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THE SOCIO-TECHNICAL IMPACT OF AI IN HRM: THE GENDER PAY GAP IN KAZAKHSTAN

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Abstract. This study investigates how Artificial Intelligence (AI) biases in Human Resource Management (HRM) contribute to the persistent 25.7% gender wage gap in Kazakhstan. The research aims to establish how algorithmic systems, often perceived as «objective», codify historical and structural discrimination into mathematical justifications for unequal pay. Utilizing an integrative literature review methodology, the study analyzed 51 peer-reviewed articles to synthesize diverse theoretical and empirical perspectives on AI's socio-technical impact. The findings identify four themes based on thematic analysis with its critical mechanisms through which bias is automated (historical mirroring, neutrality assumption, the codification of desired salary, the motherhood penalty). By specifically examining the architectural features of dominant national recruitment platforms HeadHunter.kz and Enbek.kz , the research results suggest that as Kazakhstan rapidly adopts digital tools under national initiatives, it risks institutionalizing systemic inequality. The study implies an urgent need for local algorithmic audits and regulatory frameworks to ensure that the technological transition promotes social justice rather than automating the existing wage gap.

Keywords: *human resource management (HRM), gender wage gap, gender inequality, artificial intelligence (AI), vertical segregation.*

АДАМ РЕСУРСТАРЫН БАСҚАРУДАҒЫ ЖАСАНДЫ ИНТЕЛЛЕКТІНІҢ ӘЛЕУМЕТТІК-ТЕХНИКАЛЫҚ ӘСЕРІ: ҚАЗАҚСТАНДАҒЫ ГЕНДЕРЛІК ЕҢБЕКАҚЫ АЛШАҚТЫҒЫ

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Аңдатпа. Бұл зерттеуде адам ресурстарын басқарудағы (HRM) жасанды интеллект (ЖИ) алгоритмдерінің қателіктері Қазақстандағы 25,7% гендерлік еңбекақы алшақтығының сақталуына қалай әсер ететіні қарастырылады. Зерттеудің мақсаты – жиі «объективті» деп қабылданатын алгоритмдік жүйелердің тарихи және құрылымдық кемсітушілікті тең емес еңбекақы төлеудің математикалық негіздемесіне қалай айналдыратынын анықтау. Әдебиеттерге кешенді шолу жасау әдістемесін қолдана отырып, ЖИ-дің әлеуметтік-техникалық әсеріне қатысты түрлі теориялық және эмпирикалық көзқарастарды жинақтау үшін 51 рецензияланған мақала талданды. Тақырыптық талдау нәтижесінде қателіктерді автоматтандыратын төрт негізгі тақырыбы анықталды: тарихи бейнелеу, бейтараптық болжамы, қалаулы жалақыны кодификациялау және аналық мәртебесі үшін кемсітушілік. Зерттеуде еліміздегі басты жұмысқа орналасу платформалары – HeadHunter.kz және Enbek.kz жүйелерінің архитектуралық ерекшеліктеріне ерекше назар аударылған. Зерттеу нәтижелері көрсеткендей, Қазақстан ұлттық бастамалар аясында цифрлық құралдарды қарқынды енгізе отырып, жүйелі теңсіздікті институттандыру қаупіне тап болып отыр. Зерттеу қорытындысы технологиялық көшпелі кезең еңбекақы алшақтығын автоматтандыруға емес, әлеуметтік әділеттілікке қызмет етуі үшін жергілікті алгоритмдік аудит жүргізу мен нормативтік-құқықтық базаны құрудың шұғыл қажеттілігін негіздейді.

Түйін сөздер: *дам ресурстарын басқару (HRM), гендерлік еңбекақы алшақтығы, гендерлік теңсіздік, жасанды интеллект (ЖИ), вертикалды сегментация.*

