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Article

Algorithmic barriers: Investigating student perceptions of AI bias in subjective "culture fit" hiring

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SUMMARY

The growing adoption of artificial intelligence (AI) in corporate hiring creates serious ethical concerns because it evaluates subjective parameters like "culture fit". One particular concern is that AI recruitment platforms, tasked with assessing whether a candidate's values align with a company's culture, may reinforce existing biases through pattern replication and amplification. While marketed as objective, these platforms learn from data containing embedded discriminatory patterns, creating feedback loops that systematically disadvantage underrepresented groups. Drawing on institutional isomorphism theory, prior research suggests that organizations that adopt these technologies are often driven by legitimacy-seeking rather than demonstrated fairness. We hypothesized that high school and college students would express significant concerns about AI-based culture fit assessments, perceiving these systems as likely to reinforce existing biases and systematically disadvantage marginalized applicants in hiring decisions. Our hypothesis was supported by our survey of 150 high school and early-college students in Kathmandu Valley, Nepal, revealing widespread awareness and concern about algorithmic bias among emerging workforce participants. Binary logistic regression analysis found that ethnicity significantly predicts concern about AI bias. Our research shows that emerging workforce participants perceive AI-driven hiring as a potential source of systematic barriers to workplace equity, particularly for neurodivergent, disabled, and culturally diverse applicants, highlighting the need for robust ethical oversight.

INTRODUCTION

The implementation of artificial intelligence (AI) in corporate recruitment has transformed talent acquisition with the goal of enhancing operational efficiency and objectivity. Recent industry reports indicate that between 2023 and 2024, approximately one quarter of the human resources departments in the United States adopted AI tools for recruitment, and two-thirds of organizations use AI for resume screening, interview coordination, and candidate communication (1).

Central to the shift in the use of AI in hiring is the algorithmic assessment of "culture fit," a concept academically termed Person-Organization fit, defined as the compatibility of an individual's values and beliefs and the prevailing culture of an organization (2). While strong Person-Organization fit is linked to positive outcomes like job satisfaction, its practical application often turns vague, becoming an imprecise proxy for social and personal similarity that creates homogeneity and encourages unconscious bias (3). The delegation of subjective judgment assessment to algorithms raises significant concerns across ethical, legal, and organizational domains.

Person-Organization fit assessment has transitioned from unstructured interviews to psychometric assessments including personality inventories, situational judgment tests, and emotional intelligence measures (4). More recently, Natural Language Processing (NLP) tools have emerged to screen resumes and application materials for patterns correlated with past hiring decisions (5). Video interview analysis platforms now use computer vision and voice analysis to assess candidates' emotional expressions and speech patterns (6). These systems claim to evaluate cultural alignment, but scholars still question their validity in the literature (5, 7). Therefore, these systems designed to reduce bias may instead perpetuate and amplify it (7, 8).

Machine learning models are good at pattern matching but can generate socially discriminatory outcomes when trained on biased historical data (7, 8). Amazon's experimental recruiting tool was built in 2014 and abandoned in 2018 and was found to penalize resumes containing the word 'women's' and systematically down-ranked graduates of two all-women's colleges (9). A 2023 study found that AI hiring tools can simultaneously favor female candidates in some contexts while penalizing Black male applicants with equivalent qualifications (10). A 2024 multidisciplinary survey documented that multiple commercial hiring systems demonstrated statistically significant bias against candidates with disabilities and those from non-Western cultural backgrounds (11). These findings demonstrate that algorithmic bias in hiring is not a theoretical concern but a documented empirical phenomenon.

Despite the documented bias, many companies are still adopting these AI hiring technologies. The rapid adoption of AI hiring technologies can be understood through the institutional isomorphism theory, which suggests that organizational structures and practices are often shaped by cultural and social pressures rather than demonstrated effectiveness (12). First, coercive isomorphism arises from regulatory demands, compelling organizations to adopt systems marketed as legally defensible (12). Companies may adopt AI believing they provide legal protection against discrimination lawsuits through "objective" decision-making, despite evidence that these systems can amplify bias (12). Second, normative isomorphism stems from professional standards propagated by educational institutions, consulting firms, and professional associations (12). Human resources conferences increasingly promote AI adoption as best practice, creating pressure to conform (13). Third, mimetic

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isomorphism occurs when organizations imitate competitors perceived as successful (12). When leading technology companies adopt AI screening tools, others follow to signal innovation, regardless of actual effectiveness (13).

