



PART 1

Read the text below and answer questions 1–13.

THE ETHICS OF ARTIFICIAL INTELLIGENCE IN HIRING

Artificial intelligence has become a routine component of recruitment, particularly in large organisations that receive far more applications than human staff can reasonably read. Many employers now rely on Applicant Tracking Systems (ATS), software platforms that store candidate data, filter resumes, and help recruiters manage the hiring pipeline. When a single vacancy attracts hundreds or even thousands of applicants, an ATS can automatically remove duplicates, detect missing requirements, and rank resumes according to job-related keywords. Vendors increasingly promote “AI-powered” modules that go beyond sorting, claiming to predict job performance or retention by analysing patterns in previous successful hires. These tools are adopted largely to reduce time-to-hire and to keep recruitment manageable at scale, but their growing influence raises questions about how decisions are made and who bears responsibility when outcomes seem unfair.

A central ethical issue is bias in the data used to train or configure these systems. If an employer’s historical hiring records reflect unequal opportunities or past discrimination, statistical models may learn patterns that replicate those outcomes. Even when a company intends to be neutral, an algorithm trained on past choices may interpret those choices as a template for “fit.” Bias can also enter through proxies—variables that correlate with protected traits without naming them explicitly. For example, a zip code can correlate with race or socioeconomic status, and a school attended can reflect long-standing educational inequalities. Likewise, gaps in a resume may correlate with caregiving responsibilities, including maternity, and could be unfairly interpreted as a lack of commitment. In such cases, removing explicit demographic fields does not necessarily prevent discriminatory effects, because the system can still infer sensitive characteristics indirectly.

Another area of concern is the practical meaning of transparency. Hiring tools are often presented as objective, yet candidates may not know that an algorithm assessed them, which criteria were prioritised, or how to challenge an outcome. Even within organisations, the logic may be difficult to explain. Some systems operate like “black boxes”: they produce a score or ranking without a clear, human-readable justification. Complexity is not the only problem. Vendors may treat model details as proprietary, limiting what employers can disclose. As a result, transparency is not simply about announcing that AI is



being used; it also involves documenting what the tool was designed to do, what it cannot do, and how decisions can be reviewed when an applicant believes an error occurred.

Automation can also reshape recruiter behaviour in ways that reinforce model preferences. When candidates are presented in an ordered list, staff may spend less time exploring those placed lower, especially under time pressure. This effect, sometimes described as automation bias, can make recruiters more complacent and more likely to accept the tool's judgement as correct. Over time, this may create a feedback loop. If the model favours conventional career paths—continuous employment, familiar job titles, and standard qualifications—then fewer non-traditional applicants are shortlisted, and the next round of training data becomes even more skewed toward those profiles. Some organisations try to counteract this by requiring human review of a wider set of applicants, or by using AI as a triage tool rather than as a decision-maker. In these designs, staff are trained to treat model outputs as one input among several, not as final verdicts.

Privacy concerns have expanded as hiring systems have moved beyond resumes. Some tools analyse video interviews, tracking speech rate, word choice, or facial movements, and then infer traits such as confidence or sociability. Others scrape online profiles or use third-party data brokers to enrich candidate records. These practices raise questions about consent and proportionality. Even if candidates agree to an online interview, they may not realise that micro-expressions or voice features are being measured, or how those measurements will be interpreted. The risk is not only intrusion but also function creep: data collected for hiring can be repurposed later for unrelated uses, such as employee monitoring or marketing. There are additional technical risks, including re-identification of supposedly anonymised data, or leakage through insecure storage and sharing between vendors and employers.

Because job contexts change, ethical use also depends on validation and ongoing checks. A model that appears accurate in one setting may perform poorly in another if the role, labour market, or applicant pool changes. Skills demanded for a job can evolve, and hiring practices can shift after organisational restructuring, creating what data scientists call drift. Without monitoring, a system that once seemed reliable can become outdated or discriminatory. For this reason, experts recommend auditing: testing outcomes to see whether certain groups experience systematically different selection rates, examining error patterns, and checking whether the model's criteria remain relevant to the job. Auditing can also identify when a tool is being used outside the conditions for which it was validated—for example, applying a model trained on one region or job family to a very different context.