СОЦИОТЕХНИЧЕСКОЕ ВЛИЯНИЕ ИИ В УПРАВЛЕНИИ ЧЕЛОВЕЧЕСКИМИ РЕСУРСАМИ: ГЕНДЕРНЫЙ РАЗРЫВ В ОПЛАТЕ ТРУДА В КАЗАХСТАНЕ

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Аннотация. В этом исследовании исследуется, как предубеждения в отношении искусственного интеллекта (ИИ) в управлении человеческими ресурсами (HRM) способствуют сохранению 25,7%-ного гендерного разрыва в заработной плате в Казахстане. Цель исследования - установить, как алгоритмические системы, часто воспринимаемые как «объективные», превращают историческую и структурную дискриминацию в математические обоснования неравной оплаты труда. Используя методологию комплексного обзора литературы, в исследовании были проанализированы 51 рецензируемые статьи, чтобы обобщить различные теоретические и эмпирические точки зрения на социально-техническое воздействие искусственного интеллекта. Результаты исследования выявили четыре темы, основанные на тематическом анализе с его важнейшими механизмами, с помощью которых автоматизируется предвзятость (историческое отражение, допущение нейтральности, кодификация желаемой зарплаты, наказание за материнство). Особое внимание уделяется архитектурным особенностям доминирующих национальных платформ по подбору персонала HeadHunter.kz и Enbek.kz. Результаты исследования показывают, что по мере того, как Казахстан быстро внедряет цифровые инструменты в рамках национальных инициатив, существует риск институционализации системного неравенства. Исследование предполагает настоятельную необходимость проведения местных алгоритмических аудитов и создания нормативно-правовой базы для обеспечения того, чтобы технологический переход способствовал социальной справедливости, а не автоматизации существующего разрыва в заработной плате.

Ключевые слова: *управление человеческими ресурсами (HRM), гендерный разрыв в оплате труда, гендерное неравенство, искусственный интеллект (ИИ), вертикальная сегрегация.*

Introduction

In 2026, Kazakhstan will officially observe the "Year of Digitalization and Artificial Intelligence" following an executive order signed by President Kassym-Jomart Tokayev. This initiative, which the President originally introduced during his New Year's Eve address, aims to accelerate the nation's technological evolution [1].

While the national goal is digitalization, it is worth noting the definition of Artificial Intelligence as the capacity of artificial systems, comprising algorithms and software programs, to interpret data, learn from it, and use that knowledge to perform tasks with a level of autonomy comparable to human behavior . In the context of HRM, AI is applied to support or automate processes ranging from recruitment to talent retention, always with the aim of optimizing decision-making, forecasting trends, and improving operational efficiency [2]. Before analyzing AI's role, the context of the Kazakhstani labor market must be established. Research confirms that the wage gap is deeply rooted in structural issues. Although research into this issue in the countries of Central, specifically Kazakhstan, is limited, the most significant factors are the overrepresentation of women in lower-wage industries and their underrepresentation in leadership and high-tech roles [3]. Data from the Eurasian Journal of Gender Studies (2025) shows that concentration in sectors like trade strongly correlates with maintaining the pay gap [4].

Institutional barriers and social attitudes regarding gender roles continue to exert a powerful downward pressure on female wages in Kazakhstan. This systemic discrimination, documented by Yemelina et al (2024), suggests that there is a profound disconnect between human capital and economic reward [3]. In other words, while women are meeting often exceeding educational requirements, the labor market fails to translate these qualifications into job security and pay parity. This suggests that wage is not the result of a lack of human capital (education), but rather a manifestation of structural biases that resist even high levels of professional competence

While it is argued that the disproportionate burden of domestic labor and childcare may discourage women from pursuing high-investment career paths, empirical realities suggest a more nuanced picture. Rather, the literature states that women choose jobs that might offer greater stability and reduced physical rigor, which in turn acts as a secondary driver for the wage gap [5], [6]. The state's prohibition of female labor in 299 specific occupations, which refer to highly paid roles, remains a significant factor in the country's wage gap. However, some authors state that such banning contradicts human rights. It is mostly explained with former Soviet Union (FSU) economies, where there was a gendered economic map mostly prevailing with male domains in the highest-paying sectors [7].

