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Data-driven approaches in recruitment and personnel selection

Abstract. The purpose of the present study was to investigate the impact of data-driven approaches on the efficiency of recruitment processes in Ukrainian companies. The study was conducted based on a meta-analysis of 87 scientific publications for 2016-2024. Using the Glass-Hedges methodology, the study determined the effectiveness of various analytical tools, with the highest scores demonstrated by predictive analytics with an average effect of 0.82 and CV screening systems with an indicator of 0.75. An expert survey of 24 industry professionals using the Delphi method revealed the priority of accuracy in predicting hiring success with a consensus level of 92% and speed of candidate processing with an 88% rate. Analysis of the practical aspects of implementation based on in-depth interviews with 38 HR directors identified key challenges in technical integration and staff training. The study of the specific features of implementing innovative approaches showed the highest level of digitalisation of recruitment in the IT sector (92.4%) and large companies (87.3%), which correlates with the amount of investment in relevant technologies. The developed predictive models based on the analysis of 78 thousand candidate records and 4.3 thousand completed hiring cycles showed the greatest efficiency of the XGBoost algorithm with an 89.4% accuracy of hiring success prediction and a ROC-AUC of 0.92. Comparative analysis of the effectiveness of automated CV screening systems revealed the advantage of hybrid solutions with a selection accuracy of 92.3% and a processing speed of 620 CVs per hour, while reducing the cost of processing one CV to USD 1.5. An assessment of key performance indicators showed a 43.7% reduction in time-to-hire and a 22.1% increase in quality-of-hire in companies with a data-driven approach compared to the control group, accompanied by a 20.6% increase in retention rates. The integrated assessment of the effects of analytical tools showed the highest efficiency index in the operational component (0.89) and process automation (0.88) with an economic effect (ROI) of 245% and 278%, respectively, which confirmed the feasibility of implementing data-driven approaches in recruiting for Ukrainian companies

Keywords: predictive analytics; automated systems; optimisation algorithms; labour market

INTRODUCTION

A data-driven approach to recruitment is a decision-making system based on the analysis of large amounts of data about candidates and the labour market, which involves collecting and processing information from CVs, social media, and job search platforms to automate the initial screening of candidates. The use of machine learning and artificial intelligence (AI) allows optimising the search for employees, assess the suitability of qualifications for a vacancy, and create a candidate rating system. Analytical models predict the effectiveness of future hiring, factor in the personalised requirements of recruiters, and improve the accuracy of staff selection. This approach helps to reduce human bias, ensures the objectivity of the process, expedites recruitment, and allows adapting the recruitment strategy to changes in the labour market. Tools such as resume text analysis using Natural Language Processing, neural networks for assessing competence matching, and hybrid models (e.g., GLMix with GBDT) are used to improve

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the quality of candidate selection. This approach helps recruiters to focus on the most promising candidates, optimise time and increase the efficiency of the hiring process.

N. Chernenko (2022) studied the application of AI in HR management by analysing the effects of digital technologies on the optimisation of HR processes. The researcher examined the automation of decision-making, forecasting labour needs, increasing the efficiency of management processes, improving motivation systems, and ensuring data security in the context of dynamic changes in the labour market. The analysis of the impact of digitalisation was divided into thematic blocks covering drivers of optimisation of HR processes, risks of algorithmic bias, and mechanisms for monitoring and correcting management decisions. The integration of technological innovations with managerial experience emphasises the synergy of approaches that allows adapting HR policy to the conditions of the modern market. The combination of conventional researcher's analysis with thematic segmentation contributed to a deeper understanding of the effects of digital transformations on the optimisation of HR processes.

L. Piddubna & I. Chuieva (2023) systematised digital tools for optimising HR processes in IT companies, revealing the use of AI, chatbots, cloud solutions, blockchain, distance learning platforms, virtual and augmented reality technologies to automate processes and forecast staffing needs. T. Aizenberg (2024) and O.I. Kravchuk *et al*. (2024) summarised current trends in the implementation of AI tools in international human resources (HR) management, focusing on the benefits of automating recruitment, performance evaluation, staff training, and remuneration management, as well as analysing ethical challenges, including the risks of algorithmic bias, data privacy, and the need to balance technological innovation with the human factor. The integration of the thematic division allows combining the analysis of instrumental capabilities with the consideration of ethical aspects, which contributes to a deeper understanding of the transformation of HR processes under the influence of digital technologies. M. Vedernikov *et al*. (2024) considered the use of digital tools to optimise the processes of recruitment, selection, and retention through the integration of AI technologies, data analytics, video tools, and chatbots, which helps to increase the efficiency of HR departments and make strategic decisions considering the risks of data security and algorithmic bias.

O. Dragan & M. Pylypenko (2024) analysed the influence of innovative technologies on the development of the employer's brand by automating HR processes, optimising recruitment and adaptation, improving internal communications and monitoring the company's reputation, covering key brand components, including corporate culture, working conditions, professional development opportunities, motivation and reward system, which creates the basis for competitive advantages in the labour market, and emphasising the need to invest in staff training, compliance with ethical standards and security of confidential data. O. Bekhter (2025) analysed the effects of digital technologies integration on optimisation of management processes through automation of routine operations, introduction of data analytics systems and AI algorithms for forecasting staffing needs, improving the processes of recruitment and motivation of employees, which contributes to the competitiveness of organisations in the context of intensive digitalisation of the economy.

The influence of AI and automation technologies on human resources management was analysed through the lens of transforming recruitment, training and employee engagement processes involving automated candidate assessment systems, adaptive learning and analytical platforms for sentiment monitoring, which helps to optimise HR processes while factoring in the ethical aspects, including preventing algorithmic bias, ensuring transparency of decision-making, and compliance with data privacy requirements, which creates a basis for the development of integrated models, where technological efficiency meets human control to create a sustainable human resources environment.

Analysis of existing research revealed lack of coverage of the long-term effects of algorithmic management on organisational culture and a lack of empirical data on the effectiveness of digital HR tools in various sectors of the economy. The purpose of the present study was to determine the influence of data-driven approaches on the efficiency of recruitment processes in Ukrainian companies and to develop recommendations for their optimised implementation. Objectives were to develop a methodological framework for integrating data-driven approaches; to evaluate the effectiveness of analytical tools; to investigate the specifics of implementation in companies of varied sizes.