Regulation is developing unevenly across jurisdictions. In some places, employers face specific obligations when using high-risk automated decision systems, such as conducting impact assessments or allowing candidates to request explanations. In other regions, oversight relies mainly on general anti-discrimination law, which can be difficult to apply when decision-making processes are opaque. Many companies also adopt voluntary standards, such as documenting data sources, conducting bias tests, and establishing review committees. However, voluntary measures vary in quality and may be implemented inconsistently, especially when hiring is outsourced to vendors. Stronger frameworks typically combine legal obligations with internal organisational processes, including clear responsibility for model use, independent review, and accessible channels for candidates to raise concerns.

Finally, debate continues over what “fair” hiring should mean in practice. Some define fairness as equal treatment: applying the same criteria to all candidates in the same way. Others emphasise equal opportunity, recognising that candidates start from unequal circumstances and may need barriers to be considered when evaluating merit. In this debate, AI is sometimes presented as a tool that can reduce arbitrary decisions and expand access by standardising screening. Yet the same technology can entrench inequality if organisations treat output scores as unquestionable truths, or if models are trained on patterns that reflect past exclusion. In effect, AI does not settle the ethics of hiring; it makes the underlying choices more scalable, and therefore more consequential.

Questions 1–5

Choose **TRUE** if the statement agrees with the information given in the text, choose **FALSE** if the statement contradicts the information, or choose **NOT GIVEN** if there is no information on this.

- 1 The passage suggests that employers adopt AI recruitment tools partly to cope with large applicant pools.
- 2 The passage suggests that removing explicit demographic variables does not necessarily prevent unfair outcomes.
- 3 The passage states that most candidates prefer automated screening to human review.
- 4 The passage suggests that heavy reliance on algorithmic rankings may reduce consideration of non-traditional candidates.
- 5 The passage suggests that data collected for hiring may later be used for unrelated purposes.

Questions 6–10



Complete the notes below. Choose **NO MORE THAN TWO WORDS** from the text for each answer.

AI in hiring: ethical issues

- Bias may be learned from historical **6** Even after explicit demographic fields are removed, the system may still infer sensitive **7** indirectly.
- A lack of transparency means candidates may be unaware of which **8** mattered in a decision or how to appeal.
- Privacy concerns arise because some tools analyse **9** or scrape online profiles.
- Experts recommend ongoing **10** to detect drift and assess disparate impact.

Questions 11–13

Select the correct answer.

11 What does the passage suggest about the predictive accuracy of hiring models?

- A** It remains stable as long as the underlying algorithm is not changed.
- B** It may decline when the role, labour market, or applicant population changes.
- C** It depends mainly on excluding demographic variables from the input data.
- D** It can be transferred to new contexts once it performs well in its original setting.

12 Which statement best reflects the passage’s view of regulation?

- A** General anti-discrimination law is sufficient wherever specific AI rules are absent.
- B** Voluntary standards provide a consistent alternative to formal legal obligations.
- C** Legal requirements differ across jurisdictions, while voluntary measures also vary in quality.
- D** Effective oversight depends primarily on vendors taking responsibility for model use.

13 What is the passage’s central debate about “fair” hiring?

- A** Whether fairness means applying identical criteria or accounting for unequal starting circumstances
- B** Whether each vacancy should be governed by a different technical standard
- C** Whether equal outcomes should replace all consideration of individual merit
- D** Whether model accuracy should be assessed without reference to previous exclusion

Answer Key



1. TRUE
2. TRUE
3. NOT GIVEN
4. TRUE
5. TRUE
6. hiring records
7. characteristics
8. criteria
9. video interviews
10. auditing
11. B
12. C
13. A