

# State of Al Bias in Talent Acquisition 2025

A data-driven review of AI bias, compliance, and responsible AI practices in TA.



# Foreword by Kyle Lagunas



Kyle Lagunas
Founder & Principal,
Kyle & Co



After a decade advising HR and Talent leaders on how to adopt technology responsibly, I've seen excitement around AI quickly give way to concern, especially around bias and fairness.

As AI tools embed deeper into hiring and workforce decisions, we face a defining moment: will we carry forward old inequalities, or use AI to build something better?

New and forthcoming legislation make this choice all the more urgent. Pending court cases signal that AI risk is no longer theoretical. For HR and TA leaders, and technology vendors, bias is now a legal and reputational issue.

But we must resist the temptation to simply run away from the "bias boogeyman." Instead, we need to lean in, and find real answers to the real risks we face.

This report brings a number of interesting points together to crystallize this critical conversation. It offers a grounded view of where AI is impacting TA decisions today and moves us past assumptions and toward evidence.

While bias is real, it is also measurable, manageable—and, thankfully, mitigatable.



# Executive summary

Bias in AI has become one of the most urgent and emotive issues in hiring, with high-profile lawsuits like Mobley vs.

Workday pushing the risks into the legal and media spotlight.

This report cuts through the noise with a data-rich view of how bias is playing out in real-world AI systems.

75% of HR/TA leaders cite bias as one of the top concerns with adopting Al. At the same time, they are under pressure to solve business problems using Al, creating a sharp tension.

The reality is more nuanced than the headlines suggest. While some AI systems do show bias, **85% of AI systems met** accepted fairness thresholds.

In fact, AI can be fairer than the human processes they replace. The data suggests that AI systems can deliver up to 45% fairer outcomes for women and racial minorities than human-led decisions.

That said, bias does exist in some systems, **15% of tools failed basic fairness tests**, and the gap between AI systems and different vendors varies by up to 40%.

Vendors are investing in responsible AI practices and preparing to meet AI regulations, but many have a long way to go. There's a promising level of transparency with the majority of vendors sharing publicly available documentation. Yet transparency to end-users is limited with **only 15% made aware that AI is used**.

The question is no longer whether AI can be biased, but how we manage its use in a way that improves outcomes. Done right, AI offers a real opportunity to reduce longstanding inequalities, but only if it's developed, chosen, and deployed with care.

- Concerns over bias are slowing Al adoption
  75% of HR leaders cite bias as a top concern when evaluating Al tools.
- Al can be demonstrably biased
  15% of Al systems fail standard fairness benchmarks and many academic studies identify bias in lab settings.
- Yet Al is typically more fair than humans
  In some cases, Al is up to 45% fairer for women
  and racial minorities.
- Vendors are investing in responsible Al practices
  Practices are evolving but transparency to end-users is lacking.



# About this report

This report analyzes high risk AI systems, such as those used to influence decisions in talent acquisition and intelligence, utilizing multiple data sources:

Bias audits from real systems

150+ audits of Al/automated tools using over 1 million test samples, tested for fairness using standard methods.

Survey data from vendors and practitioners

50+ responses on Responsible AI practices, transparency, and regulatory readiness.

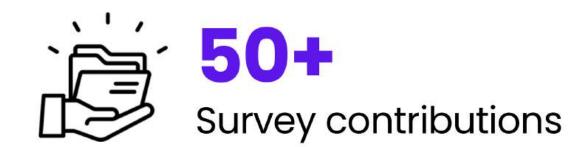
Human bias benchmark

A blend of academic and industry studies on human bias, converted into comparable fairness metrics.

Public audits and explainability reports

100+ public documents from vendors sharing audits and transparency information.











# Special thanks to our contributors





















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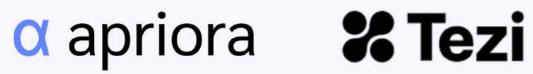






























# Table of contents

| Perception   |    |
|--|----|
| How big of a concern is Al bias?                           | 06 |
| Bias Benchmarks How biased are AI systems in practice?     | 14 |
| Al vs. Humans How fair is Al compared to humans?           | 20 |
| Al Compliance Is the industry ready for Al regulation?     | 27 |
| Vendor Practices How mature are vendors on Responsible AI? | 32 |
| Conclusion Wrapping it up                                  | 41 |



How big of a concern is Al bias?



# "Buyers are asking more questions about Albias and it's becoming a key factor in procurement decisions."

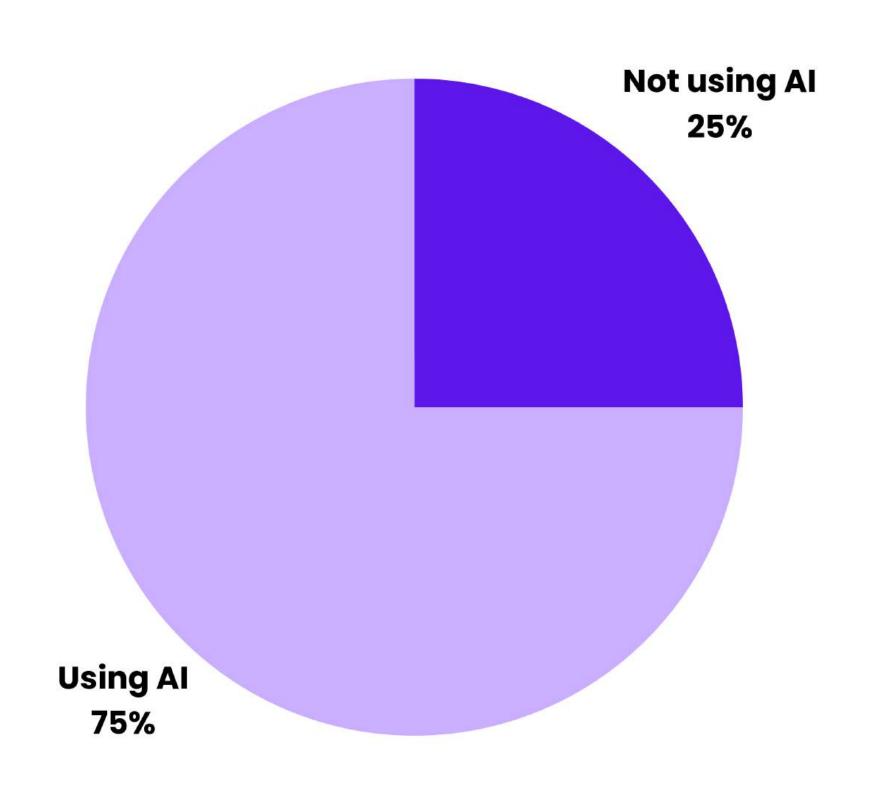


Jung-Kyu McCann
Chief Legal Officer,
Greenhouse Software



# TA is embracing Al more than ever before

ည်း Three out of four TA teams say they're already using Al or automated systems.



### What this means

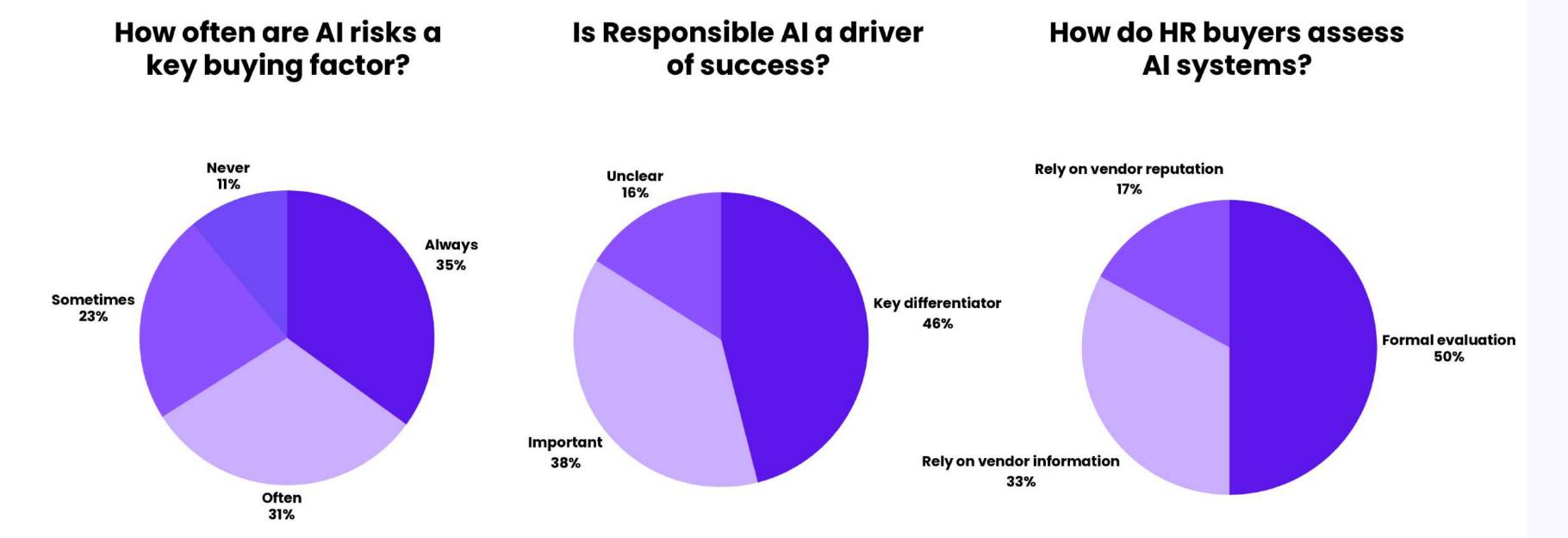
- Pressure from executives to cut the bottom line.
- Fear of missing out from all the hype about impact of Al solutions.
- Increased tangible value in Al solutions.

