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Addressing Biases in SME Hiring Practices in Kazakhstan Through AI-Driven Behavioral and Psychometric Assessments

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Abstract
Kazakhstani SMEs face hiring biases nepotism/favoritism, gender stereotypes, ethnic preferences, and barriers for vulnerable groups that depress diversity and waste talent. We synthesize recent local and international evidence and add a descriptive SME survey (N=30). Respondents report meaningful adoption of structured practices (blind screening 60%, skills tests 56.7%, structured interviews 60%, bilingual assessments 76.7%) yet still perceive strong influence of personal connections (mean 4.00/5) and non-trivial language effects (3.43/5). We outline an AI-enabled hiring stack, blind résumé parsing, proctored skills tests, structured (text/chat) interviews, and validated psychometrics, plus a fairness audit plan (adverse-impact ratio, equal-opportunity gaps, calibration). Video/micro-expression analytics are treated as experimental and non-decisive. Properly implemented with bilingual delivery and monitoring, AI can reduce bias by anonymizing early screens and enforcing uniform, job-relevant criteria. We conclude with a stepwise adoption path for SMEs and practical safeguards for Kazakhstan's context.

Keywords
Hiring Bias; SME Recruitment; Kazakhstan Labor Market; Nepotism; Algorithmic Fairness; Psychometric Assessment; Behavioral Signals; Diversity and Inclusion

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I. INTRODUCTION

Recruitment decisions shape human capital and are central to competitive success (Barocas, Hardt, & Narayanan, 2019). In Kazakhstan, SMEs employ more than 4.3 million people and contribute about 39 percent of GDP (Bureau of National Statistics, 2024 to 2025; see Table 1). Fair and meritocratic hiring in this sector matters for firm performance and for socio-economic equity. Evidence shows that current SME practices are affected by systematic biases that can produce unfair outcomes and waste talent.

Nepotism and favoritism are prominent. Managers operate inside close social networks and face communal expectations to hire relatives or acquaintances, often described as clan ties (Syzdykova & Azretbergenova, 2025). Many vacancies are filled informally rather than publicly advertised, which privileges insiders over stronger external candidates. A factorial survey from Kazakhstan shows that stated meritocratic intent often diverges from actual decisions, so favoritism still affects outcomes even where formal procedures exist (Syzdykova & Azretbergenova, 2025).

Gender bias remains visible. Stereotypes about women's commitment and leadership fitness persist, especially for mothers or women of childbearing age. Recruiters may apply different standards to female and male candidates, which sustains gaps in hiring, leadership, and pay (Hassan, 2019; Syzdykova & Azretbergenova, 2025). Recent work notes that women, including new graduates, receive fewer offers and lower pay in some contexts (UN Women, 2022; Okutayeva et al., 2025a; Okutayeva et al., 2025b).

Ethnic and national origin bias is also documented. A field experiment finds that résumés with Russian migrant names receive fewer interview invitations than equivalent résumés with ethnic Kazakh names, with stronger effects farther from traditional Russian communities and in higher skill roles (Abdulla & Mourelatos, 2025). Beyond that case, employers may favor majority groups or familiar language communities, which narrows diversity and overlooks talent.

Biases against vulnerable groups create additional barriers. People with disabilities, single parents, older workers, ex-offenders, and recent graduates face lower employment rates and persistent stereotypes. Legal quotas for persons with disabilities exist, yet only about one quarter of working-age individuals with disabilities are employed (UNDP Kazakhstan, 2021; Morgan Lewis, 2024). Employers often overestimate accommodation costs or underestimate productivity, which leads to exclusion despite qualifications (Okutayeva et al., 2025a).

These patterns undermine equal opportunity and reduce match quality for firms. Interest is growing in technological support that promotes fairer hiring. Properly designed AI can help by focusing evaluation on job-related evidence and by ignoring demographic attributes (Barocas, Hardt, & Narayanan, 2019). Behavioral and psychometric signals, including skills tests, structured interviews, and validated short scales, can reduce reliance on subjective impressions and personal connections when combined with safeguards.

The study investigates how AI can alleviate these biases in the Kazakhstani SME context. First, it documents the main bias types using existing research and recent data. Second, it examines AI-enabled methods that can make hiring more merit-based. The core hypothesis is that tools centered on demonstrated skills, behaviors, and psychometrics can reduce the effect of human bias in decisions. The goal is to inform business practice and policy so that SMEs select the most suitable candidates regardless of gender, ethnicity, or personal ties.

This study examines observable biases in SME hiring in Kazakhstan, nepotism and favoritism, gender stereotyping, ethnic and language effects, and barriers for vulnerable groups, and evaluates whether AI enabled, evidence based assessments can make recruitment more meritocratic. I focus on behavioral and psychometric tools and on the risk management side of AI adoption, including objectivity, consistency, inclusivity, and the ethical concerns around algorithmic bias and privacy. Because SMEs account for a large share of employment and output in Kazakhstan, even modest improvements in fairness and efficiency would matter at scale.

This work contributes by providing a country specific synthesis for Kazakhstan, where evidence on bias in SME hiring and on responsible AI adoption remains sparse. It contributes by centering the bilingual reality of the labor market (Kazakh and Russian) in the design of assessments and fairness checks, by specifying concrete fairness guardrails and an implementation path that local firms can replicate.

II. Methods

2.1. Research Design

We conduct a mixed-methods synthesis of peer-reviewed studies, field experiments, and official statistics on Kazakhstan's SME labor market, complemented by a bilingual online SME survey (N=30) conducted July–August 2025 (owners/HR/leads; 9 items; convenience/snowball sampling). The instrument captured adoption of structured steps, language availability, perceived bias (four Likert items), simple outcomes (shortlist diversity, time-to-hire), and readiness for AI pilots. Results are descriptive, not representative.

