

AI and Automated Decision-making Systems in Employment: A Look at State General Statutes Addressing of Bias Audits, Transparency, and Legal Accountability in the US

Brandon Burgess, Dr. Steven Cates
Purdue University Global, School of Business and Technology
2550 Northwestern Avenue, Suite 1100
West Lafayette, IN 47906
Purdue University Global, School of Business and Technology
2550 Northwestern Avenue, Suite 1100
West Lafayette, IN 47906

doi.org/10.51505/IJEBMR.2026.10710 URL: <https://doi.org/10.51505/IJEBMR.2026.10710>

Received: Jun 19, 2026, Accepted: July 01, 2026, Online Published: July 10, 2026

Abstract

Increasingly, companies are utilizing electronic decision-making systems powered by AI for the hiring, evaluation, and upskilling of employees. While automation may help, evidence suggests that algorithmic devices can replicate and potentially intensify social bias. This research examines whether the use of AI in hiring and selection is legal and fair, by creating discriminatory processes into employment practices. This study examines bias audits, transparency obligations, and new regulations such as New York City's Local Law 144 in a doctrinal legal process. This research examines whether the proposed Bias Notification Duty will enhance accountability. The study indicates that while AI facilitates efficient processes in the workplace, it also risks increasing discrimination and bias. It is known that humans design AI and they might have inherent biases. These computer professionals then create technological systems like AI that inherit these biases. HR managers and leaders have obligations for the responsible implementation of algorithmic systems to promote fairness and equality in HR processes. The findings in examining legislation addressing AI for practicing managers indicate that the integration of AI into employment decisions carries profound operational, legal, and ethical implications. As managers make greater use of automated decision-making systems, they do not avoid accountability; rather, they increase it.

Keywords: Artificial Intelligence, Employment, Legal Issues, Discrimination and Bias

Introduction

AI is becoming an increasingly significant role in important employment decisions, from resume screening to promotion and termination. Tools for employment decisions are used to predict

performance, and qualitative analysis of speech and facial expressions during interviews is currently being conducted, with candidates being scored using historical data.

New laws, such as New York City's Local Law 144, require employers to conduct an unbiased, independent audit before using an automated system in hiring or promoting (Wright et al.). Local Law 144 of 2021 regarding automated employment decision tools ("AEDT") prohibits employers and employment agencies from using an automated employment decision tool unless the tool has been subject to a bias audit within one year of the use of the tool, information about the bias audit is publicly available, and certain notices have been provided to employees or job candidates.

The technologies are said to be objective and efficient. However, Wright et al. (2024) argue that algorithms often reflect human biases that are embedded in the training data. Failing to check for bias in algorithmic systems actively will expose organizations to discrimination lawsuits.

Federal agencies, such as the EEOC, have also warned that algorithms can "screen out" applicants with disabilities or collect sensitive biometric information that may violate the Americans with Disabilities Act (ADA) (Lopez, 2025).

As AI is changing faster than regulation can keep pace with it, managers must understand both the technology and the algorithms that drive it. AI in employment can improve efficiency, but without strong transparency and bias safeguards, it risks reinforcing workplace discrimination. The purpose of this research is to identify issues and problems associated with AI in selection processes for organizations.

Understanding AI in Employment Decision-Making

Automated employment decision-making systems represent one of the most transformative applications of artificial intelligence in the modern workplace. Most of these systems use machine-learning models to predict an applicant's performance, cultural fit, or probability of staying, based on industry-specific workforce data. To improve their recruitment process and make decisions based on objective measures, employers are utilizing these systems. However, Booyse and Scheepers (2024) caution that such systems can only be as fair as the data they are fed. Some training datasets were based on gender inequities, for example, the current datasets used to determine suitability for leadership roles or assess bias in hiring on racial lines, leading to inequitable outcomes.

One of the main problems is that the workforce data has bias. As an example, if a company's historical data is biased in favor of male executives, then the algorithm may favor male candidates for leadership positions. This shows how bias can occur in something that appears to be neutral, making forms of AI extremely discriminatory. Chan (2024) argues that the design of algorithms should be aligned with the equal opportunity merit principle to ensure compliance with anti-discrimination norms.

