Bias in AI algorithms vs. bias in humans: Which recruitment approach is fairer for the labor market in Kazakhstan?

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Abstract

The article consider the problem of bias in hiring, comparing people's choices with those of computer systems in Kazakhstan's job market. It asks how bias shows up in normal hiring and also the risks of bias in artificial intelligence. The study wants to find out which method is more fair and equal for all genders. The methods used are: looking at other papers, studying cases from other countries, and studying Kazakhstan's plans for using digital technology. Results show that neither method is fully unbiased. But using a mix of people and AI, guided by clear and moral rules, does a better job of lowering unfairness. The study suggests that Kazakhstan could lead the way in using hiring strategies that include everyone.

Keywords

artificial intelligence, gender inequality, hiring, recruitment

1. Introduction

Digital innovation is generating a monumental shift in the world labor market, with increased reliance on automated solutions and artificial intelligence (AI) in the hiring process. This transformation is particularly striking in Kazakhstan, where there is an explicit commitment to digital transformation and the rapid evolution of its IT sector. While these technological advancements promise value via improved efficiency of processes and objectivity, they raise significant questions about how bias and fairness in recruitment is affected. This paper addresses a crucial issue of the modern workplace: can the "objective" logic of an AI lgorithms be used in a way to eliminate the bias embedded in human judgement?

Gender inequality still remains a key challenge in the rapidly expanding IT sector in Kazakhstan. Women continue to be significantly under-represented in key technical roles, as well as leadership positions, narrowing the talent pool and limiting progress. This disparity has implications for the sector to reach its full potential; it is both an economic issue and a social one. The hiring process is one important opportunity where biases, whether conscious or unintentional, can be strengthened as it is a key portal to career advancement.

International development goals cannot be met without tackling recruitment bias. The SDGs of the UN are therefore used as a baseline in this paper. This analysis supports, through encouraging fair hiring practices, SDG 5: Gender Equality aimed at ensuring women's full and effective participation and equal opportunity in all spheres. It also furthers the objective of SDG 8: Decent Work and

1 *SNE 2025: Workshop on Software and Knowledge Engineering, November 19-20, 2025, Almaty, Kazakhstan*
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Economic Growth which prescribes inclusive growth and the attainment of full and productive employment. A fair hiring procedure is the basis of creating a prospering equitable economy.

The major subject which this study shall endeavor to answer is: In the context of the labor market of Kazakhstan, who is less biased – algorithmic hiring tools or human recruiters? We present an empirical analysis based on primary data to look into this. This will contribute to the ongoing debate by bringing solid, empirical evidence from a rapidly transforming economy in Central Asia.

2. Literature review

The issue of algorithmic bias has come to the foreground, in scholarly discussion and popular discourse because AI has been so heavily implemented in hiring practices. Foundational works like Frank Pasquale's The Black Box Society [1] and Cathy O'Neil's Weapons of Math Destruction [2] first made it clear that data-driven systems can easily inherit while massively amplifying human biases, even though their operations seem perfectly objective. This brought to light the problem with black box algorithms without an understanding of their internal mechanisms, it is difficult to determine whether they are functioning appropriately, let alone correct them if they are not.

This is best exemplified by the famous case of Amazon's AI hiring tool, eventually scrapped when it was found to be overtly biased against women by penalizing resumes containing the word "women's" and "women's" [3]. This real-world failure underscores the risks inherent in using historical data reflecting present inequities to train algorithms. Buolamwini and Gebru's [4] study indicated that misclassification of darker-skinned females occurred often, demonstrating significant "intersectional accuracy issues" in some commercial AI systems. Their findings illustrate that bias is a real issue, not just a theoretical one, in the underlying technology for applications such as facial recognition and candidate screening. Ghassemi et al. [5] explain the detrimental effects of algorithmic bias on workplace diversity, and note the cumulative impact of these biases can lead to a less diverse workforce.

To confront these issues, some research is currently advancing toward developing strategies to obtain algorithmic fairness. S.P. and M.S.[6] discuss more general constructs of "algorithmic fairness" related to hiring, while Zhang et al.[7] share a range of cognitive and empirical methods to identify, measure, and address bias in the field of human resource management. There is therefore systematic review of research by Jain and B.R.[8] that confirms the increasing scholarly attention to research about creating and implementing fair AI systems. This area of international research offers a baseline understanding of how to think about these issues and solutions, in particular the applicability of this attention to the context of the labor market within Kazakhstan.