Table 1
Kazakhstan SME and labor/finance indicators (latest)

Indicator	Latest Figure	Reference Period	Source Note
Operating SME entities	2,099.6 thousand	Apr 1, 2025	Bureau of National Statistics (SME monitor)
Employment in SMEs	4,322.7 thousand people	Apr 1, 2025	Bureau of National Statistics (SME monitor)
SME output (current prices)	18,677.9 billion KZT	Jan–Mar 2025	Bureau of National Statistics (SME monitor)
SME share of GDP	39.3% (Jan–Sep 2024); 38.6% (Jan–Mar 2025)	See left	Bureau of National Statistics (SME monitor)
Unemployment rate (ILO)	4.6%	2025 (latest bulletin)	Labour bulletin
Youth Unemployment (15-34)	3.1%	Q2 2025	Labour bulletin
NEET Rate (15-28)	6.2%	Q1 2025	Labour bulletin
Loan Approval rate – Small business	33 %	Feb 2025 (NBK Bank Lending Survey)	NBK Bank Lending Survey
Loan Approval rate – Medium business	41 %	Feb 2025 (NBK Bank Lending Survey)	NBK Bank Lending Survey
Loan Approval rate – Large business	≈60%	Feb 2025 (NBK Bank Lending Survey)	NBK Bank Lending Survey
Subsidized SME loan stock	≈2% of GDP (2024); 1.8% (2023)	2024; 2023	World Bank Monthly Economic Update

Note. Figures shown with reference periods. Sources: Bureau of National Statistics (SME monitor; labor bulletins); National Bank of Kazakhstan, Bank Lending Survey; World Bank, Monthly Economic Update.

As shown in Table 1, SMEs are a critical component of Kazakhstan's economy, employing about 4.3 million people and accounting for approximately 39 percent of Kazakhstan's GDP. However, despite this economic weight, financing constraints remain notable: only 33 percent of small and 41 percent of medium business loans were approved as of early 2025, while subsidized SME loans comprised only 2 percent of GDP. Labor indicators reinforce the importance of equitable hiring, unemployment stood at 4.6 percent, and youth unemployment at 3.1 percent, suggesting that SME recruitment decisions directly affect national employment outcomes. These figures explain why addressing bias in SME hiring is vital: even modest efficiency or fairness gains within this large sector could have measurable macro-level effects on employment and productivity.

III. Results

3.1 These snapshot results suggest structured practices are spreading, yet perceived connections and language effects remain, motivating the bias analysis below

Sample profile. Company sizes: 1–9 (26.7%), 10–49 (36.7%), 50–99 (13.3%), 100–249 (20%), 250+ (3.3%). Industries: Services (33.3%), Trade/Retail (20%), Finance/Banking (16.7%), Manufacturing (13.3%), Construction (10%), Logistics (3.3%), IT/Digital (3.3%). Positions filled in the last 12 months: 1–3 (30%), 4–10 (33.3%), 11–30 (26.7%), 31+ (10%).

Structured practices. Blind resume screening 60%, skills tests 56.7%, structured interviews 60%, bilingual assessments 76.7%. Language availability: always two languages 46.7%, upon request 33.3%, single language 20%.

Perceived bias (Likert means, 1–5). Personal connections 4.00, language 3.43, gender 3.00, ethnicity/national origin 3.07.

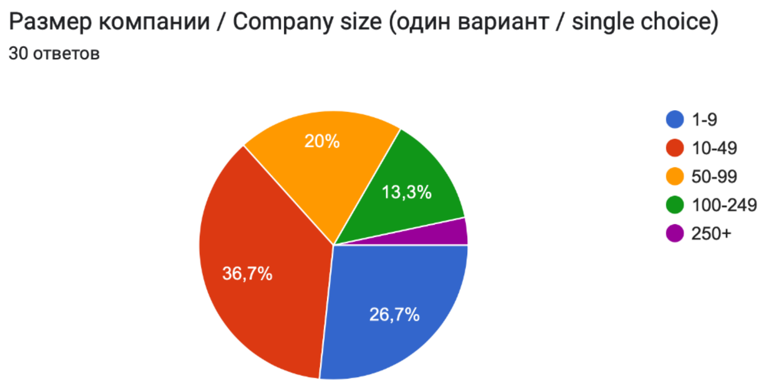
Process outcomes. Final-shortlist diversity: low 23.3%, medium 50%, high 26.7%. Time-to-hire: ≤14 days 23.3%, 15–30 56.7%, >30 20%. Complaints about hiring fairness in 12 months: Yes 40%, No 50%, Not sure 10%.

Nepotism/favoritism. “Consistent with prior evidence, connections are rated highly influential in our SME survey (mean 4.00/5), underscoring the salience of in-group hiring pressures in practice.”

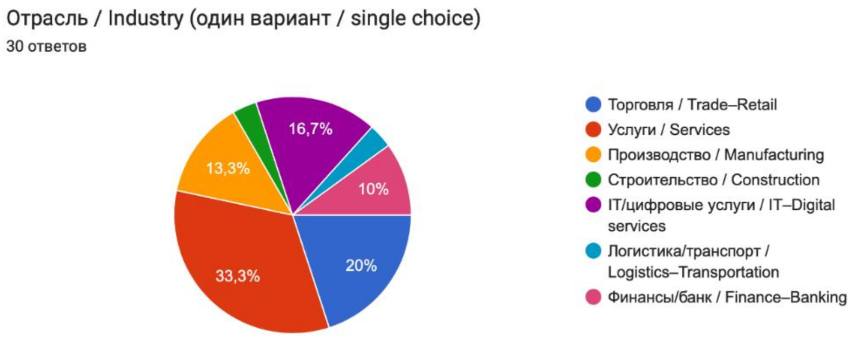
Language bias. “Language remains a non-trivial factor (mean 3.43/5) even though 76.7% of SMEs report using bilingual assessments, and 46.7% offer two languages by default.”

Gender bias. “Gender is perceived as a moderate influence (mean 3.00/5), aligning with documented under-representation patterns.”

Ethnic/national origin. “Perceived influence is near neutral (mean 3.07/5), but experimental evidence of callback gaps indicates risk; bilingual and blind early-stage evaluations remain warranted.”