Nonetheless, the «glass ceiling» in Kazakhstan is not merely a result of industry choice, but a product of vertical segregation driven by deep-seated beliefs about family roles. The data reveals a profound disparity in how the institution of marriage is valued by the labor market. In other words, unmarried women consistently earn more than their married or divorced counterparts, yet married men enjoy a staggering 20-30% wage advantage over single men. This suggests that the contribution of marital status to the overall wage gap highlights a systemic bias that prioritizes traditional family structures for men while simultaneously devaluing them for women. Regarding integration of AI systems into Kazakhstani HRM practices, they ingest that 'Married Man' is a predictor of high performance, while 'Married Woman' is a predictor of career stagnation. If an algorithm is tasked to identify a 'stable, high potential leader', it will be highly likely to learn to assign a higher score to married men. Therefore, by treating marriage as an "objective" feature, the AI effectively automates a cultural bias, transforming a social stereotype into a mathematical justification for the wage gap.

Theoretical Framework

According to the data from the Agency for Statistics of the Republic of Kazakhstan (2025), gender wage disparity constituted 25.7%, women earning less than their male counterparts [8]. If gender inequality were eliminated, the resulting surge in labor productivity could mirror global projections, such as those by the McKinsey Global Institute, which suggest that achieving financial gender parity could catalyze a 26 % increase in global GDP by 2025 [9].

To understand the roots of this disparity, it is worth looking beyond biological determinism toward the framework of social constructionism. As posited by Berger and Luckmann, gender roles and the resulting professional hierarchies are not inherent, but rather sociocultural constructs [10]. These ingrained norms and stereotypes dictate the perceived «value» of labor.

Although classical human capital theory states that a narrowing wage gap might be as the result of increasing education and professional credentials of the female labor force, the Kazakhstani labor market exhibits a profound structural contradiction. While women consistently outpace their male counterparts in academic attainment, their professional advancements are frequently exposed to collective stigmatization, particularly, where maternal status is conflated with reduced professional dedication [11]. Consequently, from a socio-technical perspective, this bias might be transformed into computational objectivity as the AI provides mathematical justification for the 25.7% wage gap reported by the Agency for Statistics of the Republic of Kazakhstan.

Table 1. Average Monthly Nominal Earnings of Employees by Gender and Region in Kazakhstan in 2024 [12]

Region / City	Average Male Salary (KZT)	Average Female Salary (KZT)
Abai	372,628	302,710
Akmola	365,895	295,049
Aktobe	442,644	310,367
Almaty Region	346,301	316,152
Atyrau	778,091	425,331
West Kazakhstan	402,257	302,824
Zhambyl	323,009	281,631
Zhetisu	291,301	294,784
Karaganda	442,153	313,551
Kostanay	378,783	310,217
Kyzylorda	380,070	312,408
Mangystau	748,673	372,534
Pavlodar	425,619	316,711
North Kazakhstan	309,311	279,682
Turkistan	320,962	276,733
Ulytau	642,467	389,202
East Kazakhstan	423,910	332,539
Astana (City)	605,963	471,807
Almaty (City)	553,250	435,050
Shymkent (City)	336,966	292,060

The «Stereotype Index» developed by Kenzheali et al. (2024) provides a vital roadmap for identifying the specific biases that AI models are likely to inherit [13]. If automated hiring tools are trained on historical data from second-tier banks, where managerial roles are predominantly male, then the AI will treat 'male' as a prerequisite for 'leadership.' Furthermore, since the study proves women possess superior soft skills that are currently under-rewarded, an AI optimized for 'salary growth' will ignore these vital competencies, focusing instead on the 'mathematical overestimation' of male candidates. Thus, the algorithm does not just reflect the stereotype index, but it scales it.

A significant research, most recently synthesized by Alpysbayev et al. (2024), explores how the gendered division of labor acts as an 'objective' anchor for professional inequality [14]. This perspective suggests that the persistent wage gap is not merely an issue of disparate skill sets, but a result of the structural expectations placed upon women as primary caregivers. Thus, it becomes evident that the labor market disproportionately rewards what is termed «greedy work» involves roles that demand round-the-clock availability and penalize any deviation for domestic duties. Because women in Kazakhstan are still culturally tasked with the bulk of childcare and household management, they are often forced to select «flexible» roles that, while appearing to be a result of objective choice, carry a significant financial penalty. This creates a nonlinear relationship between hours worked and total compensation, where those unable to commit to «greedy» schedules are systematically marginalized from high-earning trajectories.

