

# Al Decoded:

Understanding Bias in Al-Enabled Talent Acquisition (and what to do about it)





## **Key Themes of the Report**

- Defining AI in Talent Acquisition
- Al Use Cases
- Benefits of AI in Talent Acquisition
- Al Case Studies
- Bias in Al Hiring: Risk & Real-World Impact
- Bias Mitigation Framework Talent Acquisition

## **Opening**

Artificial Intelligence (AI) is reshaping how companies hire, promising speed, scalability, and data-driven objectivity. But beneath the surface lies a critical challenge: bias.

From Amazon's failed resume-screening algorithm to Al systems that devalue resumes based on race, gender, or postcode, the risk of replicating discrimination at scale is real, and growing.

As generative and predictive AI tools become embedded in Talent Acquisition, employers must reckon with their ethical and legal responsibilities. This primer equips P&C and TA leaders with a practical overview of how bias manifests in AI hiring systems, how to identify risks, and how to build safer, more equitable systems.

Whether you're exploring Al-powered tools for the first time, or seeking to refine existing systems, the insights here offer both a caution and a roadmap: Al in Talent Acquisition must be transparent, accountable, and aligned with core diversity, equity, and inclusion (DEI) values.





## 1. Defining AI in Talent Acquisition

Artificial Intelligence is increasingly embedded in our daily lives. From personalised playlists on Spotify to navigation apps like Google Maps and predictive text in email, AI is quietly shaping how we move through the world. Virtual assistants like Siri and Alexa, fraud detection in banking, and recommendation engines on Netflix are just a few examples of how AI is being used well outside the Talent Acquisition space.

But AI is now firmly taking root in P&C and hiring. In Talent Acquisition, AI can touch every stage of the talent journey, from candidate sourcing to final selection. Understanding how it works is critical to ensuring ethical, inclusive hiring.

There are two key types of AI in Talent Acquisition:

**Predictive AI:** Predictive AI: Uses historical data and machine learning (a form of AI that learns patterns from past data to make predictions or decisions) to make forecasts, such as resume scoring, psychometric profiling, and video interview analytics.

**Generative AI:** Powered by large language models (AI tools trained on massive text datasets), generative AI creates new content, enabling automated interview questions, chatbots, job descriptions, and personalised candidate messaging.

A prime example is ChatGPT (or alternatives like Gemini, Claude, Copilot and Grok) which can be used to generate interview questions, suggest edits to job descriptions, or even simulate candidate dialogue. These tools are increasingly being adopted by recruiters to draft outreach messages, summarise CVs, or assist with interview preparation.

## Al use cases in Talent Acquisition include:

Screening and ranking large applicant pools

Matching candidates to jobs based on skill and behavioural profiles

Auto-generating job ads

Managing candidate communication through chatbots

Scoring asynchronous video interviews



of talent acquisition teams are now integrating or experimenting with generative Al.

Adoption is accelerating. LinkedIn's Global 2025 Future of Recruiting study found that 37% of talent acquisition teams are now actively integrating or experimenting with generative Al in their hiring workflow, which is up from 27% just a year prior.<sup>1</sup>



## 2. The Promise: Benefits of AI in Talent Acquisition

When responsibly deployed, Al can transform talent acquisition. Key benefits include:

#### Speed & Efficiency

Al reduces manual workload by automating repetitive tasks like screening, scheduling, and communication. A LinkedIn Global Talent Trends report found that Al-led recruiting can reduce time-to-hire by up to 35%.<sup>2</sup>

Automating initial stages also frees up recruiters to focus on high-value tasks like relationship building, stakeholder alignment, and candidate experience. Some recruiters are even using tools like ChatGPT to rapidly generate customised candidate emails, internal interview summaries, or job ad iterations, reducing admin and accelerating communication cycles.

#### **Enhanced Candidate Experience**

Al-powered tools can provide 24/7 chatbot support, improve response times, and deliver more personalised communication, boosting candidate satisfaction. When candidates receive timely updates or automated follow-up, they are more likely to perceive the process as fair and respectful.

#### Fairness & Consistency

Al applies the same logic to every applicant. Unlike humans, it doesn't get tired, distracted, or swayed by gut feeling, assuming it's properly calibrated. With clearly defined and consistently applied criteria, Al can help reduce variation caused by unconscious bias.