THEORETICAL OVERVIEW

The study of the impact of AI on HR management has been actively developing in 2016-2024, covering various aspects of automation, analytics, recruitment, and talent development. Researchers systematically analyse both technological opportunities and ethical challenges of digital transformation of HR processes in a global context. T. Zimmermann *et al.* (2016) presented Initial studies of technology integration into HR processes, analysing data-driven HR management with a focus on the use of natural language processing technologies to automate candidate screening. This study laid the methodological groundwork for further research into the use of machine learning algorithms in resume analysis and identification of hidden talents, demonstrating the first steps of integrating AI into HR functions at the initial recruitment stage.

The next stage in the development of electronic HR management and recruitment was covered by R.D. Johnson *et al.* (2020), who examined the benefits of electronic HR management for attracting talent through the introduction of intelligent candidate assessment systems. The researchers emphasised the transformation of recruitment processes through the automation of routine operations and the introduction of personalised communications, which has become the basis for the further development of recruitment technologies and deeper integration of AI solutions into HR management practices.

P. Budhwar *et al.* (2022) explored the international context of AI implementation in HR, offering a comprehensive research programme that covers the transformational impact of AI on global HR practices and the ethical aspects of intercultural use of technology. This topic was expanded by L. Piddubna & I. Chuieva (2023), analysing the international practices of using digital technologies in the HR management of IT companies and global practices of implementing innovative solutions to optimise HR processes in a cross-cultural environment.

The transformation of HR analytics and learning using AI was detailed by R. Nyathani (2023a; 2023b), revealing the potential of HR data management for strategic decision-making and implementation of personalised development programmes through adaptive learning platforms. N.K. Siradhana & R.G. Arora (2023) explored the resurgence of AI in the HR field, analysing modern solutions that transform conventional approaches through intelligent talent acquisition and development systems. V. Iyer (2023) examined the revolutionary influence of AI on recruitment processes, exploring the synergy of AI technologies and conventional HR methods.

A. Charlwood & N. Guenole (2022) addressed the ethical aspects and challenges of introducing AI into HR practices, exploring the paradoxes between automation and maintaining a human-centred approach. R. Mohana & B. Revathi (2024) analysed the challenges of HR professionals adapting to the latest technologies, focusing on the transformation of professional roles. O.I. Kravchuk *et al.* (2024) developed this topic by exploring the ethical issues of using employee data in the context of digital transformation and the need to strike a balance between technological efficiency and privacy protection.

N.I. Munshi *et al.* (2023) started a systematic analysis of the use of AI in HR, with researchers considering the introduction of AI technologies in various HR functions, including recruiting, onboarding, training, and development. D.S. Surya Wuisan *et al.* (2023) explored AI integration through the SmartPLS approach, identifying the relationship between technology and business performance. Multifunctional analysis by G. Kaur *et al.* (2023) covered the transformation of conventional HR functions through the introduction of automated decision-making systems, predictive analytics, and personalised approaches to HR management.

Modern studies of 2024 demonstrated the expansion of AI application in HR. O.A. Alabi *et al.* (2024) focused on optimising customer service through HR analytics. A. Chandratreya (2024) and P. Manoharan (2024) presented comprehensive models for implementing AI to optimise HR processes. H. Sjahruddin *et al.* (2024), and N. Govarthanan & P. Anbumani (2024) highlighted the potential of intelligent technologies to ensure objective talent acquisition. T. Aizenberg (2024) analysed current trends in the use of AI tools in international management. O. Dragan & M. Pylypenko (2024) focused on the impact of AI on employer branding, and J. Dima *et al.* (2024) studied the role of the HR triad in the context of technological change. M. Vedernikov *et al.* (2024) analysed the use of digital HR-engineering tools in the context of digitalisation, and M. Faqih *et al.* (2024) investigated the impact of AI on talent acquisition processes, highlighting current opportunities and challenges in modern HR practices.

The most recent research was presented by N. Chernenko (2022), who explored the use of AI to transform traditional HR functions through the automation of routine processes and the use of predictive analytics, and O. Bekhter (2025), who investigated the influence of AI on the transformation of recruitment, training, and engagement processes to optimise the use of HR, demonstrating current trends in the industry and promising areas for the integration of intelligent technologies into HR practices. Thus, the analysis of the scientific literature demonstrated the evolution of AI research in HR from basic data analysis algorithms to integrated HR management systems. The balance between technological innovation and a human-centric approach continues to be a key challenge.

MATERIALS AND METHODS

The study was conducted from September 2023 to December 2014 and was structured into four consecutive stages according to the logic of studying the effects of data-driven approaches on HR processes:

Stage 1. Development of the methodological framework (September-December 2023). The first stage focused on the development of a methodological framework following the Braverman approach to integrating quantitative methods into HR research. A meta-analysis was conducted according to the methodology of L.V. Hedges (1981) to assess the effectiveness of various analytical tools in recruitment practice based on 87 relevant studies. The analysis covered publications describing a total of 217 companies from various sectors of the economy. The research publications were selected using the keywords "HR analytics", "data-driven recruitment", "AI in recruitment", "predictive HR" from Scopus, Web of Science, Google Scholar, and ResearchGate databases for 2016-2023. The criteria for including publications in the meta-analysis were empirical nature of the study, availability of quantitative indicators of the effectiveness of analytical tools, and a sample size of at least 30 companies.

An expert survey was conducted using the Delphi method among 24 industry experts to validate the research tools, using a modified Linstone-Turoff technique (Mahajan, 1976) to reach consensus on key performance indicators of data-driven approaches. The number of experts (n = 24) was determined following the recommendations of G.J. Skulmoski *et al.* (2007) regarding the optimal size of the expert panel for the Delphi method (20-30 people). The criteria for engaging experts were as follows: work experience in the HR field (at least 5 years), practical experience in implementing analytical tools, industry diversity, and availability of specialised expertise in HR analytics. To assess the level of consensus, a 10-point scale of significance of indicators was used, with the coefficient of variation and the level of consistency of experts' opinions calculated.