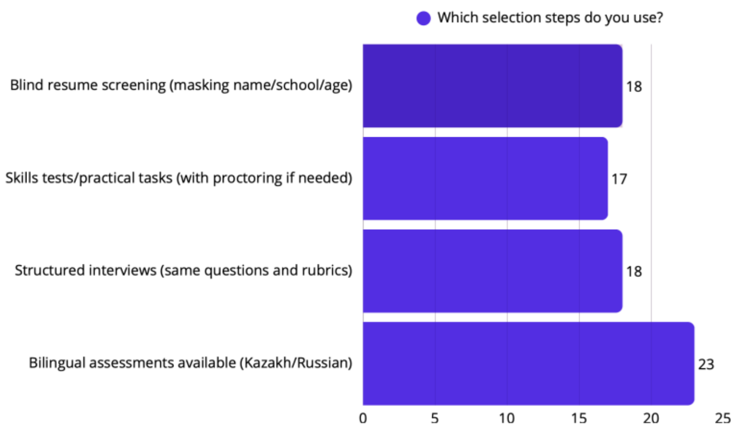


This pie chart shows the size distribution of the 30 surveyed companies. The largest share is small firms with 10–49 employees (36.7%; 11 companies), followed by micro firms with 1–9 employees (26.7%; 8 companies). Medium firms make up 20.0% (50–99 employees; 6 companies) and 13.3% (100–249 employees; 4 companies). Only one company has 250+ employees (3.3%).



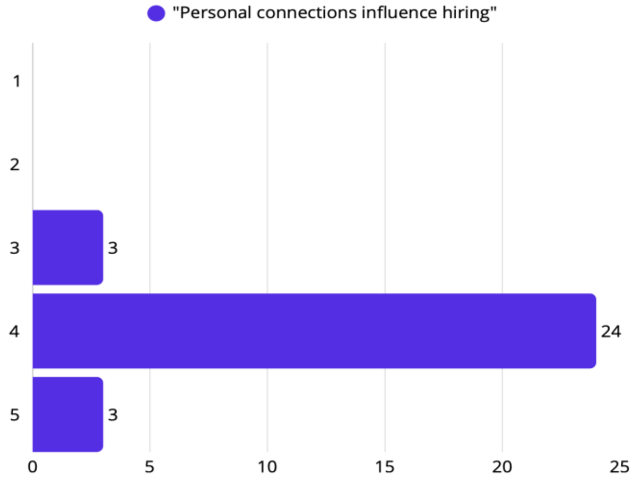
This pie chart illustrates the industry distribution of the 30 companies surveyed. The largest proportion of respondents represents the services sector (33.3%; 10 companies), followed by trade and retail (20%; 6 companies) and IT/digital services (16.7%; 5 companies). Manufacturing accounts for 13.3% (4 companies), while finance and banking (10%; 3 companies), and construction and logistics/transportation (each 3.3%; 1 company) are less represented.

This pie chart presents how many positions the surveyed companies filled over the past 12 months. The largest group (33.3%; 10 companies) reported filling 4–10 positions, followed by 30.0% (9 companies) that filled 1–3 positions. About 26.7% (8 companies) filled 11–30 positions, while only 10.0% (3 companies) filled more than 31. None of the respondents reported having filled zero positions, indicating active recruitment across most firms.



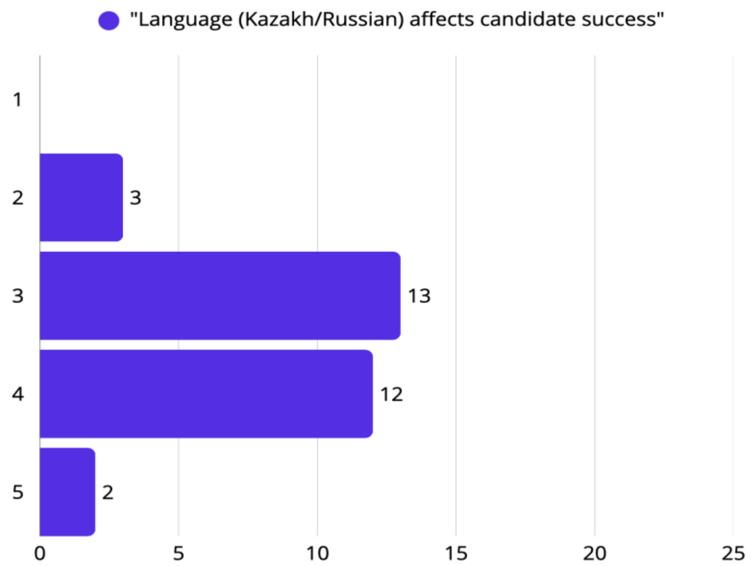
This bar chart illustrates the most common selection steps used by the surveyed companies. The majority (76.7%; 23 companies) provide bilingual assessments in Kazakh and Russian, showing a strong commitment to inclusivity. Structured interviews and blind résumé screening were equally common (60%; 18 companies each), indicating a focus on standardization and fairness in hiring. Skills or practical tests were used by 56.7% (17 companies), highlighting the importance of assessing real job performance.

This pie chart demonstrates the language availability of assessments or tasks among the surveyed companies. Nearly half of the respondents (46.7%; 14 companies) reported that assessments are always available in both Kazakh and Russian. One-third (33.3%; 10 companies) indicated that bilingual options are provided upon candidate request, while 20% (6 companies) stated that only one language is used.