However, this is only true if the AI system itself is built with fairness in mind. The consistency AI delivers is only as fair as the logic embedded in its design.

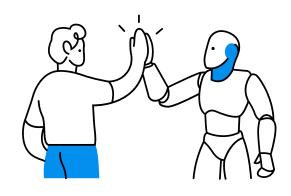
#### **Broader Reach & Diverse Talent Pools**

Al platforms can source from non-traditional databases, helping discover underrepresented or passive candidates who may not apply directly. Some tools are designed to anonymise resumes, removing names, schools, and other demographic clues to encourage more equitable screening.

Additionally, Al can be used to identify transferable skills in candidates from adjacent industries, opening up new channels for inclusive hiring.

#### **Data-Driven Decisions**

Al analytics provide TA teams with insights into what works, such as which sourcing channels produce more diverse candidates, or which assessments correlate with long-term success. These insights can be used to iterate faster and improve processes.





#### **Enhanced Attraction & Representation**

Deploying AI to support candidate experience and alleviate end-user bias has demonstrated clear success. By reducing barriers in early screening and encouraging higher application completion rates, AI can help attract more diverse candidates. The following case studies show how this technology is reshaping representation while delivering measurable business benefits.

## Case Study: AI for Inclusive Hiring

Monash University's 2023 study showed that in some cases, Alassisted hiring more than doubled the representation of women in the top 10% of short-listed candidates.<sup>3</sup> Female candidates were also more likely to complete applications when Al, not humans, handled first-round screening.<sup>4</sup> The study found strong support for this effect, showing women's completion rates rose by around 18% under Al evaluation, while men's dropped by 13%. Regression results confirmed that Al significantly increased women's participation relative to men, reshaping the demographics of the applicant pool and suggesting Al has the potential to reduce gender gaps in hiring outcomes.<sup>3</sup>





## Case Study: Power in Diversity

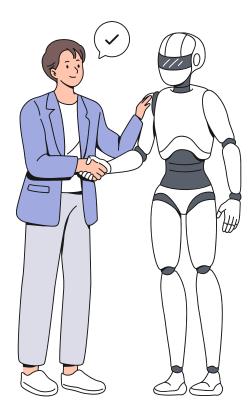
In 2022, a groundbreaking case study emerged from a leading tech firm, Innovatech, which aimed to transform its Talent Acquisition process through artificial intelligence. Faced with a staggering statistic that minorities made up only 25% of their workforce, Innovatech decided to leverage AI to create more inclusive hiring practices. By implementing an AI-driven tool that analysed resumes while removing biases related to gender, ethnicity, and age, the company saw a 50% increase in the diversity of candidates invited for interviews within the first six months. This approach not only diversified their talent pool, but also lifted employee satisfaction by 30%. Results also showed a 40% reduction in bias-related hiring errors, a 65% rise in applications for hard-to-fill roles, and a 20% higher project success rate, proving how the use of AI in Talent Acquisition can drive both equity and business performance.<sup>5</sup>

3 Mallory Avery, Andreas Leibbrandt, and Joseph Vecci, Does Artificial Intelligence Help or Hurt Gender Diversity? Evidence from Two Field Experiments on Recruitment in Tech (Melbourne: Monash University, 2023), 14-17, https://www.monash.edu/ data/assets/pdf file/0011/3279449/2023-09.pdf

4 Mallory Avery, Andreas Leibbrandt, and Joseph Vecci, Does Artificial Intelligence Help or Hurt Gender Diversity? Evidence from Two Field Experiments on Recruitment Tech (Melbourne: Monash University, 2023), 30-34, https://www.monash.edu/ data/assets/pdf file/0011/3279449/2023-09.pdf



## 3. Bias in Al Hiring Tools: Risk & Real-World Impact



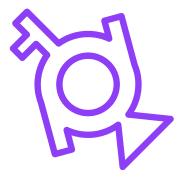
Al systems trained on biased data or applied without oversight can perpetuate, and even amplify, existing inequities. What makes Al bias particularly concerning is its scale and speed: decisions that once took days and involved human reasoning are now made in milliseconds by algorithms trained on incomplete or skewed datasets.