Stage 2. Collection of empirical data from companies working with Big Data (January-April 2024). At the second stage, a sample of companies was formed for the empirical study using the stratified selection method. Notably, the 217 companies identified in the meta-analysis served as a source of secondary data. For the empirical part of the study, companies operating in Ukraine were selected separately. Initially, 48 potential participating companies were identified. The inclusion criteria were operating in Ukraine, having an HR department or a recruitment specialist, and conducting recruitment procedures at least once a quarter. Of these, 32 companies were identified that met all the selection criteria. The final study involved 12 companies that agreed to provide the necessary information to the study based on anonymity. These companies provided anonymised data from HR systems on their recruitment processes for 2022-2024. A series of in-depth semi-structured interviews was conducted with 38 HR directors and heads of recruitment departments of the companies surveyed. The number of interviews exceeded the number of companies, as the study involved respondents from both head offices and regional divisions.

The audio recordings of the interviews were transcribed and coded using MAXQDA 2023 software for further qualitative analysis using the thematic coding method. A code system was developed to analyse the practical aspects of implementing analytical tools, which included five key categories: technical integration, staff training, data quality, budgeting, and scaling. To assess the subjective perception of the effectiveness of analytical tools, a satisfaction index was developed on a 5-point R. Likert's (1932) scale, where 1 is completely dissatisfied and 5 is completely satisfied.

Stage 3. Building forecasting models (May-September 2024). The total amount of data for analysis was more than 78 thousand records of candidates and 4.3 thousand completed hiring cycles. The analysis was conducted using Python 3.9 programming language with the corresponding libraries (pandas 2.0, scikit-learn 1.2, XGBoost 1.7) according to the Gavin-Thoros methodology. Three types of predictive models were built:

1. A model for predicting hiring success based on the XGBoost algorithm as recommended by Chen and Guestrin.
2. A model for determining the duration of the candidate search based on the Random Forest algorithm according to Brainman's methodology.
3. A neural network model for estimating the probability of employee retention based on the Hinton architecture.

The models were validated using the Bootstrap Aggregating method with a data distribution of 70% for model training and 30% for testing. The models' performance was evaluated by the metrics of forecast accuracy, area under the ROC curve (AUC), F1-score, processing time, and specificity. At the same time, the study analysed the efficiency of automated CV screening systems in the companies studied. Three types of systems were compared: rule-based algorithms, systems based on Natural Language Processing, and hybrid systems. To validate the results, the study used precision, recall, and F1-score metrics.

Stage 4. Statistical processing and data visualisation (October-December 2024). Statistical analysis of quantitative data was performed using the SPSS 27.0 software package. Descriptive statistics methods were employed to summarise the characteristics of the companies studied and inferential statistics, including correlation analysis (Pearson and Spearman coefficient), t-test for independent samples and analysis of variance (ANOVA) to identify statistically significant differences between groups of companies.

To evaluate the integrated impact of data-driven approaches on recruitment processes, a performance index was developed on a scale from 0 to 1, assessing six components: operational efficiency, quality of recruitment, data management, process automation, decision-making, and user experience. The economic effect (ROI) was calculated using formula (1):

$$ROI = ((R-C)/C) \times 100\%, \tag{1}$$

where R is the revenue from implementation, including savings on recruitment costs, reduction in the cost of the hiring process, and ROI from improving the quality of hiring; C is the cost of implementation.

All research procedures followed the ethical standards for conducting research in the social sciences (Code of Ethics..., 2009), and personal data was processed following the requirements of the General Data Protection Regulation (2016) and Ukrainian legislation on personal data protection (Law of Ukraine No. 2297-VI, 2010). A data visualisation system was developed using Tableau 2022.4 and Power BI Desktop tools to create interactive dashboards that reflect key metrics of data-driven approaches in various sectors of the Ukrainian economy.

RESULTS AND DISCUSSION

Overall effectiveness of analytical tools in HR management

The results of the meta-analysis of 87 scientific studies allowed forming a structured matrix of the effectiveness of analytical tools in HR management. The application of the Glass-Hedges methodology involved calculating the standardised difference in mean values and determining the weighting coefficients for each study, considering the sample size and statistical significance of the results. The analysis covered scientific publications for 2016-2024 following the criteria of methodological rigour and sample representativeness, including a minimum sample size of 30 subjects and the use of validated measurement tools (Table 1).

Table 1. Assessment of the effectiveness of analytical tools in recruitment practice based on the results of meta-analysis

Analytical tool	Average size effect (d)	Confidence interval (95%)	Statistical significance (p)	Number of studies (n)
Predictive analytics	0.82	0.76-0.88	<0.001	28
CV screening systems	0.75	0.69-0.81	<0.001	22
Analysis of behavioural patterns	0.71	0.65-0.77	<0.001	19
Process automation	0.68	0.62-0.74	<0.001	18

Source: compiled by the author

The results of the study demonstrated a statistically significant positive influence of all analytical tools on the efficiency of HR management processes, especially in the field of recruitment. Predictive analytics revealed the greatest efficiency with an average effect size of 0.82, which corresponded to a strong positive influence according to Cohen's interpretation of the d-statistic. The value of the confidence interval (0.76-0.88) at $p < 0.001$ confirmed the statistical reliability of the result and allowed extrapolating the conclusions to the general population of HR systems of an analogous type with high probability**.** Resume screening systems also demonstrated high efficiency with a score of 0.75, which indicated a substantial impact on the quality and speed of recruitment processes (Kotlyarevskaya, 2019).

Comparison of findings with previous studies by T. Zimmermann *et al.* (2016) and R.D. Johnson *et al.* (2020) showed a substantial increase in the effectiveness of predictive analytics in recent years, which is caused by the improvement of machine learning algorithms and the accumulation of larger amounts of data for training. The obtained findings exceeded the results presented by G. Kaur *et al.* (2023), where the average effect of analytical tools was estimated at 0.65, which is explained by methodological differences in the sample and the inclusion of more advanced machine learning algorithms in the current study.

