ai
- Karla Wagner, Fenton
- Bryce Winkelman, SeekOut
- Tim Whitley, Oklahoma State University
- Adam Wood, Future State

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