If an AI model is programmed to optimize for 'revenue per employee,' it will naturally prioritize 'greedy' work patterns. Because the algorithm cannot 'see' the domestic labor being performed at home, it interprets a woman's need for flexibility not as a social constraint, but as a lack of economic utility. Thus, the algorithm does not just observe the Kazakhstani labor market, but it mathematically enforces its most punishing features.

AI bias, or algorithmic bias, refers to systematic and repeatable errors in AI systems that result in unfair outcomes for specific demographic groups [15]. Two core mechanisms are relevant to the wage gap:

1. Source of Bias: This is the most documented form of bias. Algorithms used in hiring such as automated resume screening, are often trained on historical company data. If, for instance, a lucrative mining company in Kazakhstan historically hired 90% men for high-salary engineering roles, the algorithm learns that being male is a necessary, successful predictor for that job [16], [17].

2. Impact on the Wage Gap: By systematically ranking female candidates lower - even those with identical qualifications - the AI creates an algorithmic glass ceiling, preventing women from accessing the high-wage industries that would narrow the overall gender gap. The high-paying roles remain exclusively male-dominated, enforced by a «neutral» computer system [18].

A primary challenge in achieving algorithmic equity is the phenomenon of proxy discrimination. Even when protected attributes, such as gender, are explicitly excluded from the dataset, which is also known as «fairness through blindness», AI models can reconstruct these categories through «neutral» features. These proxies are variables that correlate strongly with gendered life experiences or professional patterns. For instance, in the Kazakhstani labor market, even if the AI does not see a «Gender» column, it sees «3-year gap in 2021» (Proxy for maternity leave) or «Member of Women's Engineering Club». Consequently, the AI does not «see» «Gender» or «Maternity Leave» columns, but only «neutral» (for example, a degree from a specific university) features to discriminate by proxy.

The integrative review is essential in solving a major problem such as the lack of local empirical AI audits. Unfortunately, there are very few studies specifically testing Kazakhstani HR algorithms for biases. The article is implementing an integrative literature review approach, which might allow the HR algorithm for AI biases. It is worth mentioning that it is known that AI in HR (Amazon's or LinkedIn's) has shown gender bias. As for the local context, there is an estimated 30% wage gap and is rapidly adopting these same AI tools [16]. Thus, without specific local regulation, where «Digital Kazakhstan» is missing, Kazakhstan is likely automating its existing wage gap.

Research Gap: There is no empirical research explaining how AI tools, which are increasingly used in Kazakhstan's «Digital Kazakhstan» initiative, interact with local gender norms and sectoral segregation (e.g., the concentration of women in education/healthcare versus men in oil/gas). To address this critical lack of data, this study poses the following research question: how do AI-driven human resource management systems (HeadHunter.kz , enbek.kz) contribute to the maintenance of the gender wage gap in Kazakhstan through the codification of proxy biases?

Methodology and Research Methods

This article is based on an integrative literature review, aiming to identify, compile, and critically analyze the main benefits and risks associated with the application of AI in Human Resource Management. The integrative review approach was implemented, because it allows for the inclusion of various types of studies enabling a comprehensive and in-depth synthesis of the knowledge available on the subject. This type of review is particularly suitable for exploring complex and multidisciplinary fields of research, such as the application of AI in HRM, where technical, organizational, ethical, and social perspectives coexist. Moreover, the integrative review provides methodological flexibility, allowing not only quantitative analysis, but also qualitative and reflective examination of the content, thereby facilitating the identification of recurring patterns, research gaps, and emerging trends in the literature [2]. To evaluate how digital recruitment operations affect the local landscape, Enbek.kz and HH.kz were selected as specific case examples. As the dominant public and private digital HR platforms in Kazakhstan, their public-facing resume structures and structural requirements (such as the 'expected salary' fields) were examined. This analysis allowed the study to map how international models of algorithmic bias manifest within Kazakhstan's actual digital recruitment infrastructure.