Bias in AI hiring tools is not always overt. It can stem from how data is collected, the assumptions baked into algorithms, or unintended correlations that are learned through training. ChatGPT and similar large language models learn from massive datasets scraped from the internet; data that includes both societal insights and embedded stereotypes. When used in hiring, even subtle phrasing differences in AI-generated candidate responses or summaries may unintentionally reinforce gender, racial, or linguistic bias.

Below, we explore the common categories of bias: gender, race, age, disability, and socioeconomic status, and how they manifest in real-world Talent Acquisition scenarios.

#### **Gender Bias**

Amazon's resume screening algorithm is one of the most well-known examples of AI gender bias. The model, trained on resumes submitted to Amazon over a ten-year period, learned to penalise resumes that included terms like "women's," "female," or referenced all-women colleges. Because the dataset disproportionately represented male applicants, the algorithm learned that male-coded attributes were more predictive of success. Although this tool was never used in production, its development revealed a major vulnerability in machine learning: the tendency to replicate and reinforce existing inequalities when trained on unbalanced data.<sup>6</sup>



Gender bias also shows up in more subtle ways. For example, AI-powered writing assistants that help draft job descriptions may recommend language such as "aggressive," "competitive," or "dominant," which are words that are shown to attract fewer female applicants. Without active intervention, these tools can reinforce gendered occupational stereotypes.



#### **Racial & Ethnic Bias**

Racial and ethnic bias in AI systems often originates from data that reflects societal disparities. In Talent Acquisition, this can mean devaluing resumes from certain regions, schools, or even those with non-Anglo names. In the 2024 University of Washington study, researchers submitted identical resumes with racially coded names and found that white-sounding names were favoured over Black or Asian ones, even when qualifications were exactly the same.<sup>7</sup>

A 2023 University of Maryland study examined whether Indeed.com's Alpowered resume ranking algorithm exhibited bias against graduates of Historically Black Colleges and Universities (HBCUs). Researchers created fictitious candidate profiles, using college attended as a proxy for prestige and race, and compared HBCU versus non-HBCU results. Overall, rankings were similar, but when controlling for variables like major, experience, and company size, HBCU alumni scored lower in many comparisons. This suggests a "prestige bias," where the algorithm may favour graduates from more familiar or highly ranked (often predominantly white) institutions over equally qualified HBCU candidates.<sup>8</sup>

In Australia, there is also growing concern about AI systems unintentionally excluding Aboriginal and Torres Strait Islander candidates. Hiring algorithms may deprioritise applicants from remote areas and community colleges, both of which disproportionately serve Indigenous populations.



#### **Age Bias**

Age discrimination in Talent Acquisition has long been a concern, and AI has the potential to either mitigate or exacerbate it. In the iTutorGroup lawsuit, the company's online application software was programmed to automatically reject older applicants (specifically, women aged 55 and over and men aged 60 and over) resulting in a settlement with the U.S. Equal Employment Opportunity Commission (EEOC). This case demonstrated how algorithmic age bias can be explicit, programmed into the logic of a system.

More often, age bias manifests subtly. Al screening tools, often trained on historical hiring data skewed toward younger candidates, may automatically penalise signals like long tenures, career breaks, or non-linear job paths, which are factors more typical of older applicants. Thus, they may prioritise youth-skewed resume patterns and screen out older applicants before a human even reviews them.<sup>10</sup>

7 Stefan Milne, "AI tools show biases in ranking job applicants' names according to perceived race and gender," UW News, October 31, 2024, <a href="https://www.washington.edu/news/2024/10/31/ai-bias-resume-screening-race-gender/">https://www.washington.edu/news/2024/10/31/ai-bias-resume-screening-race-gender/</a>.

8 Rachel Antony et al., Analyzing Unconscious Bias in Indeed's Employee Resume Search (College Park: University of Maryland, 2023), 20-27, https://drum.lib.umd.edu/items/2afb3aab-e57f-4ed3-af82-faaec9913172.

9 Daniel Wiessner, "Tutoring firm settles US agency's first bias lawsuit involving Al software," Reuters, August 11, 2023, <a href="https://www.reuters.com/legal/tutoring-firm-settles-us-agencys-first-bias-lawsuit-involving-ai-software-2023-08-10/">https://www.reuters.com/legal/tutoring-firm-settles-us-agencys-first-bias-lawsuit-involving-ai-software-2023-08-10/</a>.