1-strongly strongly disagree, 5-strongly agree
Average rating: 4.0

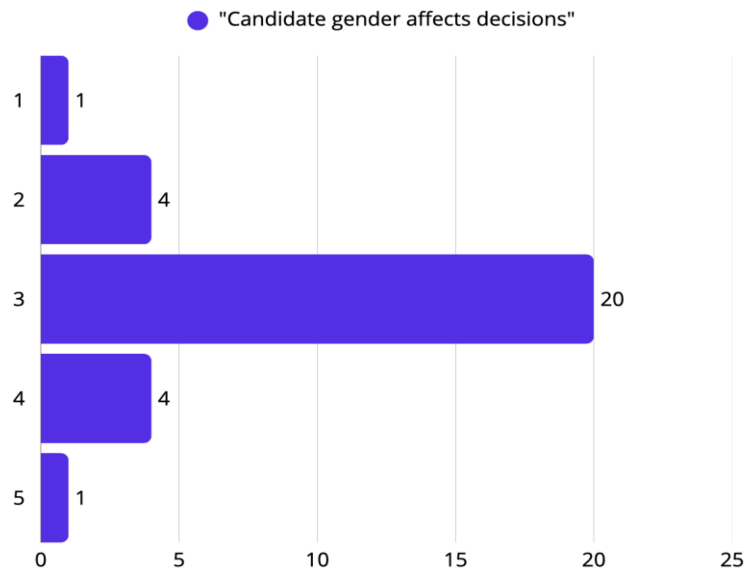
This bar chart presents responses to the statement *"Personal connections influence hiring."* The majority of participants (24 out of 30) rated this statement as **4**, indicating agreement that personal connections play a notable role in hiring. Three respondents chose **3** (neutral), and another three selected **5** (strongly agree). None of the respondents disagreed. The overall average rating of **4.0** suggests that most companies acknowledge the influence of personal relationships in recruitment, reflecting a perceived prevalence of informal or network-based hiring practices.



1-strongly strongly disagree, 5-strongly agree

Average rating: 3.43

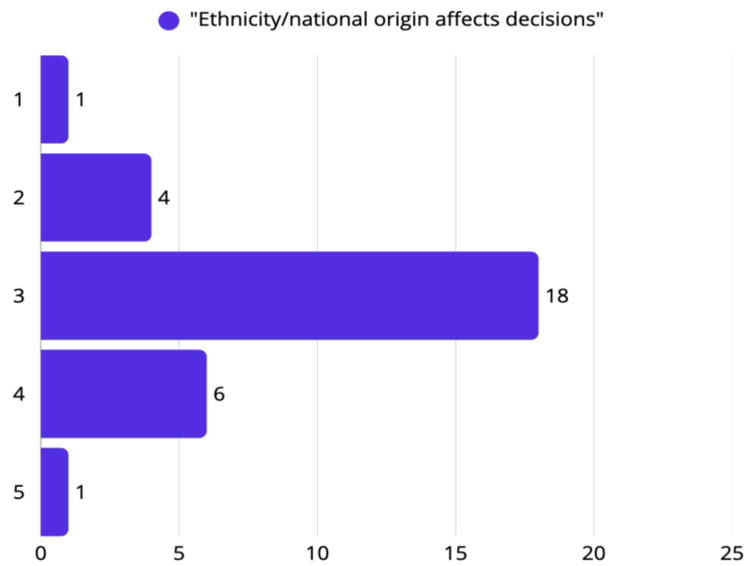
This bar chart shows respondents' perceptions of whether language (Kazakh or Russian) affects candidate success during hiring. The largest group (13 out of 30) selected **3**, indicating a neutral view, while 12 respondents rated **4**, agreeing that language influences how successful candidates are in the process. Three respondents chose **2**, and two rated **5** (strongly agree). The average score of **3.43** suggests a moderate agreement overall, implying that while language is not the main determinant, it still has a meaningful impact on candidates' chances of success.



1-strongly strongly disagree, 5-strongly agree

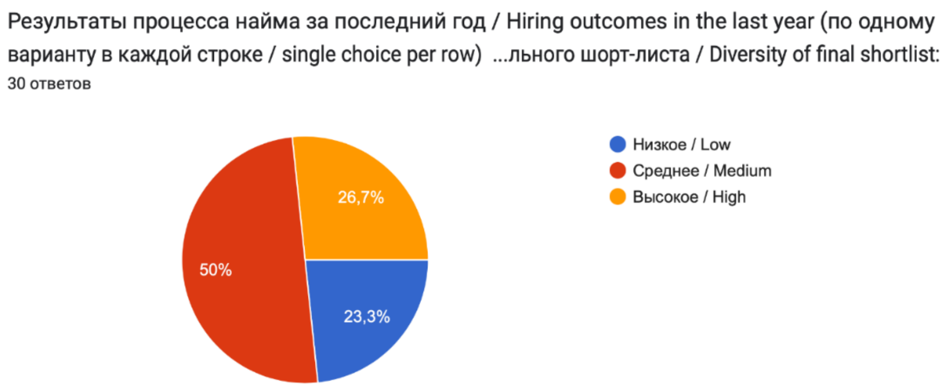
Average rating: 3.00

Most participants (20 out of 30) selected **3**, showing a neutral stance, while four respondents each rated **2** and **4**, indicating mild disagreement or agreement. Only one respondent chose **1** (strongly disagree) and one selected **5** (strongly agree). With an average rating of **3.00**, the results suggest that most participants do not perceive gender as a major factor in hiring outcomes, reflecting a generally neutral or balanced view on gender influence in decision-making.