An expert survey using the Delphi method among 24 industry experts allowed prioritising key performance indicators of data-driven approaches in HR management. The process included three consecutive rounds of the survey with interim analysis and refinement of the experts' positions. The use of a 10-point rating scale with the calculation of the coefficient of variation and Kendall's consistency index ensured statistical reliability of the results at the level of 95% confidence interval (Table 2).

Table 2. Consensus assessment of key performance indicators for data-driven approaches

Efficiency indicator	Average significance rating (1-10)	Consensus level (%)	Coefficient of variation	Rank of significance
Accuracy in predicting hiring success	9.2	92	0.11	1
Speed of candidate processing	8.8	88	0.13	2
Quality of selection by competence	8.5	85	0.15	3
Optimisation of recruitment costs	8.3	83	0.16	4
Recruitment funnel efficiency	8.1	81	0.18	5
Retention of new employees	7.9	79	0.19	6

Source: compiled by the author

The results of the expert survey showed a prominent level of consistency in the assessment of the priority of performance indicators. The greatest consensus was achieved for the accuracy of predicting hiring success (92%) and the speed of processing candidates (88%). The coefficients of variation for all indicators ranged from 0.11 to 0.19, which, according to the Linstone-Turoff methodology, indicated high consistency of expert opinions and sufficient statistical reliability of the results.

Comparison of the structure of priorities with the data of N.I. Munshi *et al.* (2023), and A. Singh & J. Pandey (2024) demonstrated a coincidence in determining the accuracy of predicting hiring success as a key performance indicator. The obtained results substantially complement previous studies with quantitative indicators of consensus and ranking of the significance of indicators, which creates a methodological basis for the systematic implementation and evaluation of data-driven approaches in HR practice.

The analysis of the relationship between performance indicators revealed a high positive correlation between the accuracy of predicting the success of recruitment and retention of new employees ($r=0.78, p<0.01$), which confirmed the thesis of R. Nyathani (2023a) about the need to use predictive analytics not only for initial selection, but also for long-term forecasting of employee performance in an organisation.

AI and Big Data in employee productivity forecasting

The analysis of the results obtained on the implementation of AI and Big Data technologies allowed determining the level of penetration of analytical tools in HR management practices and assess the effectiveness of their application in various business segments. The study covered companies of various sizes and industries, which ensured that the data was representative of different sectors of the Ukrainian economy.

Table 3 presents the results of the analysis of the level of implementation of data-driven approaches in recruitment by type of company. All the data in this table, including the number of organisations, the level of technology adoption, and the satisfaction index, were obtained from secondary sources – a meta-analysis of 87 scientific publications for 2016-2023. These publications contained information on 217 companies from different countries, of different sizes and industries from different countries. The satisfaction index values reflect aggregated data from the same publications, which used a 5-point Likert scale to assess the subjective perception of the effectiveness of analytical tools. The use of such secondary data from the meta-analysis allowed forming an objective view of global trends in the implementation of data-driven approaches in various sectors of the economy, which created a context for further analysis of the situation in Ukrainian companies.

Table 3. Level of implementation of data-driven approaches in recruitment by type of company

Company profile	Number of organisations	Implementation rate (%)	Satisfaction index (1-5)
Company size			
Large (500+ employees)	45	87.3	4.2
Medium (100-499)	89	62.8	3.8
Small (15-99)	83	31.5	3.4
Industry			
IT	68	92.4	4.5
Manufacturing	52	45.2	3.6
Retail	41	58.7	3.9
Financial sector	29	76.9	4.1
Services	27	39.8	3.5
Total	217	64.5	3.9

Source: generalised by the author of this study based on meta-analysis of 87 scientific publications and empirical research data

The study of the level revealed substantial differences depending on the size of the company and industry. The greatest level of digitalisation of HR processes was observed in the IT sector (92.4%) and in large companies (87.3%), which correlated with the technological readiness and strategic focus on digital transformation of the respective organisations. The lowest adoption rates were recorded in small enterprises (31.5%) and the service sector (39.8%), which was explained by limited resources and the specifics of business processes. The index of satisfaction with the use of analytical tools, measured on a 5-point Likert scale, also had the greatest values in the IT sector (4.5) and large companies (4.2).

The correlation analysis revealed a high positive correlation between the level of technological readiness of companies and the satisfaction index ($r = 0.83$, $p < 0.001$), which confirmed the findings of T. Aizenberg (2024) about the need for a systematic approach to the digital transformation of HR functions. At the same time, a moderate correlation was observed between company size and satisfaction index ($r = 0.62$, $p < 0.01$), which indicated the influence of organisational factors on the success of data-driven approaches.

The interviews with HR directors and heads of recruitment departments helped to identify key thematic clusters regarding the practical aspects of implementing analytical tools. The primary data was used for a deeper analysis of the practical aspects of implementing analytical tools and for developing and testing predictive models. The application of the thematic coding method in the MAXQDA 2023 programme allowed systematising the qualitative data and identify five main thematic clusters, as presented in Table 4.

Table 4. Key thematic clusters for implementing data-driven approaches in recruitment

Thematic cluster	Frequency of mention (%)	Examples of quotes	Key challenges	Solution strategies
Technical integration	92.1	"The most difficult thing is integration with existing systems"	Systems incompatibility	Phased implementation
Staff training	86.8	"It takes time for the team to adapt"	Resistance to change	Systematic training
Data quality	81.6	"Data validity is critical"	Incomplete data	Standardisation of collection
Budgeting	78.9	"ROI is not always obvious at first"	Limited resources	Pilot projects
Scaling	73.7	"It is challenging to scale successful practices"	Different divisions	Flexible adaptation

Source: compiled by the author

An analysis of the frequency of mentioning various aspects of data-driven approaches revealed that the most critical challenge continues to be the technical integration of new solutions with existing HR systems (92.1% of mentions). This result correlates with the findings of M. Vedernikov *et al.* (2024), who also noted technological barriers as the main obstacle to the digitalisation of HR processes. Staff training was the second most significant challenge (86.8% of mentions), which was consistent with the findings of O. Dragan & M. Pylypenko (2024) on the need to invest in the development of HR professionals' competencies.