Source: State of responsible Al survey, 2025



# But concerns over Al risks are catching-up

ည်း Al risk is now a commercial issue, not just a technical one.



### What this means

- There's a strong risk/reward trade-off with AI solutions. Typically, the more value the AI delivers, the more it is likely to be automating of a previously person-powered process, and the more risk there is from reduced human control.
- Organizations procuring Al solutions are waking up to the Al risks and adapting their procurement processes.
- Lawsuits about AI discrimination are gaining traction in court (e.g. Mobley vs. Workday).

Source: State of responsible AI survey, 2025

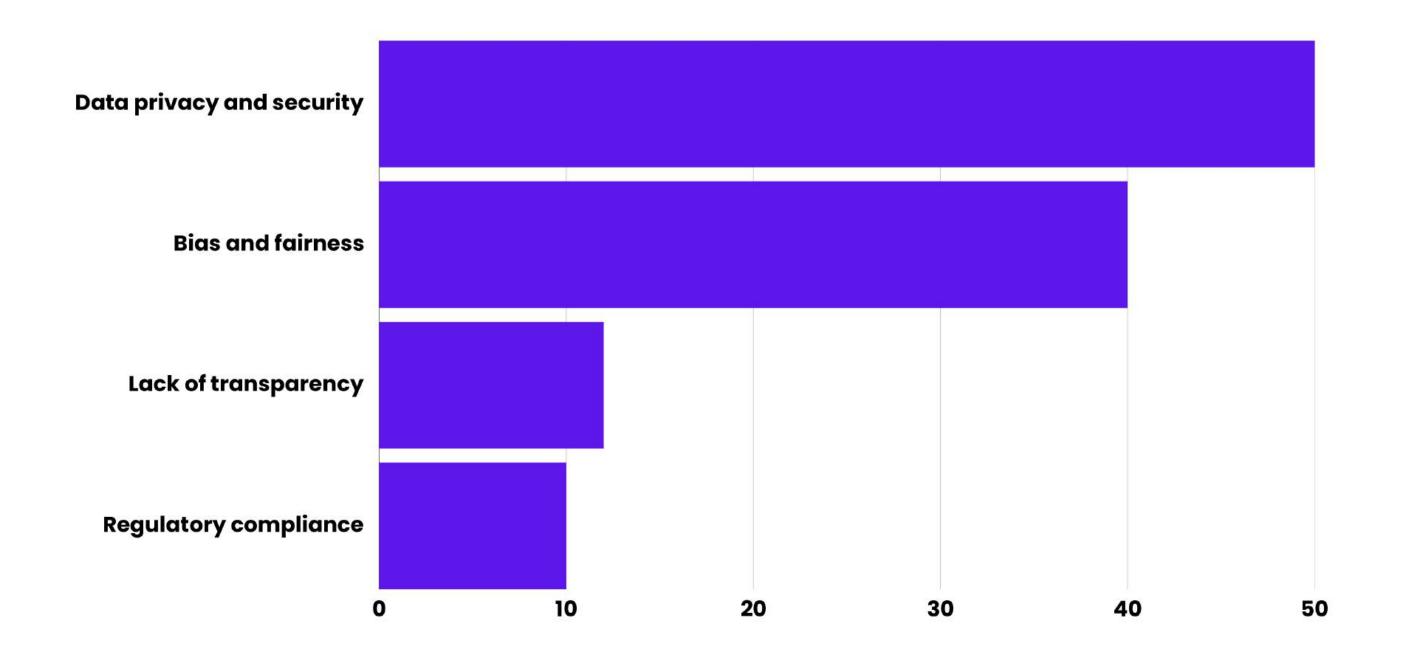


# Bias is one of the top concerns slowing Al adoption

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**75%** of HR leaders name bias as a top concern when evaluating AI, second only to data privacy.

### Top concerns for HR leaders considering AI adoption



### What this means

- Data security and privacy are longstanding software risks that most organizations have become mature in managing.
- On the other hand, bias is a largely new phenomenon compared to traditional software.
- The TA processes AI is automating inevitably surround sensitive people-oriented situations like progression, so people recognize that the potential for discriminatory bias is high.

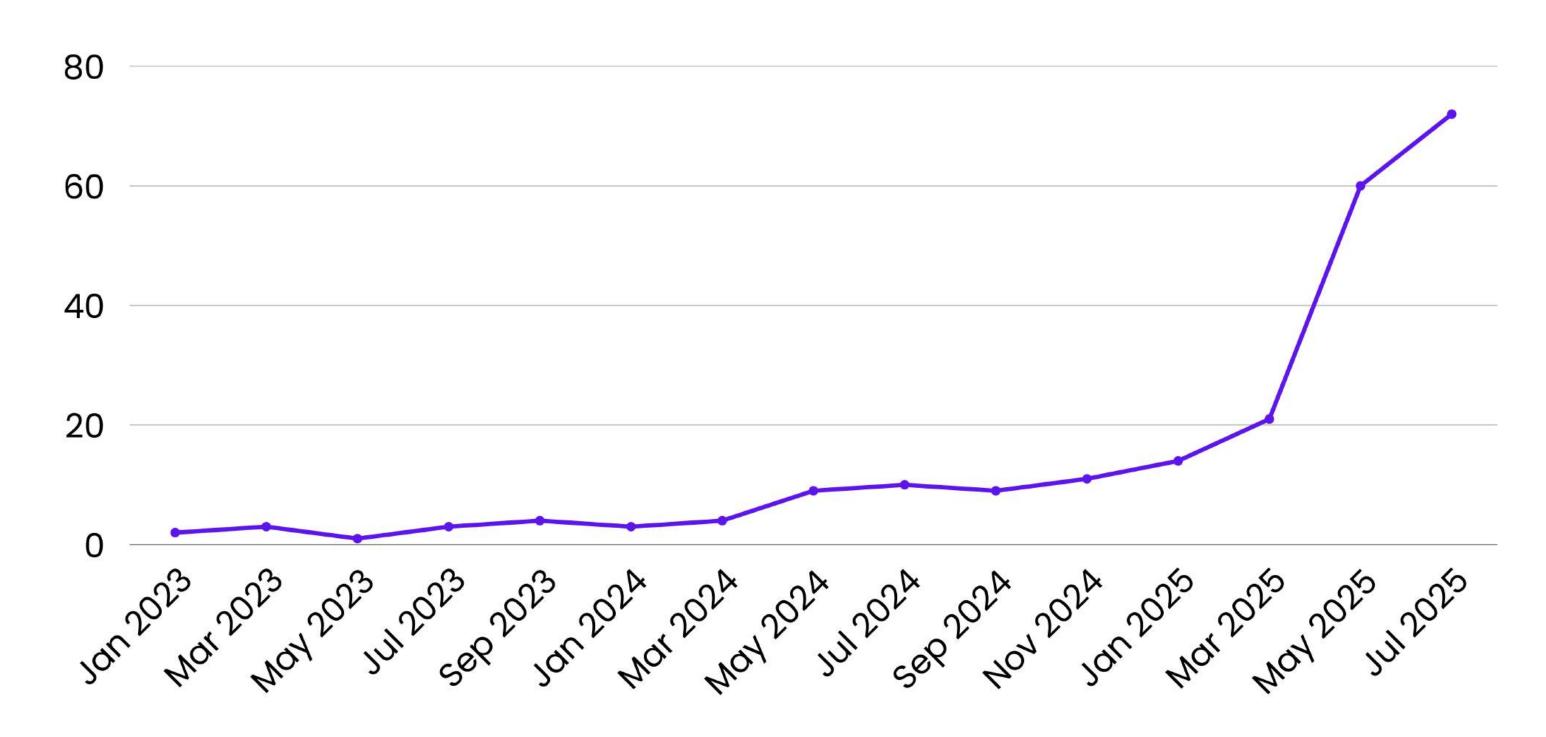
Source: State of responsible Al survey, 2025



# Mobley vs. Workday is the latest wake-up call

The collective-action ruling of the Workday case is reshaping liability of Al.