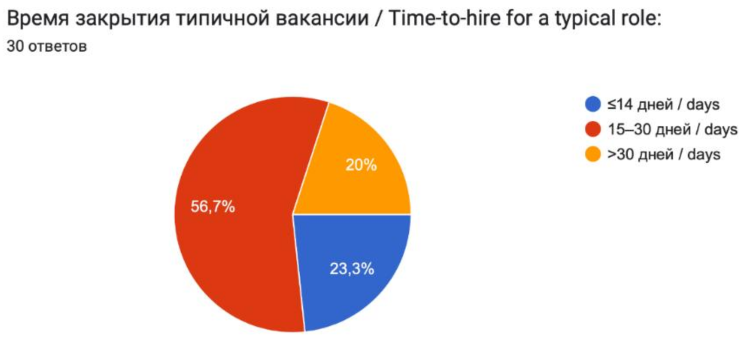


1-strongly strongly disagree, 5-strongly agree
Average rating: 3.07

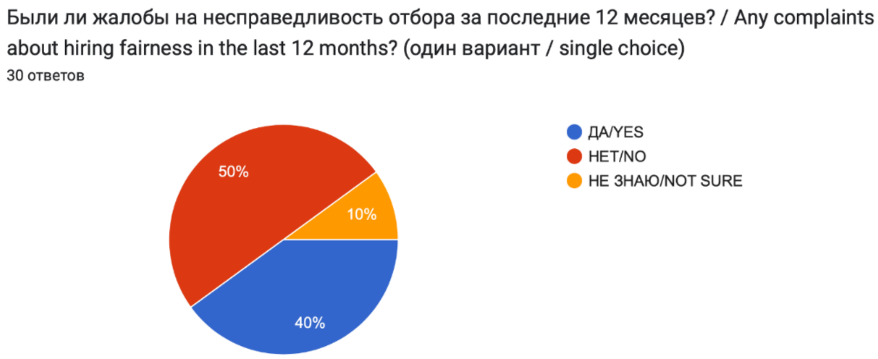
This bar chart illustrates respondents' perceptions of whether ethnicity or national origin influences hiring decisions. The majority (18 out of 30) rated the statement as **3**, showing neutrality, while six respondents rated **4**, expressing agreement that ethnicity can affect decisions. Four respondents selected **2**, one rated **1** (strongly disagree), and another **5** (strongly agree). With an average rating of **3.07**, the results indicate a slightly positive tendency toward acknowledging that ethnicity or national origin may influence hiring decisions, though most respondents remain neutral on the issue.



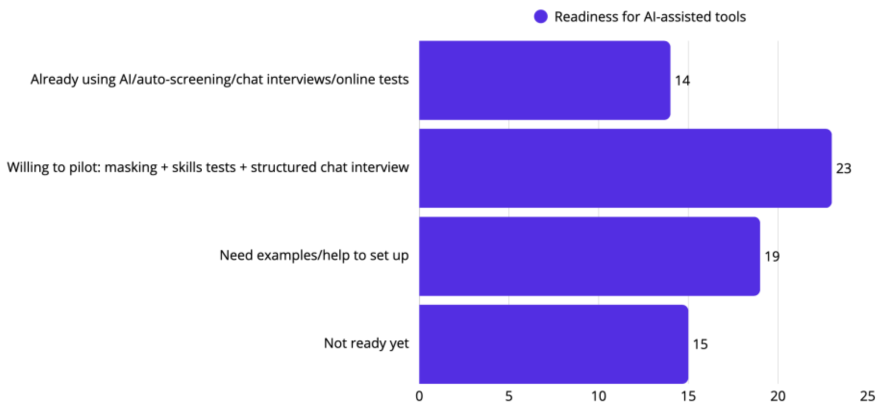
This pie chart presents the reported diversity of final shortlists in hiring outcomes over the past year. Half of the surveyed companies (50%; 15 companies) indicated a medium level of diversity among shortlisted candidates. Meanwhile, 26.7% (8 companies) reported a high level of diversity, and 23.3% (7 companies) described it as low.



This pie chart illustrates the average time required to fill a typical role among the surveyed companies. More than half of respondents (56.7%; 17 companies) reported a hiring period of 15–30 days, indicating a relatively moderate recruitment pace. Around 23.3% (7 companies) managed to close positions within 14 days, while 20% (6 companies) required over 30 days.



This pie chart illustrates whether the surveyed companies received any complaints regarding hiring fairness during the past 12 months. Half of the respondents (50%; 15 companies) reported no complaints, while 40% (12 companies) confirmed that such complaints had occurred. The remaining 10% (3 companies) were unsure or did not track this information.



This bar chart presents the readiness of surveyed companies to adopt AI-assisted recruitment tools. Nearly all respondents showed some level of openness to AI integration. The largest group (23 out of 30) expressed willingness to **pilot AI-based solutions** such as résumé masking, skills tests, and structured chat interviews. Nineteen companies indicated that they **need examples or support** before implementation, while 15 stated they are **not ready yet**. Fourteen companies reported **already using AI tools** like auto-screening and online assessments. Overall, these results demonstrate strong interest and gradual movement toward AI adoption in hiring, with most organizations open to experimentation rather than complete readiness.

3.1.1 Prevalent Biases in Kazakhstani SME Hiring Practices

Nepotism and favoritism.

SMEs in Kazakhstan often recruit through informal channels, which sustains nepotism. In collectivist settings managers face social pressure to hire acquaintances or relatives as a communal obligation, sometimes framed as clan ties (Syzdykova & Azretbergenova, 2025). Many vacancies are never advertised and are filled through personal networks. This can build trust in family firms but routinely excludes equally or more qualified outsiders and depresses competence and morale. A factorial survey from Kazakhstan shows a consistent gap between meritocratic rhetoric and actual decisions, indicating that favoritism still shapes outcomes even when formal procedures exist (Syzdykova & Azretbergenova, 2025).

Gender bias.

Traditional gender role attitudes spill into hiring. Employers may question the commitment of women of childbearing age or assume scheduling conflicts, which leads to tougher screening and lower hiring rates in some sectors. Research reports persistent differences in standards applied to women and men and continuing underrepresentation of women in leadership in Kazakhstan's SMEs (Hassan, 2019; Syzdykova & Azretbergenova, 2025). Recent work also notes that women, especially new graduates, are less likely to receive offers or competitive pay (UN Women, 2022; Okutayeva et al., 2025b).

Ethnic and regional bias.

Kazakhstan's diverse demography creates room for unequal treatment by ethnicity or origin. A field experiment finds that Russian migrant names receive fewer interview invitations than equivalent ethnic Kazakh résumés, with stronger effects away from traditional Russian communities and in higher skill jobs (Abdulla & Mourelatos, 2025). Anecdotal evidence suggests context specific preferences, for example prioritizing ethnic Kazakhs in public facing roles or favoring Russian speaking candidates in other settings. Such patterns reduce match quality and can harden social divides.

Bias against vulnerable groups.

Outcomes for persons with disabilities remain weak despite legal quotas of two to four percent for medium and large employers, with only about one quarter of working age individuals with disabilities employed according to UNDP estimates (Morgan Lewis, 2024; UNDP Kazakhstan, 2021). Employers often overestimate accommodation costs or underestimate productivity, which reflects stereotypes rather than individual capability (Okutayeva et al., 2025a). Age bias appears at both ends of the spectrum. Older candidates are seen as less adaptable, while recent graduates are rejected for lack of experience. Mothers of young children face intrusive questions and implicit penalties. People with criminal records or past addictions also report stigma that blocks reentry despite qualifications (Okutayeva et al., 2025a).Summarizing,
Across these domains the common pattern is selection based on group labels rather than verified skills. Biases can intersect, for example for a young woman with a disability, and the cumulative effect is a narrower and less capable workforce. These findings justify structured and transparent hiring with bilingual access and clear fairness monitoring, and they motivate the next section that evaluates AI supported tools for bias reduction.