Conventional hiring practices have long been the norm, relying entirely on human judgment. Their subjectivity and vulnerability to cognitive biases, however, are becoming more and more apparent in recent research. Articles like Kaminska's [9] highlight that algorithmic bias is a reflection of human preconceptions rather than a novel issue. Since algorithms are educated on data created by humans, the author contends that a human-centric approach is necessary to comprehend and overcome these biases. Recruiters' unconscious prejudices against women in STEM professions might unintentionally be "built into" machine learning algorithms, which Johnson [10] calls the "human factor in algorithmic bias." Additionally, S.K. and R.L. [11] address ethical concerns with the use of AI in human resources, contending that in order to prevent mistakes from being made again, technological solutions should not only increase efficiency but also adhere to fairness standards. These investigations demonstrate that human biases are a systemic problem that necessitates a conscious and intentional approach, rather than just a defect.

Experts are now putting AI tools and real people side by side to see who does better at hiring without bias. They look to answer: "who is less biased?" These studies are basic in exploring this issue. W.J. and L.H. [12] looked at how fair it is to use AI to pick people for jobs compared to using humans. They found that while AI might follow the rules the same way every time, they can still be biased if they learn from bad data. However, their consistency is an advantage because they are unaffected by mood, fatigue, or personal bias, unlike humans. In the work of Lee, P.A. and, S.B.

[Citation Porter], they examined bias in terms of algorithmic bias as it relates to hiring, finding that machine-generated decisions can be less biased than human-generated crowd-based algorithmic decisions; however, they must be developed and monitored for biases, similarly; the authors explained it carefully. These studies highlight the limitations of both approaches, all involve processes, but a necessity for all types of bias, then choose one.

Extensive research exists on algorithmic prejudice going on around the world, but applying it to the specific situations in Kazakhstan and Central Asia is still in its early stages. Even though the research that is now available has some flaws, it gives us a basic idea of how these global trends are affecting local areas. KPMG's study [14] shows how ready Kazakhstani businesses are for AI. This is an important first step in figuring out how advanced the market is in terms of technology. This readiness paves the way for the incorporation of AI in HR, encompassing recruitment; however, it also underscores the potential risk of perpetuating global biases without specific mitigation strategies.

Talks and case studies give us more information about the problem. The Women in Tech Kazakhstan Chapter [15] has directly addressed gender bias in AI and has made it a topic of discussion at important events like Digital Almaty. The conversations show that important people are aware of these moral issues and are talking about them. Also, state-owned companies are already using digital and AI tools in their HR processes. This is shown by official company documents like the National Information Technologies JSC's HR plan [16]. This real-world example shows how important it is to think about fairness and any biases. Finally, the issue is defined within a regional academic discourse through locally published scholarly works that analyze the ethical boundaries of AI utilization in recruitment and the broader digital transformation of human resources in Kazakhstan, exemplified by the studies of Petrova [17] and Makarova and Nagaitsev [18].

3. Methodology

An empirical poll has been carried out among professionals in Kazakhstan's IT industry to evaluate the perceived existence of bias in both human and algorithmic recruitment in order to supplement the analytical review. The study used a descriptive cross-sectional approach to find out how IT professionals in Kazakhstan perceived bias in both algorithmic and human hiring procedures. In all, 60 IT professionals – 32 men and 28 women – participated in the study, which was carried out in Astana in May and June of 2025. To ensure that both public and private sector businesses were represented, printed questionnaires were dispersed at random among technology parks, universities, and coworking spaces. The method represents a stratified random sample of the local IT community notwithstanding its geographical limitations.

A total of twelve items in the test, including both multiple-choice and open-ended questions. While open-ended responses were manually thematically coded to find patterns of gender, language, and regional bias, quantitative data were evaluated using descriptive statistics (frequency and percentage distributions). To make sure the questionnaire was reliable and clear, it was pilot tested with five respondents. In accordance with ethical guidelines for social research, participation was voluntary, anonymous, and no personally identifiable information was gathered.