The analysis of the relationships between the thematic clusters using the mutual information (MI) coefficient revealed a strong connection between the Data Quality and Technical Integration clusters (MI = 0.76), as well as between Staff Training and Scaling (MI = 0.69). This indicated the complex nature of the challenges of implementing data-driven approaches, where technical, organisational and human factors are intricately intertwined.

Respondents from different industries showed differences in prioritising challenges: representatives of the IT sector paid the most attention to data quality (93.2% of mentions in this group), while respondents from the manufacturing sector mentioned technical integration more often (96.7%). This reflected the industry specifics and the level of technological maturity of different sectors of the economy, which was consistent with the findings of L. Piddubna & I. Chuieva (2023) on the uneven digital transformation of different industries.

The study also found a correlation between the level of technological maturity of companies and the effectiveness of predicting employee productivity. Companies with a strong level of technological maturity demonstrated a 32.7% increase in the accuracy of productivity forecasting compared to companies with a basic level of technological maturity. Therewith, the largest increase in efficiency was observed in the transition from basic to medium levels of technological maturity, which indicated the existence of a certain 'efficiency threshold' in the implementation of analytical tools.

The data from the meta-analysis of global companies provided the necessary foundation for further research for several key reasons. Firstly, the analysis of 217 companies from different countries allowed creating valid benchmarks and a system of reference indicators for comparison with the Ukrainian context. This provided an opportunity to objectively assess the level of maturity of data-driven approaches in Ukrainian companies relative to global standards. Secondly, based on global data, the study identified key patterns of implementation of analytical tools in various industries and companies of different sizes. These patterns formed the research hypotheses, which were then tested on a sample of 12 Ukrainian companies. Specifically, the study found that industry specifics (the IT sector shows the greatest level of implementation) and company size (large companies were in the lead) are the determining factors of the intensity of data-driven approaches implementation.

Thirdly, the meta-analysis allowed identifying the most effective analytical tools and approaches used in global practice. This helped to develop a relevant methodological toolkit for the study of Ukrainian companies, including interview questions and focus of analysis. Fourthly, understanding the global context allowed interpreting the findings obtained from the sample of Ukrainian companies in the broader context of global trends. The implementation challenges identified in Table 4 (technical integration, staff training, data quality) can be compared with global data to identify universal and Ukraine-specific aspects.

Effectiveness of data-driven approaches in recruitment

A comparative analysis of the effectiveness of different approaches to automating recruitment processes revealed substantial differences in the performance of CV screening systems depending on the technologies applied. The study covered three types of systems: rule-based, natural language processing, and hybrid solutions that combine both approaches. The results of the evaluation are presented in Table 5.

Table 5. Comparative characteristics of automated CV screening systems

Evaluation parameter	Rule-based systems	Systems based on Natural Language Processing	Hybrid systems	Manual screening
Selection accuracy (%)	76.4	88.7	92.3	84.5
Processing speed (CV/hour)	450	780	620	15
False rejection rate (%)	18.3	8.5	5.2	12.8
Processing cost (USD/CV)	0.8	1.2	1.5	4.2
Recruiter satisfaction (1-5)	3.6	4.2	4.5	3.8
Level of automation (%)	85	92	88	0

Source: compiled by the author

The results of the study showed that hybrid systems provided the highest accuracy of candidate selection (92.3%) and the lowest false rejection rate (5.2%). This figure exceeded the accuracy of conventional manual screening (84.5%) by 7.8 percentage points, which confirmed the findings of N. Govarthanan & P. Anbumani (2024) on the potential of AI tools to improve the quality of candidate selection. Systems based on Natural Language Processing demonstrate the highest speed of CV processing (780 CVs/hour), which is 52 times higher than manual screening (15 CVs/hour). The cost-effectiveness of automated systems was manifested in a significant reduction in the cost of processing one CV compared to manual screening. The lowest cost was provided by rule-based systems (USD 0.8/CV), but they were inferior to other solutions in terms of selection accuracy and false rejection rate. Hybrid systems, despite being the most expensive among automated solutions (1.5 USD/CV), still provided 2.8 times the cost savings compared to manual screening (4.2 USD/CV).

The analysis of recruiter satisfaction, measured on a 5-point scale, revealed the highest scores for hybrid systems (4.5) and systems based on Natural Language Processing (4.2).

This indicated the significance of a balance between automating routine operations and maintaining the possibility of expert control by recruiters, which correlated with the findings of A. Charlwood & N. Guenole (2022) on the need for a human-centred approach to HR process automation. Analysis of variance (ANOVA) revealed statistically significant differences between different types of systems in terms of selection accuracy ($F = 18.7$, $p < 0.001$) and false rejection rate ($F = 22.3$, $p < 0.001$). Post-hoc tests (Tukey HSD) showed that hybrid systems are statistically significantly superior to other types for both indicators ($p<0.01$ for all pairwise comparisons). A comparative analysis of key recruitment performance indicators between companies that had implemented data-driven approaches, and the control group demonstrated considerable advantages of innovative methods across all key performance metrics. The results of the comparison presented in Table 6 were based on data for a 12-month period, which ensured that seasonal fluctuations were factored in and increased the representativeness of the sample.

Table 6. Comparison of key recruitment performance indicators

Indicator	Companies with data-driven approach	Control group	Difference (%)	Statistical significance (p)
Time-to-hire (days)	18.4	32.7	-43.7	<0.001
Cost-per-hire (USD)	820	1250	-34.4	<0.001
Quality-of-hire (1-10)	8.3	6.8	+22.1	<0.001
Retention rate (%)	89.5	74.2	+20.6	<0.001
Offer acceptance rate (%)	82.3	68.9	+19.4	<0.001
Candidate satisfaction (1-10)	8.7	7.2	+20.8	<0.001

Source: compiled by the author of this study

Companies that have implemented data-driven approaches demonstrate substantial advantages in all key recruitment performance indicators. The most significant improvement was observed in the time-to-hire indicator, where the difference was -43.7% in favour of companies with a data-driven approach (18.4 days vs. 32.7 days in the control group, $p<0.001$). This confirmed the findings of V. Iyer (2023) on the potential of analytical tools to expedite recruitment processes. A substantial decrease in cost-per-hire (-34.4%, $p < 0.001$) was accompanied by a simultaneous increase in quality-of-hire by 22.1% ($p<0.001$), which indicated a comprehensive increase in the efficiency of recruitment processes. This result contradicted the conventional speed-quality-cost dilemma, where the improvement of one parameter usually comes at the expense of others, and confirmed the transformational potential of data-driven approaches in HR.

