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ARTIFICIAL INTELLIGENCE IN RECRUITMENT: EFFECTIVENESS, RISKS AND ETHICAL LIMITATIONS

The article examines the effectiveness, risks, and ethical limitations of artificial intelligence (AI) in recruitment. A distinction is made between deterministic automation, algorithmic systems, machine learning, and generative AI, which makes it possible to avoid equating any digital HR tool with artificial intelligence. Based on a systematized review of recent academic literature, comparative and content analysis, as well as analysis of regulatory documents, the evidence regarding the impact of AI on recruitment performance is synthesized. It is shown that the strongest evidence concerns operational effects: the ability to process large volumes of applications, automate repetitive tasks, support sourcing, screening, matching, and communication, and reduce recruiters' workload. At the same time, the evidence is substantially less conclusive with respect to quality of hire, candidate experience, and the elimination of bias. The article analyzes algorithmic bias, indirect discrimination, opacity, false exclusion of qualified candidates, privacy and information-security risks, automation bias, and the potential dehumanization of recruitment. Particular attention is paid to meaningful human oversight and to the current regulatory framework, including the EU AI Act, the GDPR, and Ukrainian legislation. An author-developed matrix for assessing the appropriateness of AI use in recruitment is proposed. It combines the expected effect, strength of evidence, discrimination and privacy risks, severity of potential error, and the required level of human oversight. Three modes of AI use are substantiated: automation-preferred, AI-assisted decision-making, and human-led decision-making. The principle of proportionality between automation and risk is formulated, according to which the permissible autonomy of an AI system should decrease as the potential harm of an algorithmic outcome increases.

Keywords: artificial intelligence, recruitment, human resource management, algorithmic bias, automated decision-making, human oversight, AI ethics, discrimination.

Problem statement. Recruitment combines information-intensive, repetitive operations with decisions that can materially affect an individual's access to employment. This combination makes it attractive for algorithmic automation while simultaneously creating a need for heightened scrutiny of the consequences of such automation. AI tools are already used for sourcing candidates, screening CVs, matching candidate profiles with vacancies, ranking applicants, automating communication, supporting assessment, and generating recruitment content. However, the presence of a digital or automated function does not by itself mean that artificial intelligence is being used.

The central problem is that operational acceleration of a process does not automatically imply improvement in the quality of a hiring decision. A system may reduce the time required to process applications while simultaneously introducing new sources of error, reproducing historical inequalities, or encouraging recruiters to rely excessively on algorithmic recommendations. Therefore, the relevant question is not whether AI is "effective" in recruitment in general, but under what conditions a specific AI function creates demonstrable managerial value without producing disproportionate legal, ethical, discriminatory, or reputational risks.

Analysis of recent research and publications. Recent literature on AI in recruitment is increasingly structured around several interconnected issues rather than around the mere adoption of technology. Systematic reviews identify

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operational optimization, fairness and justice, and the protection of candidates' rights as key strands of the debate [1; 3; 8–10]. Research on algorithmic fairness shows that bias can arise not only from historical training data but also from feature selection, target variables, model design, deployment context, and human interpretation of algorithmic outputs [2; 4; 5].

Another strand focuses on candidate perceptions and procedural justice. Empirical studies show that transparency, individualized consideration, and the character of human interaction affect how candidates perceive algorithmic selection procedures [6; 7; 22]. At the same time, the literature increasingly moves away from a simple "human versus algorithm" opposition toward a human-AI collaboration perspective, in which the quality of oversight and the actual ability of a person to challenge an automated recommendation become central.

Unresolved aspects of the general problem. Despite the rapid growth of research, the literature remains fragmented in the way technological effectiveness is related to the risks of algorithmic decision-making. Operational benefits, fairness, candidate perceptions, privacy, and legal constraints are often analyzed separately. Less systematized is the question of how the permissible level of automation should vary depending on the specific AI function, the strength of evidence regarding its effect, the severity of potential error, discrimination and privacy risks, explainability, and the possibility of meaningful human oversight. This gap is particularly relevant for Ukrainian employers in the context of the formation of national AI regulation and gradual alignment with the European Union's regulatory environment.