#### Disability & Neurodivergence

Disability bias in AI hiring often arises from assumptions around communication style, physical presentation, or cognitive processing. Many AI tools use video analysis to assess candidate responses in asynchronous interviews. These systems evaluate tone, facial expressions, micromovements, and speech cadence to score candidates on attributes like confidence, enthusiasm, or emotional intelligence.

For neurodivergent individuals, such as those with autism or ADHD, these assessments can be deeply exclusionary. For example, an autistic candidate may avoid eye contact, speak in a monotone, or require extra time to formulate responses. Al systems trained on neurotypical behaviour may interpret these traits as negative, even though they are unrelated to job capability.

Physical disabilities can also impact AI-based assessments. Speech-to-text systems may misinterpret slurred or delayed speech. Facial analysis may struggle with certain muscular disorders or impairments. These technical limitations can lead to unintentional exclusion if alternative pathways are not made available.



In 2020, HireVue, a major AI video interview provider, stopped using its facial-expression analysis feature after criticism, and a US Federal Trade Commission complaint, from the Electronic Privacy Information Center, a non-profit research and advocacy organisation. The tool analysed candidates' facial movements, tone, and word choice to assess employability. Critics warned it could introduce bias, particularly against neurodivergent and disabled candidates. Although HireVue claimed audits showed no bias, the company removed it from its hiring assessments.<sup>11</sup>

However, Al offers the potential of significant benefits for neurodivergent and candidates living with a disability by providing alternative, flexible methods for engagement that may be more accessible than traditional interviews. Al can enable written assessments, asynchronous video interviews, or tools like chatbots, giving candidates greater control over timing and environment. Additionally, Al tools can integrate with assistive technologies like screen readers and speech-to-text systems, ensuring broader accessibility. For neurodivergent candidates, Al's structured format can alleviate the stress of live, unstructured interviews.



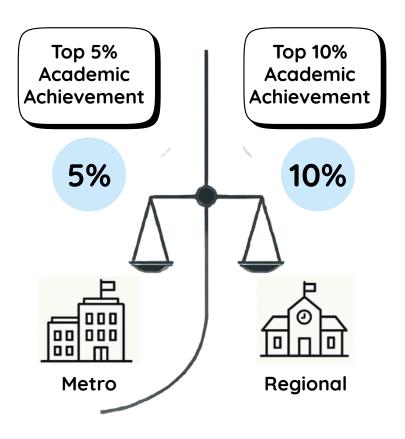
#### Socioeconomic & Educational Bias

Al's preference for "prestige" can reinforce class stratification. Hiring algorithms often prioritise candidates with continuous employment, internships at brand-name firms, or degrees from elite universities. These criteria are rarely neutral since they reflect access, privilege, and social capital.

Socioeconomic bias also appears in language. Al tools that evaluate writing samples or personal statements may favour candidates who use certain tone, phrasing, or idioms, which are often acquired through private education or professional coaching. This can disadvantage talented individuals from migrant, rural, or working-class backgrounds.

Some organisations are countering this by adopting "contextual Talent Acquisition" approaches that use AI to assess candidate achievement in light of their background. For example, recognising a top 10% academic score at a regional school as equivalent to top 5% at a major metro school. When paired with anonymised CVs and skills-first assessments, these methods can significantly expand the pipeline.

## **Contextual Talent Acquisition**





## 4. A Framework for Mitigating Bias in Al Talent Acquisition

Mitigating bias in Al-driven Talent Acquisition requires a multi-pronged approach combining technical measures, human judgment, and governance. P&C, TA and DEI professionals can take strategic yet practical actions in the following areas to ensure hiring technologies remain fair and inclusive:

#### **Inclusive Data & Design Practices**

Designing AI tools with inclusivity in mind is the first step to preventing bias. Key practices include:

**Use Representative Training Data:** Work with developers or vendors to ensure the AI is trained on data that reflects the diversity of the talent pool, rather than just historical hiring data that skews toward one group. The previously mentioned Amazon case study is a cautionary tale that shows the importance of curating balanced, bias-free datasets from the start. Ensure your AI training datasets reflect gender, racial, age, ability, and cognitive diversity. Underrepresented groups must be meaningfully included to avoid skewing models toward majority outcomes.