Of significance was the 20.6% ($p < 0.001$) increase in retention rates in companies with a data-driven approach, which indicated the long-term benefits of using analytical tools. This result was consistent with the findings of R. Nyathani (2023b) on the positive effects of analytical tools on staff retention and confirmed the hypothesis of increased staff stability due to more accurate candidate selection. An increase in offer acceptance rate by 19.4% ($p < 0.001$) and candidate satisfaction by 20.8% ($p<0.001$) in companies with a data-driven approach indicated a positive influence of analytical tools on the candidate experience and the company's attractiveness as an employer. This finding correlated with the study by O. Dragan & M. Pylypenko (2024) on the effects of innovative technologies on employer branding.

Regression analysis of the relationship between investment in data-driven tools and recruitment performance indicators revealed a statistically significant relationship ($R^2 = 0.74$, $p < 0.001$). Therewith, investments had the greatest impact on time-to-hire ($\beta = -0.68$, $p < 0.001$) and cost-per-hire ($\beta = -0.62$, $p < 0.001$), and a slightly lower impact on quality-of-hire ($\beta = 0.54$, $p < 0.01$) and retention rate ($\beta = 0.57$, $p < 0.01$). Sectoral analysis of the effectiveness of data-driven approaches in recruitment revealed the greatest benefits in the financial sector (48.9% reduction in time-to-hire) and the IT industry (26.3% increase in quality-of-hire). In the manufacturing sector, the efficiency was somewhat lower (time-to-hire reduction by 38.2%, quality-of-hire increase by 18.7%), which was in line with the findings of L. Piddubna & I. Chuieva (2023) on the sectoral specifics of the implementation of innovative HR technologies.

Predictive modelling for staff turnover analysis

The developed predictive models for optimising HR processes, specifically for analysing staff turnover, demonstrated different levels of efficiency depending on the algorithms and evaluation parameters used. Table 7 showed the results of a comparative analysis of the effectiveness of different predictive models.

Table 7. Comparative analysis of the effectiveness of predictive models in recruitment

Model type	Forecast accuracy (%)	ROC-AUC	F1-score	Processing time (ms)	Specificity (%)
XGBoost (hiring success)	89.4	0.92	0.88	245	91.2
Random Forest (search duration)	84.7	0.87	0.83	318	86.5
Neural network (retention)	82.1	0.85	0.81	412	83.8
Logistic regression	76.3	0.79	0.75	156	78.4
Decision Tree	73.8	0.76	0.72	189	75.9

Source: created by the author

The performance of the predictive models was evaluated based on a comprehensive analysis of various metrics, including prediction accuracy, area under the ROC curve, F1-score, data processing time, and specificity. The results of the study showed that the XGBoost algorithm is the most effective in predicting hiring success with an accuracy of 89.4% and a ROC-AUC of 0.92. These figures are statistically significantly higher than the results of other models (t-test, $p < 0.01$ for all pairwise comparisons).

The Random Forest model used to predict the duration of the candidate search showed the second-best performance with an accuracy of 84.7% and a ROC-AUC of 0.87. The neural network model for predicting employee retention demonstrated an accuracy of 82.1%, which was consistent with the findings of A. Mazlougui & F.Z. Alami (2025) on the potential of neural network architectures for analysing employee turnover in international companies. Conventional models of logistic regression and decision trees demonstrate the lowest performance indicators, but at the same time provide the shortest data processing time, which can be critical for real-time systems. An analysis of the effects of various factors on the accuracy of staff turnover forecasting revealed that the most significant predictors were as follows:

1. Length of service in the organisation (significance coefficient 0.86).
2. History of career growth (significance coefficient 0.82).
3. Engagement level according to surveys (significance coefficient 0.79).
4. Frequency of communication with the manager (significance coefficient 0.75).
5. Participation in corporate training programmes (significance coefficient 0.72).

This conclusion was consistent with Chernenko's (2022) findings, who also identified the key role of engagement and career development in predicting employee retention. At the same time, the present study complemented the previous findings with quantitative indicators of the significance of each factor, which allows for more targeted implementation of measures to reduce staff turnover.

The use of the XGBoost algorithm to predict hiring success revealed non-linear relationships between candidate characteristics and their future performance in the company. The partial dependence analysis showed that the relationship between work experience and hiring success has a U-shape: candidates with minimal (0-1 year) and extensive (over 7 years) experience in the relevant industry demonstrate the best results. This pattern was particularly pronounced for the IT sector and financial companies.

A prominent aspect of using predictive models was their adaptation to the specifics of different industries and types of companies. M.A. Khair *et al.* (2025) emphasised the need to develop industry benchmarks and adapt analytical tools to concrete business contexts. In this study, industry-specific versions of the models were developed for the IT sector, financial institutions, and manufacturing companies, which increased forecasting accuracy by another 3.2-5.8 percentage points compared to the universal models.

An analysis of the models' performance for different forecasting time horizons demonstrated a decrease in accuracy as the forecast period increased. For short-term forecasts (3-6 months), the accuracy of the XGBoost model was 93.7%, for medium-term forecasts (6-12 months) – 87.5%, and for long-term forecasts (over 12 months) – 79.2%. This was in line with the general patterns of predictive modelling and confirmed the need for regular model updates to ensure their effectiveness.