3.2. Potential of AI Using Behavioral and Psychometric Signals

We propose a compact, auditable stack that emphasizes skills over signals correlated with gender, ethnicity, or connections:

- **Blind resume parsing & de-identification.** Mask names/schools; score only job-relevant evidence.
- **Proctored skills tests / work samples.** Standardize tasks; compare candidates on identical criteria.
- **Structured interviews (text/chat).** Same questions and rubrics; AI decision-support highlights content relevance.
- **Validated psychometrics.** Use short, job-related scales with subgroup calibration checks.

Together, these steps reduce human discretion early, enforce uniform criteria, and generate measurable evidence for decisions. Monitoring AIR ≥ 0.80, EqOpp gaps ≤ 5 pp, and calibration ensures the stack does not reproduce historical bias. All assessments must be available in Kazakh and Russian. We caution that facial/micro-expression scoring remains contested and should be optional, used, if at all, after skill screens and never as a decisive filter. For SMEs, cloud tools enable stepwise adoption: start with masking + skills tests; add structured interviews and psychometrics as needed.

IV. Discussion

4.1. Interpretation of Findings in the Kazakhstani Context

The results show that hiring biases are real in Kazakhstan's SME sector and have local features. Nepotism and favoritism are reinforced by communal ties and by the relatively recent professionalization of HR. Gender bias reflects traditional norms and Soviet and post-Soviet legacies. Evidence that women, youth, and persons with disabilities face weaker labor-market outcomes indicates persistent attitudinal and structural barriers. The correspondence experiment on Russian migrants confirms that ethnic cues can shape callbacks. For SMEs, these patterns matter commercially and reputationally. Homogeneous teams reduce cognitive diversity, slow problem solving, and can deter diverse applicants, which locks in the pattern. The practical goal is to break this cycle with structured, auditable hiring processes described in section 3.2. Technology must be applied with safeguards because it can reproduce historical bias. If trained on past decisions, a model may down-rank candidates who do not match prior hiring patterns, such as graduates of regional universities. Accuracy of video or micro-expression analysis can also vary across groups and should be treated as experimental. Adoption should include masking of identifiers from end to end, bilingual formats in Kazakh and Russian, monitoring of adverse impact ratio and equal opportunity by subgroup on a fixed schedule, and clear triggers for retraining or threshold adjustments when fairness metrics fall below preset levels. For Kazakhstani SMEs, feasibility depends on cost and simplicity. Cloud tools make stepwise adoption realistic even without large HR teams. The recommended entry point is blind screening and proctored skills tests, followed by structured text or chat interviews and validated psychometric scales as needed. Effectiveness should be demonstrated locally through pilots that report pre and post gaps in callbacks and offers by gender, disability status, and ethnicity and that publish simple fairness dashboards. Until local evidence accumulates, treat video-based behavioral scoring as optional and non-decisive input.

These descriptive survey results suggest SMEs have begun adopting structured practices at meaningful rates while still perceiving strong influence of personal connections and some language effects. That combination justifies prioritizing blind early screening, skills-first assessments, and bilingual delivery in local pilots. Given convenience sampling and N=30, findings are directional; the next step is to track pre/post fairness metrics (DP, Equal-Opportunity gaps, calibration, AIR≥0.80) on real hiring funnels.

4.2. How AI Mitigates Specific Biases – A Closer Look

Let us revisit each major bias through the lens of AI mitigation, bringing insight from research and practical examples:

- **Mitigating Nepotism/Favoritism:** AI's most obvious impact here is by enforcing *impersonality* in early screening. If an SME uses an AI-driven system to filter applicants, the owner's nephew's application will be ranked by the same algorithm as everyone else's. If the nephew truly lacks qualifications, the AI will flag them as low-fit, whereas a human might have given them an interview as a favor. Some Central Asian companies have experimented with outsourcing initial candidate screening to AI or external firms to avoid internal pressure from nepotism. The result is a more impartial shortlist. Our findings suggest AI could also introduce candidates the hiring manager didn't originally consider – for instance, someone with a non-traditional background who excels in an online test might get recommended, effectively bypassing the usual "who do we know?" approach. However, one must acknowledge that AI can only mitigate nepotism if management is willing to heed the AI recommendations. A biased manager could always override the algorithm to hire their preferred person. Thus, a key aspect is organizational commitment: SMEs need to trust the AI's objectivity. Over time, demonstrating that AI-selected hires perform well would build confidence. Favoritism also often occurs at the interview stage (e.g., giving softball questions to a friend's referral). AI can level this by providing standardized interview frameworks and even AI interviewer bots that treat everyone the same. In essence, the process transparency introduced by AI (everyone goes through the same tests and criteria) creates social accountability – it is harder to justify bypassing a top-scoring candidate in favor of an unqualified acquaintance when data clearly shows the merit of the former.
- **Mitigating Gender Bias:** AI can reduce gender bias primarily by obscuring gender during evaluation and by using indicators that are gender-neutral. For example, if a blind audition approach is taken (akin to blind auditions in orchestras which famously increased female musician hiring), AI can mask names and pronouns in résumés or applications. An algorithm might refer to candidates by number. More subtly, AI can counteract biases like the tendency to judge women on experience and men on potential (documented in some studies) by applying the same predictive model to all. If a female candidate's attributes predict high job performance per the model, she should rank equally to a male with similar predicted performance. In the literature, some AI hiring platforms have claimed success in increasing female hires in tech roles by focusing on skill tests and structured interviews, thereby avoiding the stereotypical assumptions that might occur in unstructured settings(Hassan, 2019)(Hassan, 2019). Our

review also notes that AI can be used to sanitize job descriptions (flagging if language is inadvertently gender-biased) and broaden the reach of job ads, which in turn can attract a more diverse applicant pool. In Kazakhstan's context, encouraging more women to apply and be evaluated fairly could help close gaps. It's also worth noting that AI could mitigate the bias of penalizing maternity or career gaps – some algorithms explicitly do not consider *time since graduation* or *continuous employment duration* as a factor, unless directly relevant, focusing instead on skills. This helps mothers returning to work to not be automatically ranked lower due to a gap. One emerging practice is AI-powered returnship programs where women who took career breaks undergo skills assessments via AI and are matched to roles, proving their competencies afresh rather than being judged on the break. Such approaches could directly tackle the bias against hiring mothers or mid-career women.