Search Procedures and Inclusion/Exclusion Criteria: The literature search was conducted using the Scopus database, selected for its comprehensiveness, quality, and recognition within the international scientific community. The search was carried out in November 2025, with the aim of identifying relevant publications addressing the application of artificial intelligence in human resource management. The following combinations of search terms were used: «artificial intelligence» OR «AI» AND «gender wage gap» OR «AI biases in gender wage gap» OR «human resource management», with the requirement that these expressions appear in the title of the articles. This restriction was intended to ensure the direct thematic relevance of the selected publications .The initial search yielded 226 articles. Subsequently, filters were applied based on predefined inclusion and exclusion criteria, as outlined below [2]:

Inclusion criteria:

- Articles with titles containing expressions related to AI and HRM
- Peer-reviewed scientific publications Written in English Open access, with full text available
- Direct relevance to the topic of AI application, impacts, benefits, or risks in HRM

Exclusion criteria:

- Documents that were not scientific articles (conference proceedings, editorials, abstracts)
- Publications in languages other than English Articles without full-text access Studies that, despite a relevant title, did not substantively address the proposed theme
- Articles that were formally retracted by publishers, compromising their scientific validity After applying these criteria, the number of articles was reduced from 226 to 58. Of these, seven were not accessible in full text, and one was excluded due to formal retraction, resulting in a final sample of 51 articles, which form the basis of this integrative literature review.

Data Analysis Strategy

Following the final selection of 51 scientific articles, a categorical and thematic analysis of the content was carried out to identify the main perspectives, trends, and gaps in the existing literature on the use of artificial intelligence in human resource management. A structured database in table format was developed, in which each article was systematically coded according to predefined variables, such as:

- Area of AI application (recruitment, training, performance evaluation
- Type of technology used (machine learning, NLP, RPA)
- Main dependent and independent variables analyzed
- Keywords and central themes addressed
- Ethical, social, and organizational implications
- Year of publication, journal title, and type of study

Results

This section presents the empirical findings of the thematic analysis extracted from the final pool of reviewed literature, focusing on the specific mechanisms of algorithmic bias in HRM. This coding process enabled a critical and comparative reading of the articles, allowing for the identification of recurring patterns, thematic frequencies, methodological approaches, and facilitating or inhibiting factors for the adoption of AI in organizational contexts. The analysis was conducted manually, supported by organization tools such as Microsoft Excel, allowing for the systematization of the data into relevant analytical categories. This strategy facilitated an integrative synthesis of the findings, grounded in consolidated evidence from literature, without resorting to formal statistical analysis, as the study's focus is essentially qualitative and descriptive.

1. In the identification phase, an iterative search was conducted across five major electronic scientific databases in late 2019, constituting 226 records: Scopus (114), Web of Science (81), Science Direct (19) and IEEE Explore (12).

2. Screening Phase involved narrowing the results to relevant, unique peer-reviewed works, where 113 duplicates were identified and removed from the initial pool. The remaining records were screened by title and abstract. 41 records were excluded for not being peer-reviewed journal articles, conference papers, or reviews (books, working papers, or dissertations). After this phase, 58 publications were moved forward for full-text eligibility assessment.

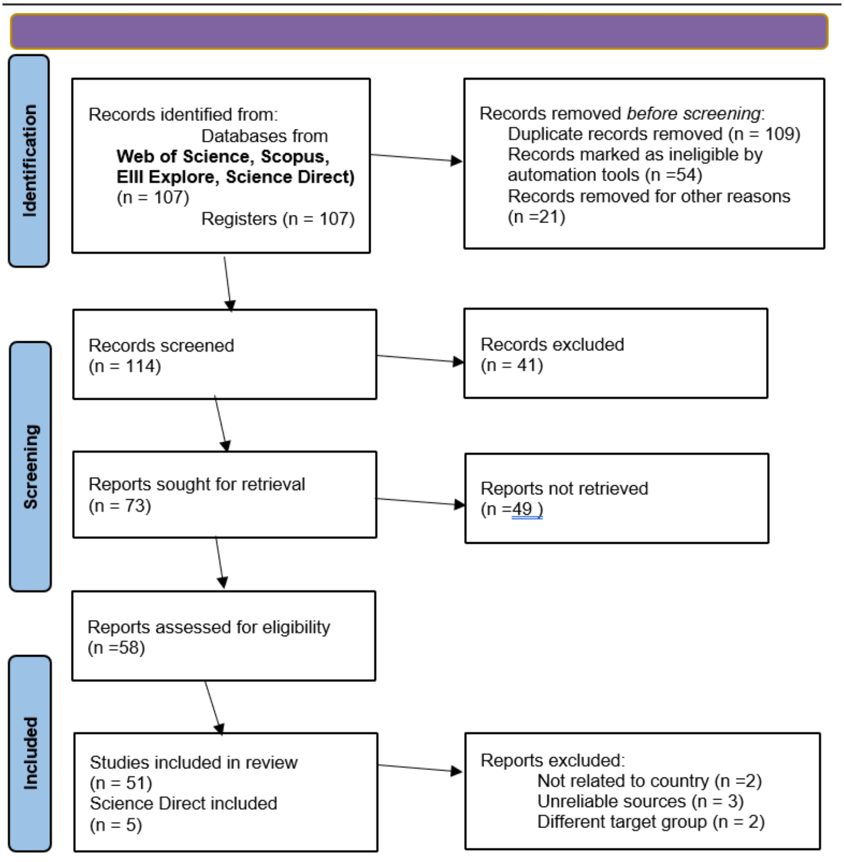
3. Inclusion Phase involved completing the systematic screening and eligibility