Despite this growing adoption, limited research has examined the perceptions of those who will be directly evaluated by these systems. The adoption of AI in hiring creates a critical gap between the organizational rationale for adopting AI and the lived experience of the people being evaluated. Recent surveys show growing skepticism among younger workers. A 2024 Deloitte survey found that over half of Generation Z and millennial workers believe AI will require them to reskill and impact their career decisions (14). Research from Morning Consult revealed that three in five Generation Z members think AI will make it harder for them to enter the workforce (15). In particular, high school and early-college students, who will increasingly encounter AI-driven hiring as they enter the workforce, remain understudied in this literature. To address this gap, we investigated the disconnect between organizational adoption and workforce perception, exploring student awareness and concerns regarding AI-driven "culture fit" assessments. We hypothesized that students, particularly those from historically marginalized ethnic groups, would report low confidence in the fairness of AI-based "culture fit" assessments and express significant concern that these systems could perpetuate discrimination. Our findings supported this hypothesis: a survey of 150 students in Kathmandu Valley, Nepal, revealed widespread skepticism about AI fairness among students, with ethnic minority students significantly more likely to express concern about AI bias than majority students. These results demonstrate that young people entering the workforce are deeply concerned about the discriminatory potential of AI hiring platforms. By employing a mixed-methods approach, we aimed to provide evidence of a growing legitimacy challenge for AI in hiring.

RESULTS

Demographic Characteristics of the Sample

Our survey captured responses from 150 participants from high schools and colleges in Kathmandu Valley, Nepal, representing the emerging workforce aged 16-20 (Mean (M)=17.8, Standard Deviation (SD)=1.2). The sample included 58% women (n=87), 41% men (n=61), and 1% non-binary (n=2), with ethnic representation combined for statistical analysis into an "ethnic majority" category (Brahmin/Chhetri; 45%, n=67) and an "ethnic minority" category (Newar, Janajati, Dalit, and other groups, 55%, n=83).

Student Awareness, Confidence, and Concerns Regarding AI in Hiring

We first asked students about their awareness, confidence, and concerns regarding the use of AI in hiring. We found a level of familiarity with AI's role in recruitment but also low confidence about AI's fairness **(Figure 1)**. 88% (n=132) of respondents reported being aware that companies use AI in hiring processes. However, higher awareness was not associated with greater acceptance. There was a moderate, statistically significant negative correlation between awareness and confidence in AI fairness ($\rho=-0.42$, $p<.001$), indicating that as awareness increases, confidence in fairness decreases. When asked to rate their confidence on a five-point Likert scale, 68% (n=102) of students rated their confidence as 1 or 2 on the five-point scale (where 1=very low and 5=very high confidence), while only 8% (n=12) indicated a rating of 4 or 5. The mean confidence score was 2.3 (SD=1.0), which falls below the scale midpoint of 3.0. Beyond confidence, we also assessed the level of concern. A large majority of students (75%, n=113) reported being "concerned" or "very concerned" about the potential for bias in the AI hiring systems. To mitigate concerns about bias, the majority of the respondents supported transparency (91%, n=136), human oversight (82%, n=123), and regular independent fairness audits (79%, n=118) **(Figure 2)**.

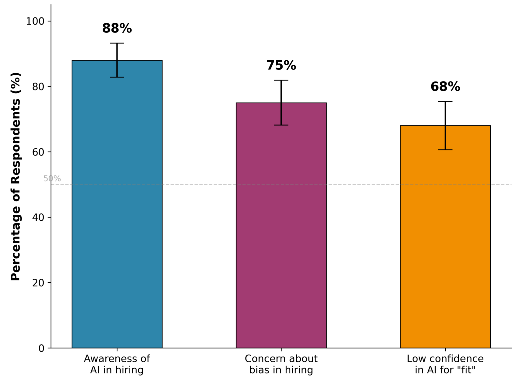

Figure 1. Student attitudes toward AI use in hiring indicate high concern and awareness. Bar graph illustrating the proportion of respondents (n=150) reporting awareness of AI use in hiring (88%), concern about bias in such systems (75%), and low confidence in AI's ability to evaluate "culture fit" (68%). Y-axis represents the percentage of respondents (%). Error bars represent 95% confidence intervals calculated using the Wilson score method for binomial proportions (32).