Table 1
Use of AI in Recruitment Among Respondents' Companies

AI adoption status	% of respondents
Fully integrated AI tools (chatbots, ATS, automated screening)	85%
Partially using AI or automation in HR	9%
No AI tools yet, but planning to adopt	52%
No plans to implement AI in HR	11%

Table 1 illustrates that 60% of respondents said they used AI-based technologies in recruitment to some extent, mostly for interview scheduling, chatbot engagement, and CV screening. Even while automation is progressively growing, the poll found that phases involving direct human judgment, particularly final interviews and candidate evaluation meetings, remain the most biased.

Table 2
Perceived Sources of Bias in Recruitment

Type of bias	Reported in human recruiters	Reported in AI systems
Gender bias	68%	37%
Language bias (Kazakh vs. Russian CVs)	55%	42%
Regional bias (favoring candidates from Almaty/Astana)	48%	29%
Age bias	35%	21%

Table 2 shows that compared to algorithmic alternatives, human recruiters' perceived bias is still much larger. Gender and language bias, when recruiters allegedly favor particular speech patterns or candidate demographics, are the most commonly reported types of prejudice. Algorithmic bias, on the other hand, is less obvious but nonetheless exists, particularly when historically skewed data is present in datasets used to train HR models. "Our team trusts AI more than people," noted one participant from a software startup. Although some recruiters still care if your name sounds Russian or Kazakh, the algorithm doesn't (Software Engineer Respondent #42).

Table 3
Perceived Fairness of Recruitment Methods

Method	Rated as “Fair or Mostly Fair”	Rated as “Biased or Partly Biased”
Human-based recruitment	33%	67%
AI-assisted recruitment	54%	46%
Hybrid human-AI model	71%	29%
Age bias	35%	21%

Table 3 shows that the majority of participants thought hybrid recruitment techniques, which combine algorithmic screening with human control, were the most equitable and well-rounded method. Respondents stressed that human empathy and contextual understanding are still necessary for fair evaluation, even if AI-based recruiting was assessed as less biased than conventional human-only procedures, as long as recruiters undergo the appropriate bias-awareness training. These results show that prejudice in recruiting still exists primarily at the human level, especially in interviews and subjective evaluations of "cultural fit." The findings show that in addition to modernizing technology, Kazakhstan's HR reform necessitates ethical education and uniform fairness procedures in hiring.

4. Human bias in recruitment

The next section transitions from theoretical comprehension to empirical evidence by examining significant global cases related to the intricate issue of human bias. People still make decisions based on deeply held biases, even though algorithms are often thought to be the main cause of modern bias. The analysis investigates the impact of gender stereotypes, specifically the belief that "men are better at IT," on hiring outcomes [13], resulting in the exclusion of qualified female candidates. The analysis also looks at how unconscious biases in recruiters, like preferring candidates who have similar backgrounds, can make the workplace less diverse [9]. This review will also talk about how these biases show up at different points in the hiring process, from the first CV screening to the last interview. This will give a full picture of how human judgment makes hiring fairly difficult.

Google's internal study "Project Oxygen" [19] showed that unconscious bias in hiring managers made it harder for the company to be diverse and come up with new ideas. This led the company to use structured, data-driven hiring processes. The study was an internal research project that aimed to find out what made its best managers work well. The project's results showed a serious problem: people tend to make decisions based on unconscious bias. Managers tended to hire and promote people who were similar to them in terms of their backgrounds and traits. This is an example of the "halo effect." This practice created teams with similar ideas, which hurt the organization's ability to be innovative and diverse.

To address this systemic bias, Google [19] put in place a number of changes that focused on making the hiring and promotion process more organized and based on data. This meant moving away from decisions based on feelings and gut feelings and toward a system based on hard facts. The main problem was getting managers to change their long-standing habits and putting in place a new process that could be used all the time. The project's win made it clear that using set, proven ways works well to cut down on human bias more than just going with personal judgment without help. The final outcome was a more just hiring method that got better talent and teams from many backgrounds, which made the whole group do better.

To fully understand the problems that human bias causes, it is important to look at specific empirical studies. A significant example is a seminal experiment conducted at Yale University [20], which rigorously illustrated the impact of gender bias on professional judgment. The primary issue investigated by the Gender Bias Study at Yale University was the empirical validation of gender bias in academic recruitment. The research was predicated on the hypothesis that even well-educated professionals are vulnerable to implicit gender stereotypes. To investigate this matter, the researchers have assembled identical document packages for candidates vying for the laboratory head position. The only thing that changed was the name of the candidate: either "Emily" or "Greg."