It is essential for individuals to understand how algorithms work and to challenge cases of algorithmic discrimination. When models operate as black boxes, employees affected by them lose agency and recourse (Kim, 2025). Workers are unable to contest inaccurate assessments because they often lack an understanding of how the algorithm evaluates factors such as communication style and work history. Apart from technical issues, Strich et al. (2021) argue that substitutive AI systems can change employees' sense of autonomy and professional identity. A loss of trust and morale occurs when employees believe that no one is behind their decision-making.

Therefore, as increasing AI usage gives power to algorithms, displacing and augmenting will occur. Although automating work may make it more efficient, it may also undermine the equal employment principles of US labor law, unless strong safeguards for transparency, accountability, and fairness are adopted.

Algorithmic Bias and Legal Risks

Algorithmic bias arises when models are created based on skewed data produce outcomes that disadvantage protected groups. According to Sonderling et al. (2022), AI has the power to reduce discrimination, but it can also amplify it. It is argued that bias typically enters through data selection, feature engineering, and feedback loops that reinforce prior hiring decisions.

All employers are responsible for discrimination if it results from their automated systems. Under Title VII of the Civil Rights Act of 1964 and the ADA, a predictor or an algorithm is a part of an automated system. People with disabilities cannot be refused jobs due to the algorithmic tools, and the failure to provide reasonable accommodations to them is prohibited under the Americans with Disabilities Act (ADA.gov., 2025).

Lopez (2025) examines how the EEOC and other federal agencies are adapting their enforcement tools to address algorithmic discrimination. For example, wearable monitoring devices that collect biometric or vital-sign data could reveal information about a disability and breach confidentiality.

Many organizations lack the expertise to assess algorithmic fairness. According to Booyse and Scheepers (2024), organizations face hurdles such as organizational inertia, limited technical knowledge, and a fear of legal exposure that hinder their ability to adopt fair AI governance. Therefore, either companies rely too heavily on vendor checks or do not conduct audits at all. Either way, it just increases legal risk. To ensure compliance, businesses must conduct structured bias audits and accountability chains.

Methodology

This doctrinal legal study examines current and potential legislation aimed at addressing Artificial Intelligence and protecting applicants and employees from employment discrimination.

This discrimination has been caused by algorithms that are biased by the faulty data used to train them.

Algorithmic bias occurs when systematic errors in [machine learning algorithms](#) produce unfair or discriminatory outcomes. It often reflects or reinforces existing socioeconomic, racial and gender biases (Jonkers & Rogers, 2026)

[Artificial intelligence](#) (AI) systems use algorithms to discover patterns and insights in data, or to predict output values from a given set of input variables. Biased algorithms can impact these insights and outputs in ways that lead to harmful decisions or actions, promote or perpetuate discrimination and inequality, and erode trust in AI and the institutions that use AI. These impacts can create legal and financial risks for businesses. For example, per the [EU AI Act](#), non-compliance with its prohibited AI practices can mean fines up to EUR 35,000,000 or 7% of worldwide annual turnover, whichever is higher (Jonkers & Rogers, 2026).

Algorithmic bias is especially concerning when found within AI systems that support life-altering decisions in areas such as [healthcare](#), law enforcement and [human resources](#). Bias can enter algorithms in many ways, such as skewed or limited training input data, subjective programming decisions or result interpretation (Jonkers & Rogers, 2026).

Mitigating algorithmic bias starts with applying [AI governance](#) principles, including transparency and [explainability](#), across the AI lifecycle.

The following legislation addresses a number of legal and ethical issues that have been caused by the use of AI in many human resource functions that have historically been performed by humans.

Federal Legislation Addressing Ai in Employment in the US

As of early 2026, there is no comprehensive federal legislation specifically governing AI in employment, as the current focus is on a "light touch" regulatory approach favoring AI development, with a new federal policy framework aimed at pre-empting state AI laws.

Federal regulation focuses on reporting requirements for AI-related job losses (e.g., the bipartisan AI-Related Job Impacts Clarity Act) and strengthening existing anti-discrimination laws rather than implementing new, specific workplace surveillance or AI hiring constraints (Jackson Lewis, 2026).