Purpose of the article. The purpose of the article is to substantiate the conditions for effective and responsible use of artificial intelligence at different stages of recruitment by comparing evidence of its impact on recruitment outcomes with algorithmic, discriminatory, ethical, and legal risks, and to develop an authorial matrix for determining an appropriate level of automation and human oversight.

To achieve this purpose, the study systematizes the main applications of AI in recruitment; synthesizes evidence regarding its impact on recruitment performance; identifies key risks; analyzes ethical and current legal requirements; substantiates the role of meaningful human oversight; and develops practical recommendations for HR functions. The methodology combines a systematized literature review, comparative analysis, content analysis, regulatory analysis, synthesis, and matrix modeling. Priority is given to peer-reviewed publications from 2023–2026, while earlier fundamental studies are used where necessary.

Presentation of the main research material. An analysis of AI in recruitment should begin with a conceptual distinction between technologies. Deterministic automation performs predefined actions according to fixed rules and does not necessarily contain an AI component. An applicant tracking system (ATS) may only store, route, or filter applications according to explicitly specified criteria. Machine-learning systems, by contrast, learn patterns from data and use them for classification, ranking, or prediction. Generative AI creates new textual or other content and may support a recruiter in drafting vacancy descriptions, messages, interview summaries, or analytical materials.

The differentiation of digital technologies in recruitment is presented in Table 1.

This distinction is important because the benefits and risks of the technologies differ substantially. Automatic interview scheduling and an algorithmic recommendation to reject an applicant cannot be evaluated according to the same criteria simply because both functions are implemented within one HR platform.

Assessing the effectiveness of AI requires a distinction between operational efficiency and the effectiveness of the staffing decision. The first includes processing speed, labor intensity, recruiter productivity, and scalability, whereas the second concerns the quality of initial selection, candidate – job fit, candidate experience, and quality of hire. This distinction is

Table 1

Distinguishing technological levels in recruitment

№	Technology level	Example in recruitment	AI?
1	Deterministic automation	Automatic receipt confirmation; interview scheduling	No
2	ATS functionality	Storage and routing of applications; rule-based filtering	Not necessarily
3	Algorithmic matching / ranking	Prioritization according to formalized rules or a model	Depends on the technology
4	Machine learning	Classification, prediction, candidate scoring	Yes
5	Generative AI	Vacancy drafts, messages, summaries, support with unstructured text	Yes

Source: compiled by the authors

fundamental because reducing the duration of an individual operation does not by itself demonstrate improvement in the final hiring decision.

The available evidence most consistently supports the potential of AI to automate information-intensive and repetitive recruitment operations. Machine-learning and natural-language-processing systems can support initial CV classification, extraction of skills information, matching of candidate profiles with job requirements, and preliminary screening. Generative AI expands recruiters' supporting capabilities through content creation, communication personalization, summarization, and work with unstructured text. A systematic review of 120 studies by Mori et al. identifies recruitment optimization as one of the three major areas of the scientific debate, alongside fairness and candidates' rights [1].

The most defensible expectations concern increased processing capacity. Unlike manual review, algorithmic systems can process large numbers of candidate profiles without a proportional increase in recruiters' working time. A systematic review of 49 peer-reviewed studies found that automated CV analysis, preliminary screening, and chatbots are among the applications most frequently associated in the literature with productivity gains [8]. Nevertheless, this does not justify automatically extending the positive effect to the entire hiring process. Overall time-to-hire also depends on interview scheduling, managerial decision speed, offer approval, and other stages that may remain outside the AI system.

A similar degree of caution is required when assessing cost-per-hire. Automation may reduce the amount of staff time devoted to repetitive operations and enable a larger applicant flow to be handled without proportional expansion of the recruitment team. However, the economic result also depends on acquisition or development costs, integration, data preparation and governance, employee training, algorithmic auditing, and subsequent monitoring. Accordingly, vendor claims of a universal percentage reduction in cost-per-hire cannot be treated as a general empirically established effect without considering organizational context and the total cost of the technology.