Ethnic and Gender Identity Differences in Perceptions of AI Fairness

Our survey showed that confidence ratings were

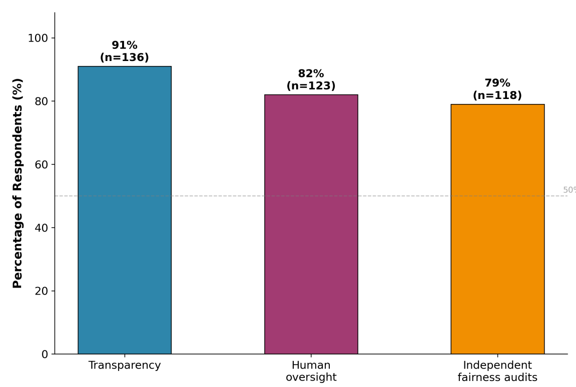

Figure 2. Student preferences for safeguards in AI hiring systems. Bar graph showing the percentage of respondents (N=150) who expressed support for each proposed safeguard mechanism: transparency (91%, n=136), human oversight (82%, n=123), and independent fairness audits (79%, n=118). Error bars represent 95% Wilson confidence intervals. All three safeguards received support from over three-quarters of respondents.

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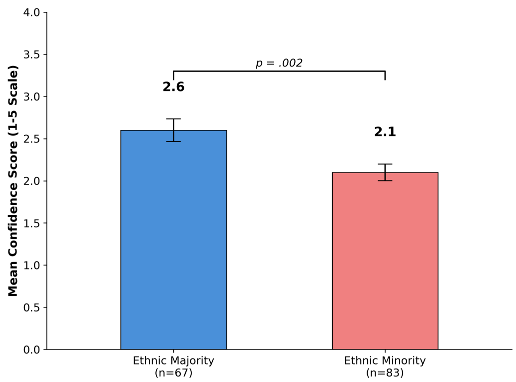

Figure 3. Confidence in AI fairness differs significantly by student ethnicity. Bar graph showing the mean confidence scores on a 5-point Likert scale (1=very low confidence, 5=very high confidence) for ethnic majority (Brahmin/Chhetri, n=67) and ethnic minority (Newar, Janajati, Dalit, and other groups, n=83) students regarding AI's ability to make fair hiring decisions. Minority students reported significantly lower confidence in AI fairness (M=2.1, SD=0.9) compared to majority students (M=2.6, SD=1.1), t(148)=3.12, *p*=.002, two-tailed independent samples t-test. Error bars represent standard error of the mean.

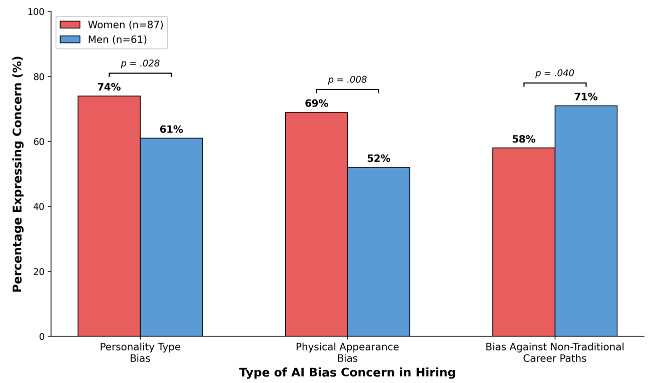

Figure 4. Gender identity differences in specific concerns regarding AI bias. Grouped bar graph showing the percentage of women (n=87) and men (n=61) who expressed concern about specific potential biases in AI hiring systems. Only concerns with statistically significant differences are displayed, as determined by chi-square tests of independence. Women expressed significantly higher concern about personality type bias ($\chi^2(1)=4.82$, *p*=.028) and physical appearance bias ($\chi^2(1)=7.13$, p=.008), while men expressed significantly higher concern about recognition of non-traditional career paths ($\chi^2(1)=4.21$, *p*=.040).

significantly lower for ethnic minority students (M=2.1, SD=0.9) than for majority students (M=2.6, SD=1.1, t(148)=3.12, *p*=.002) **(Figure 3)**. Next, we examined whether gender identity differences impacted perceptions of AI fairness. Women were significantly more concerned than men about AI systems making judgments based on personality type (74% vs. 61%, $\chi^2(1, N=148) = 4.82$, *p*=.028) and physical appearance in video interviews (69% vs. 52%, $\chi^2(1, N=148) = 7.13$, *p*=.008) **(Figure 4)**. Conversely, men were significantly more concerned about an AI's ability to recognize non-traditional career paths (71% vs. 58%, χ^2 (1, N=148) = 4.21, *p*=.040). These findings suggest that perceptions of AI fairness in hiring vary significantly by both gender identity and ethnic background.