Key Aspects of Current Federal AI Approach:

While specific regulations are scarce, federal agencies previously released guidelines on ethical AI implementation, emphasizing worker empowerment and fairness.

The AI-Related Job Impacts Clarity Act (introduced Nov 2025) seeks to mandate reporting of job displacement and layoffs caused by AI to the Department of Labor.

The [No Robot Bosses Act](#) has been proposed to protect workers from automated, AI-driven management and firing decisions (Jackson Lewis, 2026).

State vs. Federal Conflict

The Trump administration is taking steps to align federal policy on AI, aiming to set a single national standard that could restrict stricter, individual state-level legislation (such as that found in California or New York) regarding AI in the workplace.

Employers remain subject to existing, long-standing anti-discrimination laws (e.g., 1964 Civil Rights Act, Title VII) when using AI for hiring or promotions. (Jackson Lewis, 2026).

First State legislation To Address Potential Discrimination: Local Law 144: The Case for Mandatory Bias Audits

As noted by Wright et al. (2024), New York City's Local Law 144, effective in 2023, is the first U.S. law to require independent bias audits for automated employment decision tools. Mandating disclosure to employers, electoral audits, and summary reports before deployment is a requirement stipulated in the law through the exchange of mandates.

According to Groves et al. (2024), the audit system described in the law is a "test case" for making algorithms accountable. They show that, while the requirement enhances transparency, enforcement is inconsistent due to a lack of common audit metrics within the statute.

Many auditors have trouble defining what "statistically significant" bias is, and different employers define their outcomes in numerous ways. Additionally, A recent study by Clavell and González-Sendino (2024) reveals considerable technical issues and barriers in developing a detector system for bias. Federal regulations need to clarify standards for measuring discrimination and auditing these systems. Despite limitations, the law sets an important precedent.

By requiring companies to conduct audits and share the results, it safeguards transparency, a vital component of good governance. Algorithmic fairness is not just a technical matter but an obligation under the law.

State and Local General Statutes Addressing Discrimination Issues with AI in Selection Processes Today

Colorado (Colorado Artificial Intelligence Act - SB 24-205)

This Law became effective on June 30, 2026. It regulates "high-risk" AI systems used in employment, including hiring, promotion, and termination. It requires employers to conduct annual impact assessments, implement risk management policies to prevent "algorithmic discrimination," and provide notice to employees/applicants when AI is used to making decisions. Violations constitute an unfair trade practice under the state's consumer protection law.

Illinois (Human Rights Act Amendment - HB 3773)

This Law went into effect on January 1, 2026. It expressly covers AI-mediated discrimination across the entire employment lifecycle (recruitment to termination). Employers must notify employees/applicants when AI is used to influence employment decisions and must not use AI that causes a disparate impact based on protected characteristics. It explicitly bans using ZIP codes as a proxy for protected characteristics.

California (Civil Rights Council Regulations)

This Law went into effect on October 1, 2025. It amends the Fair Employment and Housing Act (FEHA) to govern Automated Decision Systems (ADS) in hiring, promotion, and termination. It requires meaningful human oversight (trained personnel able to override the AI), strict record retention for four years, and bans the use of AI that discriminates on protected traits.

New York City (Local Law 144)

As mentioned earlier, this Law went into effect on July 5, 2023. It addresses Automated Employment Decision Tools (AEDTs) used to assess candidates or employees in NYC. It mandates independent annual bias audits, public summaries of audit results, and required notices to applicants ten business days before using the tool.

Texas (Responsible AI Governance Act - HB 149/TRAIGA)

This Law went into effect on January 1, 2026. It prohibits AI systems that *intentionally* discriminate in employment, though it specifically rejects disparate impact as a standalone basis for liability. It has exclusive enforcement by the Texas Attorney General, with a 60-day cure period for employers.

Maryland (Facial Recognition Law)

This Law became effective on October 1, 2024. It prohibits employers from using facial recognition services during pre-employment interviews unless the applicant provides written consent.