The quality of initial selection and prediction of candidate suitability are more difficult to evaluate. An algorithmic system can consistently apply the same formalized criteria to a large number of applications, potentially reducing variability caused by fatigue, time pressure, or inconsistent recruiter judgment. Yet procedural standardization is not equivalent to criterion validity. A model may consistently apply features that are weakly related to future job performance or that reproduce patterns embedded in historical hiring decisions. Reviews of automated hiring systems continue to identify a gap between technological capabilities and validation in real organizational settings [9; 10].

Universal conclusions about quality of hire are especially difficult to justify. Unlike application-processing speed, quality of hire is a delayed and methodologically complex outcome that may be assessed through employee performance, probation completion, retention, managerial ratings, or other indicators. The causal contribution of a specific AI system is difficult to separate from onboarding quality, leadership, working conditions, and the organizational environment. Therefore, higher classification accuracy in an individual study should not automatically be interpreted as evidence of better hiring quality across organizations.

The impact on candidate experience is likewise ambiguous. Automation can reduce response times, improve communication availability, and provide faster information about selection progress. At the same time, transferring assessment to opaque algorithmic systems may reduce perceived procedural fairness, particularly when candidates do not understand what is being analyzed, how a result was produced, or whether a human review is possible. Empirical studies indicate that transparency can improve some dimensions of perceived fairness, but does not guarantee an overall positive attitude toward algorithmic evaluation [6; 7; 22].

Thus, the strongest evidence supports AI as a tool for scaling information processing and automating selected repetitive operations. Claims of universal reductions in hiring costs, improved candidate experience, higher quality of hire, or elimination of subjectivity require substantially greater caution. Operational efficiency is not equivalent to the effectiveness of a staffing decision.

Potential efficiency gains do not remove the need to assess risks. Unlike ordinary administrative automation, an error in a system that ranks, assesses, or recommends excluding an applicant can directly affect access to employment. AI-related risk should therefore be understood not merely as a technical characteristic of an algorithm, but as the outcome of interactions among data, model design, deployment, recruiter behavior, and organizational context.

Algorithmic bias is one of the most extensively discussed risks. Its origin is not limited to historically biased training data. If a model learns from past hiring decisions or characteristics of employees previously regarded as successful,

it may reproduce patterns formed in an already unequal labor market. Removing direct information about sex, age, or other protected characteristics does not guarantee neutrality because other variables may operate as proxies. The multidisciplinary review by Fabris et al. demonstrates that sources of unfairness can arise throughout the algorithmic hiring pipeline and that there is no universal answer to whether algorithmic systems are less biased than conventional alternatives [2].

The stage at which bias enters the recruitment funnel is particularly important. A discriminatory effect may arise before formal candidate assessment – for example, through targeted job advertising, sourcing, or the creation of an algorithmically recommended candidate pool. Certain groups may consequently be underrepresented among the people who ever receive a realistic opportunity to be considered. Subsequent equal treatment of the already formed applicant pool does not correct this initial distortion. Research on sourcing algorithms shows that an audit limited to the final selection stage may therefore fail to detect inequality generated earlier in the process [11].

A second group of risks concerns limited transparency and explainability. In rule-based systems, it is relatively straightforward to identify why a candidate failed a predefined criterion. In more complex machine-learning models, the relationship between input characteristics and the resulting score may be less evident. The black-box problem becomes especially consequential when an algorithmic score or ranking determines access to the next stage. In such circumstances, limited explainability restricts both the candidate's ability to challenge the outcome and the recruiter's ability to assess whether the recommendation is justified.

Closely related is the risk of false exclusion of qualified candidates. Algorithmic screening necessarily relies on a model of suitability. An unconventional career path, atypical wording of skills, employment gaps, or characteristics underrepresented in training data may affect a candidate's ranking irrespective of actual ability to perform the job. False negatives are particularly important because scaling the model also scales the consequences of a systematic error.