checks, 51 articles included in the final review for detailed qualitative analysis. During the detailed full-text review, it was ensured that they fit the specific scope of roles of AI biases in Human Resources Management, specifically, in the gender wage gap in Kazakhstan.

To bridge the gap between theoretical review and a highly relevant, context-specific study, local platforms like HeadHunter.kz (hh.kz), Enbek.kz were integrated into the research. A review of the digital recruitment landscape in Kazakhstan reveals that hh.kz remains the dominant market leader. According to 2019 data from SimilarWeb, the platform commanded a staggering 87.65% traffic share among job-seeking websites in the country [20]. Current industry trends confirm that hh.kz maintains its top-tier status, having integrated a Kazakh-language interface since 2014 to better serve the local population.

Under the new decree of "Year of Digitalization and Artificial Intelligence", the government is responsible for executing strategic digital and AI projects, with the Presidential Administration providing direct oversight. The order became active immediately upon signing. Reflecting these new national priorities, the primary objectives for the country's digital and artificial intelligence sectors shows the importance of algorithmic biases happening in the labor market [1].

Figure 1. PRISMA flow diagram, adopted by Page and colleagues [19]



In summary, the results highlight a consistent pattern across global literature where automated HR systems convert historical labor data into biased operational tools, setting the stage for a deeper contextual analysis in the next section.

Discussion

While the previous section categorized the core mechanisms of AI bias, this section interprets these findings within the specific socio-technical landscape of Kazakhstan's labor market. A key question is whether global AI research applies to Kazakhstan platforms like Enbek.kz and HH.kz. Although these portals operate in a specific regional market, they use standard global AI technologies, such as CV parsing, semantic matching, and candidate ranking. Therefore, they naturally inherit the same technical vulnerabilities and algorithmic biases found in international studies.

In Kazakhstan, the gender wage gap is 25.7%. When local recruitment platforms train machine learning models on historical national labor data, the algorithms copy these existing economic gaps and treat them as objective benchmarks. For example, the common feature where users input an "expected salary" interacts with the fact that female specialists in Kazakhstan often ask for lower pay than men. By automating recommendations based on these unequal inputs, local digital HRM platforms directly replicate and reinforce the regional gender pay gap.

Theme 1: «Historical Mirroring». The mechanism of algorithms lies in learning from historical data that reflects existing gendered work segregation. Cohen et al. (2025) found that AI-integrated workflows set wages based on historical patterns that are difficult to remove via simple prompts [21]. This creates a feedback loop where women are systematically steered into traditional roles (like care or administration), while men are channeled into high-paying technical fields.

As for the «Industry Proxy», sectors like Mining and Oil & Gas are high-paying and male-dominated. An AI does not need to see «Gender» to discriminate, but it only needs to see the «Industry» feature. If the AI is programmed to «optimize for high-profit potential», it will automatically favor candidates from these sectors, who are statistically more likely to be men. As for «Education Proxy», graduates from specific technical universities in Kazakhstan may be ranked higher by AI than graduates from pedagogical or medical universities, effectively creating a gender bias based on the vertical segregation of the Kazakhstani education system. It is also worth mentioning that early segregation of genders in education systems, where few girls opt for fields of interest in science, technology, engineering and mathematics [22]. Thus, societal stereotypes feed into education segregation, leading to male-dominated tech fields that create a vicious cycle.