(Schwartz, 2025).

Each of the above Laws, which have been passed, is a city or state General Statute that addresses the impact of employment discrimination based on the use of artificial intelligence.

The City of New York Local Law 144 requires independent bias audits for automated employment decision tools. Mandating disclosure to employers, electoral audits, and summary reports before deployment is a requirement stipulated in the law through the exchange of mandates.

The Colorado Artificial Intelligence Act (SB 24-205), requires employers to conduct annual impact assessments, implement risk management policies to prevent "algorithmic discrimination," and provide notice to employees/applicants when AI is used to making decisions.

The Illinois Human Rights Act Amendment (HB 3773) It requires employers to notify employees/applicants when AI is used to influence employment decisions, and it must not use AI that causes a disparate impact based on protected characteristics. It explicitly bans using ZIP codes as a proxy for protected characteristics.

The California (Civil Rights Council Regulations, 2025). This Law amends the Fair Employment and Housing Act (FEHA) to govern Automated Decision Systems (ADS) in hiring, promotion, and termination. It requires meaningful human oversight (trained personnel able to override the AI), strict record retention for four years, and bans the use of AI that discriminates on protected traits.

Texas (Responsible AI Governance Act (HB 149/TRAIGA, 2026). This Law prohibits AI systems that *intentionally* discriminate against employment, though it specifically rejects disparate impact as a standalone basis for liability. It has exclusive enforcement by the Texas Attorney General, with a 60-day cure period for employers.

Maryland (Facial Recognition Law, 2024). This Law prohibits employers from using facial recognition services during pre-employment interviews unless the applicant provides written consent. (Schwartz, 2025).

Many other states are proposing legislation similar to these stated Laws that would prohibit the use of biased AI in making employment decisions as well as evaluating the performance of employees for annual reviews (Schwartz, 2025).

These Laws provide evidence of the widespread use of biased and discriminatory artificial intelligence on poorly designed algorithms used as parameters in the creation of the AI platforms in use.

This creates a real danger for computer AI specialists as well as the human resource professionals who participated in creating algorithms and implementing them into HRM functions such as recruitment, talent management, as well as employee performance management systems.

Transparency, Accountability, and Legal Challenges in Creation and Usage of AI

Transparency lies at the heart of algorithmic governance, yet it remains elusive. Most AI vendors label model information proprietary and prevent any real inspection from the outside. Kim (2025) argues that if people do not know “who audits, what metrics are used, and how transparency obligations are enforced,” workers cannot exercise their rights of non-discrimination.

Bias Notification Duty

To bridge this gap in transparency, a proposal by Haber and Stern (2024) is the Bias Notification Duty (BND). The BND regulation would require companies to notify the oversight agency whenever they discover algorithmic bias. The agency would then investigate the source and the effect of that bias and notify affected parties. Haber and Stern (2024) state that even when attempting to address a bias, the actual cause is often hidden by society. BND turns hidden algorithmic errors into social learning opportunities by making bias incidents public.

However, BND introduces practical hurdles. Companies may worry about reputational damage or legal consequences if biases are revealed. Sharing data restrictions complicate reporting across sectors. To address these, Haber & Stern (2024) note that there must also be system transparency that supports ongoing improvements and ensures public trust.

Federal Oversight and EEOC Guidance

At the federal level, agencies are gradually adapting to the challenges of AI in employment. The federal level has agencies that are gradually learning how to integrate AI into employment processes. There is a civic initiative to identify discriminatory patterns in artificially created hiring programs nationwide, driven by concerns about fairness.

The EEOC collaborates with the Department of Justice to monitor employers that utilize algorithms to circumvent the ADA or Title VII. The EEOC approach should strike a balance between the potential impact of its forum and the need for proactive guidance and enforcement, rather than relying solely on punishment. Currently, there are no clear expectations for audits of algorithms (EEOC.gov, 2026).

