ISSE
International Journal of Service Science, Management, Engineering, and Technology
pISSN 2964-7118 eISSN 2830-604X

SOCIAL CLASS SCREENING THROUGH ARTIFICIAL INTELLIGENCE RECRUITMENT ALGORITHMS ON DIGITAL EMPLOYMENT PLATFORMS

Jeje Abdul Rojak

Universitas Islam Negeri Sunan Ampel Surabaya

correspondence: jejerozaq@yahoo.com

Abstract - *The expanding use of artificial intelligence in recruitment raises concerns about whether automated screening reproduces social inequalities embedded in educational credentials and geographic opportunity. This article examines how AI-assisted recruitment may transform university prestige and residential location into social-class filters, and how algorithmic assessments interact with recruiters' decisions to shape employment opportunities. An integrative literature review was conducted using sociological and multidisciplinary publications. The analysis compared evidence from hiring audits, studies of social stratification, algorithmic fairness research, and organizational recruitment practices. The synthesis indicates that historical training data, proxy variables, candidate ranking, and selection thresholds can reproduce advantages associated with elite education and geographic access. However, existing evidence does not establish that all recruitment platforms automatically exclude applicants from peripheral areas or non-elite universities. Research also shows that human recruiters may reinforce or counteract algorithmic disparities, making outcomes dependent on organizational decisions as well as model design. The article concludes that socially accountable recruitment requires job-relevant assessment criteria, transparent procedures, comparative bias audits, and meaningful opportunities to review disputed outcomes.*

Keywords: algorithmic hiring, artificial intelligence social class inequality, recruitment discrimination, university prestige, geographic inequality, digital labor platforms.

INTRODUCTION

The development of artificial intelligence (AI) has transformed workforce management, particularly in the search, screening, and selection of prospective employees. Organizations have begun to use digital systems to manage large volumes of applications, identify qualification fit, and rank candidates according to particular criteria. These changes show that the recruitment process is increasingly shaped by data processing and algorithm-assisted decisions (Idrus, 2025). Fourcade and Healy (2017) explain that the development of digital classification systems enables organizations to group individuals based on information that is collected and processed into particular assessments. This classification process has social consequences because it can affect individuals' opportunities to obtain resources and services. In job recruitment, digital assessment can become part of the mechanism that determines which applicants gain the opportunity to enter the next stage of selection. This situation makes recruitment technology a sociological issue related to the distribution of opportunities and social inequality.

The use of algorithms in recruitment is generally developed to help organizations increase the speed and consistency of the selection process. These systems can be used to read application documents, identify work experience, match skills to job requirements, or provide candidate recommendations to recruiters. Communication in digital environments has limitations in portraying individual characteristics comprehensively because nonverbal aspects such as vocal intonation, facial expressions, and body language are scarcely conveyed (Putra et al., 2022). However, the use of technology does not automatically make recruitment decisions free from social prejudice (Pandit et al., 2026). Köchling and Wehner (2020) explain that algorithmic decision-making in human resource management has the potential to produce unfair treatment of certain groups, especially when the data and processing procedures contain inequalities. These findings indicate that algorithms need to be understood as systems built on human choices regarding data, categories, and measures of success. When screening decisions are made using information previously shaped by social inequalities, technology can maintain the same patterns of assessment. This issue raises questions about the relationship between digital efficiency and fairness of opportunity in the labor market.

Social inequality in job recruitment was already a problem before the use of artificial intelligence became widespread. Educational background, social experience, professional networks, and the ability to meet the expectations of organizational culture can influence the assessment of prospective employees. Rivera (2012) found that the recruitment process at elite professional service firms involves assessments of cultural fit between applicants and those conducting the selection. These assessments are not entirely related to technical ability because they include shared experiences, communication styles, and social activities. These findings show that recruitment is a process of screening abilities as well as a social process that can maintain the advantages of certain groups. When organizations begin to implement AI,

the assessment measures previously used by humans have the potential to be translated into variables in digital systems. In such circumstances, university of origin, organizational experience, and the characteristics of work history can receive particular weights that affect an applicant's chances of being considered.

The problem of AI-based recruitment becomes more complex when the information used by the system relates to applicants' social class background. Individuals from families with greater economic resources may have broader opportunities to access prestigious education, additional training, professional certifications, and job networks. Conversely, applicants from peripheral areas or non-elite universities may face limited access to these opportunities even though they have abilities that match the job. Changes in labor demand in the digital era require mastery of technical, methodological, social, and personal competencies that complement one another, while inequality in access to technology and digital literacy can affect individuals' opportunities to develop competencies and prepare to enter the labor market (Darmawan, 2025). Differences in social resources can be reflected in application documents that are then read by algorithms (Altun, 2026). If a system gives higher assessments to indicators of educational prestige or particular work history without examining their relevance, the selection process risks producing screening based on prior social advantages. This problem shows that inequality can operate through information that appears neutral. The assessment of applicants needs to distinguish between job-relevant abilities and social characteristics that are only indirectly related to opportunities to obtain employment.