Another set of risks arises from the volume and nature of candidate data. CVs, profiles, test results, communication records, video and audio materials may contain extensive personal information. Risks increase when systems derive additional predictions from behavioral or biometric signals or reuse data collected for one purpose to make further inferences. The availability of a technical capability does not establish that such processing is necessary, proportionate, scientifically valid, or legally permissible.

Risks also arise through interaction between the system and the recruiter. Automation bias refers to a tendency to rely excessively on automated outputs. A numerical score or ranking may appear objective because of its quantitative form even when the model has limited validity or incomplete data. The concept of human-in-the-loop therefore has an important limitation: formal participation of a recruiter in the final decision does not ensure meaningful human oversight if that person cannot understand the system, critically review its recommendation, or realistically override it.

The ethical acceptability of AI recruitment is therefore associated with fairness, transparency, explainability, accountability, privacy, proportionality, and human oversight. Fairness is not reducible to identical application of a model: an identical procedure can produce unequal outcomes when the underlying data, features, or evaluation criteria encode structural inequality. Transparency concerns awareness of the system's role, whereas explainability concerns the ability to interpret a specific result sufficiently for verification and responsible use. Accountability requires that the use of an external technology provider not dissolve the employer's responsibility for staffing decisions.

In EU law, these principles partly acquire binding legal form. Regulation (EU) 2024/1689 (the EU AI Act) lists in Annex III employment-related AI systems intended for recruitment or selection – including targeted job advertising, analysis and filtering of job applications, and evaluation of candidates – as high-risk use cases under the conditions established by the Regulation [12]. This is important because the regulatory approach links the level of obligations to the function and potential consequences of a system rather than to the mere presence of AI.

Article 14 of the EU AI Act establishes human-oversight requirements for high-risk systems. A responsible person must be able to understand relevant capabilities and limitations, correctly interpret outputs, remain aware of automation bias, and have the possibility to disregard, override, reverse, or otherwise intervene in the system's output [12; 13]. Human oversight should therefore be substantive rather than ceremonial.

The GDPR creates a distinct but complementary layer of regulation. Article 22 provides a right not to be subject to a decision based solely on automated processing, including profiling, when it produces legal effects or similarly significantly affects the individual. The Regulation provides specific exceptions and safeguards,

including human intervention, the opportunity to express one's point of view, and the ability to contest a decision [15]. It would therefore be incorrect to describe the GDPR as an absolute prohibition of automated recruitment decisions; the legal assessment depends on the type of processing, degree of automation, consequences, legal basis, and safeguards.

For Ukrainian employers, a dedicated AI regulatory model is still developing. The Law of Ukraine "On Personal Data Protection" remains the basic act governing the processing of personal data [16]. Article 2-1 of the Labour Code of Ukraine prohibits discrimination in the field of labor [17], while the Law of Ukraine "On Principles of Preventing and Combating Discrimination in Ukraine" establishes the broader anti-discrimination framework [18]. The Ministry of Digital Transformation's White Paper and the 2026 initiative to prepare a dedicated AI law demonstrate movement toward a more specialized regulatory model and alignment with European approaches [19; 20].

The synthesis of evidence makes it possible to propose a matrix for assessing the appropriateness of AI use. Its logic is that the same technology may justify different levels of autonomy depending on the function performed, the strength of evidence regarding its effect, the nature of the data, the severity of potential error, and the need for human oversight.

The matrix for assessing the appropriateness of using artificial intelligence in recruitment is presented in Table 2.

Mode I – automation-preferred is appropriate for standardized, reversible, and relatively low-risk operations whose results do not directly determine access to employment. Examples include responses to routine organizational questions and preparation of draft communications.

Mode II – AI-assisted decision-making covers sourcing, screening, matching, and ranking, where an algorithm structures information or produces a recommendation but a person substantively reviews the result.

Mode III – human-led decision-making is appropriate for high-impact functions, including complex candidate assessment, prediction of job success, and recommendations concerning final hiring or rejection.