**Involve Diverse Stakeholders in Design:** Include input from a diverse group of employees (e.g. across genders, ethnic backgrounds, ages, and abilities) when developing or selecting Al-driven hiring tools. A broader range of perspectives can help spot biased logic or features early. If your company lacks diversity in the tech team, seek feedback from ERGs (Employee Resource Groups) or external advisors to identify blind spots in the tool's design.

**Bias-Test Algorithms Before Deployment:** Don't simply trust that an Al will be fair, test it. Run pilot screenings with synthetic or historical candidate data to see if the tool yields disproportionate rejection rates for any demographic. Continual bias testing throughout the machine learning process is necessary, along with monitoring real outcomes for any unequal impacts. If issues are found, retrain the model, adjust its parameters, or remove problematic input factors (for instance, scoring candidates on traits that might proxy for gender or race). Regular audits of the Al's decisions help ensure the system's fairness doesn't degrade over time.

**Ensure AI Explains Decisions:** If designing your own AI-enabled hiring system, ensure that the AI explains its decisions and evaluation scores in every case. This fosters transparency and provides clarity for candidates, especially when reviewing AI-generated outcomes that may impact their job prospects. Clear explanation of how decisions are made helps candidates better understand the process and builds confidence in the fairness of the tool.

**Knowledge of Prompt Engineering:** When using off-the-shelf AI tools like ChatGPT, Copilot, Claude, or Gemini, understanding prompt engineering is essential. Having robust, tested libraries of prompts used across a team rather than each person freelancing their prompts helps standardise and refine output. This approach ensures that prompts are designed to avoid perpetuating bias, improving the accuracy, fairness, and consistency of AI tools in the hiring process.



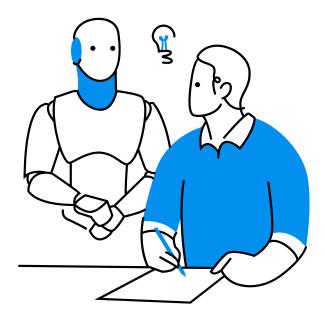
#### **Human Oversight in the Hiring Process**

Even the best AI should not operate unchecked in hiring. Human oversight provides context and ethical judgment that algorithms lack:

**Keep Humans in the Loop:** Maintain a role for recruiters or hiring managers to review Al-driven decisions before they are finalised. Use Al as a smart filter or decision support tool and not as the ultimate decision-maker. For example, human reviewers can catch if a highly qualified candidate was screened out due to a quirk in the algorithm.

**Establish Checks & Balances:** Set up a process to regularly evaluate the Al's recommendations. For example, a P&C or DEI team member could periodically sample a set of rejected applicants to ensure no qualified minority candidates are being disproportionately filtered out. If patterns of potential bias are spotted, there should be a clear protocol to pause use of the tool and investigate. Some organisations, such as Microsoft, Accenture, and Salesforce, have review panels that meet regularly to discuss Al usage broadly and flag concerns and risks.<sup>12</sup>

**Train Staff on AI Tools & Limitations:** Ensure that everyone involved in hiring understands what the AI tool does and doesn't do. Provide simple training for recruiters on how the algorithm works, what criteria it assesses, and how to interpret its scores or rankings. This empowers staff to question unusual results rather than assume the algorithm is always right. It also helps them explain decisions to candidates. By being aware of the AI's limitations (e.g. "Our chatbot scores communication skills but doesn't measure cultural fit"), humans can effectively partner with the technology, using their discretion to make the final calls.





#### **Building Cross-Functional Governance**

Bias mitigation isn't just an IT issue, it requires policy, compliance, and oversight frameworks. Building a cross-functional governance structure ensures AI in Talent Acquisition is managed holistically:

Create an Al Ethics Committee or Task Force: Bring together stakeholders from P&C, DEI, legal, compliance, and IT to form a governing body for AI in hiring. This group should establish guidelines for acceptable AI use and define what a "biased outcome" means for your organisation. They might set target metrics (e.g. the AI's recommendations should not significantly diverge from human hiring benchmarks in terms of gender or racial mix) and limits on high stakes use (perhaps mandating human interviews for final shortlisted candidates). Cross-functional governance ensures that technical decisions consider ethical and legal perspectives as well.