According to Chan (2024), if developers are made accountable for the model logic, data on which it was trained, and the path it took to decide, then equal opportunity can be operationalized through “explainable AI” frameworks, as it can effectively generate explainable AI. EEOC and courts could treat allegations of algorithmic bias more effectively when ethical AI principles are linked with existing legal ones. Still, the challenge remains balancing innovation with regulation. Lopez (2025) explains that if workplaces are too strict when adopting responsible technologies, they will never use them at all (EEOC.gov, 2026).

The Bias Notification Duty as a Complementary Framework

Haber and Stern’s (2024) proposed Bias Notification Duty (BND) offers an innovative and proactive approach to bridging the gap between internal organizational audits and external public accountability. Systematic compliance measures have traditionally relied on bias assessments conducted privately, for which regulators and the public do not have access. On the other hand, BND creates a legal requirement for firms to inform the relevant authority of algorithmic biases that are found internally or through outside audits, regardless of whether they have already been fixed. After a notification is submitted, it will trigger a formal government scrutiny and public disclosure, where relevant. Haber and Stern (2024) note that this mechanism lets regulators,

researchers, and policymakers observe similar trends in bias across industries. It also enables them to identify structural sources of discrimination that organizations may not be able to discern on their own.

The BND framework defines algorithmic bias not simply as a technical flaw, but as it originates from social issues such as history, systems, society, and inequality. Haber and Stern (2024) argue that invisible algorithmic fixes render it impossible for society to recognize that entrenched inequalities shape the datasets that govern automated decisions. When multiple employers discover that the outcomes of their automated resume-screening systems are racially biased, they may privately adjust their systems rather than sharing the information publicly. However, this means that policymakers do not have the opportunity to determine whether there is a common cause underlying these observations. In this example, the common cause would be biased data labelling or exclusionary feature engineering. If BND mandated the disclosure of incidents and experiences faced by businesses, it could help bring about systemic change.

This model has significant potential in the employment field. Mandatory bias notifications can provide insights into inequities that are broader than those of a particular firm. For example, this could be gendered language in performance assessments, algorithms that penalize career gaps arising from caregiving, or biased facial expression assessments. With this knowledge, regulators can issue more effective guidance and revise standards for algorithmic fairness across various industries.

Bias Notification Duty will not repeal an existing law, like Local Law 144 in New York City. While Local Law 144's audits check a system's fairness at a single point in time, notifications require updates as systems evolve. Employers will need to disclose new findings. This new method of reporting means that stakeholders will not just be reacting to things in the future but rather will be proactive in their efforts. Instead of algorithmic governance that just fixes things when they go wrong, there will be algorithmic governance that is transparent and accountable. However, effectively implementing this requires strong safeguards for privacy and data protection. Employers must inform their employees about bias without putting them and their algorithms at risk. Therefore, the plan presented by Haber and Stern (2024) is a conceptual shift; AI regulation will not only focus on compliance but also on shared responsibility. The Bias Notification Duty promotes fairness and trust in algorithmic employment decision-making by contributing to open disclosure and systemic learning.

Managerial Significance: Implications for Practice

For practicing managers, the integration of AI into employment decisions carries profound operational, legal, and ethical implications. As managers make greater use of automated decision-making systems, they do not avoid accountability; rather, they increase it. According to the EEOC, employers must take the necessary steps to ensure that any technology they use for hiring, promotion, and termination complies with the law (Lopez, 2025). When firms entrust algorithms to make employment decisions, they remain liable for any bias or illegal outcomes.

Consequently, managers should exercise caution when choosing, checking, and monitoring the AI tools they use to ensure they operate in a fair and legally defensible manner.

This requires HR departments, legal counsel, and data scientists to actively collaborate to review discriminatory patterns before and during deployment. Organizations must institutionalize bias audits as a mechanism for continuous quality improvement to ensure compliance and fairness. One-way companies can prevent discrimination is by embedding audit processes into daily human resources systems (Clavell & González-Sendino, 2024). By auditing data frequently rather than just once, managers can identify changes that may introduce new biases as the workforce data or algorithm model evolves. Any documented corrective actions taken because of these audits would demonstrate compliance, should regulators or affected employees question the outcomes.