Kelan (2024) explains that the use of artificial intelligence in recruitment can reinforce exclusion if issues concerning data, system design, and organizational decisions are not adequately addressed. This explanation shows that algorithmic bias cannot be understood merely as a technical error in software. Bias is also related to how organizations define the characteristics of candidates considered suitable, select training data, and use prediction results in recruitment decisions. The use of artificial intelligence (AI) to analyze user data directly enables organizations to generate personalized service recommendations and provide in-depth insights into user behavior patterns as a basis for accurate decision-making (Essa et al., 2024). On digital job-search platforms, problems can arise before applicants submit their applications if the recommendation system determines which job vacancies are displayed more often to particular groups of users. Once applications are received, automated assessment can form a candidate ranking that influences recruiters' attention. Both processes may produce an uneven distribution of opportunities. However, the existence of algorithms is not sufficient to conclude that a platform actually discriminates against applicants. Such a conclusion requires examination of the data, system outputs, and the decisions that actually take place.

The knowledge gap addressed by this article concerns the relationship between algorithmic assessment, social class markers, and the reproduction of inequality in employment opportunities. Discussions of AI in recruitment often emphasize selection efficiency or differences in assessment outcomes by demographic category. Meanwhile, discussions of social class inequality more often explain differences in access to education, professional networks, and the advantages held by certain social groups. The use of artificial intelligence (AI) in managerial decision-making not only increases operational efficiency but also raises ethical concerns because algorithms have the potential to reinforce data bias, widen demographic inequality, and reduce individual accountability when human judgment is replaced by machines (Gani & Darmawan, 2022). These two fields need to be connected to understand how digital systems can translate social differences into candidate rankings. The issue that remains insufficiently explained is how variables such as university prestige and residential location can function as social class markers in the screening process, and how their influence can be distinguished from legitimate job requirements. An explanation is also needed of the relationship between algorithmic decisions and the authority of human recruiters in maintaining or correcting inequality.

This article positions recruitment algorithms as part of a social process that brings together digital technology, the structure of educational opportunity, and power relations in the labor market. The social mobility of young people in the digital era no longer depends solely on formal employment and education, but also intersects with algorithmic systems and digital networks, where access to these skills is still shaped by inequalities between social groups (Gani et al., 2025). The discussion focuses on how screening systems use applicant information and how this process can produce different advantages based on university of origin and area of residence. Theoretically, this article is expected to clarify the relationship between digital classification and the reproduction of social class through labor recruitment mechanisms. Academically, the writing brings together the sociology of social stratification with research on algorithmic fairness and human resource management. Practically, the discussion can serve as material for organizations to consider when assessing the relevance of selection variables, the transparency of systems, and applicants' opportunities to receive fair assessments. The value of this article lies in its explanation of the conditions under which technology can reinforce or reduce inequality, without assuming that all AI systems have the same characteristics and social consequences.

Based on the above description, this article aims to examine the mechanisms of social class screening in AI-based recruitment and to explain their relationship with inequality in employment opportunities on digital platforms. The study is conducted by bringing together the literature on algorithmic bias, educational stratification, spatial inequality, and organizational decision-making. The first research question is: how can AI-based recruitment algorithms transform information about residential location and university of origin into a screening mechanism that reproduces social class inequality? The second research question is: how do algorithmic screening and recruiters' decisions shape the distribution of employment opportunities and maintain or reduce social inequality between groups of applicants?

RESEARCH METHODS

This study uses an integrative literature review method with an interpretive sociological approach to examine the relationship between recruitment algorithms, social class markers, and inequality in employment opportunities. The integrative approach was chosen because the issue under study requires combining research on algorithmic technology, social stratification, sociology of education, and organizational decision-making behavior, fields that are usually discussed separately and rarely brought into a single analytical framework. Whittemore and Knafl (2005) explain that an integrative review allows various forms of evidence to be combined in order to gain an understanding of issues that involve more than one scholarly tradition. In this study, the evidence includes empirical findings, experimental results, and conceptual arguments, which are treated as complementary sources of understanding rather than as interchangeable data. The interpretive sociological approach is used to read this literature not only as a collection of technical findings but also as an account of how digital classification, educational advantage, and power relations in the labor market interact in the screening of applicants. This approach also guides attention to how screening variables such as university prestige and residential location acquire social meaning, and how that meaning may shape the distribution of opportunities between groups of applicants.