The key criterion of the matrix is the severity of the consequences of error. The more strongly a system's output affects whether a candidate is seen, progresses to the next stage, or receives an

Table 2

Matrix for assessing the appropriateness of AI use in recruitment

AI function	Expected effect	Evidence	Bias risk	Privacy	Error impact	Human oversight	Mode
AI sourcing	Scale candidate search	Moderate	High	Moderate	Mod.-high	Substantial	II
Targeted job ads	More precise reach	Moderate	High	Mod.-high	High	Substantial	II
CV screening	Speed; scalability	High for operations; lower for selection quality	High	High	High	Critical	II
Matching / ranking	Prioritization; lower workload	Moderate	High	Mod.-high	High	Critical	II
Chatbots	Faster routine responses	Relatively high	Low	Moderate	Mostly low	Selective	I
GenAI recruiter assistant	Time saving; text support	Moderate	Moderate	Mod.-high	Low-mod.	Regular	I–II
Automated assessment	Standardization; scale	Context-dependent	High	High	High	Critical	III
Video / voice / behavior analysis	Additional assessment	Insufficient / mixed	Very high	Very high	Very high	Critical	III / avoid prohibited uses
Job-success prediction	Decision support	Mixed	High	High	Very high	Critical	III
Hiring / rejection recommendation	Final decision support	Mixed	Very high	High	Very high	Maximum	III

Note: I – automation-preferred; II – AI-assisted decision-making; III – human-led decision-making.

Source: developed by the authors on the basis of [1–15; 21]

offer, the lower the acceptable level of autonomy should be. A second criterion is the quality of evidence. Operational speed is easier to demonstrate than long-term quality of hire; therefore, expansion of system autonomy should require stronger evidence of validity than the use of the same technology for an auxiliary task.

On this basis, the study formulates an authorial principle of proportionality between automation and risk: as the potential consequences of error, discrimination and privacy risks increase, and as the evidence or explainability of results decreases, the permissible autonomy of the AI system should decline while the intensity of human oversight should increase.

Practical implementation of AI should begin not with product selection but with definition of the specific recruitment problem and the KPI that the technology is intended to improve. For automated communication, this may be response time; for screening, processing time should be assessed together with the rate of false exclusion; for predictive systems, the validity of the forecast in relation to actual job-relevant outcomes must be established. HR functions should also determine whether AI is necessary at all, because some tasks can be performed more transparently and controllably through ordinary deterministic automation.

Before systems that compare or rank candidates are deployed, the origin and representativeness of data, model criteria, and the pattern of errors should be assessed. HR functions should follow the principle of personal-data minimization, especially when using external generative AI services. The existence of a vendor-generated "fit," "potential," or "success probability" score is not evidence that the score validly predicts a professionally relevant outcome. Employers should request information about the model's intended use, validation criteria, limitations, data characteristics, and the conditions under which claimed performance was established.

The level of human oversight should correspond to the potential consequences. Selective monitoring may be sufficient for auxiliary operations; ranking, screening, and recommendations to exclude a candidate require substantive review. Recruiters should possess the competence, information, and authority necessary to reject an algorithmic recommendation. For high-impact systems, candidates should also have access to an understandable channel through which potentially erroneous outcomes can be reviewed. Monitoring should continue after deployment because changes in applicant populations, vacancies, labor-market conditions, or models themselves may alter system performance.

Accordingly, a practical model of responsible AI use has a cyclical logic: definition of the problem and KPI → assessment of whether AI is necessary → evaluation of data and privacy → validation and fairness assessment → determination of human oversight → information and review mechanisms → monitoring of actual outcomes → reassessment of continued use. This shifts attention from the fact of technology adoption to evidence of managerial value and control of its consequences.

Conclusions. The study demonstrates that the effectiveness of AI in recruitment cannot be treated as a universal characteristic of the technology. Its most defensible use concerns information-intensive, repetitive, and standardized operations where it can increase processing capacity and reduce recruiters' operational workload. At the same time, the evidence does not support automatic extrapolation of these benefits to long-term quality of hire, fairness of selection, or candidate experience.