The study paid special attention to the process of model validation. The use of the Bootstrap Aggregating method with cross-validation allowed assessing the stability of forecasts and avoiding over-training of models. The standard error of forecasting was calculated for all models, ranging from 2.1% for XGBoost to 4.7% for the decision tree model. A valuable result of the study was the development of a comprehensive model for predicting employee turnover based on data from several sources. Integration of data from the HR system (demographics, position, salary), performance management system (evaluations, KPIs), training system (training participation, training results) and engagement surveys increased the accuracy of employee retention forecasting to 88.3% compared to 82.1% for the model using only HR system data. An analysis of the practical application of predictive models in the companies studied revealed three main scenarios of use:

1. Proactive identification of employees at high risk of leaving (used by 89.4% of companies).
2. Prediction of candidates' performance at the hiring stage (used by 76.8% of companies).
3. Optimisation of onboarding and adaptation processes (used by 62.5% of companies).

The effectiveness of these scenarios was confirmed by the findings of J.A. Kempker *et al.* (2025), who demonstrated a considerable impact of data-driven approaches on the quality of candidate selection and their further integration into the organisation. This study complements these findings by quantifying the impact of predictive models on key HR metrics in Ukrainian companies.

Companies that implemented predictive models for analysing employee turnover managed to reduce voluntary resignations by 17.3% in the first year of use and by 24.5% in the second year. The ROI from reducing staff turnover was estimated at 1.2-1.8 average annual salaries per retained employee, depending on the complexity of the position and industry. Notably, the effectiveness of predictive models depended heavily on the quality of the data and the regularity of its updates. Companies that invested in a unified data warehouse and automated data collection from various sources demonstrated 18.7% higher forecasting accuracy than companies using fragmented data sources.

Integrated assessment of HR process transformation

An integrated assessment of the impact of data-driven approaches on HR processes was conducted based on a comprehensive analysis of all the aspects of analytical tools implementation studied. The evaluation process involved the synthesis of quantitative and qualitative data obtained at the previous stages of the study, which allowed forming a holistic understanding of the effectiveness of innovative approaches to HR management (Table 8).

Table 8. Integrated assessment of the impact of data-driven approaches on HR processes

Impact aspect	Performance index (0-1)	Level of process transformation (%)	ROI, %	Sustainability of results (months)
Operational efficiency	0.89	78.4	245	18
Quality of selection	0.85	72.6	186	24
Data management	0.82	68.9	162	12
Process automation	0.88	82.3	278	15
Decision-making	0.86	75.7	198	21
User experience	0.83	70.2	156	16

Source: compiled by the author

A comprehensive methodology was employed to calculate the efficiency index, which included an assessment of quantitative indicators and expert opinions on a scale from 0 to 1. The level of process transformation was calculated as a percentage change in key metrics compared to the baseline before the introduction of analytical tools. ROI was calculated using the formula provided in the research methodology, considering direct and indirect economic benefits from the implementation of data-driven approaches. The results of the integrated assessment showed that the greatest efficiency index is observed in the operational component of data-driven approaches (0.89), which correlates with a prominent level of process transformation (78.4%) and significant ROI (245%). This result confirmed the findings of N. Chernenko (2022) on the transformational potential of analytical tools for optimising HR operational processes. Process automation showed the greatest level of transformation (82.3%) and the highest ROI (278%), which can be explained by the high potential for optimising routine operations and a marked reduction in labour costs for their implementation. This conclusion was consistent with the findings of A. Mazlougui & F.Z. Alami (2025), who also noted the highest ROI from the automation of basic HR processes.

The quality of recruitment demonstrates the highest efficiency index (0.85) and the longest sustainability of results (24 months), which indicated the long-term effects of improved recruitment processes on the overall performance of the organisation. This result correlated with the findings of J.A. Kempker *et al.* (2025), who demonstrated a long-term positive effect of implementing data-driven approaches in candidate selection processes. An analysis of the transformation of HR processes by company size revealed the highest level of change in large organisations (average efficiency index of 0.88), slightly lower in medium-sized companies (0.83) and the lowest in small enterprises (0.76). This pattern can be explained by the greater resource capabilities of large companies and the higher level of formalisation of HR processes, which creates better preconditions for their digital transformation.

Sectoral analysis of HR process transformation showed the greatest scores in the IT sector (average efficiency index 0.91) and the financial sector (0.87), which was explained by the greater level of technological maturity of these industries and greater readiness to implement innovative solutions. The lowest scores were observed in the manufacturing sector (0.79) and the service sector (0.77), which was in line with the findings of M.A. Khair *et al.* (2025) on the industry specifics of the digital transformation of HR functions.

The analysis of the relationships between different aspects of the effects of data-driven approaches revealed a strong positive correlation between the indices of operational efficiency and process automation ($r = 0.86$, $p < 0.001$), as well as between the quality of recruitment and decision-making ($r = 0.82$, $p < 0.001$). This indicated the synergistic effect of introducing analytical tools, where improvements in one aspect positively influenced other components of HR processes. The study of the time dynamics of the effectiveness of data-driven approaches revealed a non-linear nature of changes with the most intensive growth during the first 6-12 months after implementation and subsequent stabilisation of indicators. This pattern was in line with the general patterns of innovative technology implementation and confirmed the need for a long-term strategic approach to the digital transformation of HR functions.

A comparative analysis of the effectiveness of different strategies for implementing data-driven approaches revealed the advantage of an incremental approach with the phased introduction of analytical tools (average effectiveness index of 0.87) compared to a radical transformation of all HR processes at the same time (average effectiveness index of 0.79). This conclusion supported the recommendations of J.A. Kempker *et al.* (2025) on the expediency of gradual introduction of innovative HR technologies with gradual adaptation of the organisation to new working methods.

The analysis of the impact of data-driven approaches on the structure of HR functions revealed a tendency to develop new specialisations, including HR analysts, HR machine learning specialists, and HR data management experts. 68.4% of the surveyed companies created new positions directly related to HR analytics and data management, reflecting the structural transformation of HR functions under the influence of digitalisation.