Qualitative Analysis of Student Concerns

To gain a deeper understanding of students' specific concerns, we also analyzed open-ended survey responses through rigorous thematic analysis. Three main themes emerged: discrimination against neurodiversity, cultural and linguistic bias, and the self-reinforcing nature of algorithmic feedback loops **(Table 1)**. For instance, one student articulated a specific fear regarding neurodiversity: "My cousin is autistic and doesn't make as much eye contact. An AI scanning video interviews would likely flag him down as ‘poor engagement’ when in fact he's just thinking differently." Another student described concerns about linguistic diversity: "I code-switch between how I speak at home and how I speak at school. Which one would the AI think has better ‘culture fit’?". These responses illustrate that students are aware of specific ways AI systems may disadvantage certain groups. Overall, the open-ended responses demonstrated a notably high level of algorithmic literacy, with students articulating specific technical mechanisms through which AI systems could perpetuate bias.

Underlying Attitudinal Structures and Predictors of Concern

To identify the underlying structure of student attitudes toward AI in hiring, we conducted a principal component analysis (PCA; see Materials and Methods for analytical details). The analysis revealed three distinct attitudinal dimensions that collectively explained 67.3% of the total variance: (1) Fairness Skepticism, reflecting the belief that AI hiring systems are inherently unfair and biased (eigenvalue=3.42, 26.8% variance); (2) Technological Determinism, capturing the perception that AI adoption is inevitable and resistance is futile (eigenvalue=2.87, 22.1% variance); and (3) Change Agency, representing the belief that young people can actively influence how AI is designed and used (eigenvalue=2.31, 18.4% variance) **(Table 2)**. Cronbach's alpha values (Fairness Skepticism α=0.84; Technological Determinism α=0.81; Change Agency α=0.79) indicate high internal consistency. Next, we determined whether there were demographic predictors of concern about AI bias. We found that different demographic characteristics significantly predicted concern about AI bias ($\chi^2(3, N=148) = 12.55$, *p*=.006). Students from ethnic minority backgrounds were 2.85 times more likely to express concern about AI bias than students from the majority ethnic group (OR=2.85, 95% CI [1.37, 5.92], *p*=.005). However, gender identity (OR=1.57, 95% CI [0.69, 3.56], *p*=.284) and first-generation student status (OR=1.23, 95% CI [0.55, 2.75], *p*=.611) were not significant predictors.

DISCUSSION

Our study demonstrated that while organizations quickly adopt AI hiring solutions under institutional pressures to signal innovation, the emerging workforce views these tools with low confidence and skepticism. This cohort's high awareness of AI in hiring, combined with its low confidence in fairness, suggests that increased familiarity does not

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Theme	Definition	Exemplar Quotes
Neurodiversity Bias	The concern that AI systems, trained predominantly on neurotypical communication patterns and social behavior, will unfairly penalize qualified candidates with conditions like autism or ADHD for exhibiting non-standard social cues (e.g., eye contact, speech patterns).	"Someone with autism might avoid eye contact while processing information deeply. AI would score this as 'poor engagement' when it's actually intense focus." "My ADHD makes me talk fast sometimes and jump between ideas. I worry a system would flag that as being nervous or dishonest, not just how my brain works."
Cultural & Linguistic Bias	The fear that AI will misinterpret cultural or linguistic variations—such as code-switching, non-standard dialects, or accents—as a lack of professionalism or "fit," thereby enforcing a monolithic, often Western, standard of communication and penalizing cultural diversity.	"I code-switch between how I speak at home and how I speak at school. Which one would the AI think has better 'culture fit'? Would it see switching as inconsistent or fake?" "My accent is not standard. An AI analyzing my speech might rate my communication skills lower, even if I'm perfectly clear and articulate in my own way."
Algorithmic Feedback Loops	The sophisticated understanding that AI systems trained on biased historical hiring data will perpetuate and amplify that bias over time, creating a self-reinforcing cycle where initial discrimination becomes increasingly entrenched as the system generates new data that confirms its original biased patterns.	"If the AI is trained on who the company hired before, and they were all from similar backgrounds, then it will just keep hiring similar people. The system gets more and more certain about its own bias over time." "It's a loop. The more it hires one type of person, the more data it has to 'prove' that's the 'right' type of person. Eventually nobody else can break in."