The selection of sources was carried out by considering relevance to the two research questions, publisher credibility, clarity of research design, and the ability of the literature to explain the technical mechanisms and social consequences of candidate screening (Aminou et al., 2025). The preferred sources include reputable journal articles, algorithmic audit studies, recruitment experiments, and conceptual studies on social inequality. Sources that discuss AI in recruitment only in general terms, without explaining how applicant information is processed, ranked, or used by recruiters, were given lower priority because they offer limited insight into the screening mechanisms examined in this article. The analysis was conducted by separating evidence on human recruitment discrimination, AI system bias, and geographic inequality so that they would not be treated as identical findings. This separation matters because evidence of unfair treatment by human recruiters does not automatically show that an algorithmic system discriminates, and evidence of unequal opportunities across regions does not by itself show that a platform excludes applicants from peripheral areas. Subsequently, the literature was compared across these categories to identify points of convergence, differences in context, and gaps in the available evidence. This comparison was then used to explain the possible relationship between screening variables and the reproduction of social class, including the conditions under which algorithmic screening and recruiters' decisions may maintain or reduce inequality between groups of applicants (Maliki & Khammam, 2026).

RESULTS AND DISCUSSIONS

Social Class Screening through Data and Algorithmic Ranking

Social class screening in AI-based recruitment can occur when information related to applicants' social standing is used as a basis for assessing employment opportunities. Digital recruitment systems generally process a number of candidate characteristics to estimate fit with a particular job. These characteristics may include level of education, work experience, skills, residential location, and other information available in application documents. The problem arises when the variables used are related to prior social advantages but do not necessarily reflect the ability to perform the job (Tayyab & Shah, 2025). In such circumstances, algorithmic assessment can turn differences in access to education and resources into differences in candidate ranking. This process does not have to involve a direct instruction to discriminate against particular groups. Inequality can develop through statistical relationships that the system learns and reuses in subsequent decisions. To understand this, it is necessary to examine how data, prediction targets, and selection criteria are determined during the development and use of algorithms.

Barocas and Selbst (2016) explain that data processing systems can produce discriminatory consequences through historical information that reflects social inequality. Algorithms can learn patterns from past decisions and use them to make new classifications without understanding the social processes that produced those patterns. In recruitment, if historical data contain more employees from particular universities, the system may link educational origin with job success. This relationship does not necessarily show that graduates of other universities have lower abilities. Differences in representation may stem from previous hiring policies, access to alumni networks, or opportunities to gain professional experience. If such data are treated as an objective representation of candidate quality, the algorithm can maintain old inequalities. This mechanism shows that the selection of training data and the determination of assessment variables have social consequences that need to be examined carefully. Algorithm-based workforce management limits the transparency of decisions and workers' room to question the results of system assessments, thereby changing the distribution of authority and opportunities in employment relations (Darmawan, 2024).

University of origin is a marker that needs attention because the education system is related to the distribution of economic, social, and cultural capital. Universities with high prestige often have alumni networks, internship opportunities, and relationships with companies that differ from those of other educational institutions. These differences can create advantages for certain graduates in the process of entering the labor market. When algorithms include

institutional prestige as an indicator of candidate fit, educational advantages can be translated into digital assessments that affect applicant rankings. The problem arises when institutional prestige is used as a substitute for individual ability without adequate competency assessment (Rajesh et al., 2025). Graduates of non-elite universities may have skills that match job requirements but receive less attention because of the characteristics of their institutions. In such circumstances, algorithms have the potential to reinforce differences in opportunities that have already been formed through the education system. This relationship is a mechanism that needs to be tested in specific recruitment systems, not a conclusion that all platforms use ranking based on campus prestige.

Gaddis (2015) conducted an audit study on the relationship between college selectivity, race, and the opportunity to receive responses from employers. The study used pairs of candidates designed to be comparable to apply for 1,008 job vacancies through a national job-search site in the United States. The results showed that degrees from elite universities were associated with a higher number of employer responses, but this advantage did not eliminate differences in treatment based on race. Black candidates from elite universities only obtained a likelihood of response comparable to that of white candidates from less selective universities. This finding shows that educational prestige can function as a source of advantage in the recruitment process. However, the study observed employer responses and did not specifically test AI algorithmic decisions. Its relevance to this article lies in understanding patterns of social assessment that have the potential to be translated into digital screening systems.

Residential location is another characteristic that can be related to social class screening through recruitment technology. Applicants who live in peripheral areas may face different transportation access, job networks, and digital infrastructure from applicants in urban centers. These differences can affect opportunities to learn about job vacancies, take part in selection, and meet certain job requirements. If a platform uses geographic distance or area of domicile as a recommendation variable, the distribution of job vacancy information can differ between users (Liu et al., 2026). The use of distance has a practical rationale for jobs that require physical presence, but setting a threshold that is too broad or does not match job needs has the potential to reduce the opportunities of applicants who are actually willing to travel. Location can also become an indirect marker of socioeconomic conditions if certain areas have different income characteristics and access to education. The use of geographic information needs to distinguish between legitimate job requirements and screening that lacks an adequate competency basis.