**Vet & Monitor AI Vendors:** If using third-party AI recruiting software, the governance team should rigorously evaluate each vendor's bias mitigation practices. Ask vendors to show evidence of how their tools perform across different demographic groups. Require transparency and ask vendors to share the results of bias audits or allow independent testing of their models. If a vendor's tool was involved in bias incidents elsewhere, treat it as a red flag. Once an AI tool is deployed, continue to monitor its outputs with the vendor's support, and don't hesitate to press for improvements or switch providers if needed. The World Economic Forum's insight report Adopting AI Responsibly: Guidelines for Procurement of AI Solutions by the Private Sector serves as an excellent starting point for building a robust AI vetting framework for responsible procurement.<sup>13</sup>

**Stay Ahead of Laws & Standards:** Regulations around AI hiring are emerging quickly, and a governance team should track and prepare for them. For example, New York City now requires employers to conduct annual bias audits of automated hiring tools and to disclose AI use to candidates. Globally, standards for "AI ethics" and fair hiring are being discussed, including in Australia. Ensuring compliance might involve updating consent forms, publishing an annual fairness report, or simply keeping documentation of your AI's evaluations. Proactively adapting your practices to meet these evolving legal requirements will protect the organisation and demonstrate a commitment to responsible AI use.

**Define Accountability & Recourse:** Governance should also outline who is responsible for outcomes. If the AI makes a problematic recommendation, who evaluates and corrects it? Establish a clear escalation path. In addition, determine how candidates can enquire about or appeal decisions. Some companies designate a point of contact (e.g. a TA leader or the ethics committee) to handle candidate questions about AI-driven rejections. Having this accountability structure means issues won't fall through the cracks.

<sup>13</sup> Adopting Al Responsibly: Guidelines for Procurement of Al Solutions by the Private Sector (Geneva: World Economic Forum, June 2023), <a href="https://www.weforum.org/publications/adopting-ai-responsibly-guidelines-for-procurement-of-ai-solutions-by-the-private-sector/">https://www.weforum.org/publications/adopting-ai-responsibly-guidelines-for-procurement-of-ai-solutions-by-the-private-sector/</a>.



#### Transparency & Communication

Transparency and open communication about AI tools build trust with both candidates and employees. Being upfront and clear about the use of AI can also improve the candidate experience while keeping the company compliant. Consider these steps:

**Disclose AI Use to Candidates:** Let applicants know when and how AI is being used in the hiring process. For instance, if you use a chatbot to screen candidates or an algorithm to grade video interviews, clearly inform candidates in advance. In some jurisdictions this is legally required. For example, the New York City law mentioned above obligates employers to notify candidates when an "automated employment decision tool" is in use. Even where it's not required, disclosure demonstrates integrity. A simple statement on job postings or career websites (e.g. "Please note an AI tool will be used to score initial assessments, but results are reviewed by our Talent Acquisition team") can set expectations and reduce confusion.

Communicate Internally & Educate Stakeholders: Within the organisation, communicate the role of AI in hiring to all relevant stakeholders, not just the AI developers, but recruiters, hiring managers, and even current employees who might refer candidates. Explain in accessible terms what the AI evaluates and how its outputs should be used. For example, clarify that an AI resume score is one input and not a definitive verdict on a candidate. Encourage a culture where hiring teams discuss and question AI results openly. The goal is to avoid a "black box" mystique; instead, everyone involved should feel comfortable understanding and explaining the system's impact on decisions.

**Provide Feedback & Preserve Candidate Experience:** Where feasible, offer candidates some feedback or insight into the hiring decision process. Many applicants feel anxious about Aldriven hiring as it can seem opaque. Without giving away proprietary details, you might share general feedback (e.g. "Your application was reviewed using an automated matching system for key qualifications, plus human review of your experience"). Additionally, ensure there is an accessible channel for candidates to ask questions or request a human review. Showing this willingness to engage not only improves your employer brand, but it can also surface issues. For example, if multiple candidates raise similar concerns about the AI process, it may signal a need to adjust the system.

**Be Ready to Explain & Justify Decisions:** In line with accountability, maintain documentation of how your AI reaches decisions and be prepared to explain those in non-technical language if challenged. This might include keeping the scoring criteria on record and logging the factors considered for each automated decision. In practice, this transparency could come into play if a candidate requests an explanation or if an external audit occurs. Companies that can clearly communicate why a candidate was or wasn't selected (e.g. "The system prioritised X skills for this role") will be better positioned to defend their practices and reassure candidates that the process was fair. Transparency serves as both a safeguard and a trust-builder. It forces the organisation to continuously check that the AI's logic is justifiable, while helping candidates feel respected throughout a high-tech hiring process.