Table 1. Thematic analysis of open-ended responses regarding perceived AI harms. The table presents the major themes identified through inductive thematic analysis of student open-ended responses (N=150), their definitions, and representative illustrative quotes from participants. Themes were identified through independent coding by two researchers followed by iterative refinement and consensus discussion. Inter-rater reliability: Cohen's κ = 0.84, indicating excellent agreement.

correspond with increased confidence. The significant negative correlation between awareness and trust indicates that the more students learn about AI hiring systems, the less they trust them **(Figure 1)**. These findings are consistent with institutional isomorphism theory. Organizations adopt AI due to mimetic and normative pressures, prioritizing data-driven trends over actual fairness. A previous study found that organizations often prioritize the perceived legitimacy of AI adoption over demonstrated effectiveness in improving hiring outcomes (17). The low confidence in AI fairness and high concern about bias reported by students suggest that organizations using AI hiring tools may face challenges in attracting candidates from this generation.

As shown in the qualitative results **(Table 1)**, student concerns reflect a high level of algorithmic literacy. Participants in this study described algorithmic feedback loops, noting that systems trained on a homogeneous workforce prefer similar candidates. This may indicate that skepticism can stem from the recognition that AI can codify existing societal biases. Previous research studies have shown that AI systems trained on neurotypical behavior patterns create systematic disadvantages for neurodivergent individuals (18, 19). Similarly, NLP systems trained on standardized language data led to systematic discrimination against speakers of non-standard dialects (20). Notably, students in our study specifically raised these same concerns about neurodiversity discrimination and language-based bias (Table 1), demonstrating awareness that aligns with the existing literature. While the logistic regression identified ethnicity as a significant predictor, the relatively wide confidence interval suggests that while the direction of the effect is robust, the precise magnitude of the risk requires larger sample sizes to estimate with high precision.

The lower confidence reported by ethnic minority students, who were significantly more likely to express concern, may be informed by historical experiences with discriminatory evaluation systems, as documented in prior research on institutional bias (21). Similarly, women's significantly higher concern about appearance-based judgments and personality-based assessments is consistent with documented patterns of gender-based evaluation bias in professional settings (22). Future research should implement an intersectional lens to study these demographic factors instead of studying them independently (23).

It is important to acknowledge potential response bias in our survey design. By providing participants with a list of potential concerns, we may have primed them to think about issues they would not have raised independently. We attempted to mitigate this limitation by including open-ended questions. The strong congruence between quantitative findings and spontaneously emerging qualitative themes

Survey Item	Factor 1: Fairness Skepticism	Factor 2: Technological Determinism	Factor 3: Change Agency
[Q14] AI learning from historically biased data	**0.82**	0.15	-0.08
[Q10] I worry AI systems will discriminate	**0.79**	0.21	0.12
[Q14] AI's inability to understand individual context	**0.75**	0.09	-0.05
[Q9] I trust AI systems to make unbiased decisions	**0.71**	-0.12	0.03
[Q15] The use of AI in hiring is inevitable	0.11	**0.84**	-0.14
[Q15] Most companies will use it in the future	0.18	**0.81**	0.07
[Q16] It is pointless to resist the adoption of AI	0.08	0.78	-0.22
[Q18] Youth activism can lead to real change	-0.09	-0.17	**0.86**
[Q17] My generation can influence how AI is designed	0.14	-0.11	**0.83**
[Q19] Important for youth to learn how AI works	0.02	-0.19	**0.79**
Eigenvalue	3.42	2.87	2.31
% Variance Explained	26.8%	22.1%	18.4%
Cronbach's α	0.84	0.81	0.79

Table 2. Principal component analysis of attitudinal factors with varimax rotated factor loadings. Varimax rotated factor loadings for the three-factor solution of student attitudes toward AI in hiring (N=150). Loadings greater than 0.50 are shown in bold to indicate strong association with that factor. Factor extraction method was Principal Component Analysis with varimax rotation. Kaiser-Meyer-Olkin measure of sampling adequacy = 0.79. Bartlett's test of sphericity: $\chi^2(105)=845.2$, $p<.001$. Total variance explained by three factors = 67.3%.