The relationship between geography and inequality in employment opportunities is supported by research by Agan and Starr (2024). Through a field experiment, they showed that the racial composition of the neighborhood where employers are located is related to patterns of discrimination against applicants. The study also found differences in geographic proximity between population groups and job vacancy locations. This situation produces layered disadvantage when certain groups face discrimination while also having fewer job opportunities in nearby areas. These findings confirm that the distribution of job opportunities has a geographic dimension that needs attention. However, this study does not prove that recruitment algorithms automatically reject candidates based on residential address. Its relevance to the article's topic lies in the possibility that digital systems reproduce geographic inequality when processing location data without considering the patterns of opportunity distribution that have already taken place.

On digital job-search platforms, the screening mechanism can operate through several stages that have different consequences. The first stage concerns determining which job vacancy information is displayed to users based on their profiles, search activity, or particular matching criteria. The next stage involves the receipt of application documents and the checking of administrative requirements. Some systems then perform candidate ranking before the results are used by human recruiters. Each stage can produce inequality through a different mechanism. Applicants who do not receive job vacancy information may never enter the selection process, while applicants with a low ranking may face a smaller chance of being examined in depth. These differences show that class screening does not always take the form of direct rejection. Inequality can be formed through reduced visibility, restricted access, or unequal prioritization. The assessment of a system needs to follow the candidate's journey from the search for information to the final decision, rather than merely examining the list of applicants that the organization has accepted.

The use of language models and document-matching systems adds to the problem of how candidate information is translated into digital assessments. Wilson and Caliskan (2024) conducted an audit of text representation models in a resume screening simulation for nine types of occupations. The study used more than 500 publicly available resumes and 500 job descriptions to test differences in matching outcomes. They found that the models studied significantly favored names associated with white groups in 85.1% of test cases. The results also showed differences based on gender as well as intersections of identity categories. These findings provide evidence that language processing systems can produce different assessments even when used for candidate matching tasks. However, this study tested racial and gender bias in a simulation, not screening based on university of origin or residential location. Therefore, these findings serve as a basis for assessing the risk of bias, not direct evidence of class discrimination on a particular platform.

Candidate ranking can produce differences in opportunities through the determination of selection thresholds. In systems that generate fit scores, organizations can set the number of candidates who will be forwarded to the interview stage. Applicants whose scores fall slightly below the threshold may not receive further attention even though the difference in ability from other candidates is relatively small. If variables related to social class influence the score, the

setting of the threshold can magnify the consequences of these differences in assessment. As a conceptual illustration, two applicants may have comparable technical competencies, but one receives additional points because of university prestige. If decisions are based solely on the final ranking, the assessment of institutional prestige can determine who has the opportunity to demonstrate their abilities through an interview. This mechanism shows that bias cannot be adequately understood by examining average scores alone. The distribution of outcomes around the decision threshold also has meaning for the equitable distribution of employment opportunities.

Raghavan et al. (2020) examined the claims and practices of providers of candidate assessment technology in algorithm-based recruitment. The study shows that assessing the fairness of a system needs to consider data sources, prediction targets, validation procedures, and the way developers check for possible bias. A system that produces consistent decisions does not necessarily have assessment measures that are relevant to job competencies. Uniform application of rules can reduce the variation in human decisions, but it does not automatically correct inequality if the rules applied use inappropriate measures. In the matter of social class, the examination of a system needs to assess whether university prestige or residential location has a justifiable relationship with job performance ability. The assessment also needs to consider the possibility that candidates from different groups receive unequal scores even though they have similar skills. This shows the need to examine the process of model formation and the outcomes of its use. The successful implementation of technology in organizations depends not only on technology investment but also requires organizational readiness to face change, strategic planning, and policy alignment to ensure that digital transformation proceeds in accordance with the stated objectives (Sinambela, 2023).

AI-based recruitment algorithms can become a social class screening mechanism when the data and assessment criteria contain markers of social advantage that are then used to determine candidates' opportunities. University of origin can link educational prestige with fit scores, while residential location can be related to access to information and opportunities to obtain employment. Inequality has the potential to develop through historical data, proxy variables, candidate ranking, and selection thresholds. However, the studies reviewed do not provide a basis for concluding that every platform automatically rejects graduates of non-elite universities or applicants from peripheral areas. Class screening is a mechanism that needs to be examined based on the characteristics of the system and its actual consequences for candidates. This discussion serves as a basis for understanding how digital processes and recruiters' decisions together shape the distribution of employment opportunities and the possible reproduction of social inequality.