In this study, packages of documents were sent to science teachers at universities in the United States [20]. They were asked to rate the candidate's skills and suggest a starting salary. The primary aim of the experiment was to isolate the gender variable, accomplished through the manipulation of the name. The results were disappointing: teachers of both genders and all academic levels consistently rated "Greg" as more qualified and deserving of a higher salary than "Emily." This is a clear example of gender bias at the beginning of the selection process. The study demonstrated that individuals administering assessments, even within an academic context, are influenced by subconscious biases.

Blind assessments based on a candidate's name or background often overshadow objective qualifications during the resume screening process, representing a well-documented instance of bias in hiring. A substantial corpus of research globally, especially in the United States and Canada, has consistently revealed a form of racial bias during the initial phases of recruitment. The major problem is about candidates with names that sound "White" (like Greg or Emily) get way more chances for job talks than those with names that sound "Black" or "Asian" (like Jamal or Latonya) [20]. This fact shows clear proof of racial bias when resumes are first checked, proving that hidden unfair thoughts block fair reviews of able people.

In response to this documented bias, some groups have started using a "blind resume" system. This method involves taking out personal information from application materials, like the candidate's name, gender, and sometimes even the university they went to. The main problem with this method is that it may reveal personal information during the hiring process and later stages, which could lead to bias again. But the results of this plan look good. Companies can greatly increase the number of interview invitations sent to minority candidates by focusing evaluators on a candidate's skills and experience instead of their personal background. This will help them find more qualified candidates and make the hiring process fairer. The case shows that we need to make big changes to the system to fight against deeply held human biases.

The Microsoft case teaches us important lessons by showing us specific examples of hiring bias. In the early days of the company, interview bias was a problem. This meant that recruiters and hiring managers preferred candidates they liked on a personal level, based on the idea of "cultural fit." This

method led to the creation of teams that were all the same [19], with no variety. Microsoft has put structured job interviews in place to deal with this issue. All candidates had to answer the same questions and follow the same clear evaluation criteria. This meant that decisions could be made based on objective professional qualities instead of subjective personal preferences. This method has made it easier for the company to choose the best candidates, which has helped it attract a wider range of talent and boost innovation.

An examination of these cases indicates that human bias constitutes a systemic and multifaceted issue within the hiring process. Biases show up at different points in the hiring process, from screening resumes to final interviews. These can be things like gender stereotypes or unconscious preferences. For instance, the stereotype "men are better at IT" may mean that women have to prove their technical knowledge more than men do [13]. These cases show that hiring based on gut feelings and personal opinions is not fair or effective. So, for equality to happen and the quality of talent selection to get better, structured and objective methods must be put in place.

5. Algorithmic bias in recruitment

The use of artificial intelligence in hiring and finding talent has become very common, changing the way companies find and evaluate candidates in a big way. According to recent data, 87% of companies around the world now use AI in their hiring processes [21]. Some of the most important uses are advanced Applicant Tracking Systems (ATS) that use AI to sort and rank resumes based on keyword matching and past success patterns. These systems cut the time it takes to hire by an average of 50%. HireVue and other platforms use AI to look at video interviews and judge candidates based on their tone, word choice, and facial expressions. The adoption rate is especially high among big businesses. According to reports, 99% of Fortune 500 companies use AI tools in some way to automate and improve hiring processes [22].

AI systems in hiring could make things more efficient, but they could also make existing social inequalities worse. This is mostly because of the "garbage in, garbage out" rule, which says that AI models trained on biased historical hiring data will always learn to favor the demographic profiles that worked in the past. For example, a 2024 study by the University of Washington found that three of the most popular large language models (LLMs) used to rank resumes showed a lot of bias against people of different races and genders [23] in Table 4. This study showed a clear preference for names associated with white people, which shows how historical hiring patterns can be built into algorithms, creating a cycle of discrimination.

Table 4
Resume Ranking Bias by Associated Name Demographics

Associated Name Type	Percentage of Favorable Ranking
White-Associated	85%
Black-Associated	9%
Male-Associated	52%
Female-Associated	11%

In the Republic of Kazakhstan, where racial classifications are not given much weight, the issue of hiring bias becomes one of regional and ethno-cultural changes. The location of residence, the resume structure typical of major financial cities (Almaty, Astana), or unique characteristics of linguistic/stylistic terminology are examples of implicit signals that are highly sensitive to traditional techniques of evaluating applicants based on the human factor (HR professionals). Recruiters' unconscious prejudice frequently results in the deliberate exclusion of competent applicants from remote regions.