### Media mentions of Mobley vs. Workday over time



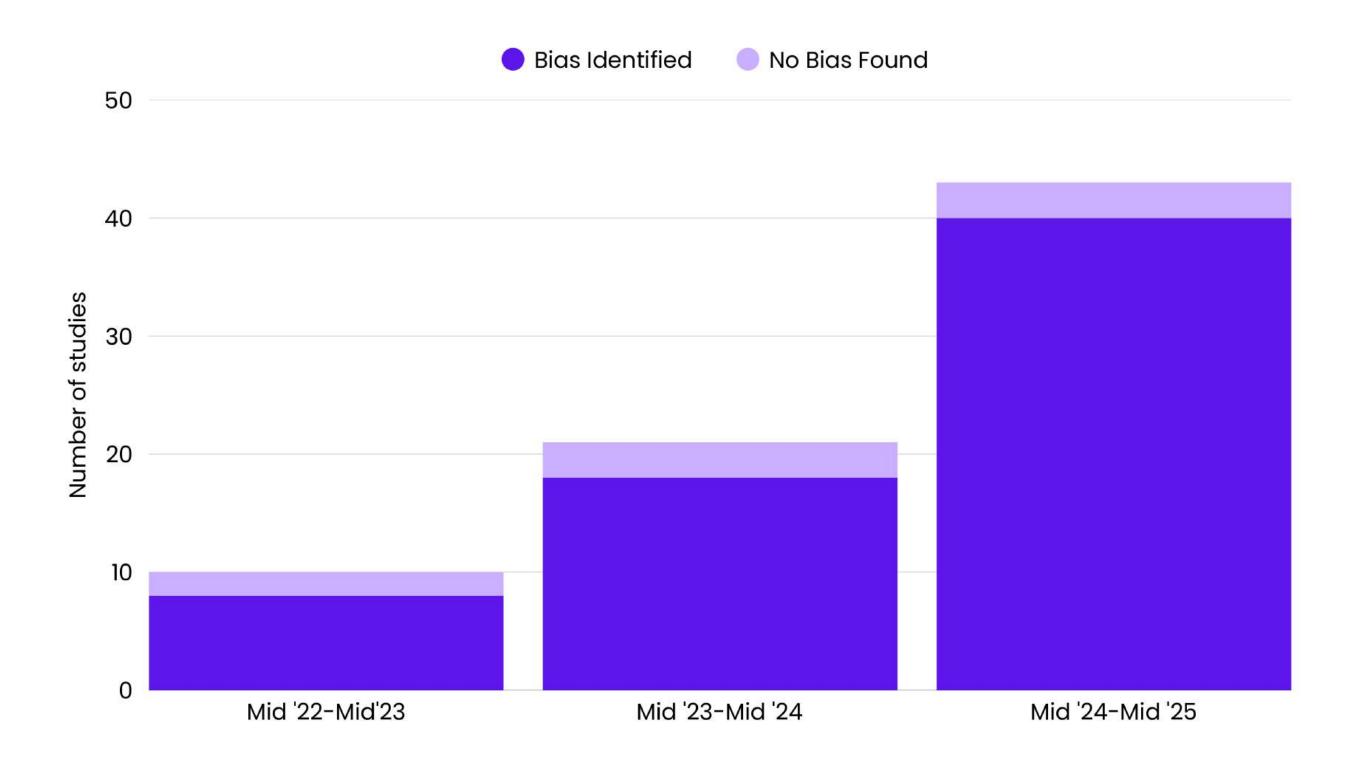
- Mobley vs. Workday is the first Al lawsuit to progress to collective action status.
- It sets a new precedent of vendors being potentially liable for employment decisions.
- Signals AI bias risks are not theoretical but reputational, legal, and financial.



# And a growing body of research finds bias in Al models

New studies are published finding that AI models have inherent biases that discriminate in employment use-cases.

### Al bias studies in HR use-cases (past 3 years)



- Because HR AI models are often trained on historical data, and human decisions are highly biased, such models can often be proven to be biased.
- It indicates the growing awareness of AI bias as an issue in this industry.
- Foundational models gives researchers access in a way they previously wouldn't have when all models were developed in-house.



# But lab results don't tell the full story

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Most bias studies don't reflect how AI is used in real-world applications.

### Techniques used in academic studies to elicit Al bias

| Technique               | Description   | Why it can be misleading   | Example study   |
|-------------------------|---|--|---|
| Name substitution       | Replacing candidate names with ones associated with specific races or genders to signal demographic attributes.                 | Most real-world AI systems remove names from being shared with AI models.  | Bloomberg article on<br>ChatGPT bias  |
| Forced binary choice    | Presenting the AI with two nearly identical candidates differing in only one attribute and asking which one should be selected. | Simplifies decision-making to a binary choice, unlike real hiring scenarios where candidates are evaluated individually. | Who Gets the Callback? Generative Al and Gender Bias  |
| Ranking from a pool     | Asking the AI to rank a group of candidates together.   | Real-world systems typically score candidates individually, so each rating is independent of the overall pool.           | First come, first hired? ChatGPT's bias for the first resume it sees                            |
| Prompting for reference | Directly asking the AI which candidate is more suitable without a structured evaluation framework.                              | Real-world systems typically provide defined criteria to evaluate against.   | Gender, Race, and<br>Intersectional Bias in<br>Resume Screening via<br>Language Model Retrieval |

- Many studies use simplified or artificial setups to test AI bias, like swapping names or forcing binary choices, that don't reflect how real AI applications operate.
- These studies raise awareness, but they often exaggerate risks or overlook how AI is actually used in structured workflows.
- To meaningfully assess Al fairness, we need testing approaches that mirror real-world systems and decisions.



How biased are Al systems in practice?

# "Just like people, some Als are fair and some are not, so it's important that you pick the right ones to work with."



Sarah Smart
Former Head of TA Product, JPMorgan Chase
Managing Partner, HorizonHuman



# How we measure and benchmark AI bias



There are two statistical techniques that capture both group-level and individual-level outcomes.

### How we measure bias

|                    | Disparate impact analysis  | Counterfactual consistency   |
|--------------------|--|--|
| What it measures   | Whether groups (e.g. male vs female) receive similar outcomes on average   | Whether attributes or proxy attributes (e.g. name) impacts the Al's judgement  |
| How it works       | Compares selection rates between demographic groups                        | Swaps variables like name,<br>gendered words, educational<br>institutions or ethnicity in identical<br>profiles and checks for changes |
| Fairness threshold | 2 80% selection rate parity<br>between groups (the "four-<br>fifths rule") | ≥ 97.5% output consistency after attribute changes   |
| Best at spotting   | Systemic gaps in treatment between groups                                  | Individual-level bias in how attributes influence outputs  |

### What this means

- Group-level bias: are outcomes similar across demographic groups like gender or race?
- Individual-level bias: would the same person receive a different result if their name or other traits were changed?
- By combining both methods, we can detect bias that might otherwise go unnoticed from systemic disparities to subtle attribute effects in how decisions are made.

Source: Warden Al methodology

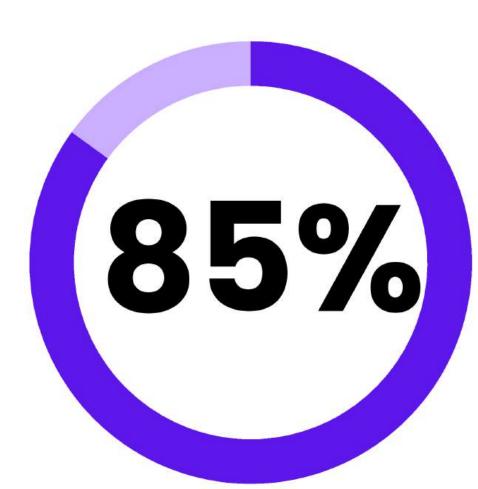


# Most Al systems meet fairness thresholds



**85%** of AI bias audits showed fairness scores within the "four-fifths rule" threshold across all tested demographic groups.

### Disparate Impact



Scored above 0.8 impact ratio for all tested groups

# Counterfactual Consistency



Scored above 97.5% consistency for all tested groups

### What this means

- Most AI systems tested met accepted fairness thresholds, suggesting bias can be identified and reduced through proper development and oversight.
- High counterfactual consistency scores indicate that many systems treat similar candidates the same, regardless of protected characteristics.
- While not perfect, these results show that fairer AI is not just possible, it's already happening in many real-world systems.

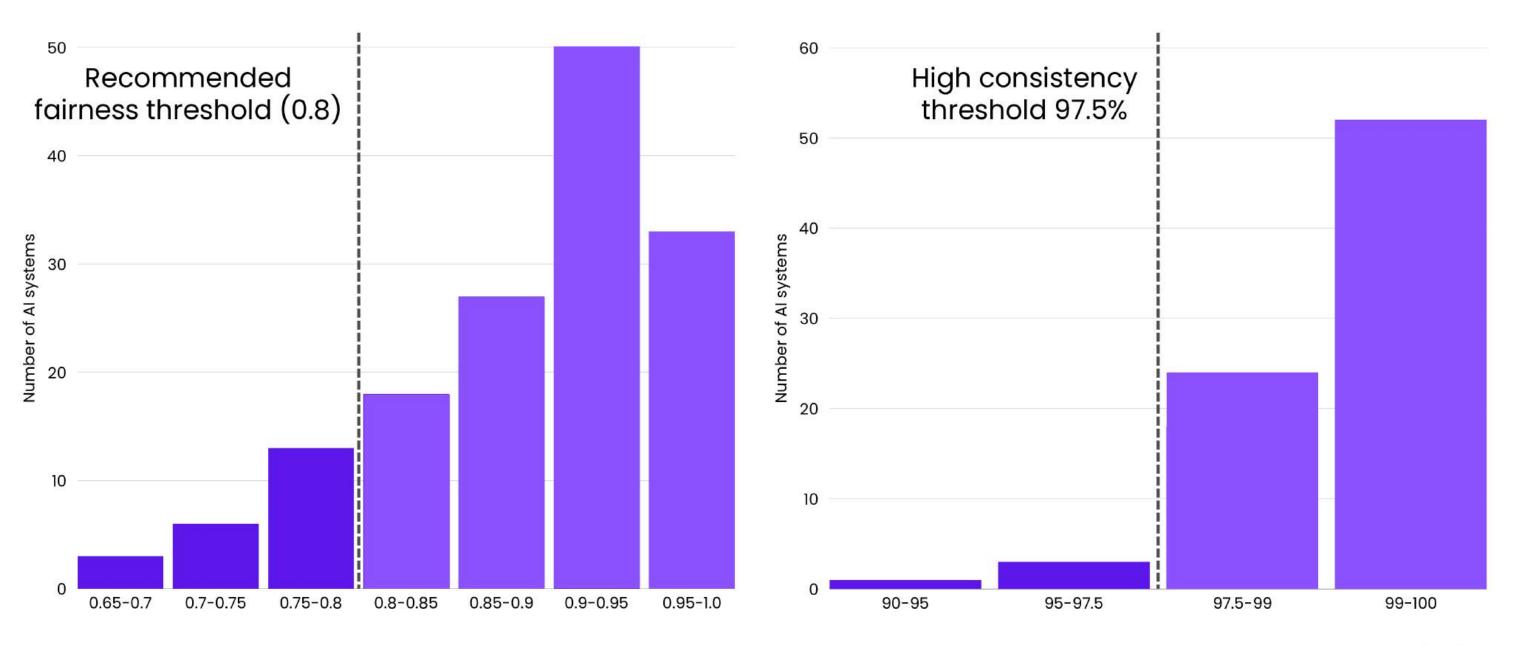
Source: Warden AI customer audit data and published online audits



# But bias varies widely between systems

ည်း Bias metrics across vendors varied by as much as 40%.