The study of the impact of data-driven approaches on corporate culture revealed positive changes in the perception of the HR function as a strategic business partner. In companies that actively implement analytical tools, the level of trust in HR solutions has increased by 34.7% compared to conventional organisations, and the involvement of line managers in HR processes has increased by 28.9%. This result confirmed the transformational potential of data-driven approaches not only at the operational level, but also at the cultural level of the organisation. The integrated assessment also helped to identify the key success factors for implementing data-driven approaches in HR:

1. Presence of a clear HR digital transformation strategy (impact on the efficiency index: +0.14).

2. Support from top management (impact on the efficiency index: +0.12).

3. Sufficient investment in technology and staff training (impact on the performance index: +0.11).

4. Gradual implementation with clear success metrics (impact on the efficiency index: +0.09).

5. Focus on data quality and data integration (impact on efficiency index: +0.08).

These findings complemented the recommendations of M.A. Khair *et al.* (2025) and N. Chernenko (2022) on the critical success factors of HR digital transformation and provided a quantitative assessment of their influence on the overall effectiveness of data-driven approaches. The results of the integrated assessment of the transformation of HR processes demonstrated a significant positive impact of data-driven approaches on all key aspects of HR management, which was confirmed by high indicators of efficiency, sustainability of results, and economic feasibility. Of particular significance is the complex nature of the transformation, where technological innovations are accompanied by changes in the organisational structure, corporate culture and decision-making approaches.

CONCLUSIONS

The integration of data-driven approaches into recruitment processes demonstrated a substantial positive influence on the efficiency of recruitment in Ukrainian companies. The methodological framework for the implementation of analytical tools, based on a meta-analysis of 87 studies, revealed the greatest efficiency of predictive analytics with a score of 0.82 and CV screening systems with a score of 0.75.

An expert survey of 24 industry professionals showed that accuracy in predicting hiring success is a key performance indicator with a 92% consensus level and an average significance score of 9.2 out of 10. The speed of candidate processing and the quality of competency-based recruitment also received high significance scores of 8.8 and 8.5 respectively, which confirmed the complex nature of the requirements for analytical tools in modern recruitment. The study of the implementation of data-driven approaches in companies of various sizes revealed considerable industry differences. The IT sector (92.4%) and large companies (87.3%) demonstrated the greatest level of recruitment digitalisation. The lowest adoption rates were observed in small businesses (31.5%) and the service sector (39.8%), due to limited resources.

A qualitative analysis of the practical aspects of implementation based on interviews with HR directors revealed critical challenges: technical integration (92.1% of mentions), staff training (86.8%), and data quality (81.6%). Successfully overcoming these challenges requires a phased implementation, systematic training, and standardisation of data collection processes. The developed predictive models based on the analysis of candidate data proved to be highly effective. The XGBoost algorithm demonstrated the greatest accuracy in predicting hiring success (89.4%), while Random Forest is effective in predicting the duration of the search (84.7%). Neural network models provide 82.1% accuracy in predicting employee retention.

The evaluation of automated CV screening systems revealed the advantage of hybrid solutions with a selection accuracy of 92.3% and the lowest false rejection rate of 5.2%. Systems based on Natural Language Processing process 780 CVs per hour while maintaining high quality of selection, which was 52 times higher than manual screening. A comparative analysis of key performance indicators demonstrated significant advantages of companies with a data-driven approach: a 43.7% reduction in time-to-hire, a 34.4% reduction in cost-per-hire, and a 22.1% improvement in hiring quality. The statistical significance of the results was confirmed at the level of $p < 0.001$.

An integrated assessment of the impact of data-driven approaches showed the highest efficiency in the areas of operations (index 0.89) and process automation (index 0.88). The ROI from the implementation of analytical tools was measured at 245% for operational efficiency and 278% for process automation. The key success factors for the implementation of data-driven approaches in HR have been identified: a clear strategy for digital transformation of HR, support from top management, sufficient investment in technology and staff training, phased implementation with clear success metrics, focus on data quality and integration. A promising area for further research is to investigate the long-term effects of data-driven approaches on corporate culture, decision-making processes, and the evolution of the HR profession in the context of growing automation and the use of AI.

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Використання data-driven підходів у рекрутингу та підборі персоналу

Анотація. Метою було дослідження впливу data-driven підходів на ефективність процесів рекрутингу в українських компаніях. Проведено дослідження на основі метааналізу 87 наукових публікацій за 2016-2024 роки. Застосування методики Ґласса-Хеджеса дозволило визначити ефективність різних аналітичних інструментів, де найвищі показники продемонстрували предиктивна аналітика з середнім ефектом 0,82 та системи скринінгу резюме з показником 0,75. Експертне опитування 24 фахівців галузі за дельфійським методом виявило пріоритетність точності прогнозування успішності найму з рівнем консенсусу 92 % та швидкості обробки кандидатів з показником 88 %. Проведений аналіз практичних аспектів впровадження на основі поглиблених інтерв'ю з 38 HR-директорами визначив ключові виклики технічної інтеграції та навчання персоналу. Дослідження особливостей впровадження інноваційних підходів засвідчило найвищий рівень діджиталізації рекрутингу в IT-секторі (92,4 %) та великих компаніях (87,3 %), що корелює з розміром інвестицій у відповідні технології. Розроблені предикативні моделі на основі аналізу 78 тисяч записів щодо кандидатів та 4,3 тисячі завершених циклів найму показали найвищу ефективність алгоритму XGBoost з точністю прогнозування успішності найму 89,4 % та показником ROC-AUC 0,92. Порівняльний аналіз ефективності автоматизованих систем скринінгу резюме виявив перевагу гібридних рішень з точністю відбору 92,3 % та швидкістю обробки 620 резюме на годину при зниженні вартості обробки одного резюме до 1,5 доларів США. Оцінка ключових показників ефективності засвідчила скорочення time-to-hire на 43,7 % та підвищення quality-of-hire на 22,1 % у компаніях з data-driven підходом порівняно з контрольною групою, що супроводжувалося зростанням retention rate на 20,6 %. Інтегрована оцінка впливу аналітичних інструментів показала найвищий індекс ефективності в операційній складовій (0,89) та автоматизації процесів (0,88) з економічним ефектом (ROI) 245 % та 278 % відповідно, що підтверджує доцільність впровадження data-driven підходів у рекрутинг українських компаній

Ключові слова: предиктивна аналітика; автоматизовані системи; алгоритми оптимізації; ринок праці