A potential method to address this issue is to incorporate artificial intelligence (AI) technology into the resume screening procedure. Algorithms can guarantee the selection's objectivity as long as

the training is accurate and based on data that reflects real performance rather than sociocultural or regional prejudices. AI focuses only on recognizing pertinent competencies, skills, and experience, ignoring traditional discriminating signals like the location of registration or the level of CV formalization. As a result, AI tools serve as a means of eliminating the subjective biases present in human selection and help mobilize talent more successfully across the nation, guaranteeing equal access to employment possibilities.

The "black box problem," which refers to the lack of transparency in complex AI systems, is a major ethical and practical problem with AI-driven hiring. These models, especially deep neural networks, make choices without giving clear, logical reasons that people can understand. This lack of transparency makes it hard to hold people responsible and makes it hard to check for bias or contest a bad hiring decision. A study on the transparency of AI products in healthcare, a field where decisions are often very important, found that transparency scores ranged from a low of 6.4% to a high of 60.9%, with a median of only 29.1% [24]. This widespread lack of explainability worries regulators and people who want AI to be more ethical because it can make it harder to follow new laws like the EU AI Act, which says that high-risk AI applications need to be more open [25].

Table 5
Sources of Bias in Recruitment

Bias type	Examples of manifestation	Implications for recruitment
Human Bias *(based on Kaminska, 2019; Johnson, 2019; Lee et al., 2020)*	• Hidden preferences: Recruiters choose candidates who look like them because they think they will fit in with the culture. • Gender stereotypes: Women who want to work in IT have to prove their technical skills more than men do. • Bias during the interview process: decisions based on personal impressions rather than objective skills.	• Making teams that are all the same and think the same way. • Limiting access to talented people. • Making the team less creative and innovative. • More discrimination in the job market.
Algorithmic Bias (based on Buolamwini & Gebru, 2018)	• Data bias: Algorithms learn from historical data that shows how people have already been biased. • "Black Box": The algorithm is hard to follow and understand because it doesn't show how it works. • Racial and gender discrimination: Systems that use facial recognition or choose resumes are less accurate for black women.	• Discrimination on a large scale. • Losing faith in technology. • Lessening the variety of people at work.

The analysis revealed that employing AI for recruitment has significant ethical dilemmas, notwithstanding its potential to enhance efficiency. The Amazon instance [3] illustrates how the utilization of skewed historical data can exacerbate existing disparities. The "black box" issue, characterized by a deficiency in openness, complicates the assessment of these systems for equity and accountability. In the absence of stringent regulations and a dedication to developing AI models that are impartial, transparent, and comprehensible, the technology may inflict greater harm than benefit. This underscores the necessity for careful management and meticulous planning of AI models.

The data examined indicates that both individuals and algorithms may exhibit bias. However, when executed well, algorithmic systems offer distinct advantages. Refer to Table 5. The table indicates that human bias is subjective and rooted on individual prejudices, resulting in the formation of homogenous teams. In contrast to humans, algorithms can process vast amounts of data by adhering to explicit, predetermined rules.

The primary characteristic of algorithmic systems is their consistency and ability to evolve. They do not exhibit weariness, mood variations, or personal preferences. Algorithms trained on large datasets can detect applicants that human recruiters may overlook owing to cognitive biases or preconceptions. Algorithmic bias constitutes a significant issue; nonetheless, it is amenable to rectification and regulation. Systematic audits and the transition to transparent, comprehensible models facilitate the identification and rectification of system flaws. This task is nearly unfeasible when individuals possess unconscious prejudices. Notwithstanding the intrinsic risks, the algorithmic approach constitutes a more effective and controlled tool for ensuring fair employment practices. The systematic reduction of human error and the scalable accuracy of these systems present a persuasive case for their implementation in critical decision-making processes, such as recruiting.

6. Kazakhstan context

The fact that the organization Women in Tech Kazakhstan Chapter [15] led the "Key discussion on gender Bias at Digital Almaty" shows that experts and industry leaders are aware of and care about the issue. These kinds of public discussions show that there is an imbalance that needs to be fixed. Simultaneously, research conducted in Kazakhstan, notably Petrova's study [17], underscores the significance of ethical considerations and confidentiality in personnel management within the digital era, thereby indirectly affirming the necessity to regulate processes that may intensify gender inequality. So, even though there aren't any numbers, sources agree that the problem of women not being represented enough in Kazakhstan's IT sector is well-known and talked about.