Distribution of Employment Opportunities and the Reproduction of Inequality through Algorithmic Recruitment

The distribution of employment opportunities is one of the social consequences that needs attention when organizations use algorithms in the recruitment process. The opportunity to obtain employment is related not only to individual ability but is also influenced by access to information, recognition of qualifications, and the mechanisms that determine who can take part in the selection stages. When digital systems give candidates different priority based on particular indicators, applicants' chances of receiving recruiters' attention can change. These differences have meaning for individuals from social groups with limited access to education and professional networks (Sharma, 2025). If a system repeatedly places certain candidates at a low ranking, the opportunity to demonstrate their abilities can become increasingly narrow. This situation shows that algorithmic decisions are related to the allocation of opportunities in the labor market. The social assessment of technology needs to consider the distribution of advantages and disadvantages among prospective workers, not merely the speed of processing applications or the system's ability to produce a list of candidates.

The relationship between social class background and employment opportunities is shown by the research of Rivera and Tilcsik (2016) on class and gender signals in elite law firm recruitment in the United States. This audit study used applications designed to have similar qualifications but differing in social class and gender markers. The results showed that male candidates with high social class markers received more responses than the other groups of candidates. Further research on employers' assessments showed that candidates from a high social class can be regarded as a better cultural fit with elite firm culture. However, this advantage was not found with the same pattern among women because of negative assessments regarding career commitment. These findings show that social class can interact with other identity categories in producing employment opportunities. Although not an AI audit, the study shows assessment mechanisms that can become problematic when translated into digital selection criteria.

Reproduction of inequality through recruitment can occur when prior social advantages are reused as the basis for obtaining new opportunities. Applicants who have access to quality education, additional training, and professional experience may be better able to meet the indicators that organizations consider valuable. If AI systems give priority to these indicators without distinguishing ability from access to resources, groups that already hold advantages can gain broader opportunities. This process has the potential to maintain inequality between social groups through decisions that appear to be based on data (Mona, 2023). The digital skills gap and the risk of algorithmic bias in the use of AI demand the application of fair and ethical technology in order to maintain inclusiveness in employment opportunities (Darmawan, 2025). In such circumstances, candidate ranking can reflect a combination of individual competence and the earlier distribution of opportunities. These differences need attention because professional ability can develop through various educational pathways and work experiences. Using a single characteristic as a general measure of candidate quality risks

reducing the recognition of other forms of competence. Unequal opportunities can then affect career development and individuals' ability to obtain economic resources in the future.

Fourcade and Healy (2013) developed the concept of classification situations to explain how economic grouping systems can shape individuals' life chances. Their study mainly used the development of credit markets as an example of a classification mechanism that creates differences in opportunities. This framework can be used conceptually to understand AI-based recruitment because candidates can also be placed in categories or rankings that affect access to opportunities. In recruitment systems, such classification can take the form of the level of candidate fit, priority recommendations, or the decision to forward an application. If classification is linked to data that reflect social standing, digital processes have the potential to maintain the advantages of groups that hold greater educational capital and networks. However, the application of the credit market framework to recruitment needs to be understood as an extension of interpretation, not a direct empirical finding. The two fields have different purposes, information, and decision-making processes.

Inequality of opportunity can develop before candidates receive a formal assessment from recruiters. Digital platforms can arrange job vacancy information based on profile matching and particular criteria so that users have different job-search experiences. If an information-offering algorithm places certain professional opportunities more often before users with an educational history or network considered superior, applicants from other groups potentially receive more limited information (Santhosh, 2026). This situation needs to be understood as a possible mechanism of the distribution of opportunities, because evidence on the practices of each platform requires separate examination. When job information is not distributed evenly, the number of applicants entering the selection stage can reflect differences in access from the outset. As a result, organizations may judge the selection system to be fair because all applications received are processed with similar rules, while some prospective applicants have previously experienced limited access to information. The assessment of fairness needs to cover the process of searching for candidates and the dissemination of employment opportunities.

The relationship between algorithmic assessment and human decisions shows that recruitment outcomes are not always determined by technology alone. Bursell and Roumbanis (2024) studied changes in the recruitment process at a large food retail company in Sweden by comparing traditional recruitment data with algorithm-based recruitment data. The study found that the implementation of the new system was related to changes in the composition of the workers recruited, including an increased representation of younger workers, women, and individuals with surnames associated with European origin. Further analysis showed different patterns of bias at the algorithmic screening stage and the recruiters' decision stage. The algorithm tended to give an advantage to female candidates in certain assessments, while human recruiters showed a preference for candidates with names associated with European origin. These findings show that changes in the diversity of recruitment outcomes can arise through the relationship between technology and human decisions, not merely as a result of model bias. The sociological approach views the transformation of the world of work and AI-based algorithmic recruitment not merely as a technical change, but as a shift in social relations, power structures, and organizational authority that connects macro-level changes with micro-level practices (Mardikaningsih, 2025).