A fundamental distinction must be made between operational efficiency and the effectiveness of the staffing decision. Faster CV analysis or communication indicates process productivity but does not prove better hiring quality. The major risks are socio-technical and arise from the interaction of data, model design, deployment, recruiter behavior, and organizational context. Algorithmic bias, false exclusion, opacity, excessive personal-data processing, and automation bias are especially consequential.

A human–AI collaboration model with differentiated allocation of functions is therefore preferable. Low-risk and reversible operations may have a high degree of automation; sourcing, screening, matching, and ranking should generally operate in an AI-assisted mode; functions that directly determine professional suitability or hiring and rejection recommendations require human-led decision-making and strong oversight. Ethical principles and legal safeguards should be integrated throughout the AI system's lifecycle rather than applied only after harm occurs.

The scientific novelty of the results lies in developing a risk-oriented approach to determining an appropriate level of automation for recruitment functions. The proposed matrix simultaneously considers the functional purpose of an AI system, the strength of evidence concerning its effect, discrimination and privacy risks, the severity of potential error, and the need for meaningful human oversight. On this basis, three modes of AI use are substantiated and the principle of proportionality between automation and risk is formulated.

The practical significance of the results lies in the possibility of using the matrix by HR functions when selecting and auditing HR-tech solutions, determining the required level of human oversight, and developing internal policies for responsible AI use. Further research should empirically test the matrix in real recruitment processes, examine the long-term impact of AI-assisted recruitment on quality of hire, study candidate responses to different levels of algorithmic intervention, and assess the use of generative AI by Ukrainian HR functions.

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ШТУЧНИЙ ІНТЕЛЕКТ У РЕКРУТИНГУ: ЕФЕКТИВНІСТЬ, РИЗИКИ ТА ЕТИЧНІ ОБМЕЖЕННЯ

Стаття присвячена оцінюванню ефективності, ризиків та етичних обмежень використання штучного інтелекту в рекрутингу. Актуальність дослідження зумовлена поширенням інтелектуальних HR-технологій, які трансформують процеси пошуку, відбору та оцінювання кандидатів, водночас створюючи нові виклики у сфері захисту персональних даних, забезпечення рівних можливостей і відповідального прийняття кадрових рішень. Розмежовано звичайну автоматизацію, алгоритмічні системи, машинне навчання та генеративний ШІ, що дає змогу уникнути некоректного ототожнення будь-якої HR-технології зі штучним інтелектом. На основі систематизованого огляду сучасних наукових праць, порівняльного та нормативно-правового аналізу встановлено, що найбільш переконливою є доказова база щодо операційних ефектів ШІ: масштабування обробки кандидатських даних, автоматизації повторюваних операцій і зниження навантаження на рекрутера. Водночас вплив на якість найму, справедливість відбору та досвід кандидата залишається контекстним і неоднозначним. Систематизовано ризики алгоритмічної упередженості, непрозорості, помилкового виключення кандидатів, надмірної обробки персональних даних, automation bias та дегуманізації рекрутингу. Проаналізовано вимоги EU AI Act, GDPR і чинного українського законодавства. Запропоновано авторську матрицю оцінювання доцільності використання ШІ, яка поєднує доказовість очікуваного ефекту, ризик дискримінації та приватності, тяжкість помилки й необхідність людського контролю. Обґрунтовано три режими застосування ШІ: automation-preferred, AI-assisted decision-making та human-led decision-making, що передбачають диференційований розподіл функцій між алгоритмами та фахівцями з управління персоналом. Сформульовано принцип пропорційності

автоматизації ризику, відповідно до якого автономність AI-системи має зменшуватися зі зростанням потенційної шкоди та невизначеності щодо валідності, справедливості й пояснюваності її результатів.

Практична значущість дослідження полягає в можливості використання запропонованих підходів для обґрунтованого вибору HR-технологій, удосконалення процедур рекрутингу та формування системи відповідального використання ШІ в управлінні персоналом.

Ключові слова: штучний інтелект, рекрутинг, управління персоналом, алгоритмічна упередженість, автоматизоване прийняття рішень, людський контроль, етика штучного інтелекту, дискримінація.

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