### Distribution of scores across Al Systems



Counterfactual consistency score (%)

### What this means

- While most audited systems meet fairness thresholds, results vary significantly from system to system.
- Even if the industry average looks strong, individual systems may still expose organizations to risk.
- This highlights the importance of choosing AI solutions carefully and monitoring them in deployment.

Source: Warden Al customer audit data and published online audits



Impact ratio range

# And bias still exists in some systems

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**15%** of AI systems did not meet fairness thresholds for all demographic groups.



### Disparate Impact

Scored below 0.8 impact ratio for at least one demographic group

### What this means

- A minority of AI systems still show statistically significant bias, failing to meet industry-standard fairness thresholds.
- These cases highlight risks where Al may disproportionately disadvantage certain demographic groups.
- Ongoing testing and oversight are critical to identify and reduce bias before deployment at scale.

Source: Warden Al customer audit data and published online audits



# Al vs. Humans How fair is Al compared to humans?

# "We are right to worry about AI bias, but we should not forget that the baseline, human only judgment, is far from bias-free."



<u>Hung Lee</u> Recruiting Brainfood

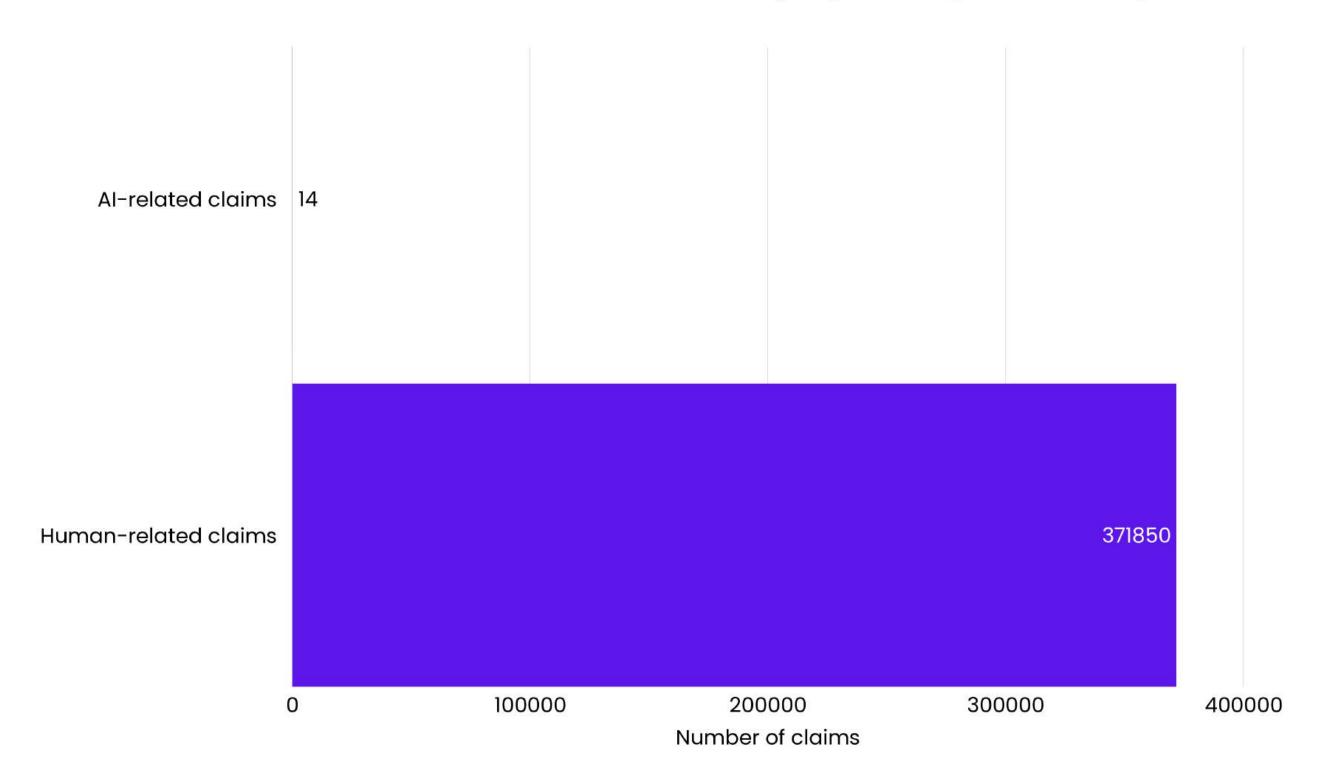


# Human bias remains a huge challenge



>99.9% of employment discrimination claims in the last five years have been related to human bias, not AI bias.

### Discrimination claims in employment (2020-2024)



### What this means

- Each year, around 100,000 employment discrimination claims are submitted in US alone.
- About 100 of these turn into lawsuits.
- The pre-Al status quo is rife with alleged and actual discrimination.

Source: US EEOC Enforcement and Litigation Statistics



# How we benchmark human bias

### **How it works**

- To compare AI systems with human decisionmaking, we created a human bias benchmark using data from multiple academic and industry studies examining bias in employment.
- These studies measured how often candidates from different sex and racial groups were selected in real-world hiring.
- We converted these findings into impact ratios, the same fairness metric we apply to AI systems, allowing a direct comparison between human and AI outcomes.

| Author                                       | Study name  | Focus                          | Link        |
|--|---|--------------------------------|-------------|
| Kubiak et al. (2023)                         | Gender equity in hiring   | Gender                         | <u>Link</u> |
| González, Cortina &<br>Rodríguez-Menés (2018 | The Role of Gender<br>Stereotypes in Hiring                                 | Gender                         | Link        |
| Quillian & Lee (2023)                        | Trends in racial and ethnic discrimination in hiring                        | Race/Ethnicity                 | <u>Link</u> |
| Banerjee, Reitz &<br>Oreopoulos (2011)       | Do Large Employers Treat Racial<br>Minorities More Fairly?                  | Race/Ethnicity                 | Link        |
| Bertrand & Mullainathan<br>(2003)            | Are Emily and Greg More<br>Employable than Lakisha and<br>Jamal?            | Race/Ethnicity                 | <u>Link</u> |
| Adamovic & Leibbrandt<br>(2022)              | A large-scale field experiment on occupational gender hiring discrimination | Gender                         | <u>Link</u> |
| Goldin & Rouse (2000)                        | Orchestrating<br>Impartiality   | Gender                         | <u>Link</u> |
| Weichselbaumer (2015)                        | Discrimination against Female<br>Migrants Wearing Headscarves               | Gender, Ethnicity,<br>Religion | Link        |
| Zschirnt & Ruedin (2016)                     | Ethnic discrimination in hiring decisions                                   | Race/Ethnicity                 | <u>Link</u> |
| Neumark, Bank & Van Nort<br>(1996)           | Sex Discrimination in Restaurant<br>Hiring                                  | Gender                         | <u>Link</u> |
| Quillian et al. (2017)                       | Meta-analysis of field experiments  | Race/Ethnicity                 | Link        |

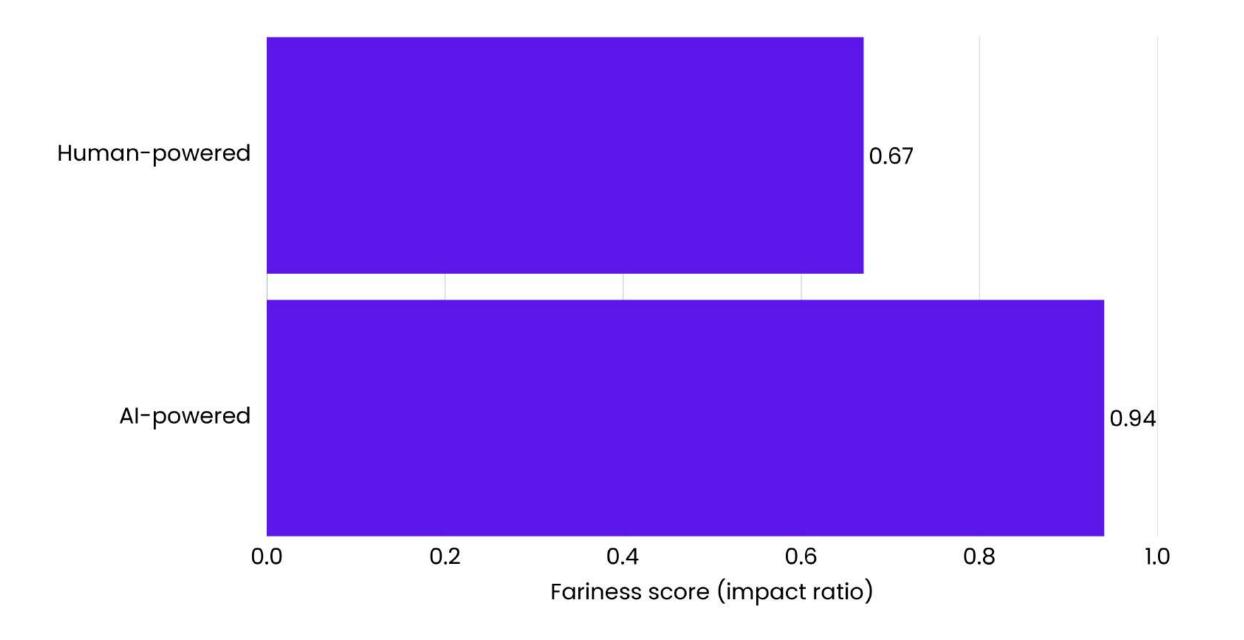


# Al systems show fairer treatment on average

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The data suggests that, on average, AI systems treat different demographic groups more fairly than humans do.