The decisions of recruiters after receiving algorithmic recommendations have a role in determining whether inequality is reinforced or reduced. Recruiters can use scores as one consideration, carry out additional checks, or choose candidates who do not hold the highest ranking. This authority has the potential to help recognize abilities that are less well represented in the data. For example, informal work experience or skills obtained through nonformal education may require further explanation before they can be compared with the qualifications of other candidates. A higher level of education tends to raise expectations regarding salary and type of job, which is reinforced by the social view that working in a large company or a government agency is more prestigious and stable than entrepreneurship (Khayru et al., 2022). However, human involvement does not necessarily produce fairer decisions. Recruiters can also be influenced by prejudice regarding university of origin, area of domicile, or the social characteristics of candidates. In such circumstances, human assessment can reinforce differences that have already been formed in the digital system. The relationship between technology and recruiters requires a clear division of responsibility so that final decisions can be examined based on reasons that are job-relevant.

Limited transparency is another problem that affects the position of applicants in AI-based recruitment. Carter (2024) explains that machine learning systems can create difficulties in proving discrimination because the relationship between input variables and decisions is not always easy to explain. In his study of European Union equality law, Carter shows that statistical complexity and limited access to system information can make it difficult for individuals to identify the reasons for disadvantageous treatment. This problem is relevant for candidates who are rejected without knowing which characteristics influenced the assessment results. Applicants may find it difficult to distinguish between rejection due to a lack of competence and the possible use of irrelevant social indicators. However, the study discusses European legal regulation and cannot directly be regarded as an explanation of all legal provisions in other countries. Its sociological value lies in the relationship between information inequality and individuals' ability to question decisions that affect their employment opportunities.

The assessment of fairness in algorithmic recruitment requires a separation between legitimate job requirements and social markers that do not have an adequate relationship with competence. An applicant's university of origin may provide information about curriculum or educational experience, but institutional prestige cannot always replace the

examination of individual skills. Likewise, area of domicile may be relevant for jobs that require physical presence at certain times, but geographic distance cannot automatically be used to infer work ability or commitment. Selection criteria need to be explained based on the tasks and abilities that are actually required. If a job can be performed remotely, the use of residential address as an indicator of candidate fit requires different consideration from jobs with fixed attendance schedules. Differences in the character of jobs show that bias checks cannot use the same assessment for all systems. Fairness requires a justifiable relationship between candidate information, job requirements, and decision outcomes.

Algorithm audits can be conducted by comparing system outputs against candidate profiles that have equivalent competencies but differ in certain social characteristics. In an audit of university of origin, for example, applicant profiles can be designed with comparable skills, experience, and achievements, while the identity of the educational institution is changed in a controlled manner. Changes in scores or rankings can be used to assess how much weight the system gives to these characteristics. A similar approach can be used to examine the use of area of domicile information while still considering the location requirements of the job (Shkajoti et al., 2026). However, differences in results in testing do not necessarily directly show discrimination without examining the relevance of the variables and the characteristics of the system. Audits need to cover data quality, the formation of comparison groups, the setting of selection thresholds, and human decisions at subsequent stages. Such checks can help organizations distinguish modeling errors from broader problems of social inequality.

Reducing inequality in digital recruitment requires attention to how organizations design and use assessment systems. Technology developers need to work with those who understand job requirements so that the variables used do not merely follow the patterns of previous candidate acceptance. Information about university of origin can be examined for its relevance to competence, while the use of location data needs to be adjusted to actual job needs (Wang, 2026). Organizations can also provide opportunities for direct ability assessment through skills tests or relevant portfolio checks. However, changing variables alone does not necessarily solve the problem if access to experience and training remains uneven. Improving the process requires evaluating selection outcomes by group of applicants, reviewing complaints, and providing opportunities to re-examine questionable decisions. The responsibility of organizations does not end with the consistent use of technology but includes assessing the social consequences of the decisions it produces.

Algorithmic screening and recruiters' decisions shape the distribution of employment opportunities through the relationship between digital classification, applicants' social capital, and human authority in determining selection outcomes. Algorithms can reinforce inequality when indicators related to social class advantages are used without examining their relevance to the job. Conversely, digital systems have the possibility of supporting more consistent assessment when they use appropriate measures of competence and are checked regularly. The decisions of human recruiters can improve or worsen this inequality, depending on how technological recommendations are used. The reproduction of social class is not a certain result of the use of AI, but a possibility that develops through the relationship between data, selection criteria, and organizational practices. The equitable distribution of opportunities requires assessment transparency, examination of proxy variables, and a clear division of responsibility between system developers and those who make recruitment decisions.

CONCLUSIONS

AI-based recruitment algorithms can function as a social class screening mechanism when information about university of origin, residential location, and applicant characteristics is used as assessment indicators without adequate examination of their relevance. Inequality has the potential to form through historical data, proxy variables, candidate ranking, and the determination of selection thresholds. This process can reinforce the advantages of groups that previously had broader access to education and professional opportunities. Nevertheless, the evidence reviewed does not show that all platforms automatically exclude applicants from peripheral areas or non-elite universities. The distribution of employment opportunities is also influenced by the decisions of human recruiters, which can reinforce or reduce algorithmic bias. The reproduction of inequality through AI is the result of the relationship between system design, social data, and organizational practices. The assessment of recruitment fairness requires a thorough examination of these mechanisms.