Theme 2: «Neutrality Assumption». The main mechanism is a false belief that AI is «objective», in other words, computers are inherently impartial, but algorithms are actually «opinions formulated in a programming language». Wellner (2020) notes that users are often subordinated to the algorithm, losing their ability to act intentionally or question biased results. This results in discrimination, making them nearly impossible to track or explain bias [23]. As the government pushes for employment digitalization via the Enbek.kz, a single biased proxy can affect the entire national labor market simultaneously.

According to Bujold A. et al. (2024), a critical accountability gap emerges within HR departments when there is a significant disparity between the technical expertise of AI developers and the knowledge of HR professionals [24]. In other words, their research highlights that many HR practitioners lack the necessary technical literacy to critically evaluate the underlying logic of the algorithms they use. As a result, HR managers often accept automated candidates rankings and «Suitability scores» as objective truth rather than questioning them for potential biases. Such discriminatory pattern effectively shields a biased technical system behind mathematical «neutrality». In addition, he argues that users often «subordinate» themselves to algorithms, treating their outputs as truthful pictures of the situation rather than biased social reflections.

Theme 3: «The Codification of "Desired Salary». The result of such a mechanism is that by filtering for «cost-effective» candidates who ask for less, the AI effectively codifies the bias where women are paid less for the same work. According to table 2, seemingly neutral data points, such as ‘expected salary’ and ‘geographic mobility’ function as algorithmic proxies for gender, effectively codifying the existing 20-30% wage gap into an automated HR workflow. Rus et al. (2022) states that simple prompts cannot remove these biases once they are embedded in the recruitment workflow [25]. As the government pushes for the digitization of employment via the Enbek.kz national port, the standardization of algorithms explained below mean that a single biased «proxy» can affect the entire national labor market, rather than just one company.

Theme 4: «The Motherhood Penalty». «Total Work Experience» penalizing Kazakhstani women for career gaps is a well-documented Proxy Bias. Research shows that automated recruitment tools have historically penalized resumes for words or patterns associated with women's life events, such as maternity leave. This results in economic exclusion, as women are ranked lower for leadership positions despite having equal educational qualifications. Criado-Perez (2019), author of «Invisible Women», provides the foundation for «Gender data gap», showing how the exclusion of caregiving roles from «professional data» skews algorithmic decision-making [26]. As a result, even if a female candidate has superior qualifications with interrupted service, the «Suitability Score» is highly likely to be lowered placing women in lower-tier bargaining positions, even rank candidates have superior qualifications. Ultimately, this discussion demonstrates that without targeted regional interventions, local digital recruitment infrastructures will continue to mirror and amplify international systemic inequalities.

Conclusion

The findings of this integrative literature review confirms that the integration of Artificial Intelligence into Human Resource Management is not merely a technical upgrade, but a socio-technical transformation that might lead to significant risks for gender wage gap. By analyzing dominant platforms of national job-seeking traffic, the study identifies that mandatory features such as ‘desired salary’ fields and ‘total work experience’ calculations mathematically codify socialized gender differences into automated filters. Furthemore, according to the findings of thematic analysis of 51 peer-reviewed journals, it is worth mentioning the key four themes.

The phenomenon of «Historical Mirroring» in Kazakhstan’s segregated labor market allows AI systems to create a feedback loop where women are systematically steered into traditional roles (like care or administration), while men are channeled into high-paying technical fields. This technical steering is compounded by the «Neutrality Assumption», where HR professionals, who are lacking the technical literacy in dominant job-seeking platforms like Enbek.kz or HeadHunter.kz , accept biased «Suitability Scores» as objective truths.

As Kazakhstan approaches the 2026 «Year of Digitalization and AI», the lack of local algorithmic audits and regulatory oversight creates an accountability gap that threatens to institutionalize historical biases. To prevent this, the study recommends mandatory bias-testing for state platforms, the removal of gender-proxy fields like career continuity, and expanded intersectional research into how language and marital status interact with algorithmic workflows. Ultimately, the transition to «Digital Kazakhstan» requires a rigorous socio-technical framework to ensure that technological evolution serves as a catalyst for equity rather than a tool for systemic exclusion.

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