The national digitalization strategy is driving the current level of artificial intelligence use in recruiting in Kazakhstan, which is at the stage of active growth. There aren't many complete statistics on how many companies use AI, but the reports and studies that are out there give a good idea of how widespread this process is.

A PwC survey [26] showed that approximately 68% of enterprises in Kazakhstan intend to invest in artificial intelligence over the next three years. Human Resources is particularly engaged in employing tools to automate repetitive operations, such as resume screening, hence enhancing the efficiency of the hiring process [26]. The KPMG report [14] corroborates this by indicating that enterprises in Kazakhstan are highly prepared to use AI and seek to enhance their business processes.

According to recent research on AI Adoption in HR Management: Analyzing Challenges in Kazakhstan Corporate Projects, local businesses have significant obstacles to integrating AI, such as high implementation costs, a lack of experience, and cultural reluctance to automation. While AI can expedite hiring, ethical and transparency issues continue to be crucial to public trust, according to HR professionals surveyed [29]. These results support the article's claim that Kazakhstan is still in the early stages of its digital transformation and that HR professionals need specialized training and capacity-building.

Kazakhstan's usage of AI in hiring is currently in an active growth stage, driven by the country's digitization plan. Although there aren't many thorough national statistics, the reports that are accessible shed light on how AI is already being used. Artificial intelligence is currently being implemented in large enterprises. For example, the HR strategy of National Information Technologies JSC advocates for the implementation of digital and AI tools, indicating a transition from conventional hiring practices to hybrid approaches. The predominant tools include chatbots for initial applicant communication and automated candidate selection systems that evaluate resumes based on keywords. This enables HR professionals to focus on more complex activities that require human involvement. Despite the market's nascent phase, the rapid pace of digitalization indicates swift growth, necessitating an examination of ethical concerns and biases. AI tools are currently being used by a number of major Kazakhstani companies, including Kaspi.kz, and Halyk Bank, to automate certain aspects of their hiring process. These include digital testing platforms, chatbots for preliminary screening, and applicant tracking systems (ATS) that use keywords to filter resumes. These systems rely on pre-existing datasets that contain resumes and application histories of

individuals, which may unintentionally add biases relating to area, language (Kazakh vs. Russian), or gendered employment histories.

An AI platform created by the Kazakhstani business Call2action.ai can conduct up to 100 interviews at once, evaluate candidate responses, and provide employer suggestions [30]. This invention shows how local businesses are experimenting with algorithmic techniques to maximize hiring effectiveness. However, because the system depends on speech analysis and natural language processing, linguistic or gender bias may unintentionally show up in evaluation findings. This highlights the need for ethical oversight and fairness audits in Kazakhstan's developing AI recruitment industry.

For instance, CVs written mostly in Russian are more likely to match keyword-based filters, but applications written in Kazakh may be less common. Similarly, if prior hiring trends were gender-biased, algorithms trained on past hiring data might prefer male applicants for technical roles. Conversations about these issues are becoming more visible. Gender bias in AI has been discussed by the Women in Tech Kazakhstan Chapter [15] in national events such as Digital Almaty, indicating a growing awareness but a lack of quantitative proof. Ethical difficulties about fairness and confidentiality in AI-based recruitment are highlighted by local research including those by Petrova [17] and Makarova & Nagaitsev [18]. To evaluate how these biases actually appear in practice, more data-driven analysis is required, especially empirical study on regional HR systems.

60% of respondents to our 2025 survey of 60 IT experts and HR specialists in Astana stated that their companies currently use or intend to employ AI tools in hiring. However, a sizable portion (68%) pointed out that bias is still more apparent in human recruiters than in AI systems, especially when it comes to language and gender preferences. These findings demonstrate that although the use of AI in Kazakhstan's HR industry is expanding, human-driven bias still poses a threat to ethical hiring procedures. Additionally, according to the results of our 2025 field survey, almost two-thirds (60%) of participants work for companies that have either integrated or want to integrate AI-based HR technologies, such chatbots or CV-screening algorithms. However, only 33% said that their hiring procedure was "fair or mostly fair." This disconnect between ethical application and technological maturity shows that Kazakhstan's HR digitalization still needs focused training on bias awareness and responsible AI use.