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suggests these concerns are authentic. The research sample consists of residents from Kathmandu Valley, Nepal, which restricts the study from representing worldwide populations. The research findings about AI concerns match the concerns expressed by Western populations (24). The cross-sectional design shows student attitudes at one point in time but cannot show how perceptions change after gaining direct experience.

With these limits, our findings provide specific recommendations for practice. Students strongly support transparency, fairness audits, and human oversight, signaling a demand for a human-in-the-loop approach rather than a rejection of technology **(Figure 2)**. Given that most respondents expressed concern about AI bias and reported low confidence in AI fairness, organizations that do not address these concerns may face challenges in attracting candidates from this demographic. Our findings suggest that organizations using AI in hiring should consider implementing the transparency, human oversight, and independent auditing mechanisms that this generation of candidates demands (25, 26). These findings indicate that AI hiring systems face a growing legitimacy challenge, as the individuals these systems evaluate report low confidence in their fairness.

MATERIALS AND METHODS

Study Design

The study was conducted in two phases in Kathmandu Valley, Nepal. Phase I (November–December 2024) consisted of survey instrument piloting and cognitive interviews to validate questions. Phase II (January–February 2025) involved data collection. The study protocol underwent independent ethical review by the Patan Academy of Health Sciences and was granted an exemption from full Institutional Review Board (IRB) review, confirming that the anonymous survey protocol posed minimal risk to participants. The survey instrument was developed through a rigorous, multi-stage process grounded in established psychometric principles drawing upon the Technology Acceptance Model, the Organizational Justice Scale, and foundational literature on algorithmic trust (27, 28, 29). An initial set of 25 survey items was generated. A content validity assessment was conducted with three independent experts, and cognitive interviews were performed with five students to validate survey clarity. The survey instrument was tested with a pilot group of 10 students who evaluated both the survey flow and completion duration. The final survey instrument consisted of 15 Likert-scale items, 5 multiple-choice questions, and 4 open-ended questions, which participants needed approximately 8-12 minutes to complete.

Participant Recruitment and Sampling

A multi-site convenience sampling strategy was utilized to achieve demographic diversity. Partnerships were established with three secondary schools in Kathmandu Valley and two community colleges that serve students from diverse caste and ethnic backgrounds. Student selection bias was minimized through the use of general-access channels for participant enrollment. Announcements were made by school counselors describing "a study on youth perspectives about the future of work." Dual consent procedures were implemented for all minor participants (aged 16–17). This required parental notification with an opt-out model and mandatory written assent from the student. Although the primary consent document referenced '17-year-olds,' the same assent protocol and comprehensibility standards were strictly applied to the 16-year-old cohort. No compensation was provided. The study initiated with 157 participants; however, 7 responses were excluded due to incomplete data or failed attention checks, resulting in a final analytical sample of 150. Sample size determination was based on practical feasibility given recruitment constraints and the goal of achieving adequate demographic diversity. A sensitivity analysis using G*Power software indicated that with N=150, the study achieved >0.80 power to detect medium effect sizes (Cohen's h=0.5) in chi-square tests of association and Cohen's d=0.5 in independent samples t-tests at $\alpha=0.05$, meeting conventional standards for social science research. This demographic data revealed that 34% (n=51) were first-generation college students. Two participants identified as non-binary; due to this small sample size, their data were included in overall descriptive statistics but excluded from binary gender identity-based comparative analyses. Students self-identified the following demographic characteristics: gender identity, ethnicity, age, current education level, parental education level (16), and employment-seeking status.

Data Collection

Data were collected using the Qualtrics online survey platform. The survey was administered in English, the primary medium of instruction in participating schools and colleges. The survey included three attention-check items which served to verify data quality. The system tracked how long participants spent on the survey, and surveys that took less than three minutes were flagged for review. Seven surveys were excluded based on this criterion. The survey was administered during regular class hours while a team member remained present to answer any questions about the procedure. No personally identifying information was collected.