The results of the discussion have theoretical implications for understanding recruitment technology as part of the process of reproducing social stratification. Algorithms cannot be separated from the structure of educational opportunity, the distribution of resources, and organizational habits that influence the formation of data and decisions. Academically, this synthesis shows the need to connect the study of algorithmic fairness with the sociology of social class to explain how applicant characteristics are translated into digital assessments. The practical implications concern the responsibility of organizations to ensure that the use of AI is based on measures of competence that are job-relevant. System developers and recruiters need to examine the possibility of bias against different groups of applicants and provide adequate explanations of the selection process. The use of technology can support consistency of decisions, but this benefit needs to be assessed together with the openness of the process and applicants' opportunity to receive treatment that can be justified.

REFERENCES

Agan, A., & S. Starr. (2024). Employers' neighborhoods and racial discrimination. The Journal of Legal Studies, 53(1), 115–158. https://doi.org/10.1086/728242

Altun, F. (2026). Opportunity inequalities in the labour market in the context of artificial intelligence and algorithmic bias (pp. 43–61). https://doi.org/10.17574/tesam.9786258595314-175152

Aminou, L., Daaif, A., Soulami, M., Chalfaouat, A., & Youssfi, M. (2025). Are cutting-edge technologies transforming classical approaches in automated hiring systems? A systematic literature review. Systems and Soft Computing, 200421. https://doi.org/10.1016/j.sasc.2025.200421

Barocas, S., & A. D. Selbst. (2016). Big data's disparate impact. California Law Review, 104(3), 671–732. https://doi.org/10.2139/ssrn.2477899

Bursell, M., & Roumbanis, L. (2024). After the algorithms: A study of meta-algorithmic judgments and diversity in the hiring process at a large multisite company. Big Data & Society, 11(1), 20539517231221758. https://doi.org/10.1177/20539517231221758

Carter, C. (2024). Why the algorithmic recruiter discriminates: The causal challenges of data-driven discrimination. Maastricht Journal of European and Comparative Law, 31(3), 333–359. https://doi.org/10.1177/1023263X241248474

Darmawan, D. (2024). Algorithmic Management in Digital Platforms and Work Dehumanization in the Gig Economy. Studi Ilmu Sosial Indonesia, 4(2), 183–216.

Darmawan, D. (2025). Job Redesign, Automation, and Digital Workforce Competencies in the Twenty-First Century. Bulletin of Science, Technology and Society, 4(3), 103–114.

Darmawan, D. (2025). Work Readiness, Digital Skills, and Employability: A Study on the Moderating Effect of Digital Skills Among College Students. Studi Ilmu Sosial Indonesia, 5(2), 157–178.

Essa, N. E., R. Mardikaningsih, & A. B. Ismail. (2024). Service Transformation through Technology: The Role of AI and Big Data in Service Science. Journal of Social Science Studies, 4(1), 193–200.

Fourcade, M., & K. Healy. (2013). Classification situations: Life-chances in the neoliberal era. Accounting, Organizations and Society, 38(8), 559–572. https://doi.org/10.1016/j.aos.2013.11.002

Fourcade, M., & K. Healy. (2017). Seeing like a market. Socio-Economic Review, 15(1), 9–29. https://doi.org/10.1093/ser/mww033

Gaddis, S. M. (2015). Discrimination in the credential society: An audit study of race and college selectivity in the labor market. Social Forces, 93(4), 1451–1479. https://doi.org/10.1093/sf/sou111

Gani, A., & D. Darmawan. (2022). Ethics and Accountability in Artificial Intelligence-Based Managerial Decision Making. Journal of Social Science Studies, 2(1), 147–152.

Gani, A., D. Darmawan, & M. Irfan. (2025). Youth Social Mobility in the Gig Economy and Digital Platform Work. International Journal of Service Science, Management, Engineering, and Technology, 7(1), 35–43.

Idrus, S. (2025). The role of artificial intelligence technology in simplifying employee recruitment and selection processes. The Journal of Academic Science, 2(6), 1647-1656. https://doi.org/10.59613/6sh4x080

Kelan, E. K. (2024). Algorithmic inclusion: Shaping the predictive algorithms of artificial intelligence in hiring. Human Resource Management Journal, 34(3), 694–707. https://doi.org/10.1111/1748-8583.12511

Khayru, R. K., D. Darmawan, & Y. Kurniawan. (2022). An Analysis of the Impact of Age, Work Experience, and Gender on Job Search Duration Among Graduates. Journal of Social Science Studies, 2(2), 139–144.