- **Mitigating Ethnic/Nationality Bias:** AI systems, if properly configured, do not "see" ethnicity – a CV parser doesn't know the ethnic connotation of a name (unless it's programmed with such data, which it shouldn't be), and a skill test certainly has no clue about ethnicity. So, in a well-implemented AI hiring process, ethnic discrimination can be dramatically reduced at the screening stage. For example, in the experiment cited where Russian names got fewer callbacks, an AI-driven callback system might actually equalize that, calling back based on qualifications only. One challenge, however, is language bias: Kazakhstan is bilingual (Kazakh and Russian). If AI assessments (like games or interviews) are only in one language, non-native speakers might be at a disadvantage. Therefore, to truly mitigate ethnic or national origin bias, AI tools used should accommodate multiple languages or otherwise ensure fairness for non-dominant language speakers. Some AI interview platforms allow answers in various languages and then translate or score them neutrally, which could be useful. Furthermore, AI can help identify bias in human decisions: by analyzing historical hiring data, AI might flag that certain ethnic groups were consistently scored lower by interviewers with no clear job-related reason. Such insight can prompt retraining of hiring staff. In essence, by standardizing evaluation criteria, AI makes it more likely that if a minority candidate has the needed competencies, they will be advanced in the process. Still, we must be wary that AI itself isn't trained on data reflecting past ethnic bias. Using diverse and unbiased training data (possibly even simulated data to balance categories) is important. Given that ethnic bias in Kazakhstan can sometimes correlate with factors like language fluency or accent, an AI analyzing, say, a video interview purely for content might inadvertently favor a fluent speaker of the expected language. To counter that, it could be programmed to focus on what is said (substance) rather than how perfectly it is said. This nuance underscores that AI design choices determine how effectively bias is mitigated.
- **Mitigating Bias Against Disabilities and Other Vulnerabilities:** AI has notable advantages here as well. For disabled candidates, technology can be the great enabler. For instance, a video interview AI might allow a deaf candidate to sign or a hard-of-hearing candidate to rely on captions without judgment—AI will just transcribe and analyze the content of answers. Or a candidate with autism, who might not excel in traditional social interviews, could demonstrate skills through an AI-monitored task where social biases are irrelevant. By providing alternative ways to showcase talent (like project simulations, online contests, etc.), AI gives individuals who might be prejudged in a face-to-face meeting a chance to let their work speak for them. Additionally, AI assessments can often be taken remotely, which helps those who may have mobility challenges or anxiety; they can perform in a comfortable environment, likely yielding a more accurate measure of their ability. One interesting development is AI-based reasonable accommodation: adaptive testing that adjusts difficulty or provides accommodations (e.g., extra time, screen-reader compatibility) dynamically, ensuring that a disability does not unfairly hinder the demonstration of competence. Our findings on employers' stereotypical fears about disabled workers(Okutayeva et al., 2025a) can be directly challenged when an AI assessment shows a disabled applicant scoring in the top percentile for relevant skills. Essentially, the data-driven evidence can override anecdotal prejudice. Similarly for older workers, if an AI-based performance test shows they are as capable (or more so) than younger peers, it counteracts the "older means slower" stereotype. And for fresh graduates, AI can reveal high aptitude and learning agility, giving them a leg up that their short CV might not. One concrete example: some companies use coding challenges (scored by AI) to hire programmers straight out of school, bypassing the resume experience requirement entirely. Those who perform well are hired, proving that lack of experience doesn't mean lack of skill. Kazakhstani SMEs struggling to find experienced talent could use such approaches to tap the youth talent pool without bias.

In light of the above, it's clear that AI offers tools to attack bias at multiple points in the hiring funnel: from sourcing to screening to interviewing to final selection. However, implementing these tools in SMEs raises practical and ethical considerations.

4.3. Challenges and Ethical Considerations in AI Adoption

AI can reduce human bias, yet it introduces its own risks. First, transparency and explainability matter. SMEs and candidates should understand why a system advances or rejects a person, for example that a coding score fell below a threshold rather than an opaque model choice. Clear reasons build trust and align with emerging legal norms. For Kazakhstan, early attention to explainability would set a sound precedent.

Second, privacy and consent are essential. Assessments can capture sensitive information, especially video and personality data. Employers should obtain informed consent, minimise collection, and require strict vendor controls. Practices such as scraping social media for personality inference are intrusive and of doubtful relevance.

Third, AI can encode bias if not audited. Training data, measurement error, and domain shift can harm accuracy for different groups. Facial analysis is particularly contested and has shown uneven performance across ethnicities. In a diverse society, systems should be locally validated or replaced with methods that rely on text and skills.

Fourth, the best outcomes come from collaboration between people and AI, not full automation (Barocas, Hardt, & Narayanan, 2019). Use AI for early screening and consistent scoring. Reserve final decisions for structured human interviews that draw on the evidence produced by the system.

Fifth, candidate acceptance requires communication. Explain that assessments give everyone an equal chance and provide simple guidance so unfamiliar interfaces do not disadvantage anyone.

Finally, AI cannot measure everything. Over reliance on what is easily quantified can miss creativity or leadership potential. A hybrid approach and an inclusive culture remain necessary beyond the hiring step.

4.4. Recommendations for Implementation and Future Research

Pilot programs: Run small pilots with selected SMEs, preferably with industry or public partners. Track pre and post outcomes such as callback and offer rates by subgroup, time to hire, and retention. Share methods and results openly, including obstacles encountered.