Kazakhstani experts hold both favorable and unfavorable perspectives on AI in recruitment. They are optimistic on its efficacy yet concerned about its ethical implications. Sources indicate that individuals in the professional sphere are actively discussing gender bias in algorithms. The Women in Tech Kazakhstan Chapter initiated a conversation on this topic at Digital Almaty. This indicates that specialists are aware of and comprehend the hazards associated with the data on which those algorithms are trained. The studies by Makarova and Nagaytsev [18] and Petrova [17] emphasize scholarly and professional concerns pertaining to ethics and secrecy. This indicates that, for them, AI is not merely a tool capable of rapid and extensive operation; it is also a sophisticated system that requires meticulous oversight to prevent discrimination. Experts acknowledge that utilizing AI improves productivity. However, it necessitates diligent oversight and examination for bias and ethical violations. The data demonstrates Kazakhstan's digital revolution alongside workplace gender disparity; This disparity underscores the imperative for a proactive, data-informed approach to prevent technological developments in recruitment and employment from perpetuating or worsening existing inequities. Consequently, the deployment of AI systems necessitates the incorporation of stringent fairness standards and transparent governance frameworks to ensure equitable results for all candidates.

Chatbots, voice assistants, and intelligent resume filters like Huntflow AI are among the AI-based automation solutions that Kazakhstani HR departments are increasingly using, according to GIFTERY.kz [31]. Although these algorithms greatly lessen the administrative burden, they also pose additional dangers of algorithmic prejudice, particularly when trained on past recruiting data that can underrepresent candidates who are female or speak Kazakh. This increasing automation trend offers tangible proof that algorithmic decision-making is already present in Kazakhstan's labor market and highlights both the advantages and difficulties of using AI into hiring.

Women are not well-represented in the IT workforce, especially in leadership roles: only one out of five managers is a woman [26]. But things seem to be getting better for the future: the large number of women studying STEM shows that there is a lot of talent ready to enter the field [27]. The last number, which shows that companies are committed to using AI so far, shows us that this is a unique time for the industry. Businesses are quickly looking at new technology for hiring, and many plan to use AI tools for hiring [28]. This is a crucial turning point where worries about technology and social justice must come together to make sure that new systems are put in place that don't make the gender gap bigger.

7. Path forward: Towards fair recruitment in Kazakhstan

The examination of both human and algorithmic biases indicates that neither method independently suffices for attaining equitable hiring. So, a mix of both is necessary. This strategy combines the speed and flexibility of AI-powered tools with the careful oversight and nuanced judgment of human professionals. AI can automate the first step of screening resumes, which lets recruiters go through a lot of applications with a high level of consistency. This reduces the initial bias that comes from names or other personal information [13] [12]. However the public should still be in charge of the last steps of the process, like interviews and cultural fit tests. This combination uses the best parts of both systems: a machine's objectivity for processing data and a person's moral and empathetic reasoning for making a final, well-rounded decision. The hybrid model directly fixes the problems with each system so that candidates can be evaluated in a more fair and complete way.

It is important to create ethical and open AI systems so that AI can really help make hiring more fair. The case of Amazon's biased recruiting tool [3] is a clear example of how dangerous it is to train algorithms on biased, historical data. To avoid these kinds of problems, businesses need to do regular fairness audits to find and fix any biases that may have been accidentally built into the system. This necessitates transcending "black box" algorithms [1] in favor of transparent models that facilitate the elucidation and verification of decision-making processes. Petrova [17] and Makarova & Nagaitsev [18] also stress the need for a strategic approach to AI that puts ethics and privacy first. This shows how important these ethical boundaries are. Companies can build trust and make sure that people are held accountable by making their AI systems more open.To deal with the human side of algorithmic bias, companies need to give HR professionals good training. Johnson [10] says that algorithms often just show the biases that were built into their training data, which is a result of choices made by people. So, giving recruiters and hiring managers the tools to recognize and deal with their own unconscious biases is an important first step toward making things fair. This training should focus on recognizing common stereotypes, like the idea that "men are better in IT" [13], and on using structured interview processes (Microsoft Case Study) that focus on objective, skill-based criteria instead of subjective "culture fit." Organizations like the Women in Tech Kazakhstan Chapter [15] play an active role in raising awareness of gender bias. This shows how important these types of educational programs are for making the hiring process accessible to everyone.