Clear information on the objectives needs to be provided to the people responsible for achieving them. Employees and applicants should understand how automated systems evaluate them and what data they rely on for their decisions. According to Wright et al. (2024), transparency builds trust and helps organizations comply with disclosure requirements, including those set forth by New York City's Local Law 144. Communicating clearly about the purpose, logic, and limits of AI tools demonstrates accountability and reinforces an inclusive workplace culture.

When employers are open about their hiring systems, it sends a positive signal to employees. It will also help managers put resources into training that teaches their organization algorithmic fairness principles. Strich et al. (2021) state that replacing human judgment with algorithms may make people feel undervalued. Training programs that explain how automation contributes to, rather than displaces, human decision-making can reduce pushbacks.

Balancing Innovation and Rights

The primary challenge in regulating AI-based employment systems is striking a balance between innovation and worker protection. On the one hand, consistency in decision-making for hiring and promotion is ensured through mechanisms such as automation, lower costs, and increased hiring effectiveness. Systems that are not regulated or poorly managed often lead to increased discrimination, undermining labor protection, and other essential systems. Numerous employers, particularly small and medium-sized organizations, want to incorporate AI into their workplaces; however, Booyse and Scheepers (2024) define AI as a complex technology that can expose organizations to liability for compliance and auditing. According to their research, the lack of access to technical expertise and financial resources makes these firms apprehensive about compulsory audits due to a fear of being subject to legal scrutiny if biases are found. Yet, choosing not to automate may mean these organizations cannot reach the highest productivity levels and standardized decision-making afforded by AI.

There is a need for reasonable innovation, according to which organizations should deploy AI tools that are explainable, auditable, and explicitly aligned with equal opportunity principles (Chan, 2024). It is better to create systems with fairness and non-discrimination protocols, rather

than relying on reviews. According to Kim (2025), non-discrimination rights must be considered at the development stage of algorithm governance. Additionally, proactively integrating fairness allows technology to be designed for fairness from the start. For instance, before systems are deployed in the workplace, developers can apply bias-mitigation techniques, such as adversarial testing and balanced training datasets, to prevent biases.

According to Wright et al. (2024), regulatory compliance mechanisms must adapt to changes in technology. As artificial intelligence tools become more diversified, ranging from parsing resumes to predicting performance, the definition of automated decision tools must be flexible enough to include recent technologies. Transparent metrics and standardized reporting formats would ensure that firms in different geographical locations can comply, and enforcement would harmonize, so that effective detection of bias does not remain confined to a few places, such as New York.

International models provide helpful guidance. Wright et al. (2024) find that the European Union AI Act categorizes algorithms related to employment as “high risk,” requiring human oversight, complete fairness documentation, and pre-deployment conformity assessments. Applying similar regulatory frameworks to the US could establish a consistent national standard whereby innovation must be accountable.

Conclusion

AI-driven decision-making systems are now critical in hiring, but their data-driven objectivity can also lead to new forms of discrimination against workers. Algorithmic discrimination is often merely a manifestation of existing social discrimination, which is deeply entrenched in the data through developer bias. New York City’s Local Law 144 and the EEOC’s guidance serve as significant landmarks on the journey toward accountability. However, their implementation is uneven and fragmented.

The proposed Bias Notification Duty would help complement bias audits. Namely, it would make bias detectable and continuously improved from diverse experiences and deployments. Business managers should not put algorithmic decision-making on autopilot, as a full audit, clear communication, and ethical oversight are needed.

Organizations should ensure that legal compliance and ethical responsibility are embedded throughout the entire lifecycle of an AI system. It should be ensured, from data collection to model testing and deployment, as this will ensure fairness and foster innovation. Due to increasing workplace automation, whether or not employment law can keep pace will depend on whether business managers, regulators, and technologists can ensure that algorithms guarantee fairness.