Data Analysis

Quantitative data were analyzed using IBM SPSS Statistics Version 28. All visualizations were generated using Python 3.9 with Matplotlib and Seaborn libraries. Descriptive statistics were calculated for all variables. The distribution of continuous variables was assessed using the Shapiro-Wilk test. When data violated assumptions of normality, non-parametric alternatives were employed. Specifically, the relationship between awareness and confidence was assessed using Spearman's rank-order correlation. Group differences in mean confidence scores were assessed using independent samples t-tests. Chi-square tests were used to examine associations between categorical variables.

PCA with varimax rotation was conducted to explore the underlying structure of attitudinal survey items. Varimax rotation was selected over oblique rotation methods (promax, oblimin) because preliminary analysis indicated low inter-factor correlations (<0.3), suggesting orthogonal factors were appropriate. The varimax method generates uncorrelated factors which help interpretation and reduce multicollinearity in future analyses. The analysis was justified by a Kaiser-Meyer-Olkin measure of 0.79 and a significant Bartlett's

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test of sphericity ($\chi^2(105)=845.2$, $p<.001$). Factors with eigenvalues greater than 1.0 were retained. The final three-factor solution was rotated using varimax rotation. Internal consistency reliability for each factor was assessed using Cronbach's alpha.

Binary logistic regression was selected as the primary method for estimating odds ratios in this cross-sectional survey design (30). Our dependent variable, "concerned about AI bias," was dichotomized such that students who selected "concerned" or "very concerned" were coded as 1, and all other responses were coded as 0. Three predictor variables were entered simultaneously: gender identity (woman=1, man=0), ethnicity (minority=1, majority=0), and first-generation student status (yes=1, no=0). Model fit was assessed using the chi-square goodness-of-fit test, and variance explained was estimated using Nagelkerke pseudo-R^2.

Qualitative data from open-ended questions were subjected to inductive thematic analysis following Braun and Clarke (31). All responses were independently read by two researchers, and initial codes were generated. Codes were grouped into potential themes through iterative comparison. Inter-rater agreement was formally assessed on a randomly selected 20% subset of responses, yielding a Cohen's Kappa of 0.84. Disagreements were resolved through discussion. The final coding scheme was applied to the entire dataset. All qualitative data were managed using NVivo software (33). Participant quotes presented were lightly edited for grammatical clarity while preserving original meaning and intent, consistent with standard qualitative research practice.

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Appendix A: Survey Instrument

Section 1: Demographics

Please answer the following questions about yourself. All responses are confi dential.

1. What is your age? _____ years
2. What is your current educational level?
• ☐ High school senior (Grade 11-12)
• ☐ First-year college/university student
• ☐ Second-year college/university student • ☐ Other (please specify): ______________
3. What is your gender identity? ☐ Woman
• ☐ Man
• ☐ Non-binary
• ☐ Prefer not to say
• ☐ Prefer to self-describe: ______________
4. Which of the following best describes your ethnic background?
• ☐ Brahmin
• ☐ Chhetri
• ☐ Newar
• ☐ Janajati (indigenous ethnic groups)
• ☐ Dalit
• ☐ Other (please specify): ______________
• ☐ Prefer not to say
5. What is your parent's or guardian's highest level of education?
• ☐ No formal education
• ☐ Primary school (grades 1-5)
• ☐ Secondary school (grades 6-10)
• ☐ Higher secondary/intermediate (grades 11-12)
• ☐ Bachelor's degree
• ☐ Master's degree or higher
• ☐ Don't know
6. Are you currently actively seeking employment (including part-time jobs, internships, or volunteer positions)?
• ☐ Yes, actively searching
• ☐ Yes, casually looking
• ☐ No, not currently seeking
• ☐ Unsure

Section 2: Awareness and General Attitudes Toward AI in Hiring

Definition: Artificial Intelligence (AI) refers to computer systems that can perform tasks that typically require human intelligence, such as reading resumes, analyzing video interviews, or making hiring recommendations.