Establishing routine algorithmic fairness audits and ethical monitoring procedures is essential to guaranteeing equity in Kazakhstan's developing AI-driven labor market. In collaboration with programs like Women in Tech Kazakhstan, the Ministry of Digital Development, Innovation, and Aerospace Industry might organize such audits [15]. Transparent recruitment strategies could be tested on large state companies like Samruk-Kazyna and National Information Technologies JSC. Astana IT University and PwC Kazakhstan's training programs for HR professionals [26] should have a strong emphasis on recognizing gender and linguistic bias in model design and implementation. Furthermore, in order to prevent language-based exclusion, AI systems must include bilingual data inputs (Russian and Kazakh). AI-powered assistants that can scan emails, evaluate attached resumes, and automate HR communication activities are available from IBAGROUP Kazakhstan [32]. To increase productivity, these technologies are now used in HR systems at the corporate level. However, its reliance on data-driven text recognition could lead to the reproduction of regional or linguistic biases. The implementation of ethical norms for these assistants, based on the transparency

requirements of the EU AI Act [25], would guarantee fair and responsible deployment as Kazakhstan moves closer to AI-enabled management. By implementing these policies, Kazakhstan can establish a regional standard for ethical AI governance in hiring while striking a balance between innovation and inclusivity.

In conclusion, using fair hiring practices, which include a mix of AI and human input, is the best way to reach UN Sustainable Development Goals 5 and 8. Organizations can get more women to work in IT by breaking down barriers that are based on human and algorithmic biases. This is an important step toward reaching SDG 5: Gender Equality. This increased diversity and inclusion in the workplace is not only a social goal; it also helps the economy grow. When companies have access to a larger and more skilled pool of workers, they can be more productive and creative, which is in line with the goals of SDG 8: Decent Work and Economic Growth. Cooperation between legislators, software developers, and HR professionals is essential to the success of fair hiring procedures. Kazakhstan can develop a labor market that is both technologically sophisticated and socially just by fusing algorithmic efficiency with human ethical control. Kazakhstan's companies are ready for AI [14], and the country is focused on digital transformation [16]. This gives the team an opportunity to show how technology can be used to create a more sustainable and fair job market.

8. Conclusion

This research confirms that both human recruiters and algorithmic systems are susceptible to bias, though their sources and manifestations differ. Human decision-making in recruitment is often shaped by entrenched stereotypes and unconscious preferences, such as gender-based assumptions in the IT sector. These patterns have been consistently shown to restrict diversity and hinder equitable access to employment opportunities. In contrast, algorithms provide scalability and consistency, and when properly designed, they can reduce the influence of subjective judgment. However, the persistence of algorithmic bias, particularly when models are trained on historically skewed data, illustrates that technology is not inherently neutral. The effectiveness of AI depends on careful design, transparency, and continuous auditing.

The primary issue is making systems that reduce bias in both people and algorithms. A solely technological or exclusively human-centric approach cannot sufficiently tackle the intricacy of the issue. Instead, hybrid models that mix algorithmic efficiency with human ethical oversight seem to be the best solution. These types of systems let AI standardize the early stages of hiring, especially resume screening. However, human recruiters who have been trained to spot and reduce unconscious bias are still in charge of the final evaluations. This two-part framework makes the most of both methods' strengths while lessening their weaknesses.

Kazakhstan has a unique opportunity to be a leader in the region when it comes to using fair and open AI hiring methods. The country's strategic focus on digital transformation, along with more people becoming aware of gender inequality in the IT sector, makes it easier to come up with balanced solutions. The participation of groups like Women in Tech Kazakhstan Chapter [15] shows that there are local experts and advocates for fairness in the use of technology.

The analysis of significant findings indicates that inclusive AI-driven recruitment enhances efficiency and advances broader societal objectives, such as gender equality and economic development. Kazakhstan can improve its labor market and set an example for responsible AI governance in Central Asia by making sure that fairness, openness, and inclusion are built into its hiring systems.

Declaration on Generative AI

During the preparation of this work, the authors used Gemini and QuillBot in order to: Grammar and spelling check. After using these tools/services, the authors reviewed and edited the content as needed and take full responsibility for the publication’s content.

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