References

- Americans with Disabilities Act, *The Americans with Disabilities Act (ADA) protects people with disabilities from discrimination*, ADA.gov., <https://www.ada.gov/>
- Booyse, D., & Scheepers, C. B. (2024). Barriers to adopting automated organizational decision-making through the use of artificial intelligence. *Management Research Review*, 47(1), 64-85. <http://dx.doi.org/10.1108/MRR-09-2021-0701>
- Chan, G. K. (2024). AI employment decision-making: integrating the equal opportunity merit principle and explainable AI. *AI & SOCIETY*, 39(3), 1027-1038. <https://doi.org/10.1007/s00146-022-01532-w>
- Clavell, G. G., & González-Sendino, R. (2024). What We Learned While Automating Bias Detection in AI Hiring Systems for Compliance with NYC Local Law 144. *arXiv preprint arXiv:2501.10371*. <https://arxiv.org/pdf/2501.10371>
- Equal Employment Opportunity Commission (2024), What is the EEOC's Role in AI?, <https://www.eeoc.gov>.
- Groves, L., Metcalf, J., Kennedy, A., Vecchione, B., & Strait, A. (2024, June). Auditing work: exploring the New York City algorithmic bias audit regime. In *Proceedings of the 2024 ACM Conference on Fairness, Accountability, and Transparency* (pp. 1107-1120). <https://dl.acm.org/doi/pdf/10.1145/3630106.3658959>
- Haber, E., & Stern, S. (2024). Bias Notification Duty. *Cardozo Arts & Ent. LJ*, 42, 295. <https://papers.ssrn.com/sol3/Delivery.cfm?abstractid=4901243>
- Kim, P. (2025). Algorithmic Governance and Non-discrimination Rights in the Workplace. *Washington University in St. Louis Legal Studies Research Paper*, (25-03), 08. <https://papers.ssrn.com/sol3/Delivery.cfm?abstractid=5182525>
- Jonker, A., Rogers, J. (2026), What is algorithmic bias? IBM.com, <https://www.ibm.com/think/topics/algorithmic-bias>
- Lopez, D. (2025). The Quest for Algorithmic Justice in the Workplace: The Equal Employment Opportunity Commission and Other Federal Responses to AI, Technology, and Enhanced Dangers of Employment Discrimination. *Seton Hall Journal of Legislation and Public Policy*, 49(3), 4. <https://scholarship.shu.edu/cgi/viewcontent.cgi?article=2137&context=shlj>
- Maurer, R., (2026), The Workday AI Lawsuit Is a Wake-Up Call for HR., *shrm.org*, <https://www.shrm.org/topics-tools/news/technology/workday-ai-lawsuit-wake-up-call-hr>.
- New Your City of Consumer and Worker Protection, *Automated Employment Decision Tools, Local Law 144*: <https://www.nyc.gov/site/dca/about/automated-employment-decision-tools.page#:~:text=Local%20Law%20144%20of%202021,rule%20on%20July%205%2C%202023> (July 5, 2023).
- Schwartz, D., AI & Hiring – The Laws Are Coming, Shipman & Goodwin, LLP., Oct. 27, 2025. <https://www.shipmangoodwin.com/insights/ai-hiring-the-laws-are-coming.html#:~:text=Illinois:%20Broad%20Notification%20Requirements,discriminatory%20outcomes%20regardless%20of%20intent>.
- Sonderling, K. E., Kelley, B. J., & Casimir, L. (2022). The Promise and the Peril: Artificial Intelligence and Employment Discrimination. *U. Miami L. Rev.*, 77, 1. <https://repository.law.miami.edu/cgi/viewcontent.cgi?article=4692&context=umlr>

- Strich, F., Mayer, A. S., & Fiedler, M. (2021). What do I do in a world of artificial intelligence? Investigating the impact of substitutive decision-making AI systems on employees' professional role identity. *Journal of the Association for Information Systems*, 22(2), 9. <https://scholar.archive.org/work/xsfrulg63jhtbaptninzbls2e/access/wayback/https://aisel.isnet.org/cgi/viewcontent.cgi?article=2000&context=jais>
- Wright, L., Muenster, R. M., Vecchione, B., Qu, T., Cai, P., Smith, A., ... & Matias, J. N. (2024, June). Null Compliance: NYC Local Law 144 and the challenges of algorithm accountability. In *Proceedings of the 2024 ACM Conference on Fairness, Accountability, and Transparency* (pp. 1701-1713). <https://doi.org/10.1145/3630106.3658998>