Guidelines and training: Provide short playbooks for owners and HR on unbiased hiring and correct use of AI outputs. Emphasize structured interviews, blind skills tests, bilingual assessments, and careful interpretation of scores so that no single metric dominates decisions.

Local calibration: Adapt tools to Kazakh and Russian language use and to local résumé formats. Build or fine tune models on local data to improve fairness and accuracy. Define success as measurable reductions in subgroup gaps during trials.

Ethical and legal framework: Update policy to cover transparency, candidate rights to explanations and appeals, and vendor security requirements. Consider independent certification for hiring tools that pass bias and privacy checks.

Ongoing bias auditing: Review funnel metrics on a regular cadence. Monitor demographic parity differences, equal opportunity gaps, calibration by subgroup, and the adverse impact ratio. Adjust thresholds, features, or retrain models when gaps persist.

Human oversight and learning loops: Keep final decisions with structured human interviews. Allow justified overrides of AI rankings and feed those cases back to improve models. Publicize positive performance outcomes to build user trust.

Future research: Compare AI assisted cohorts to traditional cohorts on performance, retention, and diversity outcomes in Kazakhstan. Study candidate perceptions of fairness and usability. Examine how introducing AI shifts SME leadership norms around evidence based hiring and inclusion.

V. Conclusion

This research set out to identify the observable biases in SME hiring practices in Kazakhstan and to evaluate how AI, utilizing behavioral and psychometric signals, can mitigate these biases. The findings clearly highlight that SME hiring in Kazakhstan is affected by multiple biases: personal connections often trump merit (nepotism), entrenched gender stereotypes limit women's opportunities, ethnic prejudices (amplified by recent events) influence callback rates, and vulnerable groups like the disabled or inexperienced are systematically sidelined due to unfounded assumptions(Syzdykova & Azretbergenova, 2025; Abdulla & Mourelatos, 2025; UN Women, 2022). These biases not only raise equity concerns but also deprive SMEs of potentially high-performing talent, ultimately impeding business growth and innovation.

On the optimistic side, the study demonstrates that AI technologies hold significant promise in counteracting these biases. By shifting the focus to candidates' actual skills, behaviors, and attributes – measured through objective means – AI can dilute the influence of human prejudices. For example, an AI-driven personality and cognitive assessment can reveal a candidate's strengths devoid of gender or ethnic context(Benjamin, 2025), a structured video interview analysis can ensure each candidate is judged uniformly on communication and problem-solving indicators(Benjamin, 2025), and machine learning models can flag the best candidates based on data rather than connections. The net effect is a hiring process that is fairer and more meritocratic, wherein decisions are justified by evidence of candidate fit rather than subjective bias. In a conceptual sense, AI serves as a "bias buffer" – it intercepts and filters out much of the bias that might occur in a traditional hiring workflow.

However, a recurring theme in our analysis is that AI is a tool, not a panacea. Its effectiveness depends on thoughtful implementation. If misused or poorly understood, AI could inadvertently introduce new biases or create the illusion of fairness where bias still lurks beneath. Therefore, to truly realize the bias-mitigation benefits, SMEs must combine AI adoption with a commitment to ethical practices and continuous learning. They should use AI outputs as enhancements to human judgment, not as unquestionable verdicts. Human oversight is essential to catch errors, interpret nuanced qualities, and ensure that the algorithm's recommendations align with the company's values and specific context. Equally, there must be vigilance to keep the AI itself fair – regularly auditing algorithms for biased patterns and updating them as needed.

The practical significance of these findings is substantial. For SME owners and managers in Kazakhstan (and similar emerging economies), embracing AI-driven hiring could mean accessing a wider talent pool and building more capable, diverse teams than ever before. In a marketplace that is increasingly competitive and dynamic, this translates to better innovation and performance. Moreover, doing so can enhance the company's reputation as an equal-opportunity employer, which can have positive feedback effects (attracting even more diverse talent and possibly customers who value inclusivity). On a societal level, reducing biases in SME hiring contributes to addressing unemployment and underemployment among marginalized groups – a step towards more inclusive economic growth. For Kazakhstan, which has articulated goals around modernizing its economy and increasing social equity, the adoption of fair AI hiring practices by thousands of SMEs could collectively move the needle on national labor market outcomes.

In conclusion, AI offers a viable pathway to mitigate long-standing hiring biases, but it must be pursued with careful design and a balanced perspective. Our research underscores that biases—whether based on kinship, gender, ethnicity, or disability—are not intractable; they can be recognized and countered by leveraging technology and science-based assessments. The future of hiring in SMEs may well be one where human intuition and machine objectivity work hand in hand: the machine ensures no worthy candidate is overlooked due to prejudice, and the human ensures that compassion, ethics, and cultural fit remain part of the equation. Such a synergy could lead to hiring decisions that are not only more just, but also more effective.

Perspectives for the Future: To fully harness AI's potential in creating fair hiring landscapes, continued collaboration between technologists, business leaders, and policymakers is vital. Investment in localized AI solutions (reflecting Kazakhstani language and cultural context) will enhance tool effectiveness. As more data becomes available from AI-mediated hiring, there is an opportunity to refine models to be even more predictive of employee success, further convincing businesses of the value of unbiased hiring. It will also be important to monitor and research the long-term impact of these practices: do employees hired through AI processes have better retention and performance? Does workplace diversity measurably improve innovation in SMEs? Initial research suggests yes, but localized studies can validate these benefits in Kazakhstan. The ultimate vision is a virtuous cycle where AI-enabled fair hiring leads to demonstrably better business outcomes, which in turn reinforces the commitment to unbiased practices.

Kazakhstan's SMEs stand at a crossroads of technological adoption and organizational development. By choosing to integrate AI thoughtfully into their HR practices, they can address deep-rooted biases that have long been accepted as "how things are" and set a new standard that talent should rise to the top based on ability alone. In doing so, they not only do what is right – providing equal opportunity – but also what is smart, by building stronger, more diverse teams for the future. The journey to unbiased hiring is a continuous one, but with AI's help, a more equitable and efficient labor market is within reach.

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