Köchling, A., & M. C. Wehner. (2020). Discriminated by an algorithm: A systematic review of discrimination and fairness by algorithmic decision-making in the context of HR recruitment and HR development. Business Research, 13, 795–848. https://doi.org/10.1007/s40685-020-00134-w

Liu, Y., Z. Chen, & Y. Ji. (2026). The algorithmic class ceiling: How AI interviews exacerbate social class inequities in hiring. Proceedings of the Academy of Management, 2026(1), https://doi.org/10.5465/amproc.2026.18321poster

Maliki, S. E., & K. Khammam. (2026). Ethical challenges of AI in recruitment: How HR can tackle bias and promote fairness: Systematic literature review (pp. 1–6). https://doi.org/10.1109/iccsc71566.2026.11650533

Mardikaningsih, R. (2025). The Deconstruction of Work and HRM Reconfiguration: Flexibility and Employer Branding in the Digital Era. International Journal of Service Science, Management, Engineering, and Technology, 8(2), 10–17.

Mona, S. (2023). AI and inequality in hiring and recruiting: A field scan. https://doi.org/10.34669/wi.cp/5.3

Pandit, S. K., K. Chakraborty, S. Rajak, S. Biswas, & I. Roy. (2026). A systematic review of technology-assisted recruitment practices and their impact on modern hiring, 147–151. https://doi.org/10.1201/9781042014446-25

Prykhodko, T. (2026). Bias in AI admission and hiring. European Journal of Interdisciplinary Issues, 3(1), 113–122. https://doi.org/10.68197/3071-9658/3.1.11

Putra, A. R., D. Darmawan, & S. Arifin. (2022). Employee Experience in the Digital Workplace: A Human Resource Management Perspective. Studi Ilmu Sosial Indonesia, 2(2), 361–384.

Raghavan, M., Barocas, S., Kleinberg, J., & Levy, K. (2020, January). Mitigating bias in algorithmic hiring: Evaluating claims and practices. In Proceedings of the 2020 conference on fairness, accountability*, and transparency* (pp. 469-481). https://doi.org/10.1145/3351095.3372828

Rajesh, D., D. L. Narayana, R. Sood, M. Sharma, M. Lourens, & A. Prakash. (2025). Bias detection and fairness in AI-based hiring systems (pp. 911–915). https://doi.org/10.1109/aece67531.2025.11386524

Rivera, L. A. (2012). Hiring as cultural matching: The case of elite professional service firms. American Sociological Review, 77(6), 999–1022. https://doi.org/10.1177/0003122412463213

Rivera, L. A., & A. Tilcsik. (2016). Class advantage, commitment penalty: The gendered effect of social class signals in an elite labor market. American Sociological Review, 81(6), 1097–1131. https://doi.org/10.1177/0003122416668154

Santhosh, S. (2026). The shifted burden of search: how digital hiring platforms reallocate screening labor to job seekers. Frontiers in Human Dynamics, 8, 1924666.https://doi.org/10.3389/fhumd.2026.1924666

Sharma, R. (2025). The Algorithmic Crucible: Exploring the Impact of AI-Driven Recruitment on Workforce Diversity and Inclusion. JANOLI International Journal of Human Resource and Management, 1(2), https://doi.org/10.64758/hbg0ke67

Shkajoti, X., M. Ullasci, M. Rondina, R. Coppola, A. Vetrò, & L. Calò. (2026). Auditing bias in AI-based hiring systems: A fairness analysis of nationality and gender discrimination. GoodIT '26: Proceedings of the 2026 International Conference on Information Technology for Social Good 411 – 419. https://doi.org/10.1145/3794786.3830781

Sinambela, E. A. (2023). Integration of Change Management and Technology Strategy in Digital Transformation. Journal of Social Science Studies, 3(1), 375–380.

Tayyab, A., & S. M. A. Shah. (2025). Algorithmic bias in AI-driven hiring platforms and its intersectional impact on social inequality: A survey of job seekers and platform users in the Global South. 2(2), 8–14. https://doi.org/10.65761/jssp.2025.21

Wang, N.-H. (2026). The algorithm-mediated inequality regime in hiring: A systematic review and integrative framework. Computers and Artificial Intelligence. 3(4):146-162. https://doi.org/10.70267/cai.v3n4.146162

Whittemore, R., & K. Knafl. (2005). The integrative review: Updated methodology. Journal of Advanced Nursing, 52(5), 546–553. https://doi.org/10.1111/j.1365-2648.2005.03621.x

Wilson, K., & A. Caliskan. (2024). Gender, race, and intersectional bias in resume screening via language model retrieval. Proceedings of the AAAI/ACM Conference on AI, Ethics, and Society, 7(1), 1578–1590. https://doi.org/10.1609/aies.v7i1.317482.