7. Before today, were you aware that some companies use AI in their hiring and recruitment decisions?
• ☐ Yes, I was aware
• ☐ No, I was not aware
• ☐ I had heard about it but didn't know details

For questions 8-12, please indicate your level of agreement with each statement using the following scale:
1 = Strongly Disagree, 2 = Disagree, 3 = Neutral/Unsure, 4 = Agree, 5 = Strongly Agree

8. I believe AI systems can fairly evaluate whether a candidate is a good "culture fit" for a company. (Culture fit means how well your personality, values, and work style match a company's way of doing things.)
• 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐
9. I trust AI systems to make unbiased hiring decisions.
• 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐
10. I worry that AI hiring systems will discriminate against certain groups of people. (Discrimination means unfairly treating people differently based on their background, identity, or characteristics.)
• 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐
11. If I knew a company used AI to evaluate job applications, I would be less likely to apply there.
• 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐
12. I would prefer that a human, not an AI, evaluate my job applications.
• 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

Section 3: Specific Concerns About AI Bias

13. How concerned are you about potential bias or unfairness in AI hiring systems?
• ☐ Very concerned
• ☐ Concerned
• ☐ Neutral/Unsure
• ☐ Not very concerned
• ☐ Not at all concerned
14. Which of the following are you personally concerned about when it comes to AI in hiring? Select all that apply.
• ☐ AI learning from historically biased data (for example, if mostly men were hired in the past, the AI might favor men)
• ☐ AI's inability to understand individual circumstances or personal context
• ☐ AI penalizing non-standard communication styles (such as accents, speaking pace, or body language differences)
• ☐ AI favoring certain personality types over others (such as extroverts over introverts)
• ☐ AI making judgments based on physical appearance in video interviews
• ☐ AI not being able to recognize non-traditional career paths, skills, or experiences
• ☐ AI reinforcing stereotypes about gender, ethnicity, or social class
• ☐ Lack of transparency about how AI makes decisions
• ☐ Other (please specify): ________________________________
• ☐ I have no concerns about AI in hiring

Section 4: Attitudes Toward AI Adoption and Change

For questions 15-20, please indicate your level of agreement:
1 = Strongly Disagree, 2 = Disagree, 3 = Neutral/Unsure, 4 = Agree, 5 = Strongly Agree

15. The use of AI in hiring is inevitable—most companies will use it in the future regardless of concerns.
• 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐
16. It is pointless to resist the adoption of AI in hiring because the technology will be used anyway.
• 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐
17. My generation can influence how AI is designed and used to make it fairer.
• 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐
18. Youth activism and speaking out about AI bias can lead to real change in how these systems work.
• 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐

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19. I believe it is important for young people to learn about how AI works so we can identify problems with it.
- 1 □ 2 □ 3 □ 4 □ 5 □

20. Companies that use AI in hiring have a responsibility to regularly check their systems for bias.
- 1 □ 2 □ 3 □ 4 □ 5 □

Section 5: Preferences for Future AI Hiring Systems

21. Which of the following safeguards or features would make you more comfortable with AI being used in hiring? Select all that apply.
- □ Human oversight—a human reviews and can override all final hiring decisions
- □ Transparency—the company clearly explains what criteria the AI uses
- □ Regular independent audits—outside experts regularly check the AI for bias
- □ Option for human-only review—applicants can request their application be reviewed only by humans
- □ Public disclosure—companies must clearly inform applicants when AI is being used
- □ Right to explanation—if rejected, applicants receive a detailed explanation of why
- □ Ability to challenge decisions—applicants can appeal or dispute AI-based decisions
- □ None of these would make me more comfortable
- □ Other (please specify): _______________________________

Section 6: Open-Ended Responses

Please take a few moments to answer the following questions in your own words. There are no right or wrong answers—we want to hear your honest thoughts and experiences.

22. Can you describe a specific scenario or situation where you think an AI system might unfairly evaluate a job candidate? Please be as detailed as possible.

23. What features, rules, or safeguards would you want to see in an AI hiring system to make you feel confident that it is treating all candidates fairly?

24. In your opinion, how will your generation (young people entering the workforce now or soon) respond to the increasing use of AI in hiring? What concerns might they have, and what actions might they take?

Section 7: Final Thoughts

25. Is there anything else you would like to share about AI in hiring, your concerns, or your hopes for the future of work?

Thank you for completing this survey!
Your responses will help us understand how young people perceive the use of AI in hiring and will contribute to efforts to make these systems fairer and more transparent. Your participation is greatly appreciated.