By focusing on inclusive data and design, human oversight, cross-functional governance, and transparency, P&C and DEI leaders can actively mitigate bias in Al-enabled Talent Acquisition. These strategies make Al adoption not just a technical implementation, but a collaborative, ethical practice. The payoff is twofold: your organisation gains the efficiency and scale benefits of Al while protecting (and even enhancing) diversity, equity, and inclusion in your talent acquisition. It's a strategic win-win that harnesses the power of Al without losing sight of fairness, ethics, or equity.

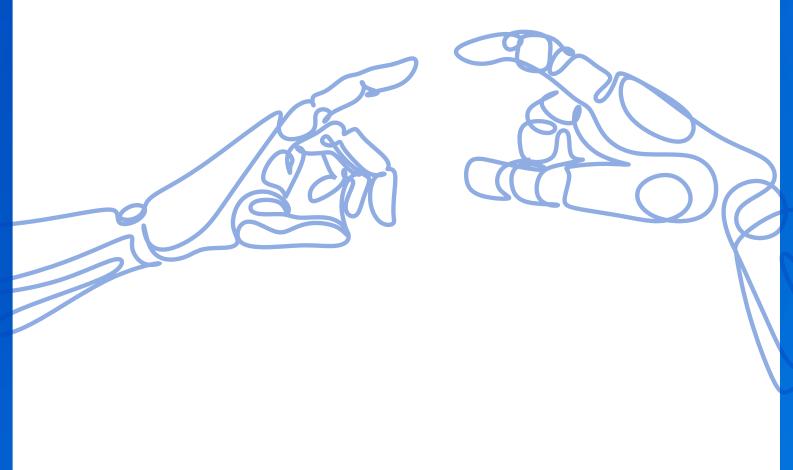


## 5. Final Thoughts

Artificial intelligence has the power to enhance how we hire, making Talent Acquisition faster, more efficient, and potentially fairer. But it also carries serious risks. Without safeguards, Al can replicate bias at scale, undermine trust among candidates and employees, and expose organisations to reputational or legal risk.

With tools like ChatGPT becoming common even in day-to-day recruiting tasks, it's more important than ever for P&C leaders to understand how generative AI works, and to ensure it does not silently embed bias into their processes.

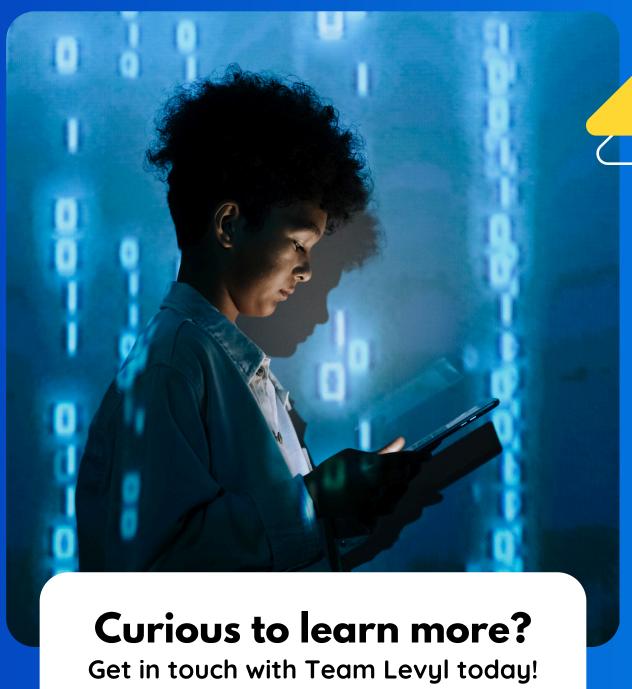
When thoughtfully designed and deployed, AI has the potential to enhance accessibility, reduce bias, and provide more flexible, skills-focused hiring pathways that accommodate people from all backgrounds and lived experiences. By prioritising inclusivity in AI development, we can create hiring processes that are fairer and more inclusive of diverse talent.





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