### Average impact ratio



### What this means

- While AI systems aren't immune to bias, data suggests they often outperform human decision-makers on average fairness metrics.
- Human decisions, by contrast, tend to reflect longstanding systemic biases, yet are rarely scrutinized to the same degree.
- The data points to a valuable opportunity: rather than avoiding Al for fear of bias, organizations can use it to raise the standard.

Source: Warden AI customer audit data; published online audits; peer-reviewed studies

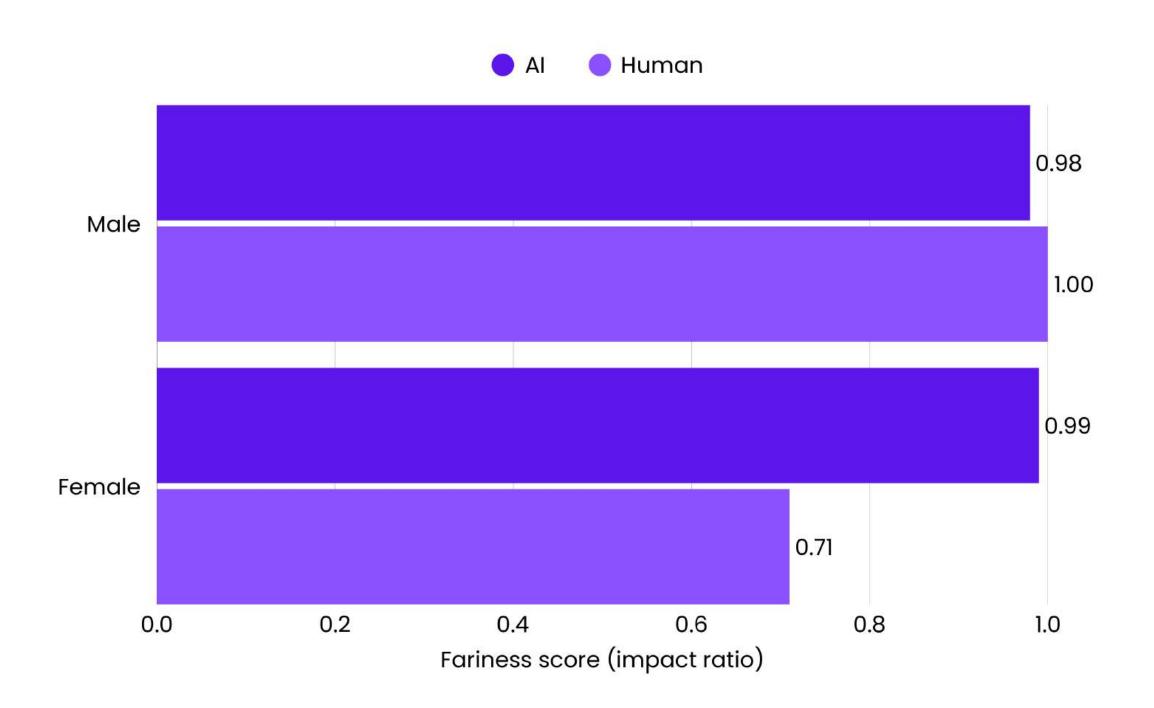


# Al could be closing the gender gap in employment

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The data suggests female candidates experience up to **39%** fairer treatment with AI.

### Disparate impact across sex



### What this means

- The data indicates that AI systems may be helping to close the gender gap, showing near-parity in outcomes between men and women, on average.
- In contrast, human-led decisions show a pronounced disparity, with women significantly less likely to experience a positive outcome.
- While not definitive, these findings suggest that AI, when properly developed and deployed, has the potential to support fairer outcomes at scale.

Source: Warden AI customer audit data; published online audits; peer-reviewed studies

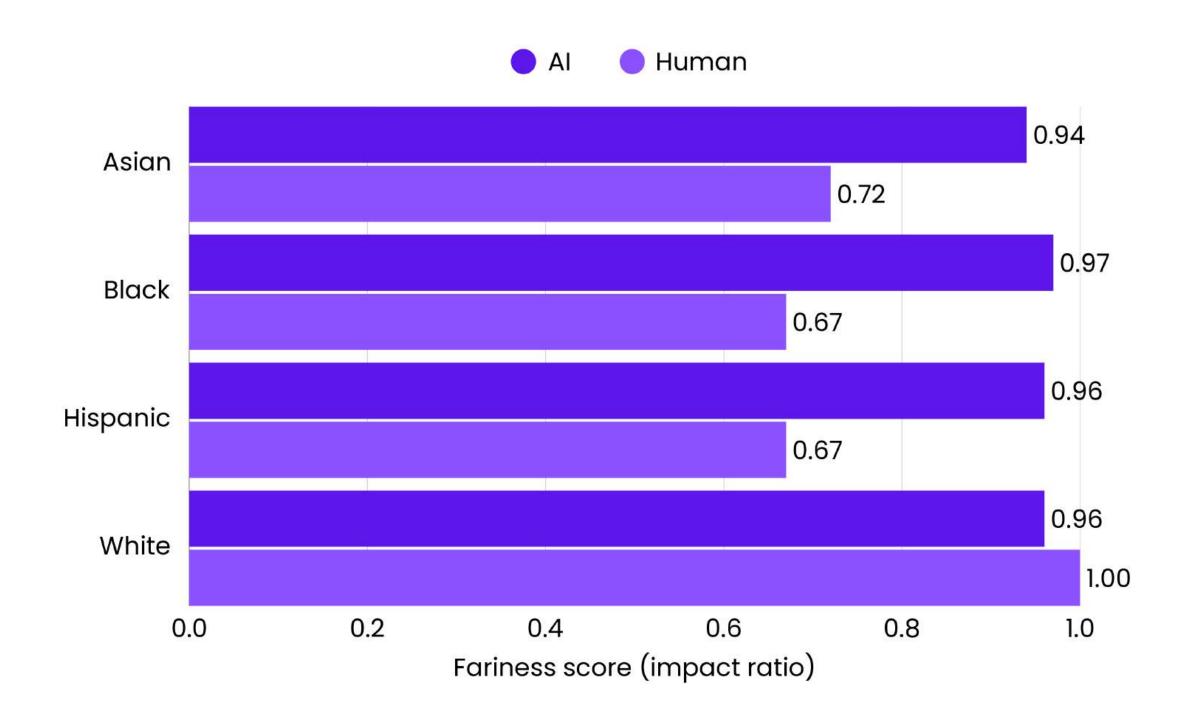


# Al could be reducing racial inequalities in employment

:Ö:

The data suggests racial minorities experience up to **45%** fairer treatment with AI.

### Disparate impact across race/ethnicity



### What this means

- The data indicates that AI systems may be reducing racial disparities, with minority groups seeing fairer outcomes compared to historical human-led decisions.
- In particular, Black and Hispanic candidates show substantially higher fairness scores under Al systems than under human judgment.
- While these findings don't eliminate the need for oversight, they highlight the potential for Al to improve equity when built and used responsibly.

Source: Warden AI customer audit data; published online audits; peer-reviewed studies



# Al Compliance Is the industry ready for Al regulation?

# "HR leaders face a patchwork of regulations across regions. Turning this into day-to-day governance is now the differentiator."



Martyn Redstone Founder, Eunomia HR



## **Al Compliance**

# Key Al regulations are emerging for the HR industry

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Amid a wave of AI regulations, several have a meaningful impact on the HR/TA space.

| Regulation        | Туре       | Region   | In effect   | Applies to                                     |
|-------------------|------------|----------|-------------|--|
| NYC Local Law 144 | Regulation | us (NYC) | Jan 2023    | Deployers (employers using AI tools)           |
| Colorado SB205    | Regulation | us (co)  | Feb 2026    | Developers and<br>deployers (broad<br>scope)   |
| EU AI Act         | Regulation | EU       | August 2026 | Developers and<br>deployers of high-risk<br>Al |
| ISO 42001         | Standard   | Global   | 2024        | Primarily developers (voluntary)               |

- Despite the wave of 100s of Al regulations & guidance, only a few have big impact on the HR/TA space.
- These regulations will likely set the requirements that others will follow (e.g. California).
- ISO 42001 is gradually emerging as a standard for process management of AI systems (in the HR space and beyond).



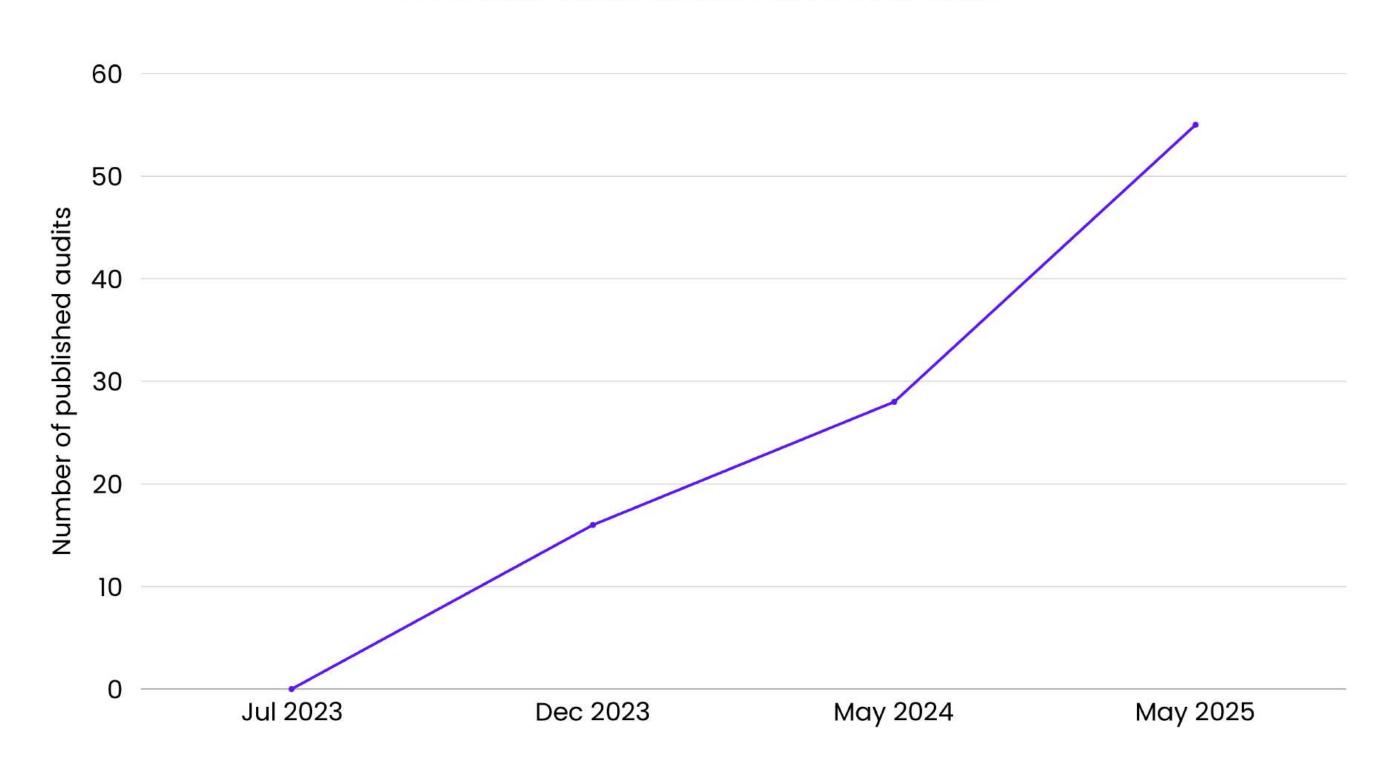
# Al Compliance

# Compliance lags behind regulation

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Two years since NYC LL 144 went into affect and compliance is growing but still lagging behind.

### NYC bias audit disclosures over time



### What this means

- After two years of the NYC LL 144 regulation being in effect and compliance is slowly growing despite a slow start.
- The NYC regulation while well-intentioned has been highly flawed and easy for people to circumvent.
- Despite this, organizations are increasingly putting pressure on vendors to demonstrate compliance and slowly the regulation is having the intended effect.

**Source: ACLU AEDT Tracking Repository** 



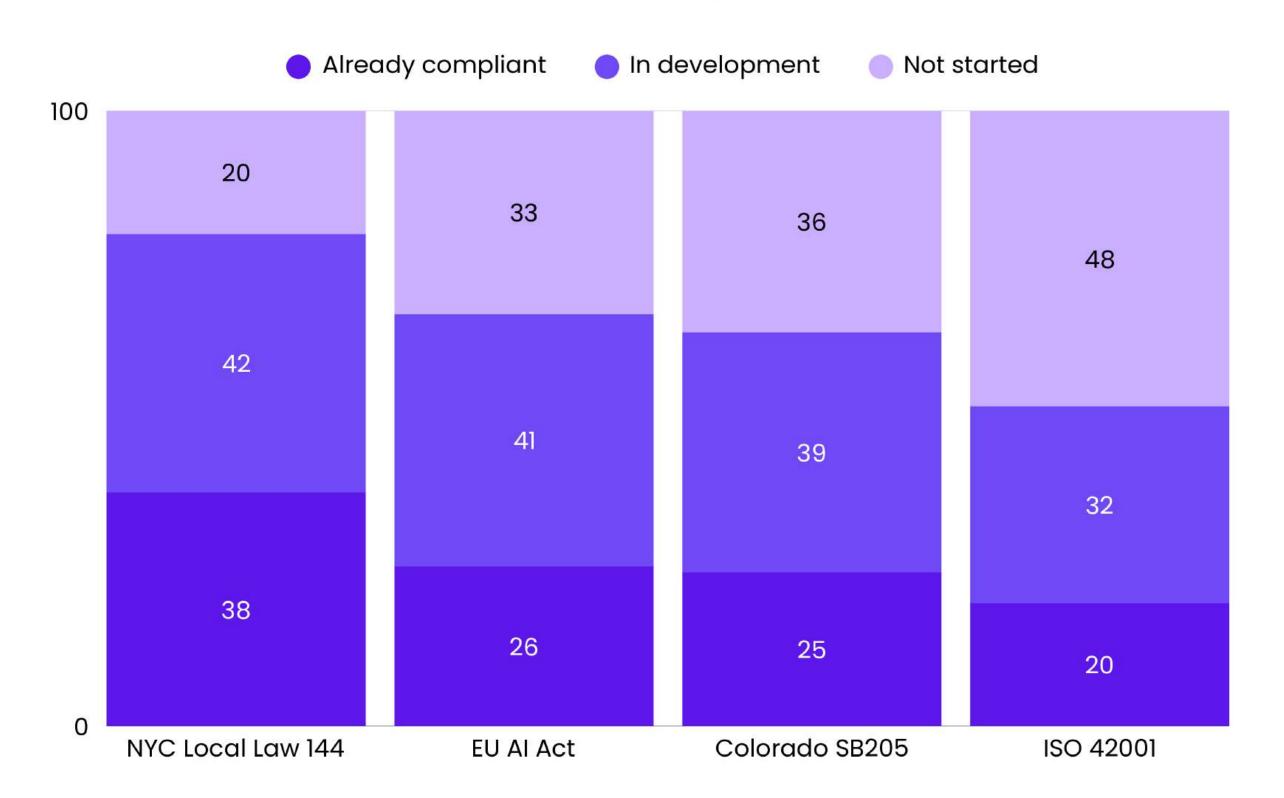
## Al Compliance

# Many are preparing for regulation but few are fully ready

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Many vendors are working on compliance with key regulations, but few are fully ready today.

### Vendor status across key Al regulations



### What this means

- Despite promising progress on compliance, the majority of vendors are still not compliant with the existing NYC regulation and few are ready for the new ones.
- On the other hand, there has been a clear wake-up call and a large proportion are actively preparing for the coming wave of regulations.

Source: State of responsible Al survey, 2025



How mature are vendors on Responsible AI?



# "Strong governance frameworks build the confidence that enables rapid AI adoption. This is what turns innovation into execution."



Trent Cotton

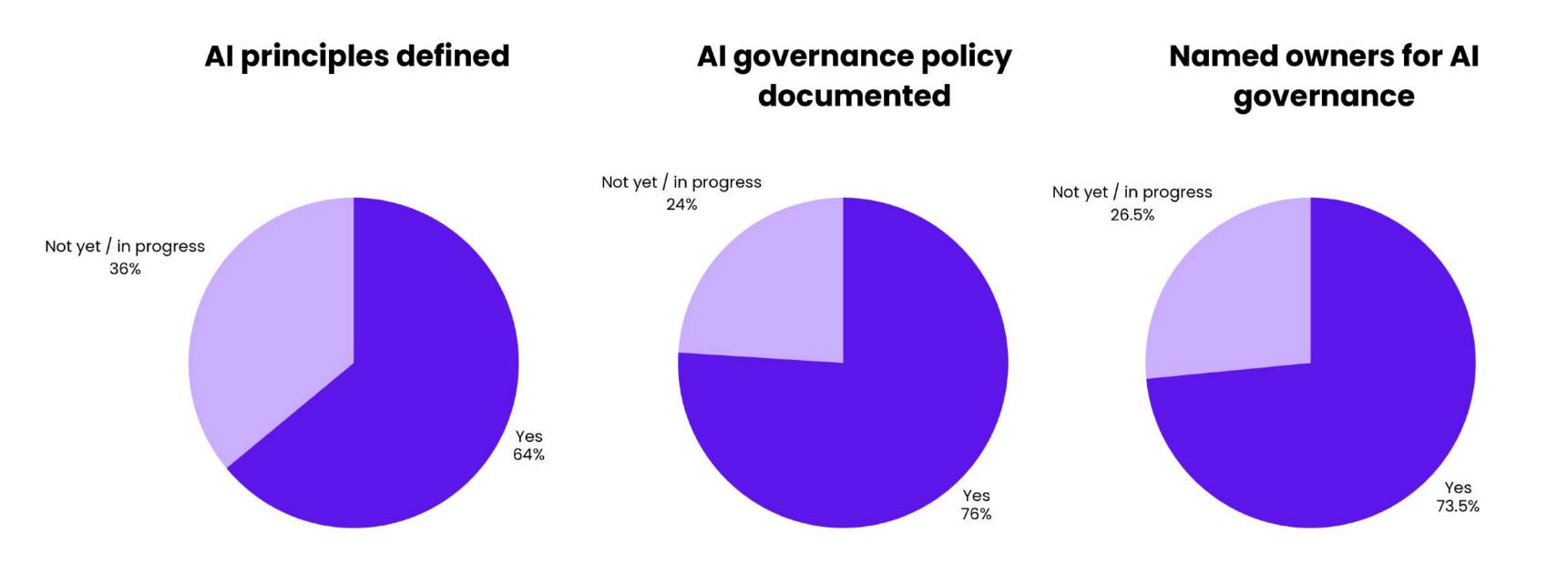
Head of TA Insights,
iCIMS



# Al governance foundations are becoming standard

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Most vendors have defined AI principles, implemented an AI policy or framework, and assigned clear ownership for AI governance.



### What this means

- These governance foundations are a positive sign that Responsible AI is being taken seriously across the ecosystem.
- But they represent the starting point, not the finish line.
- The hard part is turning principles into practice: operationalizing standards, embedding controls, and maintaining accountability in live systems.

Source: State of responsible AI survey, 2025

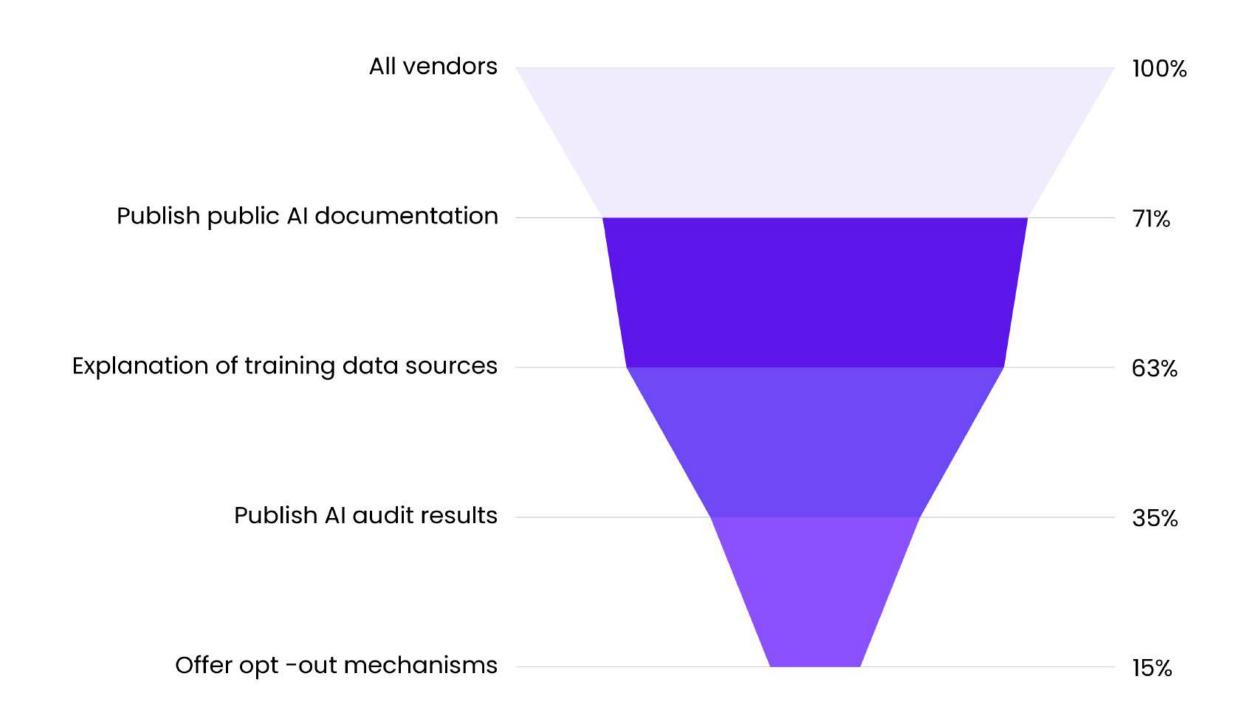


# There's a promising level of vendor-buyer transparency

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Most vendors publish detailed documentation but few offer opt-outs to end-users.

### Depth of transparency practices among Al vendors



### What this means

- Driven by employer pressure, many vendors are now proactively publishing documentation (e.g. Al explainability statements).
- But deeper transparency practices, like offering opt-outs, remain rare and unevenly adopted.
- To build real confidence with buyers and regulators, transparency needs to move beyond surface-level disclosures toward meaningful visibility and control.

Source: State of responsible AI survey, 2025

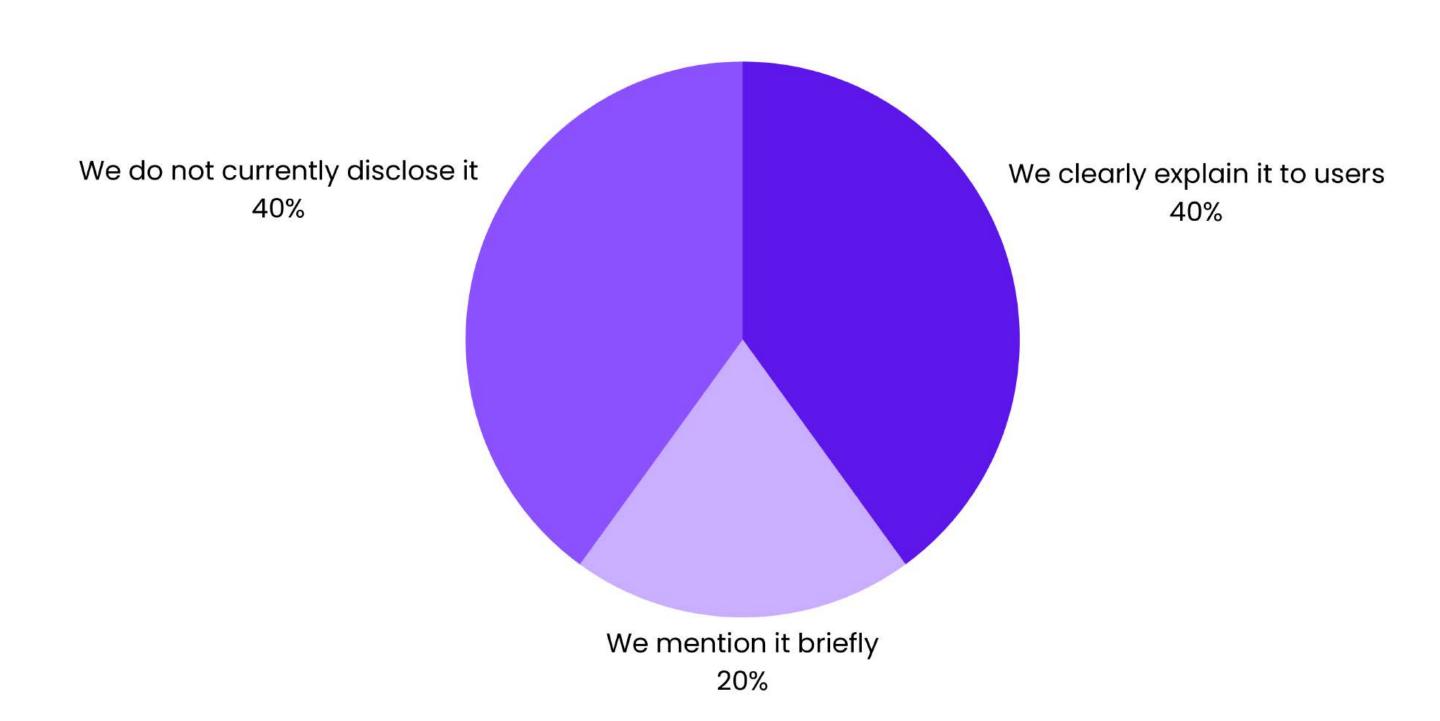


## But end-users often lack awareness of Al use

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Few vendors and HR/TA teams clearly explain how AI is being used, leaving many users unaware that AI plays a role at all.

# How transparent are Al/automated TA systems to candidates or employees?



### What this means

- This lack of transparency can undermine trust, even when the underlying system is fair or well-governed.
- There's a tension in accountability here, with vendors saying it's up to the organizations deploying the system.
- Many AI regulations explicitly require opt-out rights for human review (e.g. GDPR, EU AI Act, Colorado SB205).

Source: State of responsible AI vendor survey, 2025



# "The best way to mitigate risk is to design and deploy Al responsibly from day one."



Sultan Saidov
Co-founder and President,
Beamery

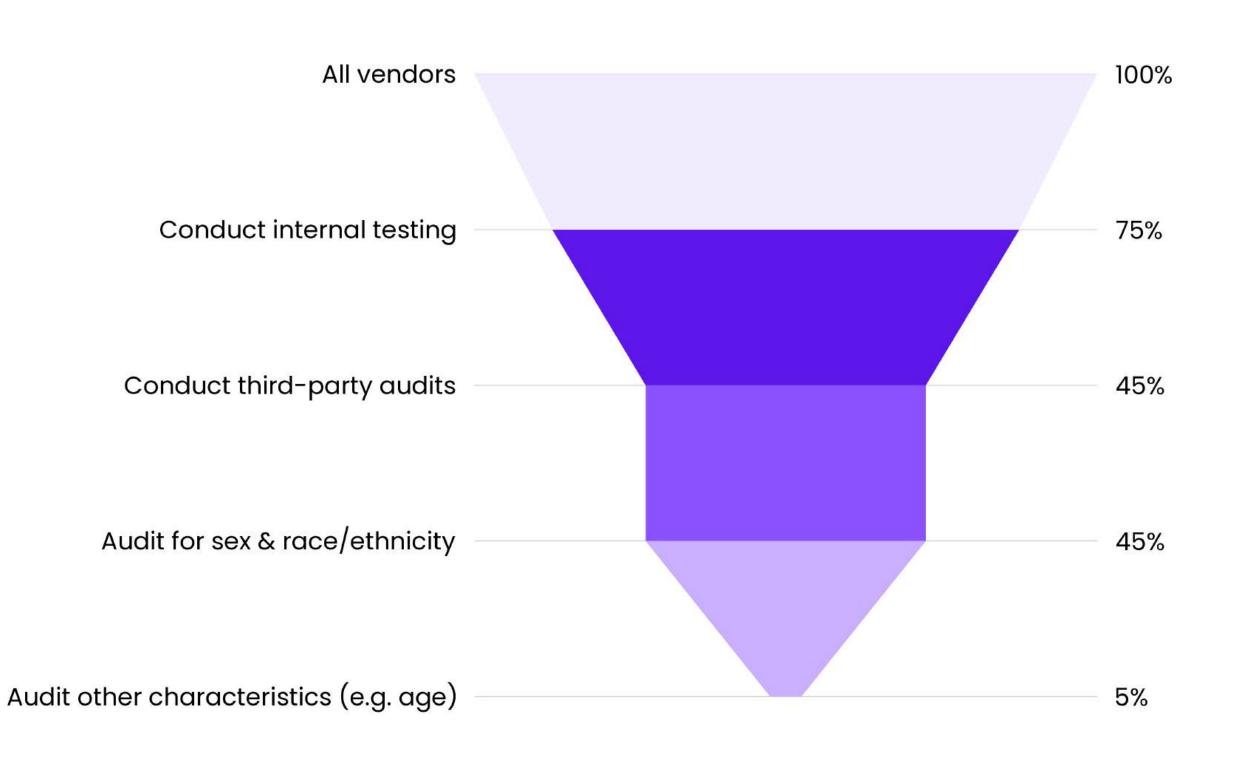


# Bias testing and auditing is becoming standard

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Bias testing is now common, at least internally if not with third-party auditing.

### Depth of bias evaluation



### What this means

- Bias testing is no longer niche with a growing number of vendors doing it.
- In 2025 we predict a shift from about 20% audited vendors to 80%, as a tipping point is reached and it becomes a table stakes expectation.
- This is driven in part by the NYC LL 144 and more significantly by buyer expectations.

Source: State of responsible Al survey, 2025



# But few audits test beyond sex and race

:Ö:

Only **5%** of bias audits cover other demographic groups like age and disability.

| Protected group    | % of audits | Common Al audits? | Notes  |
|--------------------|-------------|-------------------|--|
| Sex                | 100%        | ✓ Yes             | Standard across most audits                  |
| Race/ethnicity     | 100%        | ✓ Yes             | Standard across most audits                  |
| Age                | 5%          | A Rare            | Increasingly important (e.g. Mobley case)    |
| Disability         | 5%          | . Rare            | Increasingly important<br>(e.g. Mobley case) |
| Religion           | 2%          | × Very rare       | Typically excluded                           |
| Sexual orientation | 2%          | × Very rare       | Typically excluded                           |
| National origin    | 1%          | × Very rare       | Typically excluded                           |

### What this means

- 95% of bias audits focus on the core minimum demographic groups of sex and race/ethnicity.
- This is driven by NYC LL 144 which focuses on those two protected classes.
- Age discrimination is a particularly common risk and often overlooked (e.g. Mobley vs. Workday; iTutorGroup)

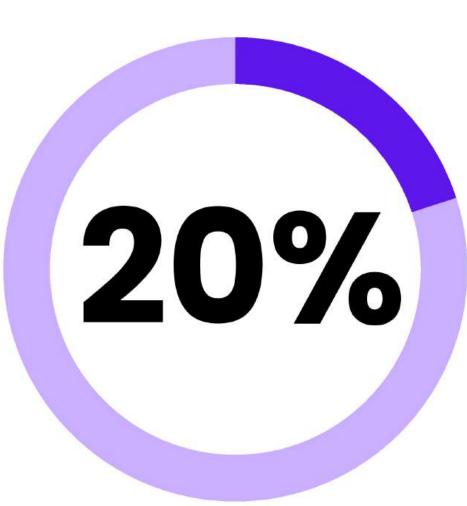
Source: Warden Al customer audit data and published online audits



# A growing number of vendors are leading the way

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20% of vendors follow best-practices for responsible Al development.



of vendors follow

all best practices

- Define and document Al governance
- Publish Responsible AI documentation
- Share audit results publicly
- Prepare for AI regulations

### What this means

- Not all vendors are equal when it comes to mitigating AI risks and being compliant.
- As scrutiny of Al systems grows, partnering with vendors who meet higher standards will be key to managing risk.
- Buyers should choose vendors who demonstrate a strong posture towards AI risk and compliance.

Source: State of responsible AI survey, 2025



# Wrapping it up **Warden Al** State of AI Bias in TA Report 2025

# Conclusions

The four implications we're seeing for Al use in HR and employment



### The stakes of getting AI wrong are growing

Mounting regulation, emerging lawsuits, and rising adoption pressure mean the cost of getting it wrong has never been higher.



### Bias is becoming a shared responsibility

As AI becomes more embedded in TA processes, responsibility for bias is increasingly shared between vendors and the organizations that deploy the tools.



### Al can improve workplace equality

When designed and deployed responsibly, AI systems can reduce inequality and help close longstanding gaps in workplace outcomes.



### Vendor choice is now a key risk decision

As AI systems take on higher-stakes decisions, vendor selection now directly shapes legal and reputational risk within the organization.



# Methodology

Data sources

### Where is our data from?

150+ Al audits using structured test datasets, covering tools across multiple TA use-cases such as screening, sourcing, and interviewing.

Over 1 million test samples, drawn from a combination of proprietary and public datasets.

50+ vendor/practitioner survey responses across TA Tech.

100+ publicly available audit and transparency reports from vendor websites.

Bias audit methodology

### Disparate impact

Measures whether outcomes differ across demographic groups (e.g. male vs. female). Systems with any group scoring <0.8 relative to the top group are flagged as potentially biased (per the "four-fifths rule").

### **Counterfactual consistency**

Swaps protected characteristics (e.g. gender, ethnicity) in otherwise identical profiles to check if outcomes change. Systems with <97.5% outcome stability are flagged as potentially biased.

Human bias benchmark

### How did we derive the human benchmark?

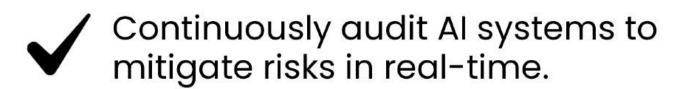
We compiled a benchmark of "typical human bias" from 10 academic and industry studies that analyzed real-world outcomes (e.g. interview callbacks, progression decisions). These results were converted into the same fairness metrics (impact ratios) to allow direct comparison with AI systems.



# About Warden Al

Warden is the platform enabling HR to adopt AI with confidence.

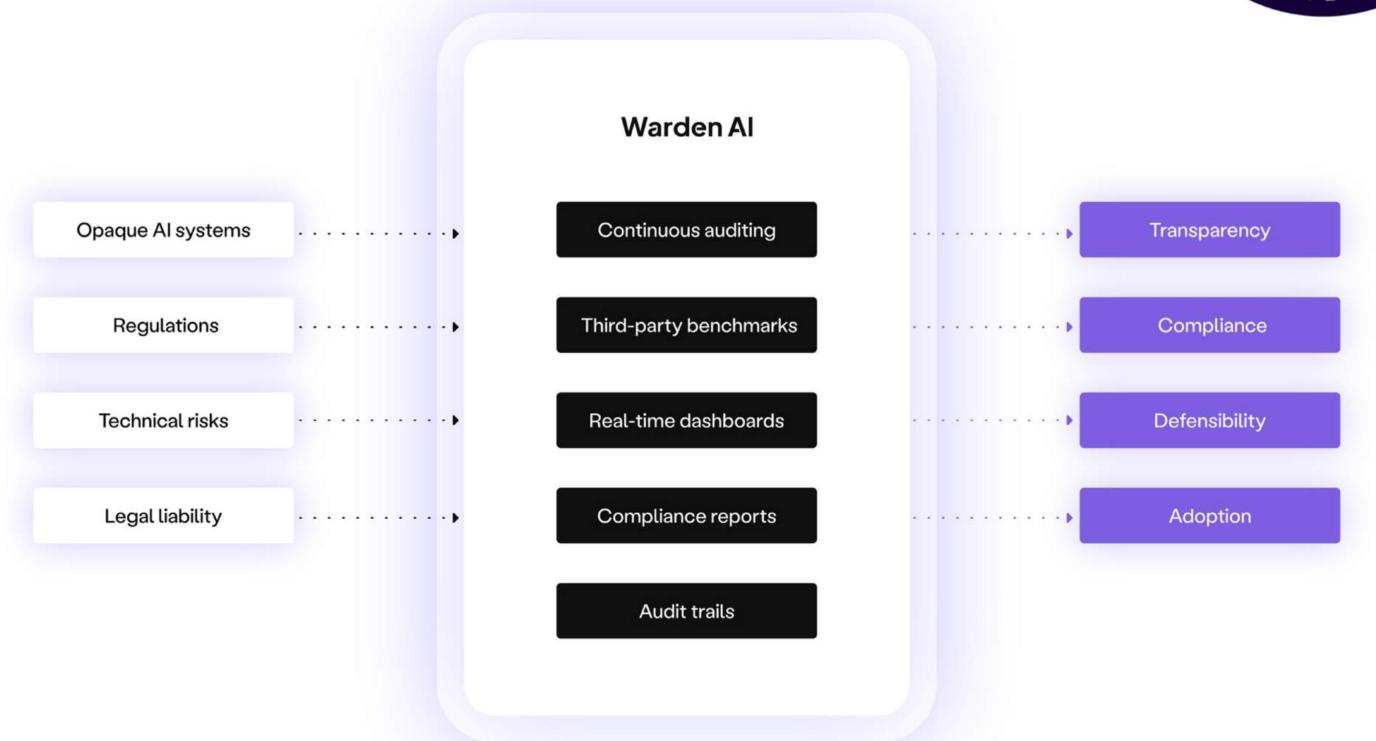
We audit and certify AI systems for fairness and compliance, helping vendors and enterprises as they develop, deploy, and defend AI solutions in HR.



Audit all protected classes and comply with Colorado SB205 with Warden's real-world dataset.

Guard against legal claims with evidence-based audit trails.

Win stakeholder buy-in with real-time dashboards